An Empirical Study for the Application of
the Evidential Reasoning Rule to
Decision Making in Financial Investment

A thesis submitted to the University of Manchester, United Kingdom for the
degree of Doctor of Business Administration in the Faculty of Humanities

December 2016

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Abstract

The aim of this thesis is to explore the adaptability of the Evidential Reasoning (ER) Rule as a method to provide a useful supporting tool for helping investors make decisions on financial investments. Decision making in financial investment often involves conflicting information and subjective judgment of the investors. Accordingly, the ER Rule, extended from the original popular Evidential Reasoning algorithm and developed for MCDM (Multiple Criteria Decision Making), is particularly suited for handling conflicts in information and to allow for judgmental weighting on the sources of evidence.

In order to do so, a specific EIA (Efficient Information Assessment) process modeled by the mass function of Dempster-Shafer Theory has been constructed such that the underlying architecture of the model satisfies the requirement of the ER rule. The fundamental concern is to define and assess “efficient information”. For this purpose, a process denoted the Efficient Information Assessment (EIA) is defined which applies the mass function of Dempster-Shafer theory. Any relevant information selected from an expert’s knowledge database is “efficient” if the data is fully in compliance with the requirement of the ER rule. The logical process of the EIA model proceeds with a set of portfolio strategies from the information recommended by top financial analysts. Then, as a result, the model enables the ER rule to make an evaluation of all strategies for helping investors make decisions.

Experiments were carried out to back-test the investment strategy using data from the China Stock Market & Accounting Research (CSMAR) Database for the four-year period between 2009 and 2012. The data contained more than 270,000 reports from more than 4,600 financial analysts. The risk-adjusted average annual return of the strategy outperformed that of the CSI300 index by as much as 10.69% for an investment horizon of six months, with the p value from Student’s t-test as low as 0.02%. The EIA model serves as the first successful application adapting the ER Rule for a new and effective decision-making process in financial investment, and this work is the only empirical study applying the ER Rule to the opinions of financial analysts, to the best of my knowledge.

Keywords: Decision Making, ER-MCDA, EIA Efficient Information Assessment, Financial Investment, Dempster-Shafer theory, ER Rule, Evidential Reasoning Rule, Financial Analysts, Investment Strategy, Experiments.
Declaration

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Dedication

I would like to dedicate my thesis to my daughters. I hope that she will be proud of her father and that she will be inspired and motivated to pursue her own higher education studies in the future.
Acknowledgement

My daughter had been born for less than one hundred days when I received an offer from Manchester Business School. At that time, I thought that this was perhaps a special gift to come from fate for my life. First of all, I immediately told my mother and my family. I said to my mother that I could comfort my father who was in another world. This was because I had been admitted by Manchester Business School, especially as I had passed the age of fifty-five. A lot of my friends asked me why I was studying for a DBA when I was already many years old and it was not really necessary at my age to study. Generally speaking, a lot of people, who are the same age as me, are focusing on making money, but I determinedly chose to study and to go to England to study even with only a rudimentary knowledge of the English language.

I clearly remember that I had also been asking myself this question: “Why did I study the DBA which was not really appropriate at my age having passed fifty-five and being aware of my destiny (life is half spent before we know what it is)?” Actually, it is a great challenge of my life behind this question. I asked myself if I should act as those who do not wish to pursue this objective. However, I decided that I did not want to leave my destiny unfulfilled and that I wished to achieve a new pinnacle in my life. Therefore, I think I should accept the fact that I am “one of those who don't want millions, but answer to their questions” (Fyodor Dostoyevsky, The Brothers Karamazov), in other words, this is because “skepticism is a resting place for human reason” (Kant) and the place of independent thinking for seeking the truth. If so, we can fully understand the true meaning of this sentence from Nietzsche: “life means for us constantly to transform into light and flame all that we are or meet with” (Nietzsche, The Joyful Wisdom, pref.)

I remember writing this sentence in my epistemology assignment: “Science provides knowledge, whereas philosophy provides wisdom. If we acquire wisdom, we may have acquired all that we need. I expect that truth will not make me financially rich, but it will surely liberate me.”

When I started to study for this DBA programme my goal was neither merely to raise the profoundness of my intellectual depth of logical thoughts and rigorous scientific analysis,
nor solely in order to develop my own style or establish my own so-called academic viewpoint, but I truly deep in my heart love to pursue the truth with wisdom, and to sublimate myself to the success of this programme.

I have reinterpreted the concept of DBA: In fact, DBA, for us, really is **Difficult But Achievable**!

I would like to give my grateful thanks to my supervisors Prof. Dong-Ling Xu, Prof. Lin Zhou, and my independent chair Prof. Jian-Bo Yang. Without their approach to help me with rigorous scientific control and discipline, I could not have successfully completed my essential academic research. In studying the ER Rule, I have substantially improved my cognition in the field of decision making for financial investment. Additionally, I am grateful to Dr. TP Sham and Dr. Dennis Wu meng-jiao for all their help and advice. Furthermore, I am grateful to AnTai College of Economics & Management, SJTU including Prof. Guohua Wan, Prof. Jian Liang, Prof, Liangyan Wang, Prof. Wei jiang and director Elaine Gao Liyun for mentoring me and for their guidance and encouragement.
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<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>ANFIS</td>
<td>Adaptive Neuro-Fuzzy Inference System</td>
</tr>
<tr>
<td>CAPM</td>
<td>Capital Asset Pricing Model</td>
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<td>CSMAR</td>
<td>China Stock Market and Accounting Research</td>
</tr>
<tr>
<td>DBA</td>
<td>Doctor of Business Administration</td>
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<td>DGAP</td>
<td>Deutsche Gesellschaft für Ad-hoc-Publizität</td>
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<td>Dempster-Shafer</td>
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<td>DST</td>
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<td>ETF</td>
<td>Exchange-Traded Fund</td>
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<td>FOD</td>
<td>Frame of Discernment</td>
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<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
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<tr>
<td>GMDH</td>
<td>Group Method of Data Handling</td>
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<td>LMFL</td>
<td>Logic-Motivated Fuzzy Logic Operators</td>
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<td>MADA</td>
<td>Multiple Attribute Decision Analysis</td>
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<td>MARS</td>
<td>Multivariate Adaptive Regression Splines</td>
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<td>MCDM</td>
<td>Multiple Criteria Decision Making</td>
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<td>MLEF</td>
<td>Multi-Layered Feed Forward</td>
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<td>MLR</td>
<td>Multinomial Logistic Regression</td>
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<td>NLP</td>
<td>Natural Language Processing</td>
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<td>NTS</td>
<td>Non-Tradable State-Owned Share</td>
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<td>NYSE</td>
<td>New York Stock Exchange</td>
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<td>RFR</td>
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<td>RSI</td>
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<td>Random Walk Hypothesis</td>
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<td>SJ</td>
<td>Subjective Judgment</td>
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<td>SOE</td>
<td>State-Owned Enterprise</td>
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<td>Support vector machine</td>
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<td>TS</td>
<td>Traded Public Stock</td>
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CHAPTER 1

Introduction

1.1 Background and Motivation

According to Marr (2013), the world has seen a widespread use of Artificial Intelligence (AI), ranging from tools such as auto text correction and voice recognition to big data applications for marketing and healthcare. One area of particular interest to us is the use of AI in financial trading. For example, high-frequency trading makes automatic investment decisions within fractions of a second using algorithms based on market data.

In the field of investment decisions, the biggest confusion for investors is how to make correct judgments and decisions: in other words, what kind of investment decision-making tools or methods should investors choose. As we know, mankind’s perception of the natural world is extremely limited and information is never complete. For example, investors are concerned with decision-making strategies for selecting suitable investable products, which they generally opt for, such as stocks to include in their portfolios to achieve high returns with bearable risks. Our long-term objective is to construct quantitative, and perhaps automated, solutions for investors making investment decisions.

There are various types of financial information that one may consider when making investment decisions, including concrete data such as historical prices, trading volumes, or macro indicators, and the less structured data such as analyst opinions, market sentiment, or government policies. Also, financial information is often imprecise and uncertain. The characteristics of diversity and uncertainty make the mass function of Dempster-Shafer Theory an ideal candidate for modeling financial information. In most cases, financial information can also be conflicting, indicating opposite directions of the price movement.

The method that we have chosen for this work is the Evidential Reasoning Rule (ER Rule), a recent advance in decision theories. The ER Rule is based on the mass function concept of the Dempster-Shafer Theory, and it is a general method that allows weighting of
different pieces of evidence. Mass function has the capability to model various types of uncertainty such as probabilistic uncertainty and unknown in a unified format (as a mass function or a belief distribution). By assigning weight and reliability parameters to each piece of evidence, the method enables the combination of conflicting pieces of evidence.

It’s been stated that around 70 to 80% of all data in organizations are in the form of unstructured information (Holzinger et al., 2013), which has not been fully exploited in the more traditional investment strategies, and thus we are interested in using unstructured data for our work. Research in market sentiment shows that news and blogs can be used for profitable trades though only for a short period of one or two days (Zhang & Skiena, 2010). There is evidence suggesting that identifying experts from non-experts and following expert opinions could lead to more precise stock price predictions (Bar-Haim, Dinur, Feldman, Fresko, & Goldstein, 2011). In addition, research indicates that recommendations by financial analysts enable profitable trades, at least for brokerage firm clients (Green, 2006). Therefore, we have chosen stock recommendations made by financial analysts, who are presumably the experts, to be the input data of our experiments.

The contemporary concept of portfolio selection is largely based on the Modern Portfolio Theory of Markowitz (1952), which gives a rigorous procedure for selecting securities under the assumption that the expected return and risk/variance of each security is known beforehand. However, our initial tests showed no clear indication for analysts’ capabilities of producing accurate forecasts for expected return or risk. Therefore, our method focuses on constructing an investment strategy directly from analyst recommendations instead of attempting to obtain return and risk before applying the Modern Portfolio Theory.

The efficient market hypothesis states that the financial market is efficient and it is impossible to achieve investment returns in excess of the market using only publicly available information. However, there is evidence showing that the Chinese stock market is less efficient than the capital markets in developed countries, and thus we have chosen recommendations published by Chinese stock analysts as our input data. From back-testing we show that it is possible to achieve excess returns by applying the ER Rule to process analyst recommendation information, due to the existence of performance persistence among Chinese financial analysts, which has not been previously demonstrated in
international accredited peer-reviewed publications, to the best of our knowledge. We have also discovered that Chinese stock analysts are biased towards positive recommendations, consistent with the literature on other markets (Yang, 2015).

1.2 Research Question

The major objective of this research is to answer the following questions:

(1) Can analyst stock recommendations be modeled as mass functions?
(2) Can the ER Rule be applied to aggregate analyst recommendations to synthesize trading strategies?
(3) Is the above approach effective?

1.3 Concept Map

Traditionally Bayesian inference has been applied to deduce event probabilities based on observed evidence. There are several issues concerning the use of Bayesian inference. The first one is a fundamental problem with using probabilities. By construction, the probability of an event implies the probability of its complement event. In addition, probability is of singleton nature in that the probability of an event is equal to the summation over the probability of each outcome in the event, prohibiting direct evidence support for an event without implicit support for its constituent events. Lastly, the use of Bayesian priors remains controversial.

Dempster-Shafer Theory was developed to generalize probabilities to basic probability assignments, or mass functions, in order to better represent the uncertain information contained in the evidence by not assigning residual probability to the complement set and not distributing ignorance over outcomes in a set. Dempster’s Rule was proposed as the method to combine mass functions of multiple pieces of evidence. It was shown that
Dempster’s rule becomes Bayesian inference when there is no ignorance in information (Yang & Xu, 2014).

However, Dempster’s rule assumes each piece of evidence is fully reliable, leading to counter-intuitive results when the pieces of evidence are highly conflicting. In reality, each piece of evidence should be given different degrees of reliability and weight, and the Evidential Reasoning (ER) rule was developed to reflect these weightings over multiple pieces of evidence (Yang & Xu, 2013). It has been demonstrated that ER rule reduces to Dempster’s rule and Bayesian inference in special cases. The evolution from Bayesian inference to Dempster’s rule to the Evidential Reasoning rule is depicted in the following chart.

*Figure 1-1: Evolution of Evidence Inference*
Our research objective is to explore a new method of investment decision making by applying the ER rule to aggregate stock recommendations made by financial analysts to formulate stock-picking strategies. The raw input is the unstructured data of financial analyst reports. There are two major structured data components in an analyst report, namely stock price forecasts and stock recommendations. The stock price forecasts are usually of six-month or one-year horizons and they are quoted in percentage intervals with respect to the price return of the market index, usually the CSI300 index, the Shanghai Composite Index, or the Shenzhen Composite Index. Each interval of price forecast has a corresponding recommendation level from Strong Buy to Strong Sell. Historical price forecasts of an analyst are used to compute the analyst’s accuracy, which is in turn used as the reliability parameter of the analyst as in the ER Rule model. Information of stock recommendations by each analyst along with reliability and equal weighting are fed into the ER Rule model for evidence combination, and the resulting mass function is converted into a probability distribution via the pignistic transformation. Investment strategies are constructed from the probability distribution for final decision making. Figure 1-2 below summarizes the important steps in our methodology.

In essence, investors are faced with uncertain financial investment environments with incomplete information, and the goal of this research is to help investors with their investment decision by providing intelligent quantitative solutions. The proposed model, termed the Efficient Information Assessment (EIA) model, aims to gather, process, and transform general unstructured financial information (financial analyst reports) into structured efficient information (weighted mass function with reliability). The Evidential Reasoning Rule, a recent advance in decision theories, is applied to the resulting efficient information for evidence fusion. The combined mass function is then converted into probability distribution for investment decision making and portfolio strategies.
Figure 1-2: Research Objective
1.4 Research Challenges and Framework

Our experimental results show that there exist experts who publish accurate stock recommendations, and their performance has some degree of persistence. However, it is hard to tell if an analyst is a real expert or if the analyst has made accurate stock recommendations by chance. To mitigate noises in analyst expertise, we would need to include more financial analysts in our input data. However, including too many analysts in the analysis would inevitably include stock recommendations from financial analysts who are less than expert.

Another challenge we face is that stock recommendations are published at different points in time in different days. Nevertheless, we need to pool the recommendations to synthesize an investment strategy despite the fact that they are made under different market conditions in different time frames. Therefore, we have another tradeoff here in that we would like to include more stock recommendations in the analysis to minimize noises but at the same time we would like to include only recommendations made under similar market conditions within a narrower time frame.

The third major challenge we encounter is that the stock market is highly competitive with investors constantly trying to take advantage of any opportunity to make excess returns. Therefore, it is hard to consistently beat an efficient stock market with high competition.

In the first part of the thesis we propose a new method for decision making in stock market investment which applies an Evidential Reasoning Rule based model to financial analyst recommendations for the Chinese stock market. Using Student’s t test, in the second part of the thesis we demonstrated the effectiveness of the method as compared to the market index. In the last part of the thesis we further analyze the behaviour of this approach, comparing it with simple methods, optimizing with respect to the weight parameter, and investigating the effects of different recommendation levels. This thesis reflects the DBA research following a roadmap that is being continually clarified, improved, and refined, during which the important research components such as my research question, research gap, literature review, experiments, hypothesis, etc., were all completed under the guidance
of our supervisor with continual discussions. The first part of the thesis describes a proposal of a new method with some initial evidence supporting its applicability, while the second part of the thesis strengthens the argument by introducing Student’s t test and validating the p-values computed for rolling portfolio experiments. In the last part of the thesis we report extended analyses on the properties of the method to help better understand the ER Rule approach and the characteristics of Chinese stock analyst recommendations, shedding light on potential future work.

1.5 Summary of Findings

We first established the existence of performance persistence in Chinese financial analysts as a foundation for applying decision theories to make investment decisions using the unstructured data of analyst opinions. An ER Rule based investment strategy is proposed and back-tested against historical data over a four-year span, demonstrating excess returns with respect to the market index of CSI300.

The performance of our ER Rule investment strategy improves with more top ranked analysts used in the analysis, peaking at around 80 analysts with a one-month report collection period, supporting the existence of non-experts that are being included as more financial analysts are incorporated into the analysis. Stock investment in a highly competitive market, where investors are constantly trying to profit, is a difficult task and the ER Rule based strategy is empirically shown to persistently outperform the market. Financial analyst reports are shown to have a long-term impact up to six months at least. Stock investment is a problem of multiple criteria decision making, of which attributes include expected return, risk, horizon, discounted maximum loss, maximum drawdown, etc. The ER Rule formulism used in this study assumes independence between different pieces of evidence. However, work has been done to extend the ER Rule to accommodate correlated pieces of evidence (Yang, Xu, Stachow, & Xu, 2015), which could be employed in future experiments.
1.6 Thesis Organization

Chapter 1 provides the background for the research, starting with the application of AI to automatic trading, the research question involving the ER Rule, a conceptual roadmap, epistemological arguments for the ER Rule, to the research framework of this study. Chapter 2 reviews relevant scientific research on portfolio theories, market efficiency, and financial analysts, as well as engineering research on trading strategies utilizing quantitative techniques or decision theories. Literature shows that the Chinese stock market could very well be only weak-form efficient and though one particular study demonstrated some initial efforts in applying DST to trading Chinese stocks, no definitive results were obtained and this work represents the first major effort in applying mass functions and the ER Rule in equity trading.

Chapter 3 details the Evidential Reasoning Rule approach, starting with a review of DST, followed by extensions with weight and reliability, leading to the description of ER Rule combination, and ending with some discussion of pros and cons. Chapter 4 puts forth two basic hypotheses of this work. The first one hypothesizes the existence of real financial experts in the market and the second one hypothesizes the effectiveness of the proposed ER Rule base investment strategy over the benchmark market index of CSI300. Chapter 4 proceeds with the construction of the Efficient Information Assessment model and the investment strategies.

Chapter 5 provides descriptive statistics about the data set used in the experiments, summarizing numbers of reports, analysts, recommendations, and stocks in the four-year span of our back-testing. Chapter 6 provides evidence for the performance persistence of Chinese financial analysts in terms of transition matrix between consecutive years and correlation between prior year accuracy and current year return. Chapter 7 shows the main results of the research, obtaining mean excess returns over benchmark CSI300 and p-values supporting the effectiveness of the ER Rule based trading strategies that use financial analyst reports as input. Model parameters are varied to demonstrate the robustness of the approach. Chapter 7 also summarizes four major findings of the work. Chapter 8 compares the trading strategies with other simple methods, followed by several optimization studies, showing the potential for improvement by using more analysts and
shorter report collection periods. Chapter 9 concludes the thesis, reviewing the weaknesses of the approach and pointing out directions for future work and practical implementations.
CHAPTER 2

Literature Review

The literature review contains two broad categories of research, the Science part and the Engineering part. The science-based literature is more concerned with observations and analyses of the behaviour or characteristics of the markets, while the engineering-based literature is concerned with constructing strategies or systems for stock prediction or trading decisions.

2.1 Modern Portfolio Theory

The contemporary concept of portfolio selection started with Modern Portfolio Theory. Markowitz (1952) considered the problem of selecting an investment portfolio among multiple securities. He divided the selection process into two stages. The first stage gives opinions about the securities’ future performance in the quantified forms of expected return and variance (or standard deviation). The second stage takes these parameters as input and produces a choice of portfolio weights on the securities (Markowitz, 1952).

In the original paper Markowitz did not delve into specific calculations of expected return and variance for the first stage. Instead he focused on the second stage, optimizing the portfolio weights by maximizing the expected return for a given variance or minimizing the variance for a given expected return (E-V rule). Markowitz stated that the optimized “efficient portfolios” trace out a series of connected parabola segments in the expected return-variance plane, or alternatively hyperbola segment(s) in the expected return-standard deviation (volatility) plane, commonly referred to as the efficient frontier.

The E-V rule implied not only diversification for the optimized portfolio, but it also implies the type of diversification and its explanation (Markowitz, 1952). Diversification
does not merely depend on the number of different securities held as securities in similar industries generally go up and down together. Therefore, in attempting to lower the overall variance small it is necessary to avoid including securities that are highly correlated among themselves and instead to diversify across industries of varying characteristics. This is because firms in industries of diverse economic properties would tend to have lower covariances than companies within similar industries (Markowitz, 1952).

Even though Markowitz gave no concrete procedures for computing the expected return and volatility of individual securities, he did mention that there could be ways to obtain reasonable probability beliefs of these two quantities by incorporating statistical methods and the opinions of experts. Our research aims at utilizing the recommendations of financial analysts for investment decisions, but we did not attempt to synthesize expected return or volatility for each stock from analyst opinions. This is because our initial experiments showed that analysts have a good idea about whether the stock is worthy of investment but it is difficult for them to give precise forecasts on the exact stock price returns or even ranges of price returns.

2.2 Capital-Market Model

![Figure 2-1: Efficient Frontier with a Risk-Free Asset](image)

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If there is a risk-free asset, the straight line is the efficient frontier. Figure 2-1 is an excerpt from the webpage titled "L’efficient frontier" (2012).

Figure 2-1 excerpted from the webpage titled "L’efficient frontier" (2012) depicts the efficient frontier in the expected return-volatility plane. All possible combinations of the securities form a region of which the left boundary is a hyperbola (Merton, 1987). If there is no risk-free asset, then the upper edge of the region is the efficient frontier ("Modern portfolio theory,"). Suppose there is a risk-free asset, namely an asset such as a government bond that pays a risk-free rate. Denote the risk-free rate as \( p \). Given a portfolio with expected return \( E_i \) and volatility \( \sigma_i \), an investor can achieve any point on the line described below in the \( \sigma \)-E plane, by allocating his funds between the risk-free asset and the portfolio (Sharpe, 1966):

\[
E = p + \left[ \frac{(E_i - p)}{\sigma_i} \right] \sigma
\]

(2-1)

Therefore each portfolio leads to a linear boundary for the combinations of \( E \) and \( \sigma \) (Sharpe, 1966). The optimal portfolio will be the one leading to the highest boundary, namely the one with the largest ratio of \( (E_i - p)/\sigma_i \), now commonly referred to as the Sharpe ratio (Sharpe, 1966). In short, we can achieve any point on the line extending from the risk-free asset through any point on the original efficient frontier. The optimal case would be a line going from the risk-free asset and tangent to the original efficient frontier, referred to as the capital market line, which forms the new efficient frontier ("Modern portfolio theory,"). The tangency portfolio is the optimal portfolio among all the risky securities, called the efficient portfolio. In the next section we discuss the efficient market hypothesis, which claims that investors are rational and the overall market portfolio would be the efficient portfolio.
2.3 Efficient Market Hypothesis

According to Malkiel (2007), Eugene Fama (1970) hypothesized the existence of efficient stock markets that accurately reflect all available information at all times. He also proposed three different types of market efficiency, namely weak form, semi-strong form, and strong-form efficiencies, depending on the financial information considered. The weak-form efficiency means that current prices reflect all past price information. In a market of weak-form efficiency, stock prices react to news announcements without delay and hence no excess returns can be obtained by examining the past pattern of price changes. The weak-form of efficiency is often explained by the random-walk model, where historical price changes do not impact future price changes. However, if new information is only gradually reflected in the stock prices, we would expect the prices to move in the same direction for prolonged periods of time. Thus, in an inefficient market, various chart patterns may allow investors to achieve excess returns. Moreover, in such a market there is generally clear evidence of momentum in share prices, and various anomalies e.g. seasonal and pre-holiday effects may occur.

Fama also considered stronger forms of efficiency where the financial information that is supposed to be reflected in stock prices included all public and private information about the company such as earnings, book values, investment opportunities, etc. In a market of the semi-strong form efficiency, all public information is readily and fully reflected in the market prices. In the strongest form of the theory, even private or insider information is instantly incorporated into market prices. In a market of strong or semi-strong form efficiencies, financial analysts and portfolio managers are not able to outperform a simple index fund that buys and holds a broad index, including all the stocks traded in the market weighted by their market capitalizations.

Efficient-market hypothesis has received much criticism from various angles. Some efforts have been attempted to invalidate market efficiency by investigating financial analyst forecasts. Compared to novice investors, analysts have long been perceived as competent processors of financial information who are less likely to misinterpret the implications of financial information (Ramnath et al., 2008). Thus, evidence of inefficient information
processing by analysts is considered substantial evidence of overall market inefficiency (Ramnath et al., 2008). It has been shown that there is a delay in the response of analysts' forecasts to news in earnings announcements (Chan et al., 1996). In addition, analysts seem to have an overreaction to good news but an under-reaction to bad news in prior year earnings (Easterwood & Nutt, 1999). However, Fama argued that apparent over-reaction to information is about as common as under-reaction, and they cannot be exploited to obtain excess returns (Fama, 1998).

2.4 Financial Analyst Forecasts

Efficient markets imply that no excess returns can be obtained in the long run. A natural question arises then as to whether forecasts made by financial analysts could be used to generate excess returns, which would invalidate the efficient market hypothesis. To date, there is no consensus among researchers on the question of whether analysts’ recommendations help investors generate abnormal profit or not (Martinez, 2010). However, there are studies showing the profitability of analyst forecasts. It has been shown that early access to changes in analyst recommendation enables profitable trades for brokerage firm clients (Green, 2006). Furthermore, changes in analyst recommendation lead to more profitable trading strategies within industries than those across industries, indicating that analysts are capable of distinguishing performance of stocks within an industry, but are not good at predicting sector/industry performance (Boni & Womack, 2006). It is also partly for this reason that our study has focused on individual stocks rather than industry sectors. Persistence has also been observed; analysts making more profitable recommendation changes in the past also do so in the future (Boni & Womack, 2006). There is evidence showing that analysts who issue more accurate forecasts also issue more profitable recommendations (Loh & Mian, 2006), which motivates the use of accuracy as reliability in our application of Evidential Reasoning theory.
2.4.1 Analyst Effectiveness

The big question is whether there are expert financial analysts who can provide accurate forecasts on stock performance that can be used to make investment decisions to achieve excess returns. Sinha, Brown, and Das (1997) find that superior forecasting ability exists and persists over time (Sinha, 1997). Loh and Mian (2006) shows that analysts with higher accuracies of earnings forecast issue profitable recommendations (both favourable and unfavourable) of stocks. The association between forecast accuracy and recommendation profitability suggests that analysts with superior forecasting skills have real stock-picking ability founded on economic rationale. Womack (1996) also reports findings of, on average, larger and longer price reactions to sell recommendation changes with a 4.7 percent initial drop and a post-recommendation drift of -9.1 percent over six months, compared to the 3 percent initial rise and 2.4 percent post-recommendation drift over one month for buy recommendation changes (Boni & Womack, 2006).

Using 1994-2003 US data, Fang and Yasuda (2014) showed that All-American (AA, a title granted by the influential Institutional Investors magazine) analysts’ buy recommendations yield significant excess returns. Interestingly, sell recommendations of most analysts have profitability. AA analysts from top-tier banks, nine underwriters with the highest Carter-Manaster ranks provided by Carter et al. (1998), outperform other groups of analysts in both buy and sell categories, achieving annualized adjusted excess returns of 3.56% and 6.9%, respectively. The sell recommendations seem to be more profitable in their experiments, but in our tests shorting based on negative analyst recommendations is not as effective as long strategies.

The market does recognize the existence of superior analysts; Park and Stice (2000) showed that forecast announcements by superior analysts as measured by past forecasting track record have a greater impact on security prices than do the forecasts of other analysts.

According to Stickel (195), forecast revisions affect prices, but prices do not immediately assimilate the information. Instead, prices continue to move in the direction of the revision for around six months after the revision. In our experiments we also find the length of six
months to be significant with regard to the effectiveness of analyst forecasts. Stickel tested an aggressive trading strategy based on the price reactions to revisions and obtained a best unadjusted excess return average of 8.22% every six months, compared to the best risk-adjusted excess return averaging 6.2% in our experiments, though the data set used by Stickel were for firms listed on the New York Stock Exchange or American Stock Exchange. The abnormal returns of the securities that performed the worst averaged -5.44 percent, again indicating the possibility of a short trading strategy.

