The Application of the Genetic Algorithm in Promoting Stock Trading Performances

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Abstract

This thesis joins the debate on utilizing the Genetic Algorithm (GA) to discover profitable trading strategies by providing an out-of-sample test of GA-based trading strategies on the CSI 300 index. Our results suggest that, with trading costs taken into consideration, GA-based trading rules consistently beat the buy-and-hold strategy in daily trading of CSI 300 index. Besides, we open up the black box of the evolution process of the GA by testing the statistical significance of the GA-based profitable trading strategies through the Fama-MacBeth regressions. In addition, this study connects the literature on the regime switching with studies on the GA-based trading strategies to construct one regime-switching Genetic Algorithm (RSGA) model and makes a comparison between the GA-based and the RSGA-based trading strategies. The empirical results show that trading strategies generated from the RSGA model consistently outperform those obtained from the GA model.

Key Word: GA; trading strategy; black box; regime-switching GA; outperformance

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1. Introduction

In financial research, there are two alternative approaches of scientific reasoning in conducting research studies, namely deductive reasoning and inductive reasoning. Deductive reasoning takes the form of a “top down” analysis and works from generalizations to specifications. Specifically, deductive reasoning starts with a theory and proposes hypotheses related to the observed data. After that, the original theory on which the hypotheses are based is confirmed or rejected according to the test results of hypotheses. In comparison, inductive reasoning works the opposite way as a kind of “bottom up” analysis. More precisely, inductive reasoning begins with specific data observations, from which hypotheses are generated. Generated hypotheses are confirmed or rejected in following tests until new theories or generalizations are reached. In financial economics, market participants are assumed to model expectations through deductive reasoning and behave with full rationality to maximize the utilities.

However, many subsequent studies emerge and challenge the assumption of deductive reasoning. Some of those studies reach the same conclusion that when facing complicated problems, market agents turn to inductive rather than deductive reasoning (Arthur (1992), Arthur (1994), Arthur, Holland, LeBaron, Palmer and Tayler (1996)). Specifically, based on data observations, market agents seek patterns and generate hypotheses to predict market movements from identified patterns. After that, market agents behave according to generated hypotheses and receive feedbacks on the validation of the hypotheses. Consequently, hypotheses accurately predicting market movements are maintained and strengthened while those with imprecise forecasts are discarded. Arthur (1994) defines the inductive way of reasoning as using simple models to fill the gaps in understanding whenever full reason or definition of the problems are not achieved. In this thesis, we attempt to leverage the GA to imitate inductive reasoning by seeking patterns in equity markets and to discover profitable filter rules.

Filter rules in equity trading are the direct results of the inductive reasoning of market agents. Theoretically, there are infinite number of patterns in stock markets and the patterns can be recognized based on prices, volumes, volatilities and any other information from stock trading activities. Market agents observe and identify patterns as potential filter rules and use them to predict market movements. Over time, each filter rule is evaluated on the accuracy of predictions. As the result, filter rules with high accuracy are kept and become popular in the market while the non-performing ones are discarded or updated. At the beginning, most of the filter rules for equity trading are based only on stock closing prices. Later on, with other information such as volumes and volatilities are also taken into consideration, filter rules become more diversified and are presented in more complicated forms. In fact, due to the high accuracy of predictions, some filter rules become popular technical indicators which even extend their practical values to now.

Although many studies have covered the filter rules for stock trading, the consensus on the forms of profitable filter rules has not been reached, which brings discounted guidance to the practices of market agents. As a result, in many cases technical analysis fails to achieve outperformances over the benchmarks such as the buy-and-hold strategy. Due to this reason, Allen and Karjalainen (1999) make the first attempt to verify whether the Genetic Algorithm (GA) can discover filter rules that consistently beat the buy-and-hold strategy. The GA was first discovered by John Holland in the 1960s to mimic the biological evolution in addressing computational problems. In the GA, solutions are presented in the form of bit-strings made up by "chromosomes" and the biological evolution proceeds through transferring "chromosomes" by generations. Technically, the evolution is implemented by crossovers and mutations of the bit-strings. Therefore, in order to apply the GA to refine filter rules, filter rules should be expressed in the form of bit-strings. In other words, each filter rule is transformed into a bit-string, and each bit-string can be correspondingly interpreted into one filter rule. This feasibility enables the GA to refine filter rules because, during the evolution, the "good genes" of trading strategies are maintained while the "bad genes" are discarded.