2.4.2 Analyst Bias

Fang and Yasuda (2014) investigated conflict of interest behaviour and found that in the post-bubble market of 2000 and 2001, top-tier non-AA’s buy recommendations performed particularly poorly as the analysts were too sluggish in down-grading former champions stocks, possibly due to conflict of interest. Lim (2001) reports that financial analysts provide positively biased estimates to build management relationships for better access to company information, in an effort to optimize forecast errors. It was also noted that this effect is more prominent for companies with greater uncertain information environments.

Hayes (1998) argues that the analyst decides on how much information to gather about a given stock based on how much commission the analyst expects would be generated from the information. It turns out that analysts’ incentives to gather information are strongest for stocks that are expected to perform well. Hayes (1998) further developed a model to show that more precise information increases the number of shares the investor buys for stocks that the investor will buy; on the other hand, for the stocks expected to be sold, more precise information could decrease the number of shares that the investor sells. Therefore, forecasts for stocks with positive prospects are likely to be more accurate than forecasts for stocks with negative prospects.

Furthermore, if there are restrictions on short sales, analysts would maximize commission revenue by following stocks they expect to perform well, because trading volume on a poorly performing stock is limited to the investors’ initial holdings of that stock (Hayes, 1998). China in particular restricts short selling in its capital market and in our experiments
we do observe a larger tendency for analysts to make buy recommendations than sell recommendations, and the buy recommendations are more profitable.

2.5 Chinese Stock Markets and Analyst Recommendations

The Park and Stice (2000) research used data for the intersection sample contained in the COMPUSAT, CRSP, and I/B/E/S databases from 1988 to 1984, which mostly (82%) consisted of widely followed firms listed on the New York Stock Exchange. The work of Loh and Mian (2006) was also done on American stocks. Here our focus turns to China, of which the stock market was developed much later and is still at an early stage. Is the Chinese stock market efficient and is it possible to earn excess return over the market index?

2.5.1 Inefficiency of the Chinese Stock Market

In an earlier report, Ang and Ma (1999) argue that when a market is not transparent, namely when the quantity and quality of information disclosed by company managers are low, the earnings forecast errors made by financial analysts would be large. They showed that the Chinese stock market was not transparent as evident from the large forecast errors made by financial analysts. Using data from the I/B/E/S database on forecasts made by individual analysts in over 50 brokerage firms for about 100 Chinese stocks over the period 1993–1995, they found that forecast errors for Chinese stocks (B shares) were about twice as large as those for Hong Kong stocks (H shares) made by a similar set of brokers. They also computed the monthly standard deviations of absolute forecast errors made by financial analysts in that month. The standard deviations for China’s stock market were over two to five times greater than those for the Hong Kong market. This suggests that there are great difficulties in forecasting earnings of Chinese companies as financial analysts missed their forecasts often and with large errors (Ang & Ma, 1999). The low transparency of Chinese companies suggests inefficiency of the stock market.
Malkiel (2007) concluded that the A-share market was not weak-form inefficient, at least as of 2007. According to Malkiel, there were many unverified examples of stock price manipulation through wash sales and other manipulative techniques. However, applying multiple variance ratio tests to the daily closing prices of both A and B share indexes between 1992 and 2007, Charles and Darne (2009) showed that A shares seemed to follow the random walk hypothesis (RWH) while the RWH was rejected for B shares. Hence, B shares seemed to be less efficient than A shares, possibly due to information asymmetry as foreign investors in B shares might have had an information disadvantage compared to domestic investors trading A shares caused by language barriers, different accounting standards and the lack of reliable information about local companies.

To test if the Chinese stock market is of stronger form efficiencies, studies have been carried out to examine the reaction of Chinese stock prices to various important news announcements such as dividend increases or cuts and bonus and rights issues (Malkiel, 2007). In an efficient market stock prices would react instantly and completely to events announcement. Observing that in China, professional mutual fund managers substantially outperform market indexes even after expenses, Malkiel (2007) supports the conclusion that China’s stock market is not semi-strong form efficient, also citing event studies by Ma (2004).

With regard to H shares, there is a widely accepted and investable index of Chinese company H shares called the FTSE/Xinhua 25 Stock Index, which is tracked by an active fund traded on the New York Stock Exchange under ticker symbol FXI (Malkiel, 2007). It is observed that active-managers are not able to outperform the FXI exchange-traded index fund, either before or after management fees, and hence the H-share market appears to be more efficient than the A-share market (Malkiel, 2007).

In a more recent article published in 2011, Chong et al. applied time-series model based trading rules to investigate the efficiency of the Chinese stock market using a dataset covering a wide period of 1991-2010. An important event was the state-owned enterprise (SOE) reform. Chong et al. (2011) noted that in the first decade after the establishment of the Shanghai stock exchange and the Shenzhen stock exchange, most of the companies listed on the two exchanges were restructured SOEs: “Before April 2005, companies listed
on the Chinese stock market had a split-share structure with roughly 1/3 freely traded public stocks (TS) and 2/3 non-tradable state-owned shares (NTS)... In April 2005, the China Securities Regulatory Commission launched a state share reform, aiming at converting the NTS state to TS. According to the latest report in Nov 2006, 90% of Chinese firms had complied with the orders to reform their share structure”. Earlier evidences of market inefficiency mostly relied on statistical significance of the autocorrelation or regression coefficients, while Chong et al. (2011) used the profitability of trading rules as the metric, which is what we have done in our experiments as well. They observed that positive returns of the trading rules mostly concentrate in the pre-SOE reform period, indicating that China’s stock market has become more efficient after the reform.

To this end, Abdirahman and Huang (2012) compared the market efficiencies for two classes of stocks in China, state owned and private companies. They elected to use the random walk model to measure the degree of market efficiency. Specifically, the model implies that the return should not correlate to the prior returns, and they have chosen a 0.1 90-day-lag autocorrelation coefficient as the threshold for market inefficiency. They collected stock price data from Dec. 31, ’06 to Dec. 31, ’11 of 1478 companies that went IPO on the Shanghai and Shenzhen stock exchanges before December 31, ‘06. Among the companies, 597 are state-owned, out of which 448 are efficient, taking up a proportion of 75%. On the other hand, 186 out of the 278 privately owned companies are efficient, taking up a proportion of 67%. Their results seem to suggest that state-owned companies are more efficient than privately owned companies, which does not support the view by Chong et al. (2011) that the SOE reform played a key role in improving the efficiency of China’s stock markets. However, Abdirahman and Huang (2012) also noted that stocks of companies with larger market capitalizations showed higher efficiencies, which could have obscured the results as SOE’s tend to have larger market caps.

2.5.2 Effectiveness and Bias of Chinese Financial Analysts

Researchers worldwide had done many studies on the earnings forecast capabilities of financial analysts compared to those of statistical models (Yue & Lin, 2008). Earlier
studies showed that earnings forecasts made by financial analysts were not any more accurate than statistical forecasts based on historical data (Yue & Lin, 2008). Later studies indicated that analyst earnings forecasts are more accurate than statistical forecasts from both simple and complex time-series models (Yue & Lin, 2008). There have not been many academic articles about the effectiveness of financial analysts in terms of earnings forecasts and stock recommendations for China’s stock market. Ang and Ma (1999) documented that even though analyst earnings forecast errors for China’s stock market appeared to be larger than those for the Hong Kong stock market, analysts were able to provide informative earnings forecasts on Chinese stocks compared to naïve forecasts for up to 7 months. Using data of the earnings forecasts on 727 listed companies published by 35 brokers in 2005, Yue and Lin (2008) found that the accuracy of analyst earnings forecasts were more accurate than simple statistical forecasts based on yearly historical data but analyst forecasts were less accurate than simple statistical methods based on quarterly historical data. Their results indicated that the development of Chinese financial analysts was still at an early stage; analysts’ earnings forecast capabilities were insufficient and the information content provided by financial analysts needed improvement.

Kan (2013) reported empirical results showing that Chinese financial analysts could distinguish sustainable earnings difference, which is more reasonable for investor pricing, and Kan (2013) concluded that to a certain extent the earnings forecast of financial analysts is effective. Hong and Wang (2012) demonstrated positive relationships between the accuracy of analyst earnings forecasts and the profitability of analyst stock recommendations, as the returns of recommendations by analysts in the top accuracy quintile exceeded those by analysts in the bottom accuracy quintile by 1.997% per month (Jianxiao, Rui, & Changsong, 2012). Xu and Liu (2008) stated that recommendations of financial analysts had only short-term and tiny effects on the prices, suggesting that the market was not efficient enough to incorporate analyst opinions and it would be possible to achieve abnormal returns using information provided by the analysts (Xu & Liu, 2008).

Zhu et al. (2007) argued that if financial analysts could dig out more data about company fundamentals for the stock price to better reflect the company information, the degree of synchronization between stock price moves and market index moves would be reduced when there are an increasing number of analysts following the stock. On the other hand, if
financial analysts focus more on the macro information about the market rather than on the micro information about the company fundamentals, the activities of financial analysts would not enhance the information content of the stock price.

Ang and Ma (1999) documented that the transparency of Chinese stocks was unrelated to the number of analysts following a stock. However, it seems that the financial analyst industry of China has matured over the years. Zhu et al. (2007) found evidence to support the view that through searching for processing information Chinese financial analysts were able to improve the information content of stock prices to include more company fundamentals to reduce post earnings announcement drift and to reflect more information about future earnings (Zhu et al., 2007).

2.6 Stock Prediction Methods

The previous sections are more concerned about the scientific understanding of investment, stock market efficiency, financial analyst forecasts and recommendations, and observations of the Chinese stock market/analysts. In this and the following sections we look at the more engineering pursuit of stock prediction for decision making and automated trading systems. Agrawal et al. (2013) provides an overview of stock prediction methods, which we summarize below. Traditionally there are two broad categories of methods for the analysis and evaluation of financial securities, namely fundamental analysis and technical analysis. Fundamental analysis investigates a company’s performance and profitability to assess its intrinsic value by studying the company’s physical qualities such as infrastructure, product sales, management team, profitability on investment, etc. The key financial indicators that fundamental analysis looks at include the price-to-book ratio, price-to-earnings ratio, PEG ratio, dividend yield, debt to equity ratio, and returns on equity. Fundamental analysis assumes that the stock has an intrinsic price and the trading price of the stock would move towards the intrinsic value over time. This is an effective method for long-term investment with advantages of a systematic approach and prediction of price changes before they appear on patterns. However, it is more difficult to formulate fundamental analysis into automation due to its often subjective interpretation. Also, it is difficult to obtain precise timings for investment or liquidation using fundamental analysis.
Technical analysis evaluates stocks by analyzing statistics of market activity, historical prices, and volume. It identifies patterns of the stock price movement including factors such as trends, peaks, bottoms, etc., assuming that future stock prices would depend on their historical values along with those of other correlated variables. Technical analysis is widely used by around 90% of the stock traders and it is effective for analyzing short-term price movement, though it could also be highly subjective and imprecise depending on individual interpretation. The key stock price indicators that technical analysis looks at include moving average, exponential moving average, moving average convergence/divergence, and relative strength index. Lately, neural network models have received much attention and they have been successfully implemented to solve time-series problems achieving improvement on multivariate prediction ability. Neural network models work by mapping input/output variables with given patterns, and they have good adaptability and robustness against missing or noisy data.

It is worth mentioning several major developments in this field. In order to predict the best performing stock, Upadhyay et. al. (2012) developed the Multinomial Logistic Regression (MLR) model which used financial ratios as criteria to assess stock performance by comparing the stock return with the market return. They tested the model on 30 companies of large market capitalization for a period of four years, resulting in a prediction accuracy of 56.8%. Mehraraet. al. (2010) applied a Multi-Layered Feed Forward (MLFF) neural network with a back-propagation learning algorithm, as well as a Group Method of Data Handling (GMDH) neural network with Genetic algorithm (GA) learning to predict stock prices of the Taiwan Stock Exchange. Their model used inputs of moving average crossover with technical analysis rules, and the results indicate that exponential moving average yields better performance than simple moving average and also GMDH achieved better forecasting and profitability compared to the MLFF neural network. Agrawal et. al. (2010) proposed an innovative approach for decision making in stock market via risk minimization using Adaptive Neuro-Fuzzy Inference System (ANFIS) based on technical indicators such as RSI (Relative Strength Index), divergence, and weighted moving averages. Manna Majumderet. al. (2010) presented a computational approach based on neural network for the prediction of movement direction of the S&P CNX Nifty 50 Index, using pre-processed data closing values 1st January, 2000 to 31st December, 2009,
yielding a maximum accuracy of 89.65% and a mean accuracy of 69.72% over a 4-year period. Ganatret et al. (2010) implemented a neural network model with inputs of closing price, turnover, interest rate, global indices, and inflation, as well as other less direct indicators such as currency rate, news, and crude price. M. M. Goswami et al. (2009) constructed a novel model that uses Candlestick Analysis with combined Case Based Reasoning and Self Organizing Map to capture profitable patterns for predicting price fluctuation. Jaaman et al. (2009) discovered the ability of a rough set approach to describe dependencies in data while removing superfluous factors among noisy stock market data, which could be useful for extracting trading rules. Atsalakis & Valavanis. (2009) provided a survey article with an emphasis on neural and neurofuzzy methods to forecast stock markets, showing that the soft computing methods were widely employed for studying stock market behavior (Atsalakis & Valavanis, 2009). Yang (2005) constructed a back-propagation neural network model to predict stock prices, using a set of variables reduced by principal component analysis, yielding satisfying test results on the Chinese stock market (Yang, 2005). Klassen (2005) applied the Levenberg-Marquardt algorithm to implement one-step-ahead forecasts of stock prices in NASDAQ and Dow Jones. Huang et al. (2004) investigated a Support vector machine (SVM) model with regard to forecasting weekly movement direction of NIKKEI 225 index. He compared the performance of SVM with other methods including Elman Backpropagation Neural Networks, Linear Discriminant Analysis, and Quadratic Discriminant Analysis, with the experiment results indicating SVM’s outperformance over other classification methods. He also proposed a model combining SVM with the other methods yielding further improvement. Rohit Choudhry et al. (2008) constructed a machine learning system with Genetic Algorithm (GA) as well as Support Vector Machines (SVM) for stock market prediction. The genetic algorithm was used to select from a variety of technical indicators the most informative input variables. His results indicated that the GA-SVM system performs better than the standalone SVM system. Lin et al. (2007) proposed a time series model for forecasting through the mechanism of independent component analysis, with intrinsic limitations under component ambiguity, correlation approximation. Agrawal et al. (2013) concluded that none of the works surveyed are sufficient to provide accurate and reliable stock predictions, which we think is not only due to model limitations but also constraints on the sources of input data used.
2.7 Market Sentiment and Opinions Trading

There is theoretical and empirical evidence supporting the view that stock prices are affected by investor sentiment (Morck et al., 1990). There are theoretical arguments that explain why the impact of sentiment on stock prices could not be removed through contrarian arbitrage, where intelligent investors bet against mispricing. Figlewski (1979) and Shiller (1984) both indicated that when stock returns are risky, contrarian arbitrage is risky as well and thus not fully effective (Figlewski, 1979; Morck et al., 1990; Shiller, 1984). As an example, consider an arbitrageur who longs underpriced stocks; he would be taking on the risk that bad fundamental news will be released and that he will receive a hit (Morck et al., 1990). Due to the risky nature of arbitrage, arbitrageurs will restrain their trade sizes, and equilibrium stock prices will be affected by investor sentiment (Morck et al., 1990). De Long et al. (1990) further argue that assuming investor sentiment to be itself stochastic, there would be further risk to arbitrage as sentiment could flip direction in a short horizon to turn against the arbitrageur (Long et al., 1990; Morck et al., 1990).

According to Morck et al. (1990), when many securities are affected by investor sentiment, arbitraging against the crowd implies taking on systemic risks and thus could be costly to arbitrageurs who are risk-averse. However, if only a few securities are affected by the investor sentiment, betting against it implies taking on risks that can be diversified away, and thus in this case arbitrageurs will be more aggressive in betting. Hence, in a perfect capital market, stock prices are significantly affected by investor sentiment only when a great many securities are affected at the same time. In a realistic market though, arbitrage activity is costly and resources will be allocated to certain securities only if the expected returns justify the costs. For any stock that is mispriced, it would only be known to a few arbitrageurs (Merton, 1987), who would have alternative uses for their capital, or who may not arbitrage for a horizon until the mispricing is arbitraged away. Furthermore, betting a large position of a security takes on idiosyncratic risks, which could be a costly move for an arbitrageur that is not sufficiently diversified. Lastly, as emphasized by Fischer Black, there is often uncertainty associated with the degree of mispricing of a security, further limiting willingness of arbitrageurs to trade on it (Black, 1986). All of the costs indicate
that the resources available for betting against the mispricing of a security are rather limited, and hence even idiosyncratic sentiment could impact stock prices.

It has been shown that media sentiment is related to stock returns and the impact of positive media sentiment on returns is higher when there is high investor attention (Siering, 2013). Based on quantitative media data of blogs and news generated by a large-scale natural language processing (NLP) text analysis system, a sentiment-based market-neutral trading strategy has been developed that consistently achieves good returns with low risks for a long period of time (Zhang & Skiena, 2010). Similarly, a knowledge-based approach for extracting investor sentiment directly from financial weblogs at high frequency, based on which a portfolio selection test was performed providing evidence for the economic utility of investor sentiments from weblogs (Klein et al., 2011). Note that there is also evidence of fraudulent deceptive campaigns spread through the Internet that has a material impact on the stock market (Siering, 2013). However, to our knowledge there has not been an accurate predictive model of the stock market based purely on investor sentiment.

Feuerriegel & Prendinger (2015) tested a simple news trading strategy using data provided by Deutsche Gesellschaft für Ad-hoc-Publizität (DGAP) about ad hoc announcements published in the English language by German companies between January 2004 and June 2011. They computed the sentiment associated with an ad hoc announcement by the Net-Optimism metric, basically dividing the difference between the number of positive words and the number of negative words by the total number of words. An upper threshold and a lower threshold for the sentiment are set. When an ad hoc announcement is published and its associated sentiment is greater than the upper threshold or smaller than the lower threshold, the position of a previous stock is closed and a new position (Buy or Short Sell) of this new stock is opened. The trading strategy achieves an average daily return of 0.0464%, higher than the average daily return of CDAX (0.0298 %), a German stock market index computed by Deutsche Börse. They performed one-sided Wilcoxon test and Student’s t test for the hypothesis that the daily returns are positive, obtaining p-values as low as 0.38% and 0.85%, respectively. However, there are several issues with their results. First of all, it is noted that the strategy performance is sensitive to the threshold choice, indicating potential over-fitting. Secondly, no risk adjustment was taken into account before applying Wilcoxon test and Student’s t test, even though it was observed that higher
volatility was associated with the higher returns of the news trading strategy. In addition, there is no concrete investment horizon with the holding period of each position spanning between two consecutive ad hoc announcements. However, there is evidence showing that news and blogs are profitable for only short periods of one or two days and almost have no predictive power for the investment return of later days (Zhang & Skiena, 2010). Bar-Haim et al. (2011) argues that it is beneficial to distinguish experts from non-experts, and following the experts results in more precise predictions (Bar-Haim et al., 2011). Therefore, in our research we have elected to focus on using analyst recommendations instead of general sentiment or market participants.

Even though it is not clear if market sentiment trading can yield profitability of longer horizons, evidence shows that insightful discoveries could be achieved by using automatically extracted information based on the news articles (Radzimski et al., 2014). Radzimski et al. (2014) analyzed unstructured data from over 200 news sources including not only financial news services and blogs but also general news broadcasters, e.g. BBC News or CNN, spanning a period from January 2013 to December 2013 (Radzimski et al., 2014). The dataset contains about 2,300,000 distinct financial news articles and over 24 million annotations of six thousand named entities. With a focus on the S&P500 companies, they constructed a relationships graph of companies measuring co-occurrences of companies in the news (Radzimski et al., 2014). They found that the daily stock returns of two companies and their co-occurrence are positively correlated for companies in the industry sectors of “Consumer Staples” and “Health Care”. These observations could aid in better portfolio optimization and mitigate investment risks (Radzimski et al., 2014).

2.8 Market Security Ensemble Model

Sham (2016) proposed a market security ensemble model to explain the short-lived market reactions to news before returning to equilibrium, which supports the view that it is difficult to consistently profit from market sentiment induced by news and events over the long term, and thus it would be more effective to turn to expert forecasts and recommendations. His arguments are reproduced below (Sham, 2016).
The security market is modeled as an ensemble comprising a large number of stocks issued by all members of individual companies in compliance with the regulatory constraints imposed by the market. Stocks all have most of their contents in common, but with differences in value.

The market macroscopically undermines details of its members being indistinguishable; and only recognizes few common microstate variables (i.e. number and unit price of shares) that have effects on the macro-state of the market ensemble.

One reason for modeling such financial security market as an ensemble is to enable the model to take into account the important economic and financial capital nature of all ensemble members. To be more specific, it is the endeavours of the management of equity capital of each membership company that have really been the main causes to make key variables of microstate change in value; and initiate so called new information finally reaching to the market. In response to new information, the market ensemble knows nothing, but treats all reactions indistinguishably as turbulences; and that will immediately die down when the efficient market ensemble reaches the new equilibrium macro-state.

The model of the security market in this research is constructed with the following underlying principles and assumptions:

The ensemble M is the macroscopic representation of the stock market, whereas the thousand members’ S of the ensemble are the microscopic representation of the stock market.

\[ S \{s_1, s_2, s_3 \ldots s_i \ldots s_n\} \in \Omega: \text{A subset of } \Omega \text{ represents individual companies issued outstanding shares, and decided releasing portion of that be the “float” to be traded under the regulations of a public market. } S_i, \text{ like any individual company, is independent under its own control and management.} \]

In our model, both \((S, M) \in \Omega; \text{ and the relation between } S \text{ and } M \text{ (total market security ensemble) is } (S \cap M), \text{ the intersection portion of } S \text{ and } M. \text{ For } ith \text{ stock } s_i, \text{ the intersection} \]
of S and M denoted $m_i$ is the float of $s_i$ to be tradable in the market. An agent $a_j$ owns the portion of the $s_i$ is $a_{ji} \in m_i$.

Figure 2-2: Market Security Ensemble Model

The microstates of ensemble are assumed indistinguishable among its members. The modeled ensemble of the stock market passively changes or rebalances to a new equilibrium macro-state as a result in response to some combined activities initiated by agents due to new exogenous information. If the market is efficient enough, macroscopically, it should be in compliance with the EMH (efficient market hypothesis).

Figure 2-3: Market Security Ensemble Model with Agent Portfolio
Where this model differs from others is that the model is not a closed system. It is an ensemble where each member has its own capital reservoir exterior to the stock market domain. Microscopically speaking, for individual members of the ensemble, only the “float” portion of the total issued authorized shares is put into the market for free trading. That is the portion of the subset \(S\) intersected with the \(M, \sum \{(s_i - m_i)\}\).

Because each member has its own capital reservoir that enables the independent agent to provide (or buy-back) continuously new (or old) investment capital into (or from) the market, the total value of the market security portfolio, as well as that of each member’s intersection portions of \(M\), changes with time. In this sense, \(M, S, A\) are all time variables.

![Figure 2-4: Private to Public Equity Evolution](image)

The main difference of this model from others is that in this model the stock market is not the whole space or domain where the action of trading is doing. The active space or domain of the model \(\Omega\) comprising the space of the stock market and spaces of all individual stocks interacted with the market. That is \(M + (S \cap M), (S, M) \in \Omega\). The portion of space of \([\Omega - M - (S \cap M)]\) in \(\Omega\) is not related to the market space \(M\), represents the non-interacted portion of subset of all individual stock: \([S - (S \cap M)] \in \Omega\). Of course, this portion of stocks is not related to the \(\beta\) return of a stock in the CAPM equation indicated by the security market line.
\[ \alpha_{S-M} = E[R_{S-M}] = E[R_S] - E[R_m] \]
\[ = E[R_S] - \beta_m E[R_{mkt}] \]
\[ \alpha_M = 0 \]

\( \alpha_{S-M} > 0 \): The portion of investment return in excess of the \( \beta \) return of a stock in the CAPM equation.

**Figure 2-5**: Security Market Line
What agents are doing in the stock market can be described as an isolated action taken on a single stock or portfolio against the market as a whole. The action can be idealized as binomial: either buy or sell based on the finalization of the judgment on the agent’s belief in the microstate of the single stock (or portfolio). This becomes new information. When an agent decided to take the initial action of buying a stock $S$ based on the new information and believed to have a higher return than that of $\beta$ return valuated by the CAPM equation, the stock $S$ on the return-risk plot will be move up on the same vertical line above the SML line. The slope of the line connected between the risk free investment and the point of stock $S$ will be larger than that of the SML. In response to this turbulence, the equilibrium of the macro-state of the market ensemble has been broken. All actions start trying to rebalance the macro-state until the new equilibrium finally reached. As a result, the expected return of the market portfolio will be higher, and the $\alpha$ values of the stock $S$ will be turn back to 0 with a higher $\beta$ return at the same risk level. The difference between two equilibrium states are determined by the weighted portion of the stock $S$ compared to the total market portfolio. Usually it is relatively insignificant.
As to the market macroscopically, individual stocks in the ensemble are indistinguishable. The market ensemble does not matter and does not care about the detail of the new information. Only when someone initiates an action based on the new information, does the market start to respond. All agents of the market will then follow the initial action and proceed with it until the macro-state of the market reaches a new equilibrium that is most likely different from the previous one. If the market is efficient, then according to the EMH, the whole process will be almost immediate. It is clear that the first initial action being taken by an agent is nothing to do with the EMH on the market macroscopically. It is completely a decision made on an individual single stock or portfolio microscopically outside the market domain. The market is in response not to the new information, but to the initial action of the first agent. This initial action, no matter whether it is buy or sell, is the fact already. There is no uncertainty in it. Therefore, as to the market macroscopically, reactions to the initial action are always determinant without uncertainty. To evaluate economic capital investment in a single company is much more predictable than in a stock market. For there is a plethora of useful information and a variety of data available together with sophisticated computational algorithms and tools for specialized analysts to provide investment recommendations at investors’ disposal, it is not worthwhile doing it by each individual investor. This will basically take care of the $\alpha$ portion of the investment return.

2.9 Dempster-Shafer Theory Applied to Financial Portfolios

The goal of the research is to gather stock recommendations made by various analysts to form an investment strategy. The task can be considered as a type of data fusion where information from various analysts is combined into a single unified view on investment opportunities (Nayak et al., 2012). In data fusion, the Dempster-Shafer (DS) theory is an effective technique that handles uncertainty and incompleteness of information (Nayak et al., 2012). While the conventional probability theory defines basic probabilities only on singleton events, the DS theory extends the traditional concept of probability to deal with evidence that provides more vague information by assigning basic probabilities to unions of singleton events (Dempster, 1967; Yang & Xu, 2013). The DS theory has been applied in various fields including object detection (Nayak et al., 2012), legal justification (Curley, 2007), and investment portfolios (Srivastava & Mock, 2002). Theoretical attempts have
been made to represent market information and financial knowledge using linear belief functions, and to integrate the knowledge using Dempster’s rule of combination (Wang et al., 2006). Linear belief functions have also been applied to the risk and return analysis of international portfolios (Merton, 1972).

Efforts have been devoted to building stock market trading systems, and most of the articles in this field focus on stock price prediction (Dymova et al., 2016), e.g. an MARS and SVR hybrid approach by integrating wavelet-based feature extraction for stock index forecasting (Chiu et al., 2013) and a system for predicting stock price and index movement using machine learning techniques as well as Trend Deterministic Data Preparation (Patel et al., 2015). According to Dymova et al. (2016) however, Kuo et al. (2001) showed that most of these works focusing on stock price prediction generally used multiple regression models and time series analysis techniques (Kendall & Ord, 1990), and the trading expert systems based on stock price forecasts led to unsatisfactory results, as noted by Haefke and Helmenstein (2000). Researchers have also applied artificial neural networks as well as genetic algorithms to constructing stock trading expert systems with poor results (Dymova et al., 2016; Baba & Kozaki, 1992; Kim & Han, 2000; Kuo et al., 2001; Mahfoud & Mani, 1996; Mehta & Bhattacharyyya, 2004).

The breakthrough realization came from incorporating an expert’s wisdom into producing reliable stock trading systems (Dymova et al., 2016). A decision support system that allows investors to include crowd recommendations in their decision making was proposed by Gottschlich and Hinz (2014). Hu et al. (2015) proposed a model for discovering stock trading rules with an evolutionary trend based on the expert’s experience which produced good results (Hu et al., 2015). Dourra and Siy (2002) attempted the first step in developing a trading system based on the wisdom of an expert wisdom utilizing fuzzy logic representation of trading rules to give signals of sell, buy and hold (Dourra & Siy, 2002). Their work was followed by that of Santiprabhob, Nguyen, Pedrycz, and Kreinovich (2001) who developed a new “Logic-Motivated Fuzzy Logic Operators” (LMFL) system which better handles human reasoning specificity during the processes of decision making (Santiprabhob et al., 2001).
Sevastianov and Dymova (2009) proposed an expert trading system based on an integration of the Dempster–Shafer Theory (DST) and Fuzzy Sets theory, enhancing the representation capability of fuzzy classifiers and remedying the drawbacks of DST in drawing inferences from mass functions by introducing the propagation rule of evidence within the fuzzy deduction scheme. Applying their approach to historical NYSE data shows reliable results and profitability even in the case when trading against a market trend that is dominating. The motivation of Sevastianov and Dymova was to improve upon previous efforts of (Dourra & Siy, 2002) and (Santiprabhob et al., 2001) to build an expert stock trading system based on fuzzy logic, which, however, suffers from artificial nontransparent fuzzy rules when handling human reasoning. Dymova et al. (2010) had also applied a similar approach to historical price data of the Warsaw Stock Exchange, obtaining a Gross Profit/Gross Loss ratio of 1.78 (Dymova et al., 2010). Dymova et al. (2012) further adapted the system to consider level 2 information, namely in-depth information on a particular stock, including not only the highest bid and lowest ask orders but the whole range of bid and ask orders at various volumes and different prices (Dymova et al., 2012). They demonstrated the advantages of the developed expert system by optimizing and testing on real Warsaw Stock Exchange data, which showed promising results.

Dymova et al. (2016) have also applied their approach to building a forex trading system, and back-testing the system on historical prices of EUR/USD, GBP/USD, EUR/CHF, USD/CHF yielded promising results. Another earlier attempt to apply DST to forex trading was done by Zhang and Ren (2013), which treats each technical indicator as a piece of evidence and combines them to form a trading model. The goal of the works cited above was to mimic the decision making process of human traders when fed with the hard data input of historical stock prices. However, in our case the input is already human opinions of financial analyst recommendations, which naturally necessitates a more general framework to accommodate the ambiguity and uncertainty in the input information.

One example of applying DST to financial analyst reports was by Xu et al. (2014) who attempted to predict the most promising industry of the next trading day by aggregating ratings for 44 industries issued by 78 securities firms over the past 10 trading days in China’s stock market (Xu et al., 2014). Their construction of mass function for each
securities firm is as follows. Denote $\Omega$ as the frame of discernment. There are four focal elements of each mass function as defined below:

$$
S_{\text{buy}} = \{ \text{industry } I \mid I \text{ is rated as “buy”} \}
$$
$$
S_{\text{overweight}} = \{ \text{industry } I \mid I \text{ is rated as “overweight”} \}
$$
$$
S_{\text{neutral}} = \{ \text{industry } I \mid I \text{ is rated as “neutral”} \}
$$
$$
S_{\text{others}} = \Omega - S_{\text{buy}} - S_{\text{overweight}} - S_{\text{neutral}}
$$

The values of a mass function are computed as follows:

$$
m(S_{\text{buy}}) = \left( \frac{44 - |S_{\text{others}}|}{44} \right) \times \frac{4|S_{\text{buy}}|}{4|S_{\text{buy}}| + |S_{\text{overweight}}| + |\text{complement of } S_{\text{neutral}}|}
$$

$$
m(S_{\text{overweight}}) = \left( \frac{44 - |S_{\text{others}}|}{44} \right) \times \frac{4|S_{\text{overweight}}|}{4|S_{\text{buy}}| + |S_{\text{overweight}}| + |\text{complement of } S_{\text{neutral}}|}
$$

$$
m(\text{complement of } S_{\text{neutral}}) = \left( \frac{44 - |S_{\text{others}}|}{44} \right) \times \frac{4|\text{complement of } S_{\text{neutral}}|}{4|S_{\text{buy}}| + |S_{\text{overweight}}| + |\text{complement of } S_{\text{neutral}}|}
$$

$$
m(\Omega) = \frac{|S_{\text{others}}|}{44}
$$

The motivation is to treat each buy rating as 4 votes and each overweight rating as one vote, and the rest of the industries that are not issued a neutral rating are considered as getting one vote as well. However, there are two non-intuitive properties of this model. First of all, $m(S_{\text{buy}})$ is proportional to the number of buy ratings the firm issues, but if the firm has strong support for only one industry and no opinions for the other industries, the industry will only get a mass value of 1/44, no matter how strong the support is. This proportionality is reminiscent of a probability approach with each industry of a buy rating carrying equal amount of support, defeating the purpose of using belief functions. Secondly, the model treats the number of industries that did not receive a rating as global ignorance, which is counter-intuitive as the number of industries without a rating merely represents ignorance of these industries and should not reflect beliefs on the industries to which a rating has been issued.
They applied Dempster’s rule to combine the mass functions of the securities firms, followed by the pignistic transformation to yield an industry of the highest pignistic probability as the predicted industry. Compared with the actual ranking of industries with respect to the stock price rise in the following trading day, the predicted industry ranks 19.85 on average, slightly better than the median 22.5 of 44 industries. A strategy of daily investment in the predicted industry (weighted with trading volumes of the stocks) with 30-day horizons yielded an average monthly rise rate of 0.59%, higher than investing in the overall industries (-0.274%) or the monthly return of -0.097% from following a simple voting strategy with 4 votes assigned to a buy rating and one vote assigned to an overweight rating or non-neutral rating. However, their analysis did not consider risk adjustment and a more rigorous hypothesis testing is lacking. In addition, their trading strategy is based on a 30-day horizon, but it is well-known that analyst forecasts are not quite as accurate in the short term and in our work we have adopted longer horizons of three to six months. There is also a concern with regard to the construction of industry portfolios consisting of trading volume weighted stocks in the industry. Since the Chinese stock market is subject to manipulations and under the table transactions, trading volumes can be greatly skewed and thus the industry portfolios constructed in this way may not properly reflect the performance of the industry. Last but not least, as mentioned above there is evidence supporting financial analysts’ capability of distinguishing performance of stocks within industry but not so much at predicting sector/industry performance [9]. In our work we focus on choosing individual stocks instead of choosing industries for the investment portfolios.

2.10 Evidential Reasoning Rule

The ER Rule was developed by Yang & Xu (2013) to extend the D-S theory to handle situations of high conflict and to enable a consistent way of combination utilizing different weightings on different pieces of evidence. The core of D-S theory is Dempster’s rule, which is conjunctive and forms a probabilistic inference process, but in cases where two pieces of evidence are in full conflict, Dempster’s rule is not well defined and is not applicable (Yang & Xu, 2013). The rule led to counter-intuitive results when used to
combine pieces of evidence that are in high or close to full conflict. Another property of Dempster’s rule, which is of concern, is that each piece of evidence is completely reliable and any proposition that is not supported by a piece of evidence will be ruled out. Namely, Dempster’s rule only accumulates consensus support, and any proposition opposed by at least one piece of evidence is rejected completely, even if the proposition receives strong support from some other evidence (Yang & Xu, 2013).

Many alternative combination rules have been developed, aiming to replace Dempster’s rule by addressing the counter-intuitive problem. One common drawback of the alternative combination rules is that they are not probabilistic in that the specificity of evidence is changed with respect to basic probability assignment and/or they do not form a process of Bayesian inference process while used in combining probability information. Yang and Xu (2013) described several of these alternative rules including Yager’s rule (Yager, 1987), Dubois and Prade’s rule (Dubois & Prade, 1988), and the PCR5 rule (Smarandache & Dezert, 2006), and discussed their weaknesses of non-probabilistic reasoning and inconsistencies. A new Evidential Reasoning rule with weight and reliability is proposed to combine weighted belief distributions with reliability, discounting the basic probability assignment with the weight and reliability parameters and assigning the residual support to the power set. To show the consistency of the new ER Rule method, it is verified that the ER rule meets the synthesis axioms for rational reasoning processes, including the axiom of no support, the axiom of consensus, the axiom of locality, and the axiom of non-dominance.

The ER Rule and approach have been applied to fields such as evolutionary game theory (Deng et al., 2014) and power transmission (Guo et al., 2012). Wu et al. (2015) applied the ER Rule to the estimation of dynamic system state under bounded noises and found the method to be more accurate than Nassreddine ‘s method using evidence theory and interval analysis (Yang et al., 2015). Rosales et al. (2015) proposed an ER Rule based approach to estimate the rate of unscheduled failures, damage, and discrepancies with regard to aircraft maintenance, by applying the ER Rule to analyze various operational variables’ historical data and the new approach yields more precise non-routine rates. Zhu et al. (2015) applied the ER Rule to the problem of research project evaluation and selection by modeling peer view information with belief structures, using a confusion matrix to compute expert
reliabilities, adopting information transformation to resolve qualitative evaluation criteria, followed by evidence combination with the ER Rule. They showed effectiveness and applicability of the method via an experimental study using data of research proposals submitted to the National Science Foundation of China. Zhou et al. (2015) looks at the problem of assessing product lifetimes utilizing both expert knowledge and failure data. Due to increasing durability of many products, especially those in the fields of national defense, it is becoming more difficult to assess product lifetimes because there is insufficient failure data. In order to gather more information within a shorter time period, multiple tests need to be run under various testing environments such as accelerating stress, high temperature, altering temperature-humidity, etc. It is then critical to aggregate all the failure data collected under different testing environments together along with expert opinions about the relationship between actual failure data and those obtained under testing environments, in order to estimate product lifetimes. To solve the problem, Zhou et al. (2015) constructed a model based on the ER approach (Yang et al., 2006), a special case of the ER Rule when the reliability and weight parameters of a piece of evidence are equal and the weights are normalized over all the pieces of evidence. Chang et al. (2016) proposed an expert system based on belief rule for classification problems where the ER approach is used as inference engine along with the differential evolution algorithm to identify the best fit parameters, weights of rules, and degrees of beliefs. The efficiency of their classifier was validated on five benchmarks, including Pima, iris, wine, glass, and cancer. The ER approach has also been used to construct mathematical formulations to aggregate quantitative measurements and qualitative judgments under different types of situations for the evaluation of corporate sustainability, demonstrated with actual data produced from three sugar manufacturers in Thailand (Bamford et al., 2014). Though a case of private equity investment has been studied by Yang et al. (2015), no report of an ER Rule application to stock market investment has been published to our knowledge.

2.11 Summary and Research Gap

We can see that since the discoveries of Modern Portfolio Theory and Efficient Market Hypothesis, inefficiencies of the stock market are still being identified. In particular, the Chinese stock market, of which efficiency is being continually improved via stages of
reforms, is still not considered semi-strong form efficient. Many techniques and methods have been investigated for automatic trading in the stock market, including various neural network models, machine learning, and artificial intelligence methods fed with historical data of prices and technical indicators, though with less than satisfying results. Please see section 2.6 for a short review of technical analysis and fundamental analysis.

Further advancement lies in the idea of incorporating human reasoning and expert knowledge into the decision-making process and the Dempster-Shafer theory (DST) has been applied by Sevastianov and Dymova (2009) and Dymoval et al. (2010, 2012, 2016) to construct trading strategies for the stock and foreign currency markets. However, their approach still largely considered only technical indicators as input. Xu et al. (2014) attempted to apply DST to predict the industry worthiest of investment based on ratings by financial analysts. However, even though using DST their model is very much based on a probability type of construction with the support for one proposition affecting the support for the negation of the proposition. It also mixes non-support with global ignorance.

The research gap that we have identified is to find a proper approach to model the often ambiguous and conflicting analyst opinions, and the ER Rule is adopted as our method of choice to aggregate recommendations of financial analysts for decision making in stock investment. Our study serves as the first attempt to apply the ER Rule in the field of stock market investment, though a case of ER Rule application to private equity investment has been studied by Yang et al. (2015).

We have elected to use pignistic probabilities in the decision making of choosing stocks for investment, but in some cases the pignistic transformation method has been shown to produce results inconsistent with Dempster’s rule (Li et al., 2014). Several alternative methods have been proposed (Daniel, 2006; Merig’o & Casanovas, 2011) including the plausibility transformation method proposed by Cobb and Shenoy (2006) which translates mass function to probability functions via plausibility ratios. Li et al. (2014) proposed the multi-scale probability transformation which distributes the mass of a focal element onto its singletons in a weighted manner with the weight of each singleton being proportional to its belief distance (defined to be the distance between the belief function and the
plausibility function) to a power. As research in this field matures we might adopt newer methods in decision making based on the final combined mass function.

The elements in a frame of discernment are required to be mutually exclusive, while in our case investing in one stock does not necessarily exclude investment in other stocks. In addition, we have only included stocks for which a recommendation has been issued in the frame of discernment, but there might be other listed stocks worthy of investment that have not been issued with a recommendation. Deng (2012) and Li et al. (2014) generalized the Dempster-Shafer Theory by relaxing the constraints on mutual exclusivity and collective exhaustiveness. Though we are not sure how Deng’s work differs from or the extent to which it can be handled by earlier models such as linear belief functions of Liu and Shenoy (1995), Liu (1996), and Liu et al. (2003), or belief functions on real numbers of Smets (2005), but the concerns with non-exclusivity and incompleteness of the frame of discernment in the context of stock investment should be investigated further (Liu, 1996; Liu et al., 2003; Liu & Shenoy, 1995; Smets, 2005).
CHAPTER 3

The Evidential Reasoning Rule

The problem we are facing is a type of information updating, where we continuously update our market view as we incorporate information from more stock analysts. The traditional method of dealing with this kind of problem is Bayesian updating, which applies Baye’s Rule sequentially to update the probability distribution, as each piece of information is included into the analysis. However, to apply the Bayesian theory, one needs full knowledge of the prior probabilities of evidence (Nayak et al., 2012). In addition, the uncertain and imprecise nature of analyst recommendations requires a more flexible approach for modeling. The Dempster-Shafer Theory extends the traditional concept of probability to handle evidence that provides more imprecise information by assigning basic probabilities to unions of singleton events. However, DST suffers from counter-intuitive issues associated with combining highly conflicting pieces of evidence using Dempster’s Rule of combination. The ER Rule has therefore been developed to aggregate conflicting information by allowing greater flexibility in the weight and reliability of evidence. One constraint with the use of the ER Rule is that the frame of discernment associated with each piece of evidence needs to be the same frame, which in our case is not a realistic assumption as each analyst is usually specialized in one industry sector and is not familiar with stocks in other sectors. Furthermore, the formulation of the ER Rule used in the study assumes independence among the pieces of evidence but analysts might affect each other especially those in the same brokerage firm. A generalized formulation of the ER Rule allowing correlations between the pieces of evidence has been developed and could be used in later studies. The ER Rule is particularly suited for selecting from various alternatives with multiple criteria, which in the case of financial investment include expected return, risk, horizon, discounted maximum loss, maximum drawdown, etc.
3.1 Basic Concepts

The DS theory is a suitable candidate for this analysis due to its capability of representing impreciseness and uncertainty (Nayak et al., 2012). To facilitate our discussion, below we describe the basics of DS theory, which is excerpted from (Yang & Xu, 2013). Let Θ={θ₁, …, θᵣ} be the set of possible outcomes which is mutually exclusive as well as collectively exhaustive, with θᵢ ∩ θⱼ = ∅ for any i, j ∈ {1, …, N} and ≠ j, where ∅ refers to an empty set. In this context, Θ is called the frame of discernment and it plays the role of sample space in the classical probability theory (Henry E. Kyburg & Teng, 2001). A Basic Probability Assignment (bpa) or mass function is a function m: 2⁰ → [0, 1], satisfying the following conditions (Shafer, 1976):

\[ m(∅) = 0 \text{ and } \sum_{E \in Θ} m(E) = 1 \]  \hspace{1cm} (3-1)

with 2⁰ or P(Θ) representing the power set of Θ, which is composed of the 2ᴺ subsets of Θ, namely

\[ P(Θ) = 2^Θ = \{ ∅, θ₁, ..., θᵣ, \{θ₁, θ₂\}, ..., \{θᵢ, θⱼ\}, ..., \{θ₁, ..., θᵣ-1\}, Θ \} \]  \hspace{1cm} (3-2)

m(E) is the mass function that is assigned to an event E and to no subset of E other than E itself. The summation of all the basic probability masses assigned to subsets of Θ is 1 and there is no mass assigned to the empty set. m(Θ) denotes global ignorance, which is the basic probability mass assigned exactly to Θ; a mass function exactly assigned to a non-singleton subset of Θ is called local ignorance. A mass function reduces to a classical probability function when there is no local or global ignorance.

3.2 Mass Functions with Weights and Reliability

Let \( w_i (0 ≤ w_i ≤ 1) \) be the weight of evidence \( e_i \), with \( w_i = 0 \) representing “not important at all” and \( w_i = 1 \) representing “the most important” (Yang & Xu, 2014). The weighted mass function for \( e_i \) is expressed as below (Yang & Xu, 2014):
where \( p_i(\theta) \) is the original mass function. In the above expression, the mass function is discounted by the weight \( w_i \), and the remaining support \((1-w_i)\) is assigned the power set instead of any subset of \( \Theta \) (Yang & Xu, 2013). The following rule applies when we combine the weighted mass functions of two independent pieces of evidence \( e_1 \) and \( e_2 \) (Yang & Xu, 2013):

\[
p_{\theta,e(2)} = \begin{cases} 
0 & \theta = \emptyset \\
\frac{m_{\theta,e(2)}}{\sum_{D \subseteq \emptyset} m_{D,e(2)}} & \emptyset \subseteq \Theta, \theta \neq \emptyset 
\end{cases}
\]

(3-4)

\[
m_{\theta,e(2)} = \left[(1-w_2)m_{\theta,1} + (1-w_1)m_{\theta,2}\right] + \sum_{B \cap \emptyset = \emptyset} m_{B,1,2} m_{C,2} \quad \forall \emptyset \subseteq \Theta
\]

\[
m_{p(\theta),e(2)} = (1-w_2)m_{p(\theta),1}
\]

The above expression shows that the joint support of two independent weighted mass functions is comprised of two components (Yang & Xu, 2014). The first component is the limited summation of the individual support from the two pieces of evidence, and the second component is the collective support represented by an orthogonal summation (Yang & Xu, 2013).

### 3.3 Pros and Cons

The advantages of the ER Rule lie in the use of mass functions and the ability to incorporate weights and reliabilities in evidence combination. Probability function only allows singleton representation of evidence, and thus the probability of an event is equal to the summation of the probabilities of the outcomes in that event. In addition, the probability assigned to an event implies that the residual probability is assigned to the complement event. Namely, belief in an event is equivalent to disbelief in the complement event. Mass functions of the Dempster-Shafer theory enable more direct support for an event without any implication of the mass assigned to its sub-events or complement event, thus better capturing the uncertainty and limitation of most practical sources of evidence.
However, it is also difficult to model such vague information using mass functions without making arbitrary quantifications.

The ER Rule is a general theory that allows weight and reliability parameters for each piece of evidence, hence promising more comprehensive data fusion. Though the reliability and weight parameters presumably carry the intuitive meanings of objective evidence quality and subjective evidence importance for the decision maker, in practice their values are up to rather arbitrary choices or data training susceptible to over-fitting. In addition, the equivalent weight representation of the ER Rule raises doubts as to whether the weight and reliability parameters are actually two separate concepts or in fact only one quantity in disguise.
CHAPTER 4

Theory and Hypotheses

4.1 Epistemology Pertinence to the Research

Epistemology is the branch of philosophy concerned with various issues of knowledge. Epistemology is about the study of knowledge. It tells properly what knowledge is as well as how to acquire it. The classic view of Plato’s tripartite: Justified True Belief (JTB) gives the answer about “what is”: “Knowledge is justified true belief.” JTB is simple and yet commonly accepted in many respects. JTB not only tells “what is”, but also provides “how to” about knowledge. Logic is a tool of “how to” advance and accumulate knowledge for human being with epistemological correctness.

Epistemology may not be known for its obvious existence in many applications, because of its implicit nature. In fact, epistemology is all over the applications if there is any relevancy. Although this research work is mainly for the partial fulfillment of this DBA, for us that is also a real opportunity with academic appropriateness. We can lie down and build up some solid foundation based upon epistemological principles in supporting this thesis that will benefit our future research work and that will be expected much in practical nature for a long time to come. In our own words, this is to “epistemologize our research”.

The evolution of the epistemology pertinence can be effectively explicated following the stages of progress in development of applications related to probabilistic theories. First it was the traditional classic deductive logic to take the early leading role in probability theory; and gradually having been forced to open the way for the participation of inductive logic as the fields of applications broadened. Since then, the Bayesian theory by formulizing a priori and a posteriori conditional probabilities has been successfully applied in almost all fields. Finally, it was the recognition of the importance of the uncertainty under the Dempster-Shafer theory of evidence became the undisputed tool to provide distributive solutions in decision making process.
Shafer officially named his theory the Dempster-Shafer Theory (DST) of Evidence. Epistemological importance can be obviously identified in many key points of the Dempster-Shafer theory i.e. the frame of discernment denoted in DST similar to the sample space in probability theory. This thesis too focuses on the concept of “Evidential Reasoning. Why are the two key words “evidence” and “reasoning” so important and worthy of being adopted as the methodology by this research? The former describes “what is knowledge”, and the latter explains “how to”. Logic provides tool giving correct reasoning to justify true belief in epistemology. Since implementation of epistemological principles to any application depends on selection of different types and rules of logic, knowing some details about logic is essentially helpful.

Deductive logic and inductive logic are two types of approach that human beings use to construe sensed information acquired from the external world; and conceptualize as knowledge in mind. As explained in “The Contemporary Notion of Induction” of the Stanford Encyclopedia of Philosophy, Traditional classic or deductive logic is based on general premises and particular conclusion. On the contrary, inductive logic is based on particular premises and general conclusion. If deductive inferences are necessary, then inductive inferences are contingent and supportive. To summarize it;

“induction is ampliative that can amplify and generalize our experience, broaden and deepen our empirical knowledge. Deduction on the other hand is explicative. Deduction orders and rearranges our knowledge without adding to its content. Of course, the contingent power of induction brings with it the risk of error. Even the best inductive methods applied to all available evidence may get it wrong.”("The Problem of Induction," 2006)

In practice, deductive logic is used to provide justification of evidence with deductive reasoning; on the other hand, inductive logic uses a statistical sampling test to justify new evidence reasoned by the acceptance of its null hypothesis. Strictly speaking, there are no contradictions between the two types because all axioms are premises proposed based upon the conditional inference of past knowledge, including the popular Kolmogorov’s probability. Evidence with subjective belief is justified by deductive logic, and evidence
with an objective sampling test is justified with the acceptance of a null hypothesis by inductive logic.

If P, then Q

(1) P is true
   Therefore, Q (deductive conclusion, no new knowledge)

(2) Q is true
   Therefore, higher probability of P (inductive conclusion, new knowledge on P)

Finally, searching for answers to solve the confrontation of conflicting evidence from different sources, this research proposed to incorporate the Evidential Reasoning Rule (that was originally proposed for Multi-Criteria Decision Making) into the construction of an EIA model supporting the decision making solution for investment in financial market.

After the long journey of epistemological and logical consideration, the selection of the Evidential Reasoning Rule for the research will become obvious.

First of all, our research subject is about decision making on investment in the financial market. The securities market is an ensemble comprising a large number of individual and independent stocks that are similar in nature but different in value. The stock market as the name reveals is the place where equities, issued by individual companies that comprise the market ensemble under regulatory constraints, are listed and traded. Secondly, there are many expert analysts using different models to predict expected returns on thousands of recommended stocks. It fits perfectly with models such as ensemble, multi agent, and MCDM systems. Financial analysts can be considered as multi agent or individual sources of evidence.

Decision making on a problem or project in most cases is a process of purposefully selecting solutions among all existing alternatives based upon assessments of information available at the time in accordance with a set of criteria on attributes common to all alternatives. Such a process is usually called Multiple Criteria Decision Making (MCDM). A method for such a purpose developed recently with wide use is Evidential Reasoning. The algorithmic details of MCDM found in the Evidential Reasoning approach are more
suitable for the purpose of this research and are used to make assessment and assignment on all pieces of evidence from different sources of analysts.

“The evidential reasoning (ER) approach is a method for multiple attribute decision analysis (MADA) under uncertainties. It improves the insightfulness and rationality of a decision making process by using a belief decision matrix (BDM) for problem modelling and the Dempster–Shafer (D–S) theory of evidence for attribute aggregation.” (Wang, Yang, Xu, & Chin, 2006)

The Evidential reasoning rule has finally been adopted with satisfaction as the underlying epistemological and logic fundamental of the research.

4.2 Problem Statements

Previously, we have defined our research questions (chapter 1.3) and have separated these into three different major points which we have set out below for further interpretation.

- Can analyst stock recommendations be modeled as mass functions?
- Can the ER Rule be applied to aggregate analyst recommendations to synthesize trading strategies?
- Is the above approach effective?

However, before preparing to answer these questions, we firstly must deal with the following substantive problems. This is because the substantive problems are assumptions and deriving conditions from our research questions.

- Why can the ER Rule be used in this field?
- Why do we want to apply the ER Rule to deal with decision making in financial investment?
- Why can the ER Rule address the gap in the Dempster-Shafer theory?
Despite having previously interpreted some of the reasons in the first three chapters, actually the explanation and speculation in the first and third chapters belongs merely to conceptual qualitative analyses but without a quantitatively analyzed and theoretical foundation - in other words, how do we justify the explanation and the speculation. We know that the ER Rule has taken a step forward in an aspect of epistemology, compared with Bayesian and Dempster-Shafer, making it effective to solve the effective combination of different information. Consequently, it is also effective for investment decisions. Why is it effective? How can we justify the effectiveness of the ER Rule for decision making in financial investment? On the other hand, these three “Why’s” are the core problems for our research. We divided our research into two steps to solve the core problem. The first step is from the angle of epistemology to examine the awareness about these problems (chapter 1.2); the second step is to try to set up Hypotheses Testing with statistical theory to justify the above problems.

4.3 Hypotheses

There are two basic hypotheses put forward in this work. The first hypothesis states that there exist real financial experts in the market and the real financial experts can be identified using their historical accuracies. The second hypothesis asserts that the risk-adjusted return of the strategy based on the ER Rule is greater than that of CSI300.

4.3.1 Hypothesis 1

Denote \( A = \{a_1, a_2, \ldots, a_n\} \) as the set of selected analysts ranked by the prior year accuracy. We define hypothesis 1 formally as

\[ H_1: \exists a_i \in A: a_i \text{ is a real expert} \]
The process of testing for hypothesis 1 is depicted in the figure below.