As the first researchers attempting to use the GA to generate profitable filter rules, Allen and Karjalainen (1999) target daily trading on S&P 500 index. The filter rules in the work of Allen and Karjalainen (1999) are based on stock closing prices, local extrema of closing prices (maximum and minimum) and averages of previous closing prices. The GA is utilized to provide the ultimately best trading strategy which assists trading by releasing buy and sell signals. However, the results of the work of Allen and Karjalainen (1999) show that, with trading costs taken into consideration, the best filter rules generated from the GA do not consistently earn excess returns over the buy-and-hold strategy in the out-of-sample periods.

From the work of Allen and Karjalainen (1999), many studies on this topic follow up. Based on Australia stock market, Pereira (1999) uses the GA to refine parameters of technical indicators over the in-sample period from 1982 to 1989. After that, technical indicators with refined parameter are evaluated during the out-of-sample period from 1990 to 1997. The results of the work of Pereira (1999) show that, the positive excess returns of the optimal rules from the GA vanish gradually. Dempster and Jones (2001) consider combinations of many technical indicators such as Adaptive Moving Average (AMA), Commodity Channel Index (CCI) and Relative Strength Index (RSI). By using the GA to initialize and update trading rules, they find that the best trading rules from the GA achieve significant profit trading US Dollar/British Pound in the out-of-sample periods.

Becker and Seshadri (2003) make further improvements on the work of Allen and Karjalainen (1999) by introducing a complexity penalizing factor to the objective fitness function and assuming monthly instead of daily trading on the S&P 500 index. The results of the work of Becker and Seshadri (2003) show that several trading rules are able to beat the buy-and-hold strategy in out-of-sample periods from 1990 to 2002. Potvin, Soriano and Vallee (2004) target 14 Canadian listed companies on TSX and acquire GA-based trading rules that are beneficial when the market is stable or in downward trends. Lohptch and Corne (2009) further investigate the work of Becker and Seshadri (2003) and find that the adopted technical strategies for daily trading can achieve excess returns over the buy-and-hold strategy on the S&P 500 index. However, their results are sensitive to the chosen data periods. In addition, they also find that, by utilizing shorter periods of time in the testes, we can generate more robust results. Kapoor, Dey and Khurana (2011) use the GA to refine parameters of technical rules for stocks listed in National Stock Exchange in India and find that the optimized rules from the GA can significantly increase the profit as compared to traditional moving average trading rules. Shin, Kim and Han (2015) take advantage of the GA to filter trading rules and find that the best rules gained can consistently beat the buy-and-hold strategy for Korea Stock Price Index 200 (KOSPI 200) futures. However, not every study on testing the GA's ability to refine trading rules achieve consistent outperformances over benchmarks in the out-of-sample periods. In fact, the designs of experiments vary from study to study. For example, the filter rules considered by Allen and Karjalainen (1999) are made up by closing prices, averages of closing prices and local extrema of closing prices. As a comparison, in the work of Dempster and Jones