![Diagram of hypothesis testing process]

Figure 4-1: Hypothesis 1 Testing

The second hypothesis states that our investment strategy based on the ER Rule is effective in that it achieves excess return over the benchmark market index of CSI300.

4.3.2 Hypothesis 2

Denote $R_S$ as the risk-adjusted strategy return and $R_C$ as the risk-adjusted return of CSI300 over the same horizon. We define hypothesis 2 as
H$_2$: The risk-adjusted return of the strategy based on the ER Rule is greater than that of CSI300, satisfying the following inequality $R_S > R_C$.

The null hypothesis is

$$H_0: R_S \leq R_C$$

The process of testing for hypothesis 2 is depicted in the figure below.

**Figure 4-2: Hypothesis 2 Testing**
4.4 Theory: The Efficient Information Assessment (EIA) Model

4.4.1 Frame of Discernment for Financial Investment

For the present study, the opinion of each analyst is viewed as a piece of evidence with an associated mass function. The frame of discernment (FOD) is defined to be the set of all listed stocks on the Shanghai and Shenzhen exchanges:

$$\Theta = \{K_1, K_2, \cdots, K_n\}$$  \hspace{1cm} (4-1)

The mass function $m_A$ for analyst $A$ has a value of 1 for the set of stocks denoted $\{K_{A_1}, K_{A_2}, K_{A_3}, \ldots, K_{A_j}\}$ to which the analyst gives a “Buy” or “Strong Buy” recommendation. The mass function takes on a value of 0 for any other set of stocks. Namely, mass function $m_A$ has only one focal element that is the set $\{K_{A_1}, K_{A_2}, K_{A_3}, \ldots, K_{A_j}\}$:

$$m_A(\Theta) = \begin{cases} 
1 & \text{if } \Theta = \{K_{A_1}, K_{A_2}, \cdots, K_{A_j}\} \\
0 & \text{otherwise} 
\end{cases}$$ \hspace{1cm} (4-2)

Strictly speaking, propositions in a frame of discernment should be mutually exclusive and collectively exhaustive (Yang & Xu, 2013). Collective exhaustivity is clearly met in this case as the number of stocks is limited. However, mutual exclusivity is a bit tricky. It requires the existence of a single stock as the true outcome among all the listed stocks. However, there might be more than one stock in the FOD that is suitable for investment, thus violating the property of a frame of discernment. The innovation here is to use mass
functions to describe analysts’ support for stocks in terms of their suitability for investment with the final goal of producing a portfolio with different proportions for the constituent stocks, without requiring the existence of a single optimal stock among the elements of the FOD. Figure 4-3 illustrates the modeling of analyst opinions as mass functions. Each stock in the frame of discernment, \( s_1 \sim s_n \), is inserted into the focal element of each analyst who has issued a Buy or Strong Buy recommendation for the stock. For \( m \) analysts, we arrive at \( m \) mass functions each having a value of 1 on a single focal element consisting of the stocks for which the analyst has issued a Buy or Strong Buy recommendation within the given report collection period. The mass functions are assigned weight and reliability parameters before being combined via the ER Rule.

4.4.2 Efficient Information Assessment (EIA)

Basic Concept and Definition

Our investment strategies utilize an Efficient Information Assessment (EIA) model. EIA denotes a process constructed to assess all the information, certain or partial, obtained from evidence pertaining to those stocks recommended by selected analysts. The underlying methodology used for assessment is defined to be efficient or not, depending on the measurement of its accuracy, relevancy, and sufficiency with regard to the evidence.

Evidence has to be either for a specific event or elements involved in the event. The objective of this research is for investment in the public equity market. The evidence pertaining to an individual stock recommended by financial analysts can be certain, partial, intervallic, or non-existent (ignorance). It is hard to be certain, and in most case it is either partial or ignorant. Therefore, uncertainty is the norm rather than the exception.
The framework used in the EIA model, other than satisfying the epistemological justification, has to be able to assess and manage the uncertain nature of evidence pertaining to individual stocks. The Dempster-Shafer Theory of evidence is the framework for this research to include ignorance as evidence. A lot of price evidence in individual stocks has interval uncertainty, namely an interval of values being assigned to a subset of the frame of discernment instead of a definitive value. As pointed out by Wang et al. (2006), the D-S theory of evidence, which lacks the ability to work on combination and
normalization of interval uncertainty, needs to be extended to accommodate the situation. The Evidential Reasoning (ER) Rule was developed for this purpose.

“...This is because the combination and normalization process of interval evidence no longer preserves the associative property that the process does not depend on the order in which evidence is combined. To preserve the property, the analytical ER Algorithm is used to combine all evidence simultaneously before the combined belief degrees are normalized which are of an interval nature as well... ”(Wang et al., 2006)

The efficient information in our case refers to stock recommendations issued by financial analysts who had issued at least five stock reports in the prior year. In essence, the EIA model consists of three stages, selection, assessment, and combination, as depicted in Figure 4-4.

Stage 1: Selection

The first stage is selection, namely selecting the stocks that top financial analysts have reviewed.

Stage 2: Assessment

The second stage is assessment, basically converting the qualitative analyst recommendations into quantitative mass functions, incorporating the weight and the reliability information.

Stage 3: Combination

The third stage is combination, applying the Evidential Reasoning Rule to aggregate the analyst opinion mass functions. The EIA model is followed by the pignistic transformation into a probability function, and then construction of investment strategies based on the final probability function.
It is worth noting that the probability function does not indicate the chance of a random event. The probability function is a representation of the analysts’ aggregate support for the profitability of individual stocks. It merely suggests the overall belief of the analysts on how worthy of investment each stock is. We could have denoted the function a belief function, but to avoid confusion over the belief function defined in Dempster-Shafer Theory, we have elected to use the notation of probability function.

4.5 Multiple Criteria Decision Analysis

In this work only one criterion of risk-adjusted return (to be defined in section 7.3) has been considered to measure the effectiveness of the strategy. However, in a more realistic setting one would consider multiple attributes such as expected return, risk, horizon, maximum drawdown, maximum loss, etc. If precise values of expected returns and risks are given, the Modern Portfolio Theory applies and one can obtain optimal portfolios based on returns and risks. However, if there are only subjective and uncertain judgments available for each of the attributes, one could apply the evidential reasoning approach for multiple-attribute decision making with uncertainty (Yang & Singh, 1994), with a decision matrix such as the table below:

**Table 4-1: Stock Alternatives and Performance Attributes**

<table>
<thead>
<tr>
<th>Alternatives (a_i)</th>
<th>Attributes (y_i)</th>
<th>Expected Return (y_1)</th>
<th>Risk (y_2)</th>
<th>Maximum Drawdown (y_3)</th>
<th>Maximum Loss (y_4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock 1 (a_s)</td>
<td>SJ_1</td>
<td>SJ_2</td>
<td>SJ_3</td>
<td>SJ_4</td>
<td>...</td>
</tr>
<tr>
<td>Stock 2 (a_s)</td>
<td>SJ_1</td>
<td>SJ_2</td>
<td>SJ_3</td>
<td>SJ_4</td>
<td>...</td>
</tr>
<tr>
<td>Stock 3 (a_s)</td>
<td>SJ_1</td>
<td>SJ_2</td>
<td>SJ_3</td>
<td>SJ_4</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

The subjective judgments SJ’s are modeled as basic probability assignments, or mass functions. Preference degrees are assigned to the subjective judgments followed by evidence combination via Dempster’s Rule (Yang & Singh, 1994). It is conceivable that one can generalize the Modern Portfolio Theory to the case where the expected returns and
risks are of uncertain and incomplete natures, and this is left for future study. As depicted in the decision matrix below, another way to formulate the investment problem into multi criteria decision making is to treat the evaluation of the stock by each analyst as an attribute, optimizing to achieve positive recommendations by as many analysts as possible:

Table 4-2: Stock Alternatives and Analyst Attributes

<table>
<thead>
<tr>
<th>Alternatives (a_i)</th>
<th>Attributes (y_3)</th>
<th>Analyst 1 (y_1)</th>
<th>Analyst 2 (y_2)</th>
<th>Analyst 3 (y_3)</th>
<th>Analyst 4 (y_4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock 1 (a_1)</td>
<td>S_11</td>
<td>S_12</td>
<td>S_13</td>
<td>S_14</td>
<td>...</td>
</tr>
<tr>
<td>Stock 2 (a_2)</td>
<td>S_21</td>
<td>S_22</td>
<td>S_23</td>
<td>S_24</td>
<td>...</td>
</tr>
<tr>
<td>Stock 3 (a_3)</td>
<td>S_31</td>
<td>S_32</td>
<td>S_33</td>
<td>S_34</td>
<td>...</td>
</tr>
</tbody>
</table>

This approach would be similar to the simple methods analyzed in Chapter 8 of the thesis targeting at meeting as many positive reviews as possible. However, different preferences can be assigned to different analysts creating a weighting of the analyst opinions.

4.6 Combination of Analyst Opinions

Analysts mostly recommend different sets of stocks, resulting in total conflicts in the framework of the DS theory, thus prohibiting the use of Dempster’s Rule for combining mass functions. The ER Rule was developed to enable a consistent combination of potentially conflicting evidence with the introduction of the weight and reliability parameters for each mass function (Yang & Xu, 2013). The weight refers to the importance of a piece of evidence as perceived by the decision maker, which is subjective and reflects the decision maker’s judgment. On the other hand, the reliability refers to the quality of a piece of evidence, which is objective and is an inherent property of the information source.

A concise formulation of the ER Rule is as follows. Denote the weight of a piece of evidence as $w$ and the reliability as $r$, an equivalent weight can be constructed using below equation:
Denote the original mass function of the piece of evidence as \( m(\theta) \). It can be converted into a mass function with weight and reliability by the following formula:

\[
\tilde{m}(\theta) = \begin{cases} 
0 & \theta = \emptyset \\
\tilde{w} \cdot m(\theta) & \theta \in \Theta \\
1 - \tilde{w} & \theta = P(\Theta) 
\end{cases}
\]  

(4-4)

Two mass functions with weight and reliability are then combined via below relation with two components:

\[
\tilde{m}_{\theta_2}(\theta) = [(1 - \tilde{w}_2) \tilde{m}_{\theta_1} + (1 - \tilde{w}_1) \tilde{m}_{\theta_2}] + \sum_{\theta_1 \cap \theta_2 = \emptyset} \tilde{m}_{\theta_1} \tilde{m}_{\theta_2} \quad \forall \theta \subseteq \Theta
\]

(4-5)

The first component inside the bracket is termed the **bounded sum of individual support**, which is the sum of the degree of individual support bounded by 1 minus the equivalent weight of the other piece of evidence (Yang & Xu, 2013). The second component of the summation is termed the **orthogonal sum of collective support**, which measures the degree of direct or intersected support from both pieces of evidence (Yang & Xu, 2013). Renormalization is applied at the end to ensure that values assigned to all focal elements of the mass function sum up to 1:

\[
p_{\theta_2}(\theta) = \begin{cases} 
0 & \theta = \emptyset \\
\frac{\tilde{m}_{\theta_2}(\theta)}{\sum_{\theta \subseteq \Theta} \tilde{m}_{\theta_2}(\theta)} & \theta \subseteq \Theta
\end{cases}
\]

(4-6)

In this formulation of the ER Rule, the mass functions to be combined are assumed to be independent. It is possible that the opinions of analysts affiliated with the same broker might be correlated to each other. This independence assumption could be relaxed in future work using a generalized form of the ER Rule.
4.7 Reliability and Weight of a Financial Analyst

The application of the ER Rule involves the reliability parameter for each piece of evidence. To determine the reliability of an analyst, we can look at the past performance of the analyst, which can be measured by historical return or historical accuracy. The historical return refers to the return that one would have realized if one had followed the recommendations of an analyst to invest. The historical accuracy of an analyst can be calculated as the percentage of forecast reports that he or she had made within a certain period of time which turned out to be true.

An arbitrary choice was made to use a period of one year to determine the annual accuracy of an analyst. In this work we have elected to use historical accuracy as the reliability parameter because it is an objective number between 0 and 1 that fits the concept of reliability naturally. Other choices of reliability e.g. using the historical return measure could be explored in future studies.

A forecast states the stock price change over a period of six months, which raises complications as to whether temporary high gains or deep losses can be considered to fulfill a forecast. To simplify our analysis, we use the stock price on the first day of the six-month period and the stock price on the last day of the six-month period to compute the stock return for determining if a forecast is realized or not.

The weight is a subjective parameter depending on the decision maker’s judgment. We have no a priori preference over the analysts and in our study the weights have been set to an equal value.

4.8 Investment Strategies

We gather reports published within the past report collection period (one month, two months, or three months). The report published by an analyst that had published fewer than five reports in the prior year is discarded. Applying the model described earlier, a mass
function is constructed for each analyst. For example, suppose Analyst 1 recommends stock $S_1$, $S_2$ and $S_3$ as Buy or Strong Buy, his or her mass function looks like the following:

$$m_1(\theta) = \begin{cases} 
1 & \theta = \{S_1, S_2, S_3\} \\
0 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (4-7)

The choices of the weight and reliability parameters will be discussed later. The ER Rule is applied to combine all the mass functions, and the result is converted into a final probability function over the stocks using Smets’ pignistic transformation (Smets & Kennes, 1994).

For example, suppose Analyst 2 recommends stock $S_2$, $S_3$ and $S_4$ as Buy or Strong Buy. The mass function is then:

$$m_2(\theta) = \begin{cases} 
1 & \theta = \{S_2, S_3, S_4\} \\
0 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (4-8)

Suppose the weights for both analysts are the same and equal to 0.5, and the reliability for Analyst 1 and 2 is $r_1 = 0.8$ and $r_2 = 0.9$ respectively. The respective equivalent weights of the analysts are:

$$\tilde{w}_1 = \frac{0.5}{1+0.5-0.8} = \frac{5}{7}$$ \hspace{1cm} (4-9)

$$\tilde{w}_2 = \frac{0.5}{1+0.5-0.9} = \frac{5}{6}$$ \hspace{1cm} (4-10)

Denoting the frame of discernment $\Theta = \{S_1, S_2, S_3, S_4\}$, multiplying the original mass function by the equivalent weight gives the mass function with weight and reliability:

$$\tilde{m}_1(\theta) = \begin{cases} 
\frac{5}{7} & \theta = \{S_1, S_2, S_3\} \\
\frac{2}{7} & \theta = p(\Theta) \\
0 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (4-11)
\[
\tilde{m}_2(\theta) = \begin{cases} 
    \frac{5}{6} & \theta = \{S_2, S_3, S_4\} \\
    \frac{1}{6} & \theta = P(\Theta) \\
    0 & \text{otherwise}
\end{cases}
\]  

Equation 4-12

The combined mass function comprising a linear sum of the discounted mass functions and an intersection term of the mass function product is then:

\[
\tilde{m}_{\theta,e(2)} = \begin{cases} 
    \frac{5}{42} & \theta = \{S_1, S_2, S_3\} \\
    \frac{5}{21} & \theta = \{S_2, S_3, S_4\} \\
    \frac{25}{42} & \theta = \{S_2, S_3\} \\
    \frac{1}{21} & \theta = P(\Theta)
\end{cases}
\]  

Renormalization to remove the \(P(\Theta)\) case yields:

\[
p_{\theta,e(2)} = \begin{cases} 
    \frac{1}{8} & \theta = \{S_1, S_2, S_3\} \\
    \frac{1}{4} & \theta = \{S_2, S_3, S_4\} \\
    \frac{5}{8} & \theta = \{S_2, S_3\}
\end{cases}
\]  

Applying Smets’ pignistic transformation, the final probabilities are obtained as follows:

\[
p(\theta) = \begin{cases} 
    \frac{1}{24} & \theta = S_1 \\
    \frac{21}{48} & \theta = S_2 \\
    \frac{21}{48} & \theta = S_3 \\
    \frac{1}{12} & \theta = S_4
\end{cases}
\]  

Equation 4-15

After obtaining the final probability, two investment strategies were followed. In the first strategy, referred to as strategy 1, we invest in all of the stocks according to the probability distribution; namely, the amount invested in each stock is proportional to the final probability assigned to it. In the second strategy, referred to as strategy 2, we select the top five stocks with the highest final probability to be included in the portfolio and invest in
them with equal proportions. The portfolio is then held for a certain investment horizon (1 month, 2 months… 6 months) before being liquidated.

It is worth nothing that the pignistic transformation is just one of the many possible ways to transform a mass function into a probability distribution. According to Dempster (2008, 2015), for each outcome in the frame of discernment, the mass function can be interpreted as a triple \( \{p, q, r\} \) with \( p \) being the probability supporting an outcome, \( q \) the probability going against an outcome, and \( r \) the degree of ambiguity associated with an outcome. For the example described in this section, given Eq. (4-14) we arrive at the following triplets:

- for \( s_1 \), \( p = 0, q = \frac{7}{8}, r = 1 - p - q = \frac{1}{8} \);
- for \( s_2 \), \( p = 0, q = 0, r = 1 - p - q = 1 \);
- for \( s_3 \), \( p = 0, q = 0, r = 1 - p - q = 1 \);
- for \( s_4 \), \( p = 0, q = \frac{3}{4}, r = 1 - p - q = \frac{1}{4} \).

There is high ambiguity in the mass function, as measured by \( r \), and hence there are numerous ways to utilize the mass function for decision making. For example, the probabilities of \( s_1, s_2, s_3 \) and \( s_4 \), denoted \( p_1, p_2, p_3, \) and \( p_4 \), respectively, can take any values satisfying all of the following conditions:

\[
0 \leq p_1, p_2, p_3, p_4 \leq 1; \\
0 \leq p_1 \leq \frac{1}{8}, \\
0 \leq p_2 \leq 1, \\
0 \leq p_3 \leq 1, \\
0 \leq p_4 \leq \frac{1}{4}, \\
p_1 + p_2 + p_3 + p_4 = 1
\]

The pignistic probabilities of Eq. (4-15) are just one of the solutions compatible with the above conditions. Another feasible choice is \( p_1 = 0, p_2 = p_3 = \frac{1}{2}, p_4 = 0 \), which would correspond to a simple voting by the two analysts as stock 2 and stock 3 both get the highest number of two votes. Evidently, there are many other possible solutions.

In this thesis we have chosen to use the pignistic probabilities because they are simple to understand and easy to use. The results reported in the following chapters also show that they work well. More discussions on this issue may be found in section 9.3.5.
CHAPTER 5

Data Collection

5.1 Analyst Reports

The input data used were analyst reports on China’s stock market, which consists of two independently operating exchanges, the Shanghai stock exchange with a market capitalization of US$4.1 trillion (August 25, 2016) ("Shanghai Stock Exchange,")) and the Shenzhen stock exchange with a market capitalization of US$3.3 trillion (August 25, 2016) ("Shenzhen Stock Exchange,"). As a measure of market performance, we refer to the CSI 300 index, which is a capitalization-weighted stock index compiled to reflect the performance of 300 stocks listed in the Shenzhen and Shanghai exchanges.

Brokers publish analyst reports on stocks regularly, which contain information such as the general market trend, the industry trend, and recommendations on individual stocks. A recommendation usually has a corresponding six-month or twelve-month forecast on the stock price move as compared to the change in CSI 300 index over the same period of time. Exact definitions of the recommendation and the forecast vary among brokerage firms. A broker might define levels of recommendation and the corresponding forecasts as in Table 5-1. For example, a Strong Buy recommendation corresponds to a forecast stating that the stock price will rise more than 20% compared to the change in CSI 300 index during the same period.
Table 5-1: Typical definitions of a broker’s recommendations and the associated forecast levels

<table>
<thead>
<tr>
<th>Recommendation</th>
<th>Forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong Buy</td>
<td>Stock price return will be higher than that of CSI 300 index by 20% in the next six months</td>
</tr>
<tr>
<td>Buy</td>
<td>Stock price will rise by 5~20% compared to CSI 300 index in the next six months</td>
</tr>
<tr>
<td>Neutral</td>
<td>Stock price will change by -10~5% compared to CSI 300 index in the next six months</td>
</tr>
<tr>
<td>Sell</td>
<td>Stock price will drop by 10~15% compared to CSI 300 index in the next six months</td>
</tr>
<tr>
<td>Strong Sell</td>
<td>Stock price return will be lower than that of CSI 300 index by 15% in the next six months</td>
</tr>
</tbody>
</table>

5.1.1 China Stock Market & Accounting Research Database

Using MySQL commands, our data are retrieved from the China Stock Market & Accounting Research (CSMAR) Database, which includes stock price information and recommendation/forecasting reports made by financial analysts on the China stock market. As the analyst reports are collected from various brokers and of different formats, the database provides a standardized definition of the recommendations and it renormalizes the recommendations by different brokers according to the standardized definition. For the sake of consistency across brokers, we used the renormalized recommendations provided by the database as opposed to the original ones provided by the brokers.
5.1.2 Data Sets for Analysis

For this work, we focus on recommendation reports with corresponding six-month forecasts. Assuming that market moves within one month are relatively small compared to those occurring over the range of six months, we aim to aggregate recommendation reports published within one month and analyze the realized return of the recommended stocks using different aggregation strategies.

We retrieved from the CSMAR database a total of 271,804 Buy and Strong Buy recommendation reports released between December 2008 and November 2012 by 4,624
analysts. A report is excluded from the dataset if its analyst published fewer than five reports in the prior year. The process of data collection is depicted in Figure 5-1.

Stock price information from the database is also retrieved. For each report, we checked the forecast reports released by its analyst in the prior year of the report date against actual stock price moves to determine the prior year annual accuracy of the analyst. Price records are also used to compute realized returns of the recommended stocks.

5.2 Data and Descriptive Statistics

5.2.1 Sample period and Data Table Columns

One- month collection period reports (.reports) from Nov 2008 to Dec 2012 (50 months) were taken as raw data and Report-Id, Stock-Code, Analyst, Recommend columns are used in the following analysis. The first three columns define a unique name for each report, stock, and analyst, respectively, while the last column shows the recommendation level. Another column Analyst Id was also added, which assigns a unique number to each analyst for easier sorting.
5.2.2 Numbers of Monthly Reports, Analysts, and Number of Covered Stocks

![Number of reports graph](image)

**Figure 5-2**: Number of Reports each month

Figure 5-2 shows the number of reports issued by the analysts in each month. We see the same pattern in different years that the peak occurs in the months of April, May, September, and November.

![Number of analysts graph](image)

**Figure 5-3**: Number of Analysts each month
Figure 5-3 indicates the number of analysts who have issued stock recommendations in each month, which ranges from 412 to 1007, with a mean of 785 and standard deviation of 180.27 during the sample period.

Similarly, Figure 5-4 presents the number of stocks which have been recommended by analysts, including Strong-Buy, Buy, Neutral, Sell, and Strong-Sell recommendations.

The exact number for the above figures can be found from the table below. And for the whole sample period, we have 3,761 analysts covered 2,202 stocks and issued 120,023 reports in total. That is to say, on average, each analyst has released about four reports during the sample period.
5.2.3 Recommendations

Consistent with our expectation, over 88% recommendation ratings are Strong-Buys and Buys, followed by Neutrals, which take up about 10%. The percentage of Sells and Strong-Sells only is less than 1%. On average, there are only one report with Sell rating and five reports with Strong-Sell rating released by analysts each month. In comparison, the number of reports with Strong-Buy and Buys are both over 1,000.
Figure 5-5: Number of Strong Buy and Buy Reports

Figure 5-6: Number of Neutral Reports

Figure 5-7: Number of Strong Sell and Sell Reports
5.2.4 Numbers of Covered Stocks per Analyst

Number of covered stocks per analyst in each month

Table 5-3: Number of covered stocks per analysts in each month

<table>
<thead>
<tr>
<th>Date</th>
<th>No. of Analysts</th>
<th>Date</th>
<th>No. of Analysts</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008/11/28</td>
<td>768</td>
<td>2011/01/31</td>
<td>711</td>
</tr>
<tr>
<td>2008/12/31</td>
<td>476</td>
<td>2011/02/28</td>
<td>490</td>
</tr>
<tr>
<td>2009/1/23</td>
<td>421</td>
<td>2011/03/31</td>
<td>954</td>
</tr>
<tr>
<td>2009/2/27</td>
<td>622</td>
<td>2011/04/29</td>
<td>897</td>
</tr>
<tr>
<td>2009/3/31</td>
<td>873</td>
<td>2011/05/31</td>
<td>653</td>
</tr>
<tr>
<td>2009/4/30</td>
<td>828</td>
<td>2011/06/30</td>
<td>605</td>
</tr>
<tr>
<td>2009/5/27</td>
<td>572</td>
<td>2011/07/29</td>
<td>717</td>
</tr>
<tr>
<td>2009/6/30</td>
<td>616</td>
<td>2011/08/31</td>
<td>809</td>
</tr>
<tr>
<td>2009/7/31</td>
<td>824</td>
<td>2011/09/30</td>
<td>519</td>
</tr>
<tr>
<td>2009/8/31</td>
<td>1,053</td>
<td>2011/10/31</td>
<td>799</td>
</tr>
<tr>
<td>2009/9/30</td>
<td>655</td>
<td>2011/11/30</td>
<td>589</td>
</tr>
<tr>
<td>2009/10/30</td>
<td>1,058</td>
<td>2011/11/30</td>
<td>548</td>
</tr>
<tr>
<td>2009/11/30</td>
<td>867</td>
<td>2011/11/30</td>
<td>480</td>
</tr>
<tr>
<td>2012/12/30</td>
<td>676</td>
<td>2011/12/30</td>
<td>430</td>
</tr>
<tr>
<td>2012/12/20</td>
<td>653</td>
<td>2012/01/31</td>
<td>579</td>
</tr>
<tr>
<td>2012/12/29</td>
<td>863</td>
<td>2012/02/29</td>
<td>604</td>
</tr>
<tr>
<td>2012/12/30</td>
<td>1,007</td>
<td>2012/03/30</td>
<td>772</td>
</tr>
<tr>
<td>2012/12/27</td>
<td>1,173</td>
<td>2012/04/27</td>
<td>1,007</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>999</td>
<td>2012/05/31</td>
<td>748</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>664</td>
<td>2012/06/29</td>
<td>633</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>650</td>
<td>2012/07/31</td>
<td>809</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>800</td>
<td>2012/08/31</td>
<td>467</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>1,084</td>
<td>2012/09/30</td>
<td>1,055</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>664</td>
<td>2012/10/31</td>
<td>883</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>933</td>
<td>2012/11/30</td>
<td>603</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>865</td>
<td>2012/12/30</td>
<td>1,243</td>
</tr>
<tr>
<td>2012/12/31</td>
<td>781</td>
<td>2012/12/30</td>
<td>802</td>
</tr>
</tbody>
</table>

Number of covered stocks per analyst in each year:

Table 5-4: Numbers of Covered Stocks per Analyst

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Analysts</th>
<th>Mean</th>
<th>Median</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>1,753</td>
<td>15.49287</td>
<td>10</td>
<td>17.26387</td>
<td>1</td>
<td>158</td>
</tr>
<tr>
<td>2010</td>
<td>2,056</td>
<td>17.73249</td>
<td>10</td>
<td>23.70328</td>
<td>1</td>
<td>359</td>
</tr>
<tr>
<td>2011</td>
<td>1,583</td>
<td>24.28301</td>
<td>13</td>
<td>37.0416</td>
<td>1</td>
<td>609</td>
</tr>
<tr>
<td>2012</td>
<td>1,853</td>
<td>25.30383</td>
<td>15</td>
<td>32.2686</td>
<td>1</td>
<td>424</td>
</tr>
</tbody>
</table>

89
Number of following analysts per stock in each month:

Table 5-5: Number of following analysts per stock in each month

<table>
<thead>
<tr>
<th>Date</th>
<th>No. of Stocks</th>
<th>Mean</th>
<th>Median</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008/11/28</td>
<td>475</td>
<td>4.157189</td>
<td>2</td>
<td>4.564026</td>
<td>1</td>
<td>33</td>
</tr>
<tr>
<td>2009/12/23</td>
<td>332</td>
<td>3.515378</td>
<td>2</td>
<td>3.109816</td>
<td>1</td>
<td>43</td>
</tr>
<tr>
<td>2009/2/27</td>
<td>405</td>
<td>3.191664</td>
<td>2</td>
<td>3.43787</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>2009/3/31</td>
<td>564</td>
<td>4.773369</td>
<td>3</td>
<td>4.679287</td>
<td>1</td>
<td>31</td>
</tr>
<tr>
<td>2009/4/30</td>
<td>618</td>
<td>5.283754</td>
<td>3</td>
<td>5.475438</td>
<td>1</td>
<td>37</td>
</tr>
<tr>
<td>2009/5/27</td>
<td>489</td>
<td>3.632283</td>
<td>2</td>
<td>4.191472</td>
<td>1</td>
<td>37</td>
</tr>
<tr>
<td>2009/6/30</td>
<td>447</td>
<td>3.773156</td>
<td>2</td>
<td>4.400868</td>
<td>1</td>
<td>38</td>
</tr>
<tr>
<td>2009/7/31</td>
<td>531</td>
<td>4.635015</td>
<td>3</td>
<td>5.158977</td>
<td>1</td>
<td>37</td>
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<tr>
<td>2009/8/31</td>
<td>774</td>
<td>7.064475</td>
<td>4</td>
<td>7.139228</td>
<td>1</td>
<td>44</td>
</tr>
<tr>
<td>2009/9/30</td>
<td>461</td>
<td>4.679587</td>
<td>3</td>
<td>5.365586</td>
<td>1</td>
<td>33</td>
</tr>
<tr>
<td>2009/10/30</td>
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<td>6.170163</td>
<td>4</td>
<td>6.659453</td>
<td>1</td>
<td>47</td>
</tr>
<tr>
<td>2009/11/30</td>
<td>531</td>
<td>4.410256</td>
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<td>5.770766</td>
<td>1</td>
<td>62</td>
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<tr>
<td>2009/12/31</td>
<td>527</td>
<td>4.292541</td>
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<td>5.910376</td>
<td>1</td>
<td>38</td>
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<tr>
<td>2010/1/29</td>
<td>540</td>
<td>4.547786</td>
<td>3</td>
<td>5.257926</td>
<td>1</td>
<td>38</td>
</tr>
<tr>
<td>2010/2/28</td>
<td>457</td>
<td>4.567999</td>
<td>2</td>
<td>5.519923</td>
<td>1</td>
<td>46</td>
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<tr>
<td>2010/3/31</td>
<td>855</td>
<td>6.434752</td>
<td>3</td>
<td>7.68083</td>
<td>1</td>
<td>55</td>
</tr>
<tr>
<td>2010/4/30</td>
<td>929</td>
<td>5.781053</td>
<td>3</td>
<td>7.598685</td>
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<td>84</td>
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<td>2010/5/31</td>
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<td>4.013994</td>
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<td>5.000228</td>
<td>1</td>
<td>56</td>
</tr>
<tr>
<td>2010/6/30</td>
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<td>4.044413</td>
<td>2</td>
<td>5.378465</td>
<td>1</td>
<td>56</td>
</tr>
<tr>
<td>2010/7/30</td>
<td>614</td>
<td>4.608913</td>
<td>3</td>
<td>5.782186</td>
<td>1</td>
<td>56</td>
</tr>
<tr>
<td>2010/8/31</td>
<td>1,055</td>
<td>7.08901</td>
<td>3</td>
<td>7.193714</td>
<td>1</td>
<td>48</td>
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<tr>
<td>2010/9/30</td>
<td>563</td>
<td>5.125118</td>
<td>3</td>
<td>6.51161</td>
<td>1</td>
<td>48</td>
</tr>
<tr>
<td>2010/10/29</td>
<td>938</td>
<td>5.555336</td>
<td>4</td>
<td>5.543755</td>
<td>1</td>
<td>43</td>
</tr>
<tr>
<td>2010/11/30</td>
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<td>4.541128</td>
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<td>5.415173</td>
<td>1</td>
<td>43</td>
</tr>
<tr>
<td>2010/12/31</td>
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<td>4.626564</td>
<td>3</td>
<td>5.437665</td>
<td>1</td>
<td>43</td>
</tr>
</tbody>
</table>

Number of following analysts per stock in each year:

Table 5-6: Number of following analysts per stock in each year

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Analysts</th>
<th>No. of covered stocks per analyst</th>
<th>Mean</th>
<th>Median</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>1,250</td>
<td>22.2048</td>
<td>10</td>
<td>28.43466</td>
<td>1</td>
<td>219</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>1,619</td>
<td>22.80111</td>
<td>13</td>
<td>29.11847</td>
<td>1</td>
<td>239</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>1,898</td>
<td>20.25922</td>
<td>11</td>
<td>25.28013</td>
<td>1</td>
<td>196</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>1,769</td>
<td>26.68739</td>
<td>13</td>
<td>33.22554</td>
<td>1</td>
<td>255</td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 6

Performance Persistence of Financial Analysts

6.1 Performance Measures of Analysts

The premise of this research relies on the assumption that stocks recommended by financial analysts do achieve excess returns. It is well known that not all recommendations are profitable and therefore it is important for investors to identify top-performing analysts who make effective recommendations. Since there is no way for investors to know beforehand how well an analyst will perform, an investor can only make decisions based on the analyst’s past performance which can be defined by accuracy or return.

6.2 Accuracy and Return

The accuracy of an analyst can be measured by the percentage of forecast reports published by the analyst which turned out to be true in the prior year. A forecast states the change in stock price over a period of six months, which raises complications as to whether temporary high gains or deep losses can be deemed as fulfilling a forecast. To simplify our analysis, we use the stock price on the first day of the six-month and the stock price on the last day of the six-month period to compute the stock return for determining if a forecast is realized or not. Another performance measure is the return realized if one invests in the stocks that an analyst recommended, in equal proportions for a horizon of six months.

6.3 Transition Matrix and Correlations

As a simple trial, we focused on the stocks for which an analyst had issued a Buy or Strong Buy recommendation within the one-month period of January 2012, discarding all other recommendations. We checked the correlations between the analyst’s prior year annual
accuracy and the realized six-month return of the stocks that had been issued a Strong Buy or Buy recommendation in January 2012. We rank the reports by their analysts’ prior year accuracy, and compute the correlation for the top 100, 200, 300, and 400 reports.

The annual accuracy of financial analysts between consecutive years was compared and it is shown that there is a distinct tendency for top-performing analysts to remain top performing in the next year. Specifically, the analysts were ranked according to their annual accuracy, and divided into quintiles. Table 6-1 is a transition matrix where each cell shows the percentage of analysts in 2011 quintile that turns out to be in the corresponding 2012 quintile. We see that 43.31% of the top quintile analysts of 2011 remain in the top quintile in 2012, which is a clear indication of persistence, as pure randomness would lead to a percentage of 20%. The conditional probability for the analysts to stay in the same quintile is highest for the top quintile analysts, which is consistent with other studies on the performance persistence of financial professionals, e.g. the conditional probability for private equity fund managers to stay in the same tercile is highest for managers in the top and bottom terciles (Braun et al., 2015).

Table 6-1: Transition matrix of analyst quintiles as ranked by their annual accuracy

<table>
<thead>
<tr>
<th></th>
<th>2012</th>
<th>Top quintile</th>
<th>Second quintile</th>
<th>Third quintile</th>
<th>Fourth quintile</th>
<th>Fifth quintile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top quintile</td>
<td>43.31%</td>
<td>16.93%</td>
<td>6.69%</td>
<td>3.94%</td>
<td>1.18%</td>
<td></td>
</tr>
<tr>
<td>Second quintile</td>
<td>14.23%</td>
<td>28.85%</td>
<td>18.58%</td>
<td>8.70%</td>
<td>0.40%</td>
<td></td>
</tr>
<tr>
<td>Third quintile</td>
<td>5.51%</td>
<td>20.08%</td>
<td>22.44%</td>
<td>12.21%</td>
<td>5.51%</td>
<td></td>
</tr>
<tr>
<td>Fourth quintile</td>
<td>2.37%</td>
<td>3.56%</td>
<td>11.07%</td>
<td>27.67%</td>
<td>21.34%</td>
<td></td>
</tr>
<tr>
<td>Fifth quintile</td>
<td>0.39%</td>
<td>1.97%</td>
<td>6.30%</td>
<td>13.39%</td>
<td>31.10%</td>
<td></td>
</tr>
</tbody>
</table>

To strengthen the argument of performance persistence, transition matrices from 2009 to 2010 and from 2010 to 2011 are computed and shown in Table 6-2 and Table 6-3. The top quintile transition probabilities are 46.15% and 48.80% respectively, again demonstrating strong performance persistence for the top financial analysts.
Table 6-2: Transition matrix of analyst quintiles from 2009 to 2010

<table>
<thead>
<tr>
<th></th>
<th>2009</th>
<th>2010</th>
<th>Top quintile</th>
<th>Second quintile</th>
<th>Third quintile</th>
<th>Fourth quintile</th>
<th>Fifth quintile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top quintile</td>
<td>46.15%</td>
<td>21.15%</td>
<td>11.06%</td>
<td>2.40%</td>
<td>0.48%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second quintile</td>
<td>18.27%</td>
<td>28.85%</td>
<td>21.15%</td>
<td>9.62%</td>
<td>2.88%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Third quintile</td>
<td>11.06%</td>
<td>17.31%</td>
<td>23.56%</td>
<td>23.08%</td>
<td>9.13%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fourth quintile</td>
<td>5.29%</td>
<td>9.13%</td>
<td>17.79%</td>
<td>21.15%</td>
<td>25.96%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fifth quintile</td>
<td>7.21%</td>
<td>7.21%</td>
<td>7.69%</td>
<td>15.39%</td>
<td>34.14%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6-3: Transition matrix of analyst quintiles from 2010 to 2011

<table>
<thead>
<tr>
<th></th>
<th>2010</th>
<th>2011</th>
<th>Top quintile</th>
<th>Second quintile</th>
<th>Third quintile</th>
<th>Fourth quintile</th>
<th>Fifth quintile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top quintile</td>
<td>48.80%</td>
<td>19.60%</td>
<td>5.20%</td>
<td>0.80%</td>
<td>0.80%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second quintile</td>
<td>13.20%</td>
<td>35.20%</td>
<td>17.20%</td>
<td>6.00%</td>
<td>1.60%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Third quintile</td>
<td>5.58%</td>
<td>17.53%</td>
<td>26.30%</td>
<td>18.73%</td>
<td>5.18%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fourth quintile</td>
<td>1.60%</td>
<td>7.60%</td>
<td>15.60%</td>
<td>28.00%</td>
<td>20.40%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fifth quintile</td>
<td>2.40%</td>
<td>2.00%</td>
<td>7.60%</td>
<td>17.20%</td>
<td>36.00%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Intuitively, we would expect that higher accuracies correspond to higher realized return. Indeed, positive correlations were observed between the two variables for the top-performing analysts, but the correlation diminishes when more analysts were included. Table 6-2 shows the correlation coefficient between prior year accuracy and realized return for the reports published in January 2012, as well as the p-value from one-tailed hypothesis testing for significant positive linear correlation. If only the top 100 reports are included, the correlation is high at 16% with a p-value of 0.056. However, if the top 300 reports or all of the 398 reports are included, the correlation is close to 0. Even though 16% does not seem to be a very high coefficient, the correlation is between accuracy and return, two quantities of very different measures. In addition, many of the top analysts have high accuracies, making it difficult to discern their linear relationships with stock returns.
However, the p-value of 5.6% from one-tailed hypothesis testing supports the view that there is significant positive linear relationship between prior year accuracy and current year return.

**Table 6-4**: Correlation coefficient between the 2011 accuracy of top-performing analysts who published reports in January 2012 and the realized return of the stocks recommended by these reports. Also listed is the p-value from one-tailed hypothesis testing for significant positive linear correlation between the prior year accuracy and current year stock return.

<table>
<thead>
<tr>
<th></th>
<th>All reports</th>
<th>Top 100 reports</th>
<th>Top 200 reports</th>
<th>Top 300 reports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>-0.5%</td>
<td>16%</td>
<td>13%</td>
<td>-3%</td>
</tr>
<tr>
<td>p-value (one tailed)</td>
<td>16%</td>
<td>5.6%</td>
<td>3.3%</td>
<td>30%</td>
</tr>
</tbody>
</table>

We have seen statistically significant evidence supporting performance persistence of financial analysts. There is a much higher than random percentage for the top-performing analysts as measured by report accuracy to stay top performing in the following year. With respect to the realized return of recommendations, overall there is no correlation between prior year accuracy and current year return, and therefore there is no significant performance persistence if all of the analysts are included. However, for the top-performing group of analysts, there is significant positive correlation between prior year accuracy and current year return, indicating performance persistency for the top analysts. To be more statistically rigorous, we could perform an ordinary least-squares regression for the current annual accuracy or realized return on prior year annual accuracy or realized return to see if the coefficient on the lagged accuracy/return is positive and statistically significant, following the approach adopted by Braun et al. (2015).
CHAPTER 7

ER Rule and Portfolio Selection

7.1 Single-Month Experiment

Given the positive correlations between historical accuracy and realized return, we expect that stocks recommended by top-performing analysts of 2011 would yield excess returns. As an initial test, we retrieved from the CSMAR database the Buy and Strong Buy recommendation reports released in January 2012 by analysts who had published at least five reports in 2011, identifying 398 recommendation reports in total. We focus on recommendation reports with corresponding six-month forecasts. Assuming that market moves within one month are relatively small compared to those occurring over the range of six months, we aim to aggregate recommendation reports published within one month and analyze the realized return of the recommended stocks using different aggregation strategies.

Stock price information from the database is also retrieved. For each analyst of these reports, his or her forecast reports released in the prior year of 2011 were checked against actual stock price moves to determine the prior year annual accuracy of the analyst. For the 398 reports published in January 2012, the price records in 2012 were used to compute the realized return of the recommended stocks. Recall from Section 4.8 that two strategies are proposed in this work. In strategy 1 we invest in all of the stocks according to the combined probability distribution while in strategy 2 we invest with equal proportions in the top five stocks with the highest combined probability.

Strategy 1 of Evidential Reasoning (ER Strat1) was applied with the weight and reliability set to the analyst’s prior year annual accuracy. Note that this is different from subsequent experiments where reliability was set to the analyst’s prior year annual accuracy but the weight was set to be a constant value equal to (1/number of top analysts used). The reason for the change was that there was no prior preference over the analysts and therefore the
decision maker would assign equal weights to the analysts. For the sake of computation time, in different cases we used only recommendations by the top 10, 20, ..., or 50 analysts, where analysts are ranked in descending order of their prior year annual accuracy. Both the weight and the reliability parameters are set to the prior year accuracy. Some analysts had a prior year accuracy of 1, and in this case the equivalent weight is often computed to be 1.000003 due to the precision of the particular software used. When this happens, the equivalent weight is adjusted to 0.999.

Shown in the table below are the six-month returns of the two strategies compared to those of CSI300. Note that the return associated with each analyst report is computed as the stock price return from the publication date of the report to six months after the publication date. Namely, the return of each report refers to different investment periods. The CSI300 return is computed as the average over the report returns and thus it can vary when different numbers of reports with different dates are used. The strategy return is similarly computed as the weighted average of the report returns. In subsequent experiments returns are made consistent referring to an investment horizon starting from the end of the report collection period.

It can be seen that strategy 1 outperforms CSI300 in all cases, and strategy 1 return peaks at around 20 to 30 analysts. On the other hand, strategy 2 is worse for the case of 10 analysts, but it achieves a much higher return of 24.28% for the other cases of more analysts, potentially because the opinions of the analysts converge to a few optimal stocks.

Table 7-1: Returns of the portfolios constructed in different scenarios

<table>
<thead>
<tr>
<th>No. of Top Analysts</th>
<th>No. of Reports</th>
<th>CSI300 Return</th>
<th>ER Strat1 Return</th>
<th>ER Strat2 Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>31</td>
<td>0.42%</td>
<td>6.78%</td>
<td>-8.61%</td>
</tr>
<tr>
<td>20</td>
<td>64</td>
<td>0.01%</td>
<td>12.01%</td>
<td>24.28%</td>
</tr>
<tr>
<td>30</td>
<td>87</td>
<td>-0.18%</td>
<td>10.09%</td>
<td>24.28%</td>
</tr>
<tr>
<td>40</td>
<td>109</td>
<td>-0.18%</td>
<td>6.15%</td>
<td>24.28%</td>
</tr>
<tr>
<td>50</td>
<td>132</td>
<td>-0.17%</td>
<td>3.74%</td>
<td>24.28%</td>
</tr>
</tbody>
</table>
7.2 Rolling Portfolio Experiments

To further demonstrate the robustness of the investment strategy, it was tested on a wider dataset by repeating the experiment once every report collection period (for example in three month intervals) from December 2008 to December 2012 to obtain multiple data points of the investment return. In other words, at the end of every report collection period, a new investment portfolio is constructed according to the above-mentioned strategy, which is then held for the duration of the investment horizon (such as six months) before liquidation. The rolling portfolio process is depicted in the figure below:

![Figure 7-1: Process of Rolling Portfolio Investment](image)

For the construction of each investment portfolio, recommendations from the top 40 analysts are used. The weight parameter is set to $1/40$, namely $(1/\text{number of top analysts included})$, and the reliability parameter is set to the analyst’s prior year annual accuracy. For analysts with a prior year accuracy of 1, the equivalent weight is set to 0.999 for the ER Rule to be applicable, because in the case of full reliability, the ER Rule reduces to Dempster’s Rule and it would be impossible to combine the fully conflicting analyst opinions. The top 10 stocks with the highest combined probabilities were used for strategy 2 instead of top 5 stocks as in the single-month experiment due to conventional wisdom for better diversification.
7.3 Risk Adjustment and Annualized Returns

We would like to compare returns from the investment strategies with those achieved by the market index of CSI300 in the same periods. It is important to take risks into account for fair comparisons. Below formula in line with Capital Market Model is adopted to compute risk-adjusted returns:

\[ R'_A = RFR + \sigma_m / \sigma_A \times (R_A - RFR) \] (7-1)

\( R_A \) denotes the return of the ER Rule investment strategy. \( RFR \) denotes the risk-free rate. \( \sigma_m \) refers to the standard deviation of the returns of CSI300, while \( \sigma_A \) refers to the standard deviation of the returns of the ER Rule investment strategy. A note about the risk-free rates: due to a lack of access to the interbank market for individual investors, government-issued repurchase rates and the interbank offered rates are of little relevance to individual investors (He, 2007). Hence, savings rate issued by the People’s Bank of China are used as the risk-free rates in this study (He, 2007). The strategy is based on different investment horizons and the risk-adjusted returns were annualized in the final results by the following expression:

\[ \text{Annualized Return} = (1 + \text{Raw Return})^{\frac{1}{\text{horizon}}} - 1 \] (7-2)

7.4 Log-Normality of Stock Returns and Student’s t Test

Consistent with the ideal conditions adopted by Black and Scholes (1973), the distribution of possible stock prices is assumed lognormal, and hence the log stock returns are assumed normally distributed, and thus Student’s t test is adopted instead of the non-parametric Wilcoxon test (Black & Scholes, 1973). Student’s t test was applied to the log stock price return over log market return to assess the significance of the existence of excess returns over the market index.
7.5 Results of P-Values and Annualized Excess Returns

For each period, the natural log of the market return of CSI300 was subtracted from the natural log of the risk-adjusted return of the investment strategy. Right-tailed Student’s t-test was then applied to the differences to compute a p-value for the excess return of the investment strategy with regard to the market index. The hypothesis here is that the investment strategy achieves risk-adjusted excess returns. A low p-value represents a small chance of null hypothesis, indicating statistical significance of our hypothesis. We generally look for p-values lower than 5%. Throughout the tables in this thesis, p-values less than 10% and greater than 1% are marked with one asterisk, p-values less than 1% and greater than 0.1% are marked with two asterisks, and p-values less than 0.1% are marked with three asterisks.

Similar to the approach adopted by Stefan and Helmut (2015), initially we computed the p-values for excess returns assuming normal distributions of stock returns instead of lognormal distributions, and the p-values are shown in the tables below (Feuerriegel & Prendinger, 2015). Please note that the p-values and excess returns are rounded to 10^-4 throughout the thesis.

Table 7-2: Strategy 1 p-value for excess return over CSI300 assuming normal distribution (rounded to 10^-4)

<table>
<thead>
<tr>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment Horizon</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Month</td>
<td>59.50%</td>
<td>37.49%</td>
<td>77.92%</td>
</tr>
<tr>
<td>2 Months</td>
<td>*7.84%</td>
<td>18.75%</td>
<td>87.40%</td>
</tr>
<tr>
<td>3 Months</td>
<td>*8.77%</td>
<td>21.00%</td>
<td>60.76%</td>
</tr>
<tr>
<td>4 Months</td>
<td>*3.49%</td>
<td>*4.10%</td>
<td>49.95%</td>
</tr>
<tr>
<td>5 Months</td>
<td>*7.73%</td>
<td>*6.14%</td>
<td>59.96%</td>
</tr>
<tr>
<td>6 Months</td>
<td>*5.81%</td>
<td>12.07%</td>
<td>39.35%</td>
</tr>
</tbody>
</table>
Table 7-3: Strategy 2 p-value for excess return over CSI300 assuming normal distribution (rounded to $10^{-4}$)

<table>
<thead>
<tr>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>28.56%</td>
<td>40.03%</td>
<td>74.72%</td>
</tr>
<tr>
<td>2 Months</td>
<td>*7.90%</td>
<td>18.88%</td>
<td>78.79%</td>
</tr>
<tr>
<td>3 Months</td>
<td>*1.68%</td>
<td>11.47%</td>
<td>14.78%</td>
</tr>
<tr>
<td>4 Months</td>
<td>**0.31%</td>
<td>*2.86%</td>
<td>27.04%</td>
</tr>
<tr>
<td>5 Months</td>
<td>**0.34%</td>
<td>**0.83%</td>
<td>39.63%</td>
</tr>
<tr>
<td>6 Months</td>
<td>***0.06%</td>
<td>***0.09%</td>
<td>17.42%</td>
</tr>
</tbody>
</table>

The p-values were then recomputed under the assumption of lognormal distribution for the stock returns, and the revised p-values are shown in Table 7-4 and Table 7-5. The revised p-values are generally better, though only by small amounts. The p-values computed for different choices of report collection period and investment horizon for the two scenarios are summarized in the tables below, where p-values between 1% and 5% are marked with one asterisk and p-values below 1% are marked with two asterisks:

Table 7-4: Strategy 1 p-value for excess return over CSI300 assuming lognormal distribution (rounded to $10^{-4}$)

<table>
<thead>
<tr>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>58.99%</td>
<td>37.19%</td>
<td>78.92%</td>
</tr>
<tr>
<td>2 Months</td>
<td>*7.36%</td>
<td>19.12%</td>
<td>87.92%</td>
</tr>
<tr>
<td>3 Months</td>
<td>*8.24%</td>
<td>20.10%</td>
<td>61.20%</td>
</tr>
<tr>
<td>4 Months</td>
<td>*2.47%</td>
<td>*3.43%</td>
<td>50.73%</td>
</tr>
<tr>
<td>5 Months</td>
<td>*4.76%</td>
<td>*5.93%</td>
<td>63.44%</td>
</tr>
<tr>
<td>6 Months</td>
<td>*3.96%</td>
<td>11.05%</td>
<td>39.09%</td>
</tr>
</tbody>
</table>
Table 7-5: Strategy 2 p-value for excess return over CSI300 assuming lognormal distribution (rounded to $10^{-4}$)

<table>
<thead>
<tr>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>28.42%</td>
<td>39.31%</td>
<td>75.24%</td>
</tr>
<tr>
<td>2 Months</td>
<td>6.96%</td>
<td>18.98%</td>
<td>79.21%</td>
</tr>
<tr>
<td>3 Months</td>
<td>*1.14%</td>
<td>11.30%</td>
<td>15.60%</td>
</tr>
<tr>
<td>4 Months</td>
<td>**0.12%</td>
<td>*2.70%</td>
<td>26.53%</td>
</tr>
<tr>
<td>5 Months</td>
<td>***0.09%</td>
<td>**0.92%</td>
<td>42.31%</td>
</tr>
<tr>
<td>6 Months</td>
<td>***0.02%</td>
<td>**0.99%</td>
<td>18.72%</td>
</tr>
</tbody>
</table>

The p-values are smaller for a longer investment horizon, which is expected as the recommendations are based on six-month forecasts and in the shorter terms market fluctuations would dominate. The p-values are smaller for shorter report collection periods as well, probably because the market conditions change too much over the span of three months for the reports to be considered altogether. Similarly, the p-values are large for the case of three-month report collection period, which makes sense as the analyst recommendations are based on six-month forecasts, and variations in market conditions and company performances within three months would make it inappropriate to pool all the recommendations together to synthesize an investment decision.

For the case of two-month report collection period, the p values for strategy 1 are lower than 10% for investment horizons of four months and five months, and the p value is slightly larger than 10% for the case of six-month horizon, indicating mild statistical significance for excess returns of the strategy compared to the market index. For strategy 2 with two-month report collection period, the p-values are a lot smaller, lower than 3% for four-month horizon and lower than 1% for five-month and six-month horizons. The p-values are the smallest for one-month report collection period, lower than 10% for strategy 1 with investment horizons longer than one month and lower than 2% for strategy 2 with investment horizons longer than two months.
The p-values indicate statistical significance for cases with one-month report collection period and longer investment horizons, demonstrating the effectiveness of the ER Rule investment strategy. The p-values are smaller for strategy 2, reaching a low of 0.02% for 6-month horizon with one-month report collection, and in this case the average annualized excess return is 10.69%, as shown in Table 7-7. The highest excess return obtained is 13.90% by strategy 2 with two-month collection and five-month horizon, while the average excess return of hedge funds is estimated to be 6.7% according to Penguin Group (Coggan, 2011; "Hedge fund," ; Mallaby, 2010). The maximum mean excess return occurring at the 5-month horizon could be due to the fact that reports are collected within the past months which would be expired with respect to their forecasts upon liquidation six months after the investment on current month end, and a 5-month horizon could better match the mix of reports with different expirations.

The performance of strategy 1 is worse than strategy 2, which seems to suggest that diversification is not effective. However, diversification only works if the securities are not highly correlated. The recommendations of analysts might have high correlations and in this case diversification merely includes more stocks that are not good performers. Again, analyst opinions seem incompatible with the Modern Portfolio Theory in that they do not lead to estimates of return and risk directly, and therefore a simple diversification approach might not be applicable. In addition, strategy 1 might have included many penny stocks which “tend to react more unsystematically to trends and news announcements and, consequently, may introduce a larger noise component” (Feuerriegel & Prendinger, 2015). In addition, the ER Rule is a conjunctive probabilistic reasoning process that might be more compatible with strategy 2 which is more selective than strategy 1.
The above results support the following three hypotheses:

1. There exist experts among financial analysts in the sense that the stocks they recommend outperform the market.
2. The ER Rule is useful for making investment decisions by aggregating the stock recommendations from financial analysts. The ER Rule can be applied to construct investment strategies from analyst opinions to achieve excess returns.
(3) Validity of the efficient market hypothesis (EMH) is challenged, at least in the Chinese stock market. EMH by Eugene Fama states that the market is efficient in absorbing information and the stock price reflects all available information instantly. Thus, it is not possible to earn investment returns in excess of the market return. Using financial analyst reports as input, the proposed strategy is shown to consistently achieve excess returns over the market index in China’s stock market. Since analyst reports contain fundamental information about the companies, this result invalidates the hypothesis of semi-strong form market efficiency in China.