(2001), filter rules appear in the form of complex technical indicators. Another noticeable difference on experiment designs of studies is about the trading frequency. Allen and Karjalainen (1999) assume daily trading while Becker and Seshadri (2003) take on monthly trading in their work. In addition to these two differences existing in the designs of experiments, there still are many aspects from which previous literature can be differentiated. Studies test GA-based filter rules with specific forms in certain stock markets but there is no conclusion on whether the experiment designs directly impact the results. In fact, most of previous literature has tested GA-based filter rules on S&P 500 index and Dow Jones Industrial index (Allen and Karjalainen (1999), Yu and Tina (2000), Becker and Seshadri (2003), Potvin, Soriano and Vallee (2004), Yu, Chen and Kuo (2005) etc.). Another field where literature on GA-based filter rules gather is foreign exchange (Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Jones (1999), Dempster, Payne, Romahi and Thompson (2000), Dempster and Jones (2001) etc.). In other studies, O'Neill, Brabazon and Ryan analyze a number of markets including UK's FTSE, Japan's Nikkei and the German DAX. In addition, Kapoor, Dey and Khurana (2011) test GA-based filter rules on stocks listed in National Stock Exchange in India while Shin, Kim and Han (2015) target Korea Stock Price Index 200 futures. Overall, the debate on the effectiveness of GA to discover filter rules that consistently beat the buy-and-hold benchmark is still on-going.

The first objective of this thesis is to join the literature debate concerning the effectiveness of the GA on discovering superior trading strategies by providing an out-of-sample test of GA-based trading rules in the Chinese stock market. There have been many studies covering GA-based filter rules but few relevant literature has paid attention to the Chinese stock market. However, Chinese stock market is volatile and the market climates switch frequently. Also, market speculations and manipulations are common in China's stock market as a result of the unusual market structure. In addition, the Chinese stock market is greatly influenced by the government. These unique features of the Chinese stock make it difficult to apply technical analysis to discover profitable strategies. Thus, by testing whether the GA is able to consistently discover profitable trading strategies in such a unique market environment, we can shed new lights to the effectiveness of the GA method.

The second contribution of this thesis is that we attempt to open up the black box of the GA by testing the statistical significance of profitable trading rules. More precisely, previous studies have tested GA-based filter rules with different experiment designs on various financial markets. However, among those studies that find consistent outperforming rules, no explanations have been provided why certain technical strategies are ultimately selected by the GA while others are not. Namely, the statistical significance of the generated profitable strategies has not been demonstrated. In this thesis, in addition to testing whether the GA-based rules can consistently beat the benchmark in Chinese stock market, we also perform statistical analysis to explain why certain strategies are chosen as the best ones during the testing periods.

Third, this thesis makes a methodological contribution to the studies on GA-based filter rules by connecting the literature on regime switching to that on the GA. When reviewing previous literature on GA-based trading rules, we find that the majority of studies are identical in one aspect of experiment designs. Namely, the GA is used to refine trading rules by narrowing the solution space to one ultimate optimal strategy. Correspondingly, in each experiment the conclusion about the effectiveness of GA in discovering superior trading rules are based on the performance of the single adopted strategy in the out-of-sample period. However, financial markets may go through significant changes and display different dynamics, which turns previously performing trading strategies into losers as the result. For instance, during the global financial crisis in 2008, stock return pattern experienced significant variations with regard to the mean, volatility and correlation. Profitable trading strategies before the crisis end up with significant losses. Thus, for the sake of changed market dynamics, it is not optimal to stick with one fixed strategy all the time in trading. Actually, some previous studies have verified this concern. Pereira (1999) investigates GA-based trading rules and evaluates the single optimal rule in the out-of-sample period from 1990 to 1997. The results show that the trading rule cannot beat the benchmark over the entire out-of-sample period. In fact, when examining the strategy performances in sub-periods, Pereira finds that excess returns are positive first but decline over time and end up being negative during the last couple of years. In other words, the best trading rule from the GA works well at first but becomes inferior gradually. Dempster and Jones (2001) realize that GA-based strategies may not persistently deliver superior performances as the market changes its dynamics. Thus they update filter rules regularly to make the trading strategy more adaptive to the market. Besides, Potvin, Soriano and Vallee (2004) target 14 Canadian listed companies on TSX and acquire GA-based technical trading rules that are beneficial only when the market is stable or in downward trends. From these three studies, we concern that, even if GA-based trading rules can deliver superior performances than the benchmark in some cases, the trading rules cannot handle every market climate and their outperformances may not persist over time. Maringer and Ramtohul (2012) connect regime switching to the recurrent reinforcement learning (RRL) algorithm to form the regime-switching recurrent reinforcement learning (RSRRL) model and apply it in the trading of component stocks of Dow Jones Industrial Average index. According to the out-of-sample results, the RSRRL model achieve better performances than the RRL model, which demonstrates the benefit of considering regime switching in the RRL algorithm. Thus in this thesis, we are motivated to connect regime switching to the GA and test whether the regime-switching GA (RSGA) can outperform the GA in discovering profitable trading strategies.