7.6 Robustness Study

7.6.1 Varying Number of Analysts

To see how sensitive the strategy is to the input parameters, we varied the number of top ranked analysts of which stock recommendations are included in the dataset. The p-values and average risk-adjusted excess returns are shown in Table 7-8 through Table 7-11. Overall the ER Rule strategies perform better than the market index for one-month and two-month report collection periods. Using as few as 5 analysts gives good performance compared to the market index potentially due to the fact that the top 5 analysts are indeed experts providing valuable opinions. The performance of strategy 1 worsens when more analysts are used possibly due to the inclusion of low performing stocks recommended by non-expert analysts. On the other hand, strategy 2 is more selective and invests in only the top 10 stocks of which selection could be refined by incorporating more analyst opinions, and we observe that strategy 2 performance improves with the analyst number.

The performance of strategy 2 seems to have a relatively flat peak around 40 to 100 top analysts used in the analysis, demonstrating insensitivity of the strategy to parameter choice. For example, Table 7-9 and Table 7-11 show that the out-performance of Strategy 2 over the market index is fairly robust with a minimum p-value less than 0.01% and a maximum mean risk-adjusted excess return over CSI300 of 12.34% achieved at 80 analysts for the case of one-month report collection period.
The experiments have been carried out in Matlab and using 80 to 100 analysts requires several hours for the computation of one p-value. The computation time would be much shorter if the experiments were done in C or Fortran. However, since the computation time of ER Rule grows exponentially in the number of mass functions as one starts using more analysts and reports, approximate methods to compute the ER Rule might become necessary for the strategy to be practical.

**Table 7-8: Strategy 1 p-value for excess return over CSI300 for different numbers of analysts used in the calculations**

<table>
<thead>
<tr>
<th>Number of analysts</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>***0.05%</td>
<td>**0.69%</td>
<td>*3.03%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>**0.77%</td>
<td>12.96%</td>
<td>27.30%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>*3.15%</td>
<td>19.91%</td>
<td>46.92%</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>*2.47%</td>
<td>*3.43%</td>
<td>50.73%</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td>*4.64%</td>
<td>12.26%</td>
<td>29.94%</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>*4.52%</td>
<td>11.66%</td>
<td>36.13%</td>
<td></td>
</tr>
</tbody>
</table>

**Table 7-9: Strategy 2 p-value for excess return over CSI300 for different numbers of analysts used in the calculations**

<table>
<thead>
<tr>
<th>Number of analysts</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>***0.07%</td>
<td>**0.53%</td>
<td>10.10%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>**0.39%</td>
<td>*8.64%</td>
<td>46.04%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>**0.34%</td>
<td>10.92%</td>
<td>23.11%</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>**0.12%</td>
<td>*2.70%</td>
<td>26.53%</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td>***0.00%</td>
<td>*1.61%</td>
<td>17.89%</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>***0.01%</td>
<td>**0.86%</td>
<td>13.91%</td>
<td></td>
</tr>
</tbody>
</table>
Table 7-10: Average Strategy 1 excess return over CSI300 for different numbers of analysts used in the calculations

<table>
<thead>
<tr>
<th>Number of analysts</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td></td>
<td>7.81%</td>
<td>9.16%</td>
<td>8.75%</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>8.52%</td>
<td>4.50%</td>
<td>4.17%</td>
</tr>
<tr>
<td>20</td>
<td></td>
<td>7.43%</td>
<td>3.86%</td>
<td>0.86%</td>
</tr>
<tr>
<td>40</td>
<td></td>
<td>7.28%</td>
<td>7.55%</td>
<td>5.44%</td>
</tr>
<tr>
<td>80</td>
<td></td>
<td>6.90%</td>
<td>5.87%</td>
<td>4.28%</td>
</tr>
<tr>
<td>100</td>
<td></td>
<td>6.99%</td>
<td>5.99%</td>
<td>2.98%</td>
</tr>
</tbody>
</table>

Table 7-11: Average Strategy 2 excess return over CSI300 for different numbers of analysts used in the calculations

<table>
<thead>
<tr>
<th>Number of analysts</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td></td>
<td>9.07%</td>
<td>10.36%</td>
<td>6.28%</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>7.10%</td>
<td>6.04%</td>
<td>0.66%</td>
</tr>
<tr>
<td>20</td>
<td></td>
<td>7.78%</td>
<td>5.24%</td>
<td>5.49%</td>
</tr>
<tr>
<td>40</td>
<td></td>
<td>9.22%</td>
<td>11.38%</td>
<td>6.57%</td>
</tr>
<tr>
<td>80</td>
<td></td>
<td>12.34%</td>
<td>10.05%</td>
<td>6.71%</td>
</tr>
<tr>
<td>100</td>
<td></td>
<td>12.03%</td>
<td>10.84%</td>
<td>7.21%</td>
</tr>
</tbody>
</table>

Figure 7-3 suggests that the risk-adjusted excess return first increases with the number of analysts and then gradually decreases. A very simplified explanation for the initial increase is as follows. Suppose the return of each analyst can be represented by an independent variable $X_i$ with the same standard deviation $\sigma$ and a different mean $\mu_i$. If we include $m$ analysts in our strategy, the expected average return is:
\[ E \left( \frac{1}{m} \sum_{i=1}^{m} X_i \right) = \frac{1}{m} \sum_{i=1}^{m} \mu_i \]  

Equation 7-3

The variance of the average return is:

\[ \text{Var} \left( \frac{1}{m} \sum_{i=1}^{m} X_i \right) = \frac{\sigma^2}{m} \]  

Equation 7-4

For simplicity, the market return standard deviation \( \sigma_m \) is assumed to be 1, and the risk-free rate is assumed 0 in Eq. (7-1). The mean market return is also assumed to be 0. From Eq. (7-3) and Eq. (7-4), the risk-adjusted mean return is computed to be (return divided by standard deviation):

\[ \text{risk adjusted return} = \frac{\sqrt{m}}{\sigma} \left( \frac{\sum_{i=1}^{m} \mu_i}{m} \right) \]  

Equation 7-5

It can be seen that the risk-adjusted return grows with the square root of the number of analysts assuming stable mean returns \( \mu \)'s, which is consistent with the usual concept of diversification for risk reduction. The risk-adjusted return worsens with analyst numbers greater than 80 potentially due to the inclusion of more non-expert analysts with lower \( \mu \)'s into the analysis. As a numerical demonstration, let us assume the \( \mu \) of the \( i^{th} \) analyst goes down as \( 1/i \) for \( i<40 \), as \( 1/i^{0.52} \) for \( 40\leq i<80 \), and as \( 1/i^{0.57} \) for \( i>80 \). The \( \mu \)'s seem small but recall what is of concern is the excess returns over market index and not the absolute returns. The standard deviation \( \sigma \) is assumed to be 1.5. The resulting risk-adjusted return as a function of the number of analysts is plotted in Figure 7-4, which resembles the behaviour seen in Figure 7-3 (with the data point of 600 analysts being an outlier) with the initial rise due to diversification followed by a graduate decrease due to the inclusion of worse preforming analysts. In reality, stocks are correlated and as more analysts are included the assumption of independence between analysts breaks down. Therefore, the assumption of such a fast degrading performance in analysts might not be needed to obtain this particular behaviour in risk-adjusted returns, but the simple model illustrates major mechanisms behind the observation.
Figure 7-2: Strategy 2 mean risk-adjusted excess return over CSI300 for the case of 1-month report collection

Figure 7-3: Strategy 2 excess return p-values for the case of 1-month report collection
7.6.2 Varying Number of Stocks

The next input parameter that we tried varying is the number of stocks to invest for strategy 2. Table 7-12 and Table 7-13 show the p-values and average risk-adjusted returns for the cases of six-month horizon with choices of 5, 10, 20, 40 and 100 stocks used in strategy 2 investment. Again the p-values are generally low across the board though for the case of three-month report collection periods where the p-values can be larger than 10%. The p-values are higher for the case of five stocks to invest for strategy 2 compared to the cases with more stocks, potentially due to insufficient diversification. The optimal choice of stock number seems to peak between 10 and 40, and this would need to come from more detailed data training in practical applications, but the initial testing demonstrated robustness of the strategy with respect to the number of top analysts used and the number of stocks included in strategy 2.

Figure 7-4: Simulated risk-adjusted returns as a function of number of analysts
Table 7-12: Strategy 2 p-values for excess return over CSI300 for the cases of different numbers of stocks used for the investment strategy

<table>
<thead>
<tr>
<th>Number of stocks</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td><strong>0.33%</strong></td>
<td>*5.05%</td>
<td>15.11%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>*<strong>0.02%</strong></td>
<td>**0.99%</td>
<td>18.72%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>*<strong>0.05%</strong></td>
<td>*2.07%</td>
<td>*8.47%</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>*<strong>0.01%</strong></td>
<td>*1.48%</td>
<td>*5.11%</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>*<strong>0.02%</strong></td>
<td>**0.97%</td>
<td>*4.19%</td>
<td></td>
</tr>
</tbody>
</table>

Table 7-13: Average Strategy 2 excess returns over CSI300 for the cases of different numbers of stocks used for the investment strategy

<table>
<thead>
<tr>
<th>Number of stocks</th>
<th>Report collection period</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>8.30%</td>
<td>9.04%</td>
<td>8.93%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>10.69%</td>
<td>11.38%</td>
<td>6.57%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>9.02%</td>
<td>8.58%</td>
<td>8.39%</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>10.91%</td>
<td>8.57%</td>
<td>7.34%</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>10.87%</td>
<td>10.08%</td>
<td>7.71%</td>
<td></td>
</tr>
</tbody>
</table>

7.7 Normalized Equivalent Weight

In the previous calculations, the equivalent weight for each analyst is not normalized, which is appropriate if analyst opinions do influence each other. In the extreme case where analysts make recommendations in total isolation uninfluenced by other analysts, the equivalent weights should be normalized to sum up to 1 before applying ER Rule to aggregate the mass functions, essentially using the original ER algorithm (J.-B. Yang, Liu, Wang, Sii, & Wang, 2006). Specifically, for the equivalent weight of each analyst \( \hat{w} = w/(1 + w - r) \), this was normalized over all of the analysts \( j \) in consideration:
\( \vec{w} \rightarrow \frac{\vec{w}}{\sum_j \vec{w}} \)  \hspace{1cm} (7-6)

Table 7-14: Strategy 1 p-value for excess return over CSI300 with normalized equivalent weights

<table>
<thead>
<tr>
<th>Investment Horizon</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Months</td>
<td>**0.12%</td>
<td>*4.00%</td>
<td>*7.66%</td>
</tr>
<tr>
<td>5 Months</td>
<td>***0.06%</td>
<td>**0.96%</td>
<td>17.59%</td>
</tr>
<tr>
<td>6 Months</td>
<td>***0.01%</td>
<td>**0.99%</td>
<td>*2.13%</td>
</tr>
</tbody>
</table>

Table 7-15: Strategy 2 p-value for excess return over CSI300 with normalized equivalent weights

<table>
<thead>
<tr>
<th>Investment Horizon</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Months</td>
<td>**0.35%</td>
<td>*8.97%</td>
<td>*2.89%</td>
</tr>
<tr>
<td>5 Months</td>
<td>**0.20%</td>
<td>*3.85%</td>
<td>35.57%</td>
</tr>
<tr>
<td>6 Months</td>
<td>***0.02%</td>
<td>*2.33%</td>
<td>11.64%</td>
</tr>
</tbody>
</table>

Table 7-16: Strategy 1 annualized excess return over CSI300 with normalized equivalent weights

<table>
<thead>
<tr>
<th>Investment Horizon</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Months</td>
<td>7.29%</td>
<td>9.39%</td>
<td>7.29%</td>
</tr>
<tr>
<td>5 Months</td>
<td>5.01%</td>
<td>10.28%</td>
<td>5.01%</td>
</tr>
<tr>
<td>6 Months</td>
<td>9.81%</td>
<td>9.97%</td>
<td>9.32%</td>
</tr>
</tbody>
</table>
Table 7-17: Strategy 2 annualized excess return over CSI300 with normalized equivalent weights

<table>
<thead>
<tr>
<th>Investment Horizon</th>
<th>1 Month</th>
<th>2 Months</th>
<th>3 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Months</td>
<td>9.80%</td>
<td>8.12%</td>
<td>9.80%</td>
</tr>
<tr>
<td>5 Months</td>
<td>2.16%</td>
<td>8.78%</td>
<td>2.16%</td>
</tr>
<tr>
<td>6 Months</td>
<td>9.65%</td>
<td>9.33%</td>
<td>5.10%</td>
</tr>
</tbody>
</table>

For simplicity, only p-values for the cases with investment horizons of four months and longer are computed. Using normalized equivalent weights greatly reduces the p-values for strategy 1 from 40% and above to below 10% for the case of three-month report collection and below 1% from 2~10% for one-month and two-month report collection periods. The p-values for strategy 1 are reduced to be less than those of strategy 2. For strategy 2, only p-values of the cases with three-month report collection periods are reduced and the effects of using normalized equivalent weights on cases with one-month or two-month report collection periods are less clear. Similarly, the excess returns of strategy 1 are generally improved by using normalized equivalent weights but those of strategy 2 are worsened. It is possible that since strategy 1 includes more stocks in its portfolio, the decision weights need to be distributed over the analysts for them to be compatible with strategy 1. On the other hand, strategy 2 only invests in a few selected stocks, and the decision process needs to focus on picking out the star stocks recommended by star analysts in order for strategy 2 to achieve optimal performance. There is ongoing theoretical research into the implications of weight normalization, and in the future it is possible to apply more up-to-date results to further elucidate the impact of weight normalization on analyst opinions and the two proposed strategies.
7.8 Findings

The chart below summarizes the major questions that this research aims to address:

Figure 7-5: Research Questions

7.8.1 Existence of Experts

According to the transition matrix in section 6.3, there is a 35% chance for a top quintile analyst to remain in the top quintile the following year. We show that analysts as a group include experts, but it is difficult to identify individual analysts as experts due to the noise in their performance. We find that there is performance tradeoff between minimizing statistical noise and including only experts in that using too few analysts would increase noise but using too many analysts would include non-experts. Empirical evidence suggests that including top 80 analysts balances the tradeoff and gives the best performance.

7.8.2 Empirical Study for the Usefulness of ER Rule

We show empirically that the ER rule is effective in making financial investment decisions, even though consistently outperforming the market is extremely difficult. We have successfully applied the ER Rule to construct stock investment strategies utilizing stock
recommendations made by financial analysts. The problem of stock investment we are solving is a hard problem. First, there are large volumes of heterogeneous information to consider, which could be of great uncertainty and conflicts. Therefore, it is difficult to fuse different sources of information to synthesize effective investment strategies. Second, the stock market is highly competitive with investors constantly trying to take profits. According to the efficient market hypothesis, it is impossible to consistently beat the market return in the long term. Over the years along with stages of economic and financial reforms, the Chinese stock market has evolved from being weak-form inefficient to weak-form efficient, though it is still contested as to whether the Chinese stock market is now semi-strong form efficient or not. Results of this work support the view that the Chinese stock market is still not semi-strong form efficient by showing that utilizing information of analyst recommendations one could potentially obtain excess returns over a period of four years, with p-values from right-tailed Student’s t test as low as 0.02% and mean annualized excess returns as high as 13.9%. The demonstration of using unstructured data of analyst reports for effective investment decisions is a side contribution of this work.

7.8.3 Tradeoff between Statistical Errors and Report Relevance

Analyst reports are published at different time points on different days. This presents an immediate problem if analyst stock recommendations are only effective for a very short time window. Since stock recommendations are published at different times on different days, to gather sufficient stock recommendations into our analysis we would inevitably need to include reports published within a longer period of time, which requires the effective duration of analyst stock recommendations to be much longer. There is also a tradeoff between minimizing statistical errors by including more reports within a wider time window and including only reports made under the same market conditions with similar effective horizons, which relates directly to the following finding.
7.8.4 Long-Term Effectiveness of Stock Recommendations by Financial Analysts

Zhang and Skiena (2010) showed that the market reacts to news and events rather quickly and there is only a very short window of one to two days after the announcement of an event within which a trader can take profit from the event. Therefore, it is also thought that while financial analysts are capable of making accurate earnings forecasts out to six months or a year, the market reacts very quickly to the publication of an analyst stock report and it would not be possible to profit from analyst stock recommendations since it would be difficult to outpace the market. The experimental results show that based on reports collected within a one-month or two-month window, six-month investments reach p-values less than 1% and mean risk-adjusted excess returns greater than 10%. Six-month investments based on reports collected within a three-month window perform worse, with p-value at 18.72% and mean risk-adjusted excess return at 6.57%, indicating mild statistical significance. Thus, it seems that the market does not fully absorb the information provided in analyst reports right away, and it is possible to achieve long-term profits up to six months by following analyst recommendations. However, this phenomenon could be unique to China’s stock market, and in more developed countries the stock market might be more efficient so that financial analyst reports do not possess long-term effectiveness.
CHAPTER 8

Comparisons and Optimizations

8.1 Comparisons with Simple Methods

Even though the ER Rule strategies achieve excess returns with respect to the market index, the outperformance could just be a result of good analyst recommendations and not contributable to the ER Rule method itself. For further clarification, we compute the risk-adjusted excess returns of ER Rule strategies (using recommendations from top ranked 40 analysts) with respect to the following three simple methods. The cases considered in this section are of six-month investment horizons.

Simple method 1: invest in the 10 stocks with the highest numbers of occurrences among the recommendation reports published by the top 40 analysts

Simple method 2: invest in the stocks recommended by the analyst with the highest accuracy (for equal accuracies, rank by chronological order)

Simple method 3: invest in all of the stocks recommended by the top 40 analysts in equal amounts

Table 8-1: P-values for the risk-adjusted excess returns of ER strategies over simple methods

<table>
<thead>
<tr>
<th>Collection Period</th>
<th>Scenarios</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1– Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>92.94%</td>
<td>33.43%</td>
<td>79.19%</td>
<td>78.17%</td>
<td>14.09%</td>
<td>44.93%</td>
<td></td>
</tr>
<tr>
<td>2 Months</td>
<td>93.34%</td>
<td>55.81%</td>
<td>77.13%</td>
<td>71.62%</td>
<td>27.95%</td>
<td>33.10%</td>
<td></td>
</tr>
<tr>
<td>3 Months</td>
<td>98.43%</td>
<td>78.83%</td>
<td>83.05%</td>
<td>98.07%</td>
<td>66.98%</td>
<td>65.59%</td>
<td></td>
</tr>
</tbody>
</table>
Table 8-2: Average risk-adjusted excess returns of ER strategies over simple methods

<table>
<thead>
<tr>
<th>Collection Period</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1 – Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>-5.65%</td>
<td>2.42%</td>
<td>-3.30%</td>
<td>-2.24%</td>
<td>5.83%</td>
<td>0.10%</td>
</tr>
<tr>
<td>2 Months</td>
<td>-7.12%</td>
<td>-1.06%</td>
<td>-4.05%</td>
<td>-1.86%</td>
<td>4.21%</td>
<td>1.21%</td>
</tr>
<tr>
<td>3 Months</td>
<td>-14.63%</td>
<td>-8.11%</td>
<td>-5.97%</td>
<td>-10.45%</td>
<td>-3.93%</td>
<td>-1.78%</td>
</tr>
</tbody>
</table>

For each round of investment, we subtract the risk-adjusted return of ER strategies by the risk-adjusted returns of simple methods to obtain excess returns. Table 8-1 shows the p-values for the existence of positive excess returns, and Table 8-2 shows the average excess returns. The p-values for ER Strategy 1 over simple methods are mostly over 50% and the average excess returns are mostly negative, indicating that ER strategy 1 is not any better than simple methods, possibly because ER strategy 1 selects a vast number of stocks to invest, defeating the purpose of conjunctive probabilistic reasoning of the ER Rule. The current ER strategies assume a common frame of discernment for all the analysts, and as a result pooling analyst opinions together assuming they know all stocks equally well is more or less equivalent to taking a poll by the analysts. In future work it might be better to define a separate frame of discernment for each analyst depending on his or her area of expertise or familiar industry sectors.

ER strategy 2 seems comparable or slightly better than simple method 2 and simple method 3, but simple method 1 dominates all the methods. Previously it has been shown that using reports from the top 80 analysts outperforms using only the top 40 analysts. Thus, in order to demonstrate the effectiveness of the ER strategies, a comparison was made between the performance of the ER strategies using top 80 analysts and that of simple methods. The resulting p-values and average risk-adjusted excess returns are listed in Table 8-3 and Table 8-4. It seems that simple methods are still generally better than the ER strategies when using reports from top 80 analysts, but the case of ER Strategy 2 with one-month report collection period outperforms all three simple methods, albeit with very mild statistical significance. Even though definitive evidence has not been obtained supporting the superiority of ER strategies over other methods, the results demonstrate
good potential for the ER Rule based approach to outperform given further optimization, possibly using recommendations from more analysts with shorter report collection periods.

Figure 7-3 shows the mean risk-adjusted excess return of strategy 2 versus the number of top analysts used. To further compare the performance of strategy 2 and simple method 1, we plot the mean risk-adjusted excess return of simple method 1 versus the number of top analysts on the same graph in Figure 8-1, where the solid line refers to strategy 2 and the dashed line refers to simple method 1. It can be seen that even though simple method 1 seems to perform slightly better with fewer analysts, it decays much faster than strategy 2 when larger numbers of analysts are used. Simple method 1 is a voting method that more or less corresponds to the linear summation in the ER Rule of combination, while the ER Rule is more selective in that it has a second product term that amplifies the common opinions of analysts. It is possible that the effectiveness of the ER Rule in extracting valuable information is more prominent when we have a wider and more diverse set of analysts.

**Figure 8-1**: Mean risk-adjusted excess returns of strategy 2 and simple method 1 over CSI300 for the case of 1-month report collection
Table 8-3: P-values for the risk-adjusted excess returns of ER strategies using top 80 analysts over simple methods

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1 – Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>68.44%</td>
<td>35.40%</td>
<td>73.59%</td>
<td>14.46%</td>
<td>*8.81%</td>
<td>13.35%</td>
</tr>
<tr>
<td>2 Months</td>
<td>94.04%</td>
<td>72.83%</td>
<td>72.88%</td>
<td>91.20%</td>
<td>66.88%</td>
<td>61.17%</td>
</tr>
<tr>
<td>3 Months</td>
<td>93.96%</td>
<td>73.05%</td>
<td>73.01%</td>
<td>91.12%</td>
<td>67.22%</td>
<td>61.47%</td>
</tr>
</tbody>
</table>

Table 8-4: Average risk-adjusted excess returns of ER strategies using top 80 analysts over simple methods

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1 – Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>-2.40%</td>
<td>2.04%</td>
<td>-2.78%</td>
<td>3.04%</td>
<td>7.47%</td>
<td>2.65%</td>
</tr>
<tr>
<td>2 Months</td>
<td>-11.82%</td>
<td>-6.16%</td>
<td>-3.65%</td>
<td>-9.38%</td>
<td>-3.72%</td>
<td>-1.21%</td>
</tr>
<tr>
<td>3 Months</td>
<td>-11.79%</td>
<td>-6.22%</td>
<td>-3.66%</td>
<td>-9.36%</td>
<td>-3.79%</td>
<td>-1.24%</td>
</tr>
</tbody>
</table>

8.2 Multi-Segment Mass Function

In previous experiments, only one focal element was constructed for the mass function of each financial analyst. There could be information loss from pooling together all the recommendations made by a single financial analyst within a prolonged period into one single focal element. In the experiment of this section, the mass functions were refined by dividing the report collection period into equal time segments, and construct a separate focal element for the reports collected within each segment. For example, suppose the report collection period is divided into four equal time segments, and in each segment, there are Buy or Strong Buy recommendations for the following stocks:

1\(^{st}\) segment: \{A, B\}; 2\(^{nd}\) segment: \{B, C\}; 3\(^{rd}\) segment: \{A, B\}; 4\(^{th}\) segment: \{A, B, C\}

The recommended stocks in each segment forms a focal element to which an equal proportion of mass is assigned. If the sets of recommended stocks in different segments are the same, their masses simply add up. Therefore, for our example the masses are:
\[ m(\{A, B\}) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}, \quad m(\{B, C\}) = \frac{1}{4}, \quad m(\{A, B, C\}) = \frac{1}{4} \quad (8-1) \]

Table 8-5 and Table 8-6 show the performance of 4-segment ER strategies (six-month horizon) with respect to simple methods. Comparing the two tables to Table 8-1 and Table 8-2, it can be seen that for ER strategy 1, this approach worsens the case of one-month report collection and improves the cases of two-month and three-month report collection periods. For ER Strategy 2, the 4-segment approach worsens the cases of one-month and two-month report collection periods and improves the case of three-month report collection period. It makes sense for the method to improve cases of longer report collection period by refining the time relevance of the reports. For the case of one-month report collection period, further dividing the time intervals might reduce the capacity of mass functions to represent uncertainties and push them closer to probability functions, and therefore the 4-segment approach worsens cases of one-month report collection. ER Strategy 2 is more selective than ER Strategy 1 by picking the top stocks among vast choices, and thus it is more applicable for a larger pool of inhomogeneous reports. In any case, the changes by using the 4-segment approach are small and the way we are double counting the occurrences of recommended stocks in different segments is questionable. It might make sense to simply use a shorter report collection period instead.

Table 8-5: P-Value comparisons between 4-Segment ER Strategies and Simple Methods (6-month horizon)

<table>
<thead>
<tr>
<th>Collection Period</th>
<th>Strategies</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1 – Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>93.95%</td>
<td>37.14%</td>
<td>83.10%</td>
<td>88.70%</td>
<td>18.00%</td>
<td>60.42%</td>
<td></td>
</tr>
<tr>
<td>2 Months</td>
<td>84.26%</td>
<td>44.45%</td>
<td>62.79%</td>
<td>91.12%</td>
<td>40.96%</td>
<td>58.24%</td>
<td></td>
</tr>
<tr>
<td>3 Months</td>
<td>97.60%</td>
<td>75.66%</td>
<td>79.11%</td>
<td>94.67%</td>
<td>50.06%</td>
<td>31.06%</td>
<td></td>
</tr>
</tbody>
</table>
Table 8-6: Average excess returns comparisons of 4-Segment ER Strategies and Simple Methods (6-month horizon)

<table>
<thead>
<tr>
<th>Collection Period</th>
<th>Strategies</th>
<th>ER 1 – Simple 1</th>
<th>ER 1 – Simple 2</th>
<th>ER 1 – Simple 3</th>
<th>ER 2 – Simple 1</th>
<th>ER 2 – Simple 2</th>
<th>ER 2 – Simple 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>-6.32%</td>
<td>1.75%</td>
<td>-3.97%</td>
<td>-3.17%</td>
<td>4.90%</td>
<td>-0.83%</td>
<td></td>
</tr>
<tr>
<td>2 months</td>
<td>-4.58%</td>
<td>1.49%</td>
<td>-1.51%</td>
<td>-4.32%</td>
<td>1.74%</td>
<td>-1.25%</td>
<td></td>
</tr>
<tr>
<td>3 months</td>
<td>-13.49%</td>
<td>-6.97%</td>
<td>-4.83%</td>
<td>-5.98%</td>
<td>0.54%</td>
<td>2.68%</td>
<td></td>
</tr>
</tbody>
</table>

8.3 Functional Form Optimization

Previously we have chosen the weight and reliability parameters using intuitive argument. The model can be reformulated to depend only on a single parameter of equivalent weight. We would like to explore optimizations over the parameter. In principle, there are 40 equivalent weights of the 40 analysts, and a proper optimization would involve 40 dimensions. To simplify the optimization process, we adopt a parameterization of the equivalent weight using a single parameter alpha. The functional form is as follows: \( w_{eq} = k^{-\alpha}/N \), where \( k \) is the ranking (1…40) of the financial analysts in terms of past annual accuracy and \( N \) is the normalization factor while \( \alpha \) is the functional parameter. The lower the alpha, the more equal the weights become. In the extreme case of zero alpha, all the analysts carry equal weights. When alpha is higher, the weight concentrates on the higher ranked analysts and the opinions of the bottom analysts are suppressed.