In order to test whether consistent outperforming trading rules in the Chinese stock market can be discovered by the GA, we choose CSI 300 index as the data and our experiments follow the framework of the work of Allen and Karjalainen (1999) except for forms of trading rules. More precisely, the filter rules in the work of Allen and Karjalainen (1999) are based on current closing prices, averages of previous closing prices and local extrema of closing prices. But in our experiments, we use refined technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and Bollinger Band, which is similar to the work of Dempster and Jones (2001). According to our experiment results, the optimized trading rules from the GA can consistently add value to both the buy-and-hold strategy and the actively managed portfolio. Specifically, in the out-of-sample period from 2010.01 to 2015.11, while the buy-and-hold strategy for CSI 300 index achieves an cumulative return of 6.12% with a Sharpe ratio of 0.0024, GA-based strategies obtain an cumulative return of at least 106% with the lowest Sharpe ratio being 1.00. Besides, GA-based strategies also bring benefits to the actively managed portfolio by increasing the original cumulative return by more than 100% during the out-of-sample period from 2010.01 to 2015.11. In fact, we also find that the data over-fitting alleviation mechanism in the work of Allen and Karjalainen (1999) is essential to the consistent outperformances achieved. When splitting the data into the training (in-sample) and the testing (out-of-sample) periods, there is a significant discrepancy in the strategy performances between the in-sample and the out-of-sample periods. However, if we instead divide the data into training (in-sample), evaluation (in-sample), and testing periods (out-of-sample) and use the evaluation period to relieve the extent of data mining, trading strategies achieve similar performances in the in-sample and the out-of-sample periods.

With regard to the statistical tests on GA-based trading strategies, our rationale is to use another approach to address the same problem solved by the GA. If two different methods exploring the identical solution space reach similar results, the effectiveness of each method on addressing the presented problem is verified by the other one. In the statistical way, we define the market into several states based on the technical indicators refined by the GA. By regressing daily realized returns on market states using the Fama-MacBeth regressions (Fama and MacBeth, 1973), we acquire the numerical associations between each market states and the realized returns. Then conclusions on the significance of each association are obtained through t-tests. We find that, the market states significantly related to positive realized returns match the buy-signals from GA-based trading strategies. Besides, the market states significantly related to negative realized returns also match the sell-signals from GA-based trading strategies. Take one GA-based strategy for example, signals for taking long position of CSI 300 index are released whenever the condition "DIFF>DEA & MACD histogram is increasing" is met during the period from 2005.01 to 2009.12. Over the same period, the market state reflected by the condition "DIFF>DEA & MACD histogram is increasing" is significantly associated with positive realized returns. Specifically, the t-statistic of this association is 2.89 in the Fama-MacBeth regression. Namely, the GA and the statistical methods provide identical trading strategy during the same period of time. Therefore, on the one hand, through the comparisons we verify the effectiveness of the GA on finding profitable trading strategies. On the other hand, we open up the black box of the GA and explain why the GA ultimately choose certain trading strategies as the best ones.

The regime-switching GA (RSGA) model is the result of combining literature on GA-based trading strategy and that on regime switching. Ang and Bekaert (1999) concluded that high-volatility regime and low-volatility regime exist in equity market. Maringer and Ramtohul (2012) connect regime switching with the recurrent reinforcement learning (RRL) algorithm to form the regime-switching recurrent reinforcement learning (RSRRL) model. In the work of Maringer and Ramtohul (2012), the volatilities are utilized to switch between regimes. Due to the frequent changes of dynamics in the Chinese stock market, the volatility is one of the most important factors to concern when trading stocks. Therefore, in this thesis, we attempt to identify 2 market regimes based on volatilities and generate regime-specific trading strategies from the GA method. More precisely, based on the predicted volatilities from GARCH (1, 1) model in the out-of-sample period, the GA comes up with a volatility threshold and segregates the market into two regimes accordingly. Then GA-based trading strategies specific to each regime are generated and the exact strategy in effect is determined by the existing regimes. The experiment outcomes show that, the optimal trading strategy from the RSGA model achieves a cumulative return of 168% with a Sharpe ratio of 1.17 in the out-of-sample period from 2010.01 to 2015.11, compared to the GA-based strategy which obtains a cumulative return of 106% with a Sharpe ratio around 1.00. In summary, considering regime switching makes GA-based rules more adaptive to the market and delivers significantly higher returns with lower risks.

Overall, this thesis contributes to the literature along three lines. First, we provide an out-of-sample test on the effectiveness of GA based on the framework of the work of Allen and Karjalainen (1999) using the CSI 300 index from the Chinese stock market, Second, we present a clearer picture from statistical analysis to explain why certain trading rules are discovered by the GA in testes. Third, we make a methodological contribution to the literature on GA-based filter rules by connecting regime switching with the GA and use the regime-switching GA to generate better trading strategies than those from the GA.

The remaining parts of the thesis is organized as follows. In section 2 we conduct literature review. Section 3 elaborates on the methodology. Section 4 describes the data, experiments and results. Section 5 presents conclusions and implications.

2. Literature Review

Section 2 presents the literature review of this thesis. There have been abundant studies covering the topic of leveraging GA to identify superior technical trading rules. Since technical analysis belongs to the inductive reasoning, literature review starts by reviewing studies on the inductive reasoning and filter rules. After that, we go through some important researches on utilizing the GA to discover technical trading rules. Last but not least, we present studies on the regime-switching model. Specifically, section 2.1 reviews the studies on inductive reasoning; section 2.2 presents literature on filter rules; section 2.3 displays literature on GA-based technical trading rules; section 2.4 reviews studies on regime switching; section 2.5 identify the gaps in literature and presents the contributions of this thesis.

2.1 Inductive Reasoning

Over time, there has been assumptions of the nature of market participants – either homogeneous or heterogeneous. On the one hand, if all the participants are homogeneous, there will be one single, objective forecasting shared by everyone. In this case, participants resort to deductive reasoning because this logic can reach a determinacy under homogeneity. On the other hand, heterogeneity eliminates such objective expectation and participants make their own prediction based on the information they have, which includes historical prices, volumes, estimation of others' belief and so on. Due to the indeterminacy in forming expectations by deductive reasoning, a more realistic assumption in the real world is that, market participants are heterogeneous and they turn to inductive reasoning in making prediction. (W. Brian Arthur, John H Holland et al. 1996). Even though all the participants share the available information consisting of historical prices, past trading volumes and previous dividends, different traders still rely on different assumption and approach to take advantage of the shared information, which will, lead to the lack of identical forecasting model and volatile outcomes. Besides, heterogeneous participants will never have an objective way to know the expectation models of each other. In this case, deductive reasoning ends up with indeterminacy. Instead of deducing the expectations, market participants come up with various hypothesis based on gathered information and verify the accuracy by corresponding performance in the real market (Blume and Easley, 1990). As a result of this, each participant constantly forms and updates "market hypotheses" subjectively – those hypotheses predicting market movements well will be retained and used as trading signals and the underperforming ones will be discarded. From time to time, the filter mechanism will make it clear which hypotheses work well and market participants learn and adapt during the whole process. Therefore, the inductive reasoning is defined as the process where market participants generate, test and replace hypothetical models on a continuing bases.