We have set \( \alpha \) to be 0.001, 0.01, 0.1, 0.5, 1, 2, 4, and 8. The p-value and excess return results are listed in the tables below.

Table 8-7: Strategy 1 P-values (40 analysts) rounded to \( 10^{-4} \) for six-month horizon

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>***0.00%</td>
<td>***0.00%</td>
<td>***0.00%</td>
<td>***0.01%</td>
<td>***0.06%</td>
<td>*8.62%</td>
<td>18.15%</td>
<td>18.48%</td>
</tr>
<tr>
<td>2 months</td>
<td>**0.99%</td>
<td>**0.99%</td>
<td>**0.97%</td>
<td>**0.93%</td>
<td>*1.45%</td>
<td>*9.65%</td>
<td>14.51%</td>
<td>14.66%</td>
</tr>
<tr>
<td>3 months</td>
<td>*2.16%</td>
<td>*2.17%</td>
<td>*2.33%</td>
<td>*3.14%</td>
<td>*4.64%</td>
<td>*7.72%</td>
<td>10.98%</td>
<td>11.15%</td>
</tr>
</tbody>
</table>
Table 8-8: Strategy 1 Average Annualized Excess Return rounded to $10^{-4}$ for six-month horizon

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td></td>
<td>11.22%</td>
<td>11.20%</td>
<td>11.03%</td>
<td>10.11%</td>
<td>8.73%</td>
<td>6.07%</td>
<td>4.90%</td>
<td>4.86%</td>
</tr>
<tr>
<td>2 months</td>
<td></td>
<td>10.10%</td>
<td>10.08%</td>
<td>9.95%</td>
<td>9.29%</td>
<td>8.53%</td>
<td>7.57%</td>
<td>7.18%</td>
<td>7.17%</td>
</tr>
<tr>
<td>3 months</td>
<td></td>
<td>9.31%</td>
<td>9.30%</td>
<td>9.15%</td>
<td>8.73%</td>
<td>9.21%</td>
<td>10.87%</td>
<td>10.55%</td>
<td>10.50%</td>
</tr>
</tbody>
</table>

Table 8-9: Strategy 2 P-values (40 analysts) rounded to $10^{-4}$ for six-month horizon

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td></td>
<td><strong>0.12%</strong></td>
<td><strong>0.17%</strong></td>
<td>*<strong>0.06%</strong></td>
<td>*<strong>0.02%</strong></td>
<td>*<strong>0.08%</strong></td>
<td>*<strong>0.67%</strong></td>
<td>*<strong>0.68%</strong></td>
<td>*<strong>0.95%</strong></td>
</tr>
<tr>
<td>2 months</td>
<td></td>
<td>*2.30%</td>
<td>*1.96%</td>
<td>*2.48%</td>
<td>*1.70%</td>
<td>*0.23%</td>
<td>*0.97%</td>
<td>*1.22%</td>
<td>*<strong>0.80%</strong></td>
</tr>
<tr>
<td>3 months</td>
<td></td>
<td>*5.66%</td>
<td>*5.66%</td>
<td>*3.48%</td>
<td>*5.99%</td>
<td>*4.27%</td>
<td>*4.92%</td>
<td>*6.72%</td>
<td>*7.76%</td>
</tr>
</tbody>
</table>

Table 8-10: Strategy 2 Average Annualized Excess Return rounded to $10^{-4}$ for six-month horizon

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td></td>
<td>7.85%</td>
<td>7.63%</td>
<td>8.68%</td>
<td>9.90%</td>
<td>9.09%</td>
<td>7.23%</td>
<td>6.94%</td>
<td>6.80%</td>
</tr>
<tr>
<td>2 months</td>
<td></td>
<td>10.07%</td>
<td>9.98%</td>
<td>9.95%</td>
<td>9.29%</td>
<td>8.53%</td>
<td>7.57%</td>
<td>7.18%</td>
<td>7.17%</td>
</tr>
<tr>
<td>3 months</td>
<td></td>
<td>7.37%</td>
<td>7.37%</td>
<td>7.55%</td>
<td>7.29%</td>
<td>12.11%</td>
<td>12.38%</td>
<td>10.90%</td>
<td>10.62%</td>
</tr>
</tbody>
</table>

The p-value highlighted in blue is the minimum achieved for the strategy with the corresponding report collection period. The average annualized excess return highlighted in blue is the maximum achieved for the strategy with the corresponding report collection period. For strategy 1, the p-values are comparable to those of the previous results using normalized equivalent weights, but the optimized maximum average risk-adjusted excess returns of 11.22%, 10.10%, and 9.31% for one-, two-, and three-month report collection periods respectively, are better than those of the previous results of using normalized equivalent weights, 9.81%, 9.97%, and 9.32%. For strategy 2, the optimized minimum p-values of 0.02%, 0.23%, and 3.48% for one-, two-, and three-month report collection periods respectively, are much improved from those of the previous results of using
normalized equivalent weights, 0.02%, 2.33%, and 11.64%. The optimized maximum average risk-adjusted excess returns for strategy 2 are 9.9%, 10.07%, and 12.38%, which are also much improved from those of the previous results of using normalized equivalent weights, 9.65%, 9.33%, and 5.10%. For strategy 1, it seems like lower alpha values lead to more significant p-values and higher average risk-adjusted excess returns, which raises doubts as to whether the opinions of the analysts should be differentiated by assigning different weights, or should their opinions be simply pooled together in an averaged fashion. On the other hand, an alpha value of 0.5 seems to yield the best performance for strategy 2.

To verify if the ranking of analysts in terms of their prior year annual accuracy actually makes an impact, another experiment was conducted, which uses recommendations from the top ranked 20 analysts and the bottom ranked 20 analysts. Parameter $k$ refers to the ranking within the pooled 40 analysts. For example, $k$ equal to 20 refers to the top 20th ranked analyst, but $k$ equal to 21 refers to the bottom 20th ranked analyst.

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td></td>
<td>***0.08%</td>
<td>***0.08%</td>
<td>***0.07%</td>
<td>***0.04%</td>
<td>**0.11%</td>
<td>8.69%</td>
<td>18.15%</td>
<td>18.48%</td>
</tr>
<tr>
<td>2 months</td>
<td></td>
<td>*1.29%</td>
<td>*1.29%</td>
<td>*1.26%</td>
<td>*1.17%</td>
<td>*1.63%</td>
<td>*9.66%</td>
<td>14.51%</td>
<td>14.66%</td>
</tr>
<tr>
<td>3 months</td>
<td></td>
<td>*5.38%</td>
<td>*5.38%</td>
<td>*5.44%</td>
<td>*5.43%</td>
<td>*4.97%</td>
<td>*7.77%</td>
<td>10.98%</td>
<td>11.15%</td>
</tr>
</tbody>
</table>

Table 8-11: Strategy 1 P-values (40 analysts) rounded to $10^{-4}$ for six-month horizon using top 20 and bottom 20 analysts

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha</th>
<th>0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td></td>
<td>8.69%</td>
<td>8.69%</td>
<td>8.72%</td>
<td>8.69%</td>
<td>8.18%</td>
<td>6.06%</td>
<td>4.90%</td>
<td>4.86%</td>
</tr>
<tr>
<td>2 months</td>
<td></td>
<td>9.24%</td>
<td>9.23%</td>
<td>9.15%</td>
<td>8.76%</td>
<td>8.30%</td>
<td>7.56%</td>
<td>7.18%</td>
<td>7.17%</td>
</tr>
<tr>
<td>3 months</td>
<td></td>
<td>7.01%</td>
<td>7.01%</td>
<td>7.03%</td>
<td>7.34%</td>
<td>8.62%</td>
<td>10.85%</td>
<td>10.55%</td>
<td>10.50%</td>
</tr>
</tbody>
</table>

Table 8-12: Strategy 1 Average Annualized Excess Return rounded to $10^{-4}$ for six-month horizon using top 20 and bottom 20 analysts
Table 8-13: Strategy 2 P-values (40 analysts) rounded to $10^{-4}$ for six-month horizon using top 20 and bottom 20 analysts

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha 0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>*1.95%</td>
<td>*1.95%</td>
<td>*1.48%</td>
<td>**0.12%</td>
<td>**0.10%</td>
<td>**0.67%</td>
<td>**0.67%</td>
<td>*1.12%</td>
</tr>
<tr>
<td>2 months</td>
<td>11.80%</td>
<td>*8.32%</td>
<td>*6.99%</td>
<td>*5.92%</td>
<td>**0.30%</td>
<td>*1.21%</td>
<td>*1.61%</td>
<td>*1.21%</td>
</tr>
<tr>
<td>3 months</td>
<td>31.06%</td>
<td>31.06%</td>
<td>36.75%</td>
<td>15.10%</td>
<td>*2.93%</td>
<td>*4.73%</td>
<td>*6.22%</td>
<td>*8.14%</td>
</tr>
</tbody>
</table>

Table 8-14: Strategy 2 Average Annualized Excess Return rounded to $10^{-4}$ for six-month horizon using top 20 and bottom 20 analysts

<table>
<thead>
<tr>
<th>Report Collection Period</th>
<th>Alpha 0.001</th>
<th>0.01</th>
<th>0.1</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>*5.52%</td>
<td>*5.52%</td>
<td>*5.76%</td>
<td>*8.22%</td>
<td>*8.97%</td>
<td>*7.24%</td>
<td>*6.90%</td>
<td>*6.64%</td>
</tr>
<tr>
<td>2 months</td>
<td>*5.71%</td>
<td>*6.13%</td>
<td>*6.34%</td>
<td>*6.69%</td>
<td>14.08%</td>
<td>11.12%</td>
<td>10.05%</td>
<td>10.73%</td>
</tr>
<tr>
<td>3 months</td>
<td>*2.29%</td>
<td>*2.29%</td>
<td>*1.46%</td>
<td>*4.56%</td>
<td>12.78%</td>
<td>12.60%</td>
<td>11.16%</td>
<td>10.40%</td>
</tr>
</tbody>
</table>

For strategy 1, the optimal alpha value with respect to the p-value is increased in this case, going up to 0.5 or 1 for different report collection periods. The mean excess return peaks at an alpha value of up to 2. For strategy 2, the optimal alpha parameters for both the p-value and the mean excess return are consistently at 1. The optimal alpha values have risen to lower the weights on bottom ranked analysts as they are worse performing in this case. Counter-intuitively, the maximal mean excess return achieved is 14.08% by strategy 2 with alpha equal to 1 and a two-month report collection period, higher than the maximal value of 12.38% obtained using top 40 analysts with alpha equal to 2 and a three-month report collection period. This shows that the ER Rule approach can potentially extract valuable information from recommendations made by lower ranked analysts as well instead of simply averaging the opinions of the analysts, which would lead to worse performance using top 20 and bottom 20 analysts than using only top 40 analysts.
8.4 Separation of Recommendation Levels

Up until this point, we have been using both Strong Buy and Buy report information in our strategies. To investigate the differences among the recommendation levels, the differences were tested between cases using only Strong Buy reports, only Buy reports, only Neutral reports, only Sell reports, only Strong Sell reports, and both Sell and Strong Sell reports. For the case of one-month collection, there were 24 months in which no Sell reports were published, and there were four months in which no Strong Sell reports were published, and there were three months in which neither Sell nor Strong Sell report was published. The months in which no report of our chosen recommendation level was published were simply skipped in our calculation of p-value and mean excess return. If there were fewer than 10 Sell or Strong Sell report issued in a month, ER strategy 2 invests in all of them for the respective recommendation level. The average risk-adjusted returns for strategy 1 and strategy 2 (10 stocks) using reports of different recommendation levels with one-month report collection period and six-month investment horizon are listed in the tables below:

Table 8-15: Strategy 1 (investing in a distribution of stocks) p-values

<table>
<thead>
<tr>
<th>No. of Analysts</th>
<th>Strong Buy</th>
<th>Buy</th>
<th>Neutral</th>
<th>Sell</th>
<th>Strong Sell</th>
<th>Strong Buy &amp; Buy</th>
<th>Strong Sell &amp; Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>*2.15%</td>
<td>20.65%</td>
<td>11.13%</td>
<td>36.07%</td>
<td>77.30%</td>
<td>*3.15%</td>
<td>62.81%</td>
</tr>
<tr>
<td>40</td>
<td>*5.73%</td>
<td>19.74%</td>
<td>10.32%</td>
<td>36.21%</td>
<td>75.61%</td>
<td>*3.96%</td>
<td>62.49%</td>
</tr>
<tr>
<td>80</td>
<td>*5.81%</td>
<td>19.21%</td>
<td>10.24%</td>
<td>36.28%</td>
<td>75.54%</td>
<td>*4.64%</td>
<td>62.45%</td>
</tr>
</tbody>
</table>

Table 8-16: Strategy 1 (investing in a distribution of stocks) average risk-adjusted excess returns

<table>
<thead>
<tr>
<th>No. of Analysts</th>
<th>Strong Buy</th>
<th>Buy</th>
<th>Neutral</th>
<th>Sell</th>
<th>Strong Sell</th>
<th>Strong Buy &amp; Buy</th>
<th>Strong Sell &amp; Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>6.87%</td>
<td>2.65%</td>
<td>5.16%</td>
<td>2.81%</td>
<td>-3.08%</td>
<td>7.43%</td>
<td>-1.22%</td>
</tr>
<tr>
<td>40</td>
<td>5.61%</td>
<td>2.75%</td>
<td>5.24%</td>
<td>2.78%</td>
<td>-2.84%</td>
<td>7.28%</td>
<td>-1.18%</td>
</tr>
<tr>
<td>80</td>
<td>5.55%</td>
<td>2.83%</td>
<td>5.17%</td>
<td>2.76%</td>
<td>-2.83%</td>
<td>6.90%</td>
<td>-1.18%</td>
</tr>
</tbody>
</table>
For strategy 1, it can be seen that the p-values are smaller for using both Strong Buy and Buy reports than using only Buy reports or using only Strong Buy reports, except for the case of 20 analysts. The mean excess returns for using both Strong Buy and Buy reports are higher than those for the cases of using only Buy reports or using only Strong Buy reports. The results indicate that ER Rule is effective in extracting valuable information from multiple sources and not simply averaging their effects. Using only Buy reports is slightly worse than using only Neutral reports, which needs further examinations. Using only Strong Sell reports gives the most negative excess returns, but using both Strong Sell and Sell reports gives less negative abnormal returns, potentially because analysts are biased towards Buy recommendations or the model is not suitable for combining negative information.

For strategy 2, using Strong Buy and Buy reports does not seem to perform better than using Strong Buy reports alone, though the difference diminishes as we go to higher number of analysts. Since strategy 2 only focuses on the top 10 stocks, it is possible that the effectiveness of ER Rule is not prominent until we have more stock recommendations in consideration.

Table 8-17: Strategy 2 (investing in top 10 stocks) p-values

<table>
<thead>
<tr>
<th>No. of Analysts</th>
<th>Strong Buy</th>
<th>Buy</th>
<th>Neutral</th>
<th>Sell</th>
<th>Strong Sell</th>
<th>Strong Buy &amp; Buy</th>
<th>Strong Sell &amp; Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>***0.14%</td>
<td>*6.84%</td>
<td>***0.31%</td>
<td>40.10%</td>
<td>71.12%</td>
<td>***0.34%</td>
<td>58.97%</td>
</tr>
<tr>
<td>40</td>
<td>***0.09%</td>
<td>*6.83%</td>
<td>***0.15%</td>
<td>40.10%</td>
<td>66.58%</td>
<td>***0.12%</td>
<td>57.12%</td>
</tr>
<tr>
<td>80</td>
<td>***0.09%</td>
<td>13.18%</td>
<td>***0.68%</td>
<td>40.10%</td>
<td>69.08%</td>
<td>***0.00%</td>
<td>57.08%</td>
</tr>
</tbody>
</table>

Table 8-18: Strategy 2 (investing in top 10 stocks) average risk-adjusted excess returns

<table>
<thead>
<tr>
<th>No. of Analysts</th>
<th>Strong Buy</th>
<th>Buy</th>
<th>Neutral</th>
<th>Sell</th>
<th>Strong Sell</th>
<th>Strong Buy &amp; Buy</th>
<th>Strong Sell &amp; Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>9.06%</td>
<td>3.96%</td>
<td>8.12%</td>
<td>1.94%</td>
<td>-2.26%</td>
<td>7.78%</td>
<td>-0.90%</td>
</tr>
<tr>
<td>40</td>
<td>12.54%</td>
<td>3.93%</td>
<td>9.05%</td>
<td>1.94%</td>
<td>-1.75%</td>
<td>9.22%</td>
<td>-0.73%</td>
</tr>
<tr>
<td>80</td>
<td>12.50%</td>
<td>2.77%</td>
<td>7.46%</td>
<td>1.94%</td>
<td>-2.03%</td>
<td>12.34%</td>
<td>-0.73%</td>
</tr>
</tbody>
</table>
CHAPTER 9

Conclusion

We have built a model of analyst opinions based on their recommendation reports and established an investment strategy applying the ER Rule to combine analyst opinions for decision making in financial investment. Back-testing the investment strategy on historical stock prices and analyst reports from the CSMAR Database yielded an average annualized market excess return as high as 13.9% with a low p-value of 0.92% in the case of strategy 2 with two-month report collection and five-month investment horizon, supporting the effectiveness of the ER Rule as applied in decision making in financial investment and the existence of experts among the financial analysts. The results also suggest that the efficient market hypothesis in the case of China’s stock market may be incomplete and require further revisions.

The core research approach is evidential reasoning and combination of analyst opinions. We diversified risks by selecting a portfolio of stocks, inspired by Markowitz’s Modern Portfolio Theory (MPT). Markowitz had proposed relying on expert knowledge to assess the returns and risks of individual securities. However, our initial study showed that analyst forecasts were not sufficient for estimating the precise risk and return of each stock for MPT to be applicable. Therefore, our strategy was turned to a direct investment decision from analyst recommendations.

We have created an EIA model for applying the ER Rule to decision making in stock investment. This includes modeling analyst recommendations by mass functions, assigning weight and reliability to each analyst, combining weighted mass functions with ER Rule, providing a portfolio strategy based on the combined mass function.

To clarify whether analyst capability does play a key role in the effectiveness of the ER Rule strategies, the strategies were applied to recommendations by the top 20 analysts as
ranked by their prior year accuracy and to recommendations by the bottom 20 analysts. Looking at the excess returns of the strategies compared to the market index, it was observed that using recommendations by the bottom analysts yields worse risk-adjusted returns than using recommendations by the top analysts, with ER strategy 2 using bottom analysts even underperforming the market index significantly. The results show that analyst opinions indeed have a decisive impact on the performance of the strategies.

9.1 Findings

As described in more detail in Section 7.8, we have demonstrated the existence of experts among financial analysts in that they persistently provide effective stock reports. The performance of our ER Rule investment strategy improves as we include more top ranked analysts in the analysis, and the performance peaks around 80 analysts with a one-month report collection period, suggesting that there are non-experts that are included as more financial analysts are included into the analysis. We have empirically shown the usefulness of the ER Rule in solving the difficult problem of stock investment in a highly competitive market where investors are constantly trying to profit. Lastly, the effectiveness horizon of financial analyst reports is shown to be long-term, up to six months at least. The problem of stock investment is inherently of multiple criteria nature; the ER Rule is suitable for selections among various alternatives with multiple attributes, which include expected return, risk, horizon, discounted maximum loss, maximum drawdown, etc. in the case of financial investment. The ER Rule has also been extended to accommodate correlated pieces of evidence (Yang, Xu, Stachow, & Xu, 2015), and the new approach could be employed in future experiments.

9.2 Weakness and Optimization

A natural criticism of the ER approach is whether it outperforms simple methods using recommendations by top analysts. ER Rule strategies were compared with several simple
methods using top analyst reports, and no clear evidence was found supporting either method being significantly better than the other one, though ER Rule strategy 1 seems worse off than simple methods while ER Rule strategy 2 could be slightly better than simple methods. The comparable performances of the methods could be a result of using only recommendations from top analysts, in which case the effectiveness of decision-making methods is not easily distinguishable. In order to elucidate this issue, we might need to carry out comparisons using a wider selection of analysts.

Attempts were made to fine-tune the mass functions by dividing the report collection period into several segments, with the reports collected in each segment used to construct one focal element of the mass function. However, no significant improvement was observed by using more segments. As the forecast horizon of six months is rather long compared to the duration of the segments, further fine-tuning of the report collection period might not have so big an impact.

Optimization could improve the performance of the ER Rule approach, e.g. differentiation between “Buy” and “Strong Buy”, allocation of masses to take into account recommendation frequencies on stocks, choices of the weight and the reliability, etc. Initial studies on separating reports of different recommendations show that the ER Rule is effective in extracting useful information from among Strong Buy and Buy reports, as using both Strong Buy and Buy reports yields higher risk-adjusted returns than using only Strong Buy or using only Buy reports, even though using only Strong Buy reports gives better risk-adjusted returns than using only Buy reports. However, the ER Rule is not so effective in combining Strong Sell and Sell reports, as using both Strong Sell and Sell reports gives return values between those of using only Strong Sell and using only Sell reports, which is what one might expect from any typical method of merging information. However, using only Strong Sell reports does yield the most negative abnormal returns with respect to the market index, suggesting the possibility of long-short strategies to optimize profits. In any case, this work only serves as a demonstration of the methodology and leaves further optimization and comparisons with other methods to future studies.

Another dimension of optimization is to explore the choices of the weight and the reliability. We elected to optimize the equivalent weight parameter, which incorporates the
effects of both the weight and the reliability parameters. Optimizing against all the individual weights of the analyst would be computationally intensive, and therefore to simplify calculations an exponential functional form of the equivalent weight with respect to the ranking of the financial analyst was adopted, characterized by a single parameter of alpha. It turns out that for ER Rule strategies using recommendations from the top 40 analysts, the optimized alpha is close to zero, indicating that the opinions of the top 40 analysts are likely to be equally important. However, if the ER Rule strategies are applied to recommendations by both the top 20 analysts and the bottom 20 analysts, the optimized alpha increases to 0.5 or 1, suggesting that the opinions of less competent analysts should be weighted down.

One question about our approach is that financial analysts often focus on different industry sectors, and thus the frame of discernment of an analyst is really only confined to stocks in his or her area of expertise and not all the listed stocks as in our model. One natural way to handle differing frames of discernment is through the method of minimum commitment (Janez and Appriou, 1998), which extends the FOD of each mass function to the full frame before combination. In our case, the extended mass functions would have larger focal elements and they would be free of total conflicts. Thus, Dempster’s rule of combination could be applied in place of ER Rule. More investigation is needed in this direction.

The motivation behind using mass function for describing analyst opinions is to be able to incorporate diverse information sources of different characteristics. In the future we hope to generalize the methodology to include information such as blogs, news media, market sentiments, company fundamentals, in addition to analyst opinions and technical analysis.

9.3 Future work

9.3.1 Separation of Recommendation Levels into Multiple Focal Elements

In our experiments we have grouped all the stocks with a Strong Buy or Buy recommendation from an analyst into a single focal element of the analyst’s mass function.
Even though subsequent tests show that this approach works better than using only stocks with Strong Buy recommendations or using only stocks with Buy recommendations, it is possible that one can improve the performance of the strategy by constructing separate focal elements for Strong Buy reports and Buy reports, on which mass function values are to be obtained via data training.

9.3.2 Separation of Industry Sectors and Frames of Discernment

We have assumed that all the analysts have a common frame of discernment consisting of all the stocks for which a recommendation has been issued during the report collection period. However, in reality, each analyst has a different area of expertise, so the frame of discernment for the analyst should be confined to stocks in the particular industry sector which the analyst is familiar with. Therefore, one would apply the ER strategy to analysts of the same industry sector to construct a portfolio for that sector. Then, one could treat each industry portfolio as an asset to be included in an overall portfolio using conventional portfolio management methods.

9.3.3 Negative Recommendations

Only positive recommendations, namely Buy and Strong Buy, are included into the main experiments. Test results reported in Section 8.4 show that Neutral recommendations are actually positive recommendations possibly due to the analyst bias towards longing stocks rather than shorting stocks, and Neutral recommendations could in fact be more positive than Buy recommendations. One could construct a separate focal element for stocks with Neutral recommendations similar to those for Buy or Strong Buy recommendations, and assign a mass function value based on data training. For negative recommendations of Sell and Strong Sell, we propose to construct a focal element equal to the complement of the set of stocks with Sell or Strong Sell recommendations. Namely, negative belief in these stocks is represented as positive belief in the complement set of stocks.
9.3.4 Weights and Reliabilities

We have chosen a set of weight and reliability parameters based on very preliminary arguments. In practice, one would obtain these parameters by data training and update them regularly to reflect current abilities and conditions of the financial analysts in relation to the market trends.

9.3.5 Probability Transformation

As explained in Section 4.8, the pignistic transformation adopted in this research is only one of the possible methods for probability transformation from mass function to probability distribution. More research is needed to investigate the ambiguity of a combined mass function as measured by the triplet representation in order to improve the robustness of decision making from a mass function.

It is evident from section 4.8 that there is high ambiguity in the mass function constructed from the approach proposed in this work. One can potentially incorporate more information to reduce the ambiguity e.g. by including stock forecasts of return and risk provided in analyst reports along with stock recommendations.

9.4 Practical Issues

To put the ER strategy into use, practical issues must be considered. For example, one would consider the nominal return and the return volatility separately along with the Sharpe ratio of the strategy. One would also look at the maximum loss and maximum drawdown for the duration of the investment horizon, as these two indicators strongly influence a trader’s stop-loss decisions.

A more technical issue is that at the moment it is not possible to short A-shares or the indices. However, to realize the excess returns of the ER strategy with respect to the market, one would need to long the selected stocks while shorting the market index at the
same time. The good news is that it is actually possible to short CSI300 futures out to six
months, and as our strategies are of six-month horizons, this in principle would work.
Unfortunately, since it is not possible to short current index, the futures are generally lower
priced than the current index, providing ineffective hedging for our selected stocks. A
remedy is to use synthetic forwards constructed from call-put parity that are available for
the 50ETF index though more tests need to be done to verify the excess return of the ER
strategy with respect to the 50ETF index.
Appendix A

Pilot Study

1. Motivation

Initially, we planned to follow the two-stage investment process proposed by Markowitz (1952). The first stage is to estimate the expected return and volatility of individual securities, and in our pilot study we aimed to use analyst forecasts to compute probability distributions of stock price returns.

2. Basic Scheme

2.1 Frame of Discernment

Analyst forecasts on stock price returns are in the form of percentage ranges with respect to the market index CSI300. The ranges adopted by different brokerage houses are slightly different, and we incorporated them to produce the following set of possible forecast ranges to be our frame of discernment: \( \Theta = \{A, B, C, D, E, F, G\} \)
2.2 Weights and Reliabilities

Weight refers to the importance of a piece of evidence. For the first pilot study, we assume the weights are the same and normalized to 1 among all the analysts.

Reliability refers to the quality of a piece of evidence. We use the historical accuracy of an analyst's forecasts to represent his or her reliability.

2.3 Example Calculation

Suppose there are two analysts forecasting the performance of a same stock concurrently. Analyst 1 makes a forecast of A while analyst 2 makes a forecast of B.

Mass functions:

\[ p_1 = \begin{cases} \{A\} & 1 \end{cases} \]

\[ p_2 = \begin{cases} \{B\} & 1 \end{cases} \]
2.4 Weighted Belief Distribution w/ Reliability

Assume analyst 1 has weight \( w_1 \) and reliability \( r_1 \), while analyst 2 has weight \( w_2 \) and reliability \( r_2 \). Denote the power set as \( P \):

\[
P = \{ \emptyset, A, B, C, D, E, \{A, B\}, \{A, C\}, \{A, D\}, \{A, E\}, \{B, C\}, \{B, D\}, \{B, E\}, \{A, B, C\}, \{A, B, D\}, \{A, B, E\}, \{A, C, D\}, \{A, C, E\}, \{A, D, E\}, \{B, C, D\}, \{B, C, E\}, \{B, D, E\}, \{C, D, E\}, \{A, B, C, D\}, \{A, B, C, E\}, \{A, B, D, E\}, \{A, C, D, E\}, \{B, C, D, E\}, \{A, B, C, D, E\} \}
\]

Mass functions with weights and reliabilities are related to the original ones by:

\[
\tilde{m}_{\Theta,i} = \begin{cases} 
0 & \theta = \emptyset \\
\tilde{w}_i p_{\Theta,i} & \theta \subseteq \Theta, \theta \neq \emptyset \\
1 - \tilde{w}_i & \theta = P(\Theta) 
\end{cases}
\]

, where \( \tilde{w}_i = c_{rw,i}w_i \) and \( c_{rw,i} = \frac{1}{1 + w_i - r_i} \). The new mass functions thus become:

\[
m_1 = \begin{array}{c|c}
\{A\} & \frac{w_1}{1 + w_1 - r_1} \\
P & \frac{(1-r_1)}{1 + w_1 - r_1}
\end{array}
\]

, 

\[
m_2 = \begin{array}{c|c}
\{B\} & \frac{w_2}{1 + w_2 - r_2} \\
P & \frac{(1-r_2)}{1 + w_2 - r_2}
\end{array}
\]

2.5 Evidence Combination

The Evidential Reasoning Rule of combination is expressed as a ratio of intermediary mass functions (\( m \) hat):

\[
m_{\Theta,e(i)} = [m_1 \oplus \cdots \oplus m_i](\theta) = \begin{cases} 
0 & \theta = \emptyset \\
\frac{\tilde{m}_{\Theta,e(i)}}{\sum_{\Theta \subseteq \Theta} \tilde{m}_{\Theta,e(i)} + \tilde{m}_{P(\Theta),e(i)}} & \theta \neq \emptyset 
\end{cases}
\]
\[ m_{T, e(i)} = (1 - w_i) m_{T, e(i-1)} + m_{P(e), e(i-1)} + \sum_{B \cap C = \emptyset} m_{B, e(i-1)} m_{C, i} \quad \forall \emptyset \subseteq \emptyset \]

\[ m_{P(e), e(i)} = (1 - w_i) m_{P(e), e(i-1)} \]

where the \( w_i \) above refers to the adjusted weight:

\[ \bar{w}_i = c_{rw,i} w_i \]

\[ c_{rw,i} = 1/(1+w_i - r_i) \]

Denote \( c_i = 1/(1+w_i - r_i) \), we obtain intermediary mass function:

\[
\begin{align*}
\text{A} & & w_1(1-r_2)c_1c_2 \\
\text{B} & & w_2(1-r_1)c_1c_2 \\
\text{P} & & (1-r_1)(1-r_2)c_1c_2
\end{align*}
\]

After normalization,

\[
\begin{align*}
\text{A} & & m_{e(2)}(A)/[ m_{e(2)}(A) + m_{e(2)}(B) ] \\
\text{B} & & m_{e(2)}(B)/[ m_{e(2)}(A) + m_{e(2)}(B) ] \\
\text{P} & & (1-r_2)(1-r_2)/[ m_{e(2)}(A) + m_{e(2)}(B) ]
\end{align*}
\]

Renormalizing to exclude the power set, the final combined mass function is:

\[
\begin{align*}
\text{A} & & m_{e(2)}(A)/[ m_{e(2)}(A) + m_{e(2)}(B) ] \\
\text{B} & & m_{e(2)}(B)/[ m_{e(2)}(A) + m_{e(2)}(B) ]
\end{align*}
\]

2.6 Probability Transformation

Smet’s pignistic transformation is used to obtain probability: \( p(\{A\}) = m(\{A, B, C\})/3 \).

Fictitious Forecast:
For each stock, there are only one to three reports. To neutralize potential bias, we create a fictitious belief function based on the assumption of lognormal distribution:

\[ f(x) = \begin{cases} 
\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln(x) - \mu)^2}{2\sigma^2}}, & \text{if } x \geq 0; \\
0, & \text{if } x < 0.
\end{cases} \]

where volatility \( \sigma \) is derived from the daily stock price returns between 2012/11/21 and 2012/12/21, and the drift \( \mu \) is assumed to be zero.

3. Data Set

Forecasts made in the one week between 2012/12/24 and 2012/12/28 as stored in the China Stock Market & Accounting Research (CSMAR) Database.

As an initial trial, we use only 21 analyst reports with the lowest id’s as defined in the CSMAR database among the 80 forecast reports identified in the period.

4. One-Week Experiment

4.1 Trading Strategies

We compare the investment returns obtained by below two trading strategies:

(i) On 2012/12/31, buy all stocks identified by the reports in equal amount, and sell them on 2013/06/30.

(ii) For each stock, apply ER Rule to obtain combined probability for six-month return being higher than that of CSI300 by 20%. Select the top five stocks in accordance with this probability. On 2012/12/31, buy these top five stocks in equal amount, and sell them on 2013/06/30.
4.2 Results

The return obtained for trading strategy (i) is 0.97 while that obtained for strategy (ii) is lower at 0.85.

<table>
<thead>
<tr>
<th>Stkcd</th>
<th>Combined probability of &gt;20%</th>
<th>Realized Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>002327</td>
<td>0.6611</td>
<td>0.77546478</td>
</tr>
<tr>
<td>000921</td>
<td>0.8519</td>
<td>1.052174004</td>
</tr>
<tr>
<td>000861</td>
<td>0.6243</td>
<td>0.689421665</td>
</tr>
<tr>
<td>000012</td>
<td>0.5866</td>
<td>1.141624497</td>
</tr>
<tr>
<td>000596</td>
<td>0.2849</td>
<td>0.615021868</td>
</tr>
<tr>
<td>002158</td>
<td>0.1613</td>
<td>0.957540199</td>
</tr>
<tr>
<td>002341</td>
<td>0.161</td>
<td>1.620583921</td>
</tr>
<tr>
<td>000903</td>
<td>0.1574</td>
<td>0.710129223</td>
</tr>
<tr>
<td>002309</td>
<td>0.1445</td>
<td>0.985625467</td>
</tr>
<tr>
<td>000562</td>
<td>0.1427</td>
<td>0.932625529</td>
</tr>
<tr>
<td>002316</td>
<td>0.129</td>
<td>1.336666519</td>
</tr>
<tr>
<td>002029</td>
<td>0.0934</td>
<td>0.568061229</td>
</tr>
<tr>
<td>002262</td>
<td>0.0894</td>
<td>1.148597918</td>
</tr>
<tr>
<td>002142</td>
<td>0.0863</td>
<td>0.819148745</td>
</tr>
<tr>
<td>002073</td>
<td>0.0695</td>
<td>1.152472497</td>
</tr>
<tr>
<td>000100</td>
<td>0.0415</td>
<td>1.036528326</td>
</tr>
<tr>
<td>002254</td>
<td>0.0065</td>
<td>0.952832147</td>
</tr>
<tr>
<td>000596</td>
<td></td>
<td></td>
</tr>
<tr>
<td>002073</td>
<td></td>
<td>0.970854031</td>
</tr>
<tr>
<td>002327</td>
<td></td>
<td>0.854741363</td>
</tr>
<tr>
<td>002327</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.3 Discussion

The results seem to suggest that ER Rule has a negative effect on the decision making of stock investment. However, in our case due to the few number of stock analyst forecasts, the ER Rule result is dominated by the fictitious belief functions, and the fact that ER Rule result is worse suggests that the stock analysts actually make more accurate forecasts than the fictitious ones. Therefore, the initial results obtained here are actually positive results and warrant further research.
5. One-Month Experiment

5.1 Data Set

Reports made in the whole month of Feb, 2012
Only look at stocks for which there are at least ten forecasts (145 reports)
Filter for six-month forecasts based on the benchmark of CSI300 (19 reports)
Not using any fictitious forecasts

5.2 Results

No clear correlation between combined probability and realized return

<table>
<thead>
<tr>
<th>StockCode</th>
<th>realized return</th>
<th>G (&lt;-10%)</th>
<th>F (-10——5%)</th>
<th>E (±5%)</th>
<th>D (5%——10%)</th>
<th>C (10%——15%)</th>
<th>B (15%——20%)</th>
<th>A (&gt;20%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>625</td>
<td>2.1658</td>
<td>0</td>
<td>0</td>
<td>0.2666</td>
<td>0.624</td>
<td>0.1097</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>858</td>
<td>1.311</td>
<td>0</td>
<td>0.0348</td>
<td>0.0348</td>
<td>0.3595</td>
<td>0.4839</td>
<td>0.087</td>
<td>0</td>
</tr>
<tr>
<td>600017</td>
<td>1.2779</td>
<td>0</td>
<td>0.1264</td>
<td>0</td>
<td>0.3717</td>
<td>0.3717</td>
<td>0.1302</td>
<td></td>
</tr>
<tr>
<td>600535</td>
<td>1.2471</td>
<td>0</td>
<td>0.2245</td>
<td>0.1496</td>
<td>0.3584</td>
<td>0.2884</td>
<td>0.049</td>
<td></td>
</tr>
<tr>
<td>600276</td>
<td>1.0116</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.12137</td>
<td>0.30038</td>
<td>0.098094</td>
<td>0.48015</td>
</tr>
</tbody>
</table>

Perhaps needs more data points. Maybe should revisit how the forecasts are retrieved and processed to see what we missed.
Appendix B

Data Processing and Computation

1. Raw Data Processing

The raw data of recommendation reports we received contain information about the report ID, stock code, and the stock prices on the investment date, one month after the investment date, all the way to six months after the investment date. The format of the data files consists of the columns described below:

<table>
<thead>
<tr>
<th>ReportId</th>
<th>StockCode</th>
<th>StockIndex</th>
<th>ReportDate</th>
<th>NumerOfStocks</th>
<th>InvestmentDate</th>
</tr>
</thead>
<tbody>
<tr>
<td>InvestmentPrice</td>
<td>InvestmentIndex</td>
<td>FirstMonth</td>
<td>FirstMonthPrice</td>
<td>FirstMonthIndex</td>
<td>SecondMonth</td>
</tr>
<tr>
<td>SecondMonthPrice</td>
<td>SecondMonthIndex</td>
<td>ThirdMonth</td>
<td>ThirdMonthPrice</td>
<td>ThirdMonthIndex</td>
<td>FourthMonth</td>
</tr>
<tr>
<td>FourthMonthPrice</td>
<td>FourthMonthIndex</td>
<td>FifthMonth</td>
<td>FifthMonthPrice</td>
<td>FifthMonthIndex</td>
<td>LiquidationDate</td>
</tr>
<tr>
<td>LiquidPrice</td>
<td>LiquidIndex</td>
<td>StartDate</td>
<td>EndDate</td>
<td>Analyst</td>
<td>Recommend</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Rank</td>
<td>AnalystIndex</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1.1 Processing of Raw Data

The raw data tables list the recommendation reports in chronological order, and we process the files to reorder the reports by the analyst’s accuracy, so we list the reports by the analyst with the highest accuracy followed by the reports by the analyst with the second highest accuracy, etc. We also add a column showing the number of reports each analyst issues within the report collection period as well as unique indices running from 1 up for each analyst, stock, and report. The script to process each monthly data file is as follows:
function output = seg_process_one_month( datestr, NoSegs )
    format long;
    infile = strcat( datestr, '.reports');

    fid = fopen( infile );
    out =
textscan(fid,'%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s
%s%s%s%s%s%s%s%s%s%s','delimiter','	');
    fclose(fid);

    [dummy, ncols] =size(out);
    [nrows, dummy] = size(out{1});

    % retrieve columns needed with the first title row removed
    for i=1:(nrows-1)
        % these are strings
        ReportId(i) = out{1}(i+1);
        StockCode(i) = out{2}(i+1);
        AnalystIndex(i) = out{33}(i+1);

        % convert to date data type
        ReportDates(i) = datetime(out{4}(i+1),'InputFormat','yyyy-MM-dd');

        % these are numbers
        InvestmentPrice = str2double(out{7}(i+1));
        InvestmentIndex = str2double(out{8}(i+1));
        FourthMonthPrice = str2double(out{19}(i+1));
        FourthMonthIndex = str2double(out{20}(i+1));
        FifthMonthPrice = str2double(out{22}(i+1));
        FifthMonthIndex = str2double(out{23}(i+1));
        LiquidPrice = str2double(out{25}(i+1));
        LiquidIndex = str2double(out{26}(i+1));
% we only need the returns
FourthPriceReturn(i) = FourthMonthPrice / InvestmentPrice - 1;
FourthIndexReturn(i) = FourthMonthIndex / InvestmentIndex - 1;
FifthPriceReturn(i) = FifthMonthPrice / InvestmentPrice - 1;
FifthIndexReturn(i) = FifthMonthIndex / InvestmentIndex - 1;
LiquidPriceReturn(i) = LiquidPrice / InvestmentPrice - 1;
LiquidIndexReturn(i) = LiquidIndex / InvestmentIndex - 1;

Accuracy(i) = str2double(out{31}(i+1));
AnalystIndexNo(i) = str2double(AnalystIndex(i));
end

MinDate = min(ReportDates);
MaxDate = max(ReportDates);
Increment = (MaxDate - MinDate)/NoSegs;
for i=1:(nrows-1)
  for j=1:(NoSegs -1)
    if ReportDates(i) < (MinDate + j * Increment) & ReportDates(i) >= (MinDate + (j-1) * Increment)
      MassSeg(i) = j;
    end
  end
end

if ReportDates(i) <= (MinDate + NoSegs * Increment) & ReportDates(i) >= (MinDate + (NoSegs-1) * Increment)
  MassSeg(i) = NoSegs;
end
end

% first, sort by ascending AnalystIndexNo
[ReportId, StockCode, FourthPriceReturn, FourthIndexReturn, FifthPriceReturn, FifthIndexReturn, LiquidPriceReturn, LiquidIndexReturn, Accuracy, AnalystIndex, AnalystIndexNo, MassSeg ] = sortingSeg( AnalystIndexNo, ReportId, StockCode, FourthPriceReturn, FourthIndexReturn, FifthPriceReturn, FifthIndexReturn, LiquidPriceReturn, LiquidIndexReturn, Accuracy, AnalystIndex, AnalystIndexNo, MassSeg );

% secondly, sort by descending accuracy
NAccuracy = - Accuracy;

[ReportId, StockCode, FourthPriceReturn, FourthIndexReturn, FifthPriceReturn, FifthIndexReturn, LiquidPriceReturn, LiquidIndexReturn, Accuracy, AnalystIndex, AnalystIndexNo, MassSeg ] = sortingSeg( NAccuracy, ReportId, StockCode, FourthPriceReturn, FourthIndexReturn, FifthPriceReturn, FifthIndexReturn, LiquidPriceReturn, LiquidIndexReturn, Accuracy, AnalystIndex, AnalystIndexNo, MassSeg );

% retrieve unique lists of analysts and stocks
UniqueAnalysts = unique(AnalystIndex, 'stable' );
UniqueStocks = unique( StockCode, 'stable' );

% create indices to unique lists
for i=1:length(StockCode)
    StockCount(i) = find( strcmp(UniqueStocks, StockCode(i)));
end
for i=1:length(AnalystIndex)
    AnalystCount(i) = find( strcmp(UniqueAnalysts, AnalystIndex(i)));
end

% count the number of occurrences of each analyst count to get the number of stocks for each analyst
NoStocks = zeros(size(AnalystCount));
for i = 1:length(AnalystCount)
    NoStocks(i) = sum(AnalystCount==AnalystCount(i));
convert strings to numbers to be put into a big matrix with other numbers
for i = 1:length(StockCode)
    StockCodeNo(i) = str2double(StockCode(i));
end

convert strings to numbers to be put into a big matrix with other numbers
for i = 1:length(ReportId)
    ReportIdNo(i) = str2double(ReportId(i));
end

output matrices for different dates
FourthM = [StockCodeNo', StockCount', ReportIdNo', NoStocks', AnalystCount',
FourthPriceReturn', FourthIndexReturn', Accuracy', MassSeg'];
FifthM = [StockCodeNo', StockCount', ReportIdNo', NoStocks', AnalystCount',
FifthPriceReturn', FifthIndexReturn', Accuracy', MassSeg'];
LiquidM = [StockCodeNo', StockCount', ReportIdNo', NoStocks', AnalystCount',
LiquidPriceReturn', LiquidIndexReturn', Accuracy', MassSeg'];

header = strcat('Seg', num2str(NoSegs));
outfile = strcat(strcat(header, 'Fourth'), strcat(datestr, '.csv'));
%csvwrite(outfile, FourthM);
dlmwrite(outfile, FourthM, 'delimiter', ',', 'precision', 9);

outfile = strcat(strcat(header, 'Fifth'), strcat(datestr, '.csv'));
%csvwrite(outfile, FifthM);
dlmwrite(outfile, FifthM, 'delimiter', ',', 'precision', 9);

outfile = strcat(strcat(header, 'Liquid'), strcat(datestr, '.csv'));
%csvwrite(outfile, LiquidM);
dlmwrite(outfile, LiquidM, 'delimiter', ',', 'precision', 9);
output = 1;

% StockCode| Stock cnt| ReportId| # of stocks| Analystcnt| stkrtn | csi300 rtn | Accuracy
------------------------------------------------------------------------------------------------------------------------

To process all the monthly data files, we run the script below which calls the above script to process each month consecutively:
------------------------------------------------------------------------------------------------------------------------

%function [ success ] = seg_process_all_months( monthsfile, NoSegs )
function [ success ] = seg_process_all_months( monthsfile, NoSegs )
  format long;
  i=1;
  fid = fopen(monthsfile);
  datestr = fgetl(fid);

  while ischar(datestr)
    disp([ 'process ' datestr ]);
    seg_process_one_month( datestr, NoSegs );
    datestr= fgetl(fid);
    i = i + 1;
  end

  fclose(fid);

------------------------------------------------------------------------------------------------------------------------
2. Evidential Reasoning Rule Strategies Computations

2.1 Program Flowchart

2.2 Scripts

% tag = Fourth, Fifth, or Liquid
% Nanalysts = 40

function success = writeAvgAdjXsRtn( tag, Nanalysts, NoSegs, Sce2Stks )

monthsfile = 'months.csv';
riskFreeRtns = csvread('RiskFreeRtn.csv');
riskFreeRtns = riskFreeRtns';
i=1;
fid = fopen(monthsfile);

datestr = fgetl(fid);
while ischar(datestr)
    [sce1rtn, csirtn] = rcalcSegW(datestr, tag, 1, Nanalysts, NoSegs, Sce2Stks, 0);
    [sce2rtn, csirtn] = rcalcSegW(datestr, tag, 2, Nanalysts, NoSegs, Sce2Stks, 0);
    output(i,1) = sce1rtn;
    output(i,2) = sce2rtn;
    output(i,3) = csirtn;
    datestr = fgetl(fid);
    i = i + 1;
end

sce1rtns = output(:,1);
sce2rtns = output(:,2);
 csirtns = output(:,3);
stdCSI = std(csirtns);
stdSce1 = std(sce1rtns);
stdSce2 = std(sce2rtns);
riskAdjSce1Rtns = riskFreeRtns + stdCSI / stdSce1 .* (sce1rtns - riskFreeRtns);
riskAdjSce2Rtns = riskFreeRtns + stdCSI / stdSce2 .* (sce2rtns - riskFreeRtns);
AnnuRAsce1rtns = (1+riskAdjSce1Rtns).^2 - 1;
AnnuRAsce2rtns = (1+riskAdjSce2Rtns).^2 - 1;
AnnuCSIrtns = (1+csirtns).^2 - 1;

[h1, p1] = ttest( riskAdjSce1Rtns - csirtns, 0, 'tail','right');
[h2, p2] = ttest( riskAdjSce2Rtns - csirtns, 0, 'tail','right');
output(1,4) = round(10^4*p1)*10^(-4);
output(2,4) = round(10^4*p2)*10^(-4);
output(3,4) = round((10^4*mean(AnnuRAsece1rtns-AnnuCSIrtns))*10^(-4));
output(4,4) = round((10^4*mean(AnnuRAsece2rtns-AnnuCSIrtns))*10^(-4));

% output scenario 1 and 2 returns and CSI300 returns
outfile = strcat( tag, 'AvgAdjXsRtn.csv');
csvwrite( outfile, output );
fclose(fid);

success = 1;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [ sceRtn, csiRtn] = rcalcSegW( datestr, tag, sce, Nanalysts, NoSegs, Sce2Stks, isWorst )

% output variables:
sizes -- dimensions of input data matrix
nRpts -- number of reports
nStks -- number of stocks
nMasses -- number of analysts/masses
accys -- historical annual accuracy
nTop -- number of top analysts to consider
stkrtns -- return of the stock referenced by each report
stks -- stocks referenced by the reports
csiRtn -- return of the market index of CSI300

readData;

% setIndices(i, j) = 1 if stock j is in the ith set, 0 otherwise
setIndices = zeros(1, nStks);
i = 1; % report count
j = 1; % analyst count

% if using the bottom analysts; find the i and j indices for the starting row
if isWorst
    while j < (nMasses - nTop)
        % number of stocks for this analyst
        nStksAna = M(i, 4);
i = i + nStksAna;
j = j + 1;
    end
end

% for the time being set reliability equal to weight equal to 1/ntop
assignParams;

nStksAna = M(i, 4); % number of stocks for this analyst
% find the set of stocks recommended by this analyst
[rSets, i] = findStksSeg(M, nStks, nStksAna, i, NoSegs);

nSets = 0;
db = 0;
% construct the focal element for each segment
loopThroughSegs;
mass = initializeMass(weq, einds, nSets);
oldnSets = nSets;

j = j + 1;
while i <= nRpts & j <= nTop % focus only on reports produced by the top 20 analys for now
assignParams;

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nStksAna = M(i, 4); % number of stocks for this analyst

oldi = i;

% find the stocks recommended by this analyst
[rSets, i] = findStksSeg(M, nStks, nStksAna, i, NoSegs);

% construct the focal element for each segment
loopThroughSegs;
newMass = initializeMass( weq, einds, nSets);

mass = ERcombineSegW(mass, newMass, setIndices, oldnSets, nSets, weq, nStks, debug);

j = j + 1;
oldnSets= nSets;
end

% normalization
nMass = normalizeMass(mass, nSets);

% Smets' probability transformation
probs = probSmets(nStks, setIndices, nMass, nSets);

index = find(probs == max(probs(:)));

% get returns correspond to the unique list of stocks
ustkrtns = uniqueStkRtns(stks, nStks, stkrtns);

if scenario == 1 % invest in a distribution of stocks
rt = runSce1(stks, nStks, ustkrtns, probs);
elseif scenario == 2 % invest in top 5 stocks equally
rt = runSce2(stks, nStks, ustkrtns, probs, Sce2Stks);
end

sceRtn = rtn;

---------------------------------------------------------------------------------

header = strcat( 'Seg', num2str(NoSegs));
filename = strcat( header, strcat(strcat( tag, datestr),'.csv'));
disp(filename);
M = csvread( filename );
scenario = sce;% 1 for distribution, 2 for top 5 stocks
sizes = size(M);
nRpts = sizes(1); % number of reports
nStks = max( M(:,2) ); % number of stocks
nMasses = max( M(:,5) ); % number of analysts, number of masses
accys = M(:, 8);
nTop = Nanalysts; % number of top analysts to consider
stkrtns = M( :, 6); % return of the stock referenced by each report
stks = M(:,2); % stocks referenced by the reports
csiRtn = M(1,7); % return of the market index of CSI300

% assignParams.m
r = accys(i);
w = 1/nTop;
weq = w / (1 + w - r )

% loopThroughSegs.m
einds = [];

---------------------------------------------------------------------------------
forseg = 1:NoSegs
rSet = rSets(:,seg);

    % if found recommended stocks
if sum(rSet)>0
    % find the set index for this set of recommended stocks
    % if not found, eind will be nSets plus 1
    [ eind, flag ] = findSetIndexSeg(nSets, nStks, rSet, setIndices);
    if ~flag
        nSets = eind;
        % insert new set into the array
        forind = 1: nStks
            setIndices( eind, ind ) = rSet( ind );
        end
    end
    einds = [ eindseind ];
end
end

---------------------------------------------------------------------------------
---------------------------------------------------------------------------------
---------------------------------------------------------------------------------
---------------------------------------------------------------------------------
---------------------------------------------------------------------------------

function mass = initializeMass( weq, einds, nSets )
mass = zeros( nSets+1, 1 );
forind= 1:length(einds)
mass( 1 + einds(ind) ) = mass( 1 + einds(ind) ) + weq/length(einds);
end
mass( 1 ) = 1 - weq;

---------------------------------------------------------------------------------
---------------------------------------------------------------------------------
---------------------------------------------------------------------------------

functionfinalMass  = ERcombineSegW( mass, newMass, setIndices, oldnSets, nSets, w, nStks, debug )
% disp('ERcombie');
finalMass = zeros( nSets+1, 1 );
finalMass(1) = (1-w)*mass( 1 ); % equation (33) in Yang's paper

for i=2:(nSets+1)
%disp(num2str(i));
if i<=(oldnSets+1)
    finalMass( i ) = (1-w)*mass(i)+mass(1)*newMass(i) ;% linear addition part
else
    finalMass( i ) = mass(1)*newMass(i); % linear addition part
end

% note that mass(1) is the power set, so we subtract i by 1 to get the set index
currSet = setIndices( i-1, :); % intersection part

for j=2:(oldnSets+1)
    for k=2:(nSets+1)
        oldSet = setIndices( j-1, :);
        newSet = setIndices( k-1, :);

        hit = 1;
        l = 1;
        while l<= nStks& hit
            if (oldSet(l)*newSet(l)) ~= currSet(l)
                hit = 0;
            end
            l = l + 1;
        end
        if hit
            finalMass( i ) = finalMass( i ) + mass( j ) * newMass( k );
        end
    end
end
end
if debug
newMass
mass
end

total = 0;
for i = 1:(nSets+1)
total = total + finalMass(i);
end

for i = 1:(nSets+1)
finalMass(i) = finalMass(i)/total;
end

function nMass = normalizeMass( mass, nSets )
nMass = zeros( nSets, 1 );
tot = 0;
for i = 2:(nSets+1)
tot = tot + mass( i );
end

for i = 1:nSets
nMass(i) = mass( i+1 )/tot;
end

function probs = probSmets( nStks, setIndices, nMass, nSets )
probs = zeros( nStks, 1 );
for i = 1:nSets
    tot = 0;
    % number of stocks in this set
    for j = 1:nStks
        tot = tot + setIndices(i,j);
    end
    % Smet's probability transformation
    if tot ~= 0
        for j = 1:nStks
            if setIndices(i,j)
                probs(j) =_probs(j) + nMass(i)/tot;
            end
        end
    end
end

function rtn = runSce1( stks, nStks, ustkrtns, probs )

    rtn = 0;
    for i = 1:nStks
        rtn = rtn + probs(i) * ustkrtns(i);
    end

function rtn = runSce2( stks, nStks, ustkrtns, probs, Sce2Stks )

    % negate probs to sort in descending order
    [temp, sortindices] = sort( -probs);

    n2use = Sce2Stks; % number of stocks to invest in for scenario 2
    tempsum = 0;

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for i=1:n2use
    tempsum = tempsum + ustkrtns(sortindices(i));
end

rtn = tempsum/n2use;