Arthur (1992) argues that when dealing with complex or ill-defined problems, economic agents move away from the standard notion of rationality and are forced to rely on inductive reasoning. Economic agents generate, monitor and update their internal models and hypotheses of faced problems. Arthur (1992) also proposes that, in order for the deductive reasoning to get into a rational expectation equilibrium, several conditions must be met. First, each agent should have full knowledge of the problem. Second, each agent has perfect ability to compute the solution. Third, there is only one unique solution. Fourth, each agent is aware that other agents satisfy the first and the second conditions. Furthermore, Arthur (1994) lists two reasons why deductive rationality fails to work under complication. First, the logic apparatus of market agents cannot catch up once the complexity of faced problems exceeds certain level. Second, under complication agents no longer get to be aware precisely of other agents' beliefs. For the sake of these two reasons, objective and shared assumptions do not apply anymore and correspondingly, the deductive reasoning which comes from perfect logic procedure cease to apply. As a result, human in complicated situations are considered to possess bounded rationality and their behaviors are instead described by inductive reasoning. When considering the operation of equity markets, we find that many previous literature has challenged the perfect deductions of fully rational investors from efficient market theory and defined the way market participants behave as one example of inductive reasoning with bounded rationality. Shiller (1989) shows that trading volume and volatilities in equity markets are large rather than being small or zero as proposed by efficient market theory. Besides, O'Hara (1995) demonstrates that trading volume and volatilities display significant autocorrelation as opposed to the conclusion of efficient market theory that neither trading volume nor volatilities are serially correlated. Arthur, Holland, LeBaron, Palmer and Tayler (1996) demonstrate that traders do not agree with the efficient market theory which assumes market agents are identical in the sense that they share rational expectations of financial assets and incorporate all information into pricing assets and there is no way to achieve consistent speculative profit. By contrast, traders regard the market as imperfectly rational that the existence of "market psychology" makes speculative chances possible. Arthur, Holland, LeBaron, Palmer and Tayler (1996) also show that deductive reasoning leads to an indeterminacy whenever the heterogeneity of agents are introduced in. As the result of failed deductive reasoning, agents must turn to inductive reasoning to from their expectations. Specifically, market agents gathered observed data and come up with several subjective hypotheses, which can be verified by only their corresponding performances in the market.

There are some advantages of the inductive reasoning structure. First of all, biases of any fixed forecasting model will be avoided through the competence among different models.

Secondly, inductive reasoning enables heterogeneity to exist rather than having an identical expectation. In addition, this structure better reflects the real market, where volatile models will be derived by participants as a results of the recognition differences among participants.

2.2 Filter Rules

In stock market, both individual and institutional investors have been broadly leveraging technical analysis in the investing process to construct, adjust and terminate the portfolio. However, the reality shows that, due to the complexity of stock market structure, investors performing technical analysis manually frequently end up suffering from losses. Therefore, over the years, the effectiveness of technical analysis in promoting stock trading performance has always been a focus of research and many results show that, most of the trading patterns based on these rules do not work well((Alexander, 1961), (Fama and Blume, 1966), Allen and Karjalainen, 1999)). Basically, filter rules evolve by taking on more complicated forms and requiring more information to make. Originally, filter rules are simply based on the maximum, minimum and average of closing prices with some mark-ups during certain period of time ((Alexander, 1961), (Fama and Blume, 1966), (William, Josef and Blake, 1992)). Later on, on the one hand, more complex considerations have been given to forming what are known by market participants nowadays as technical indicators including RSI (Relative Strength Index), Bollinger Band and so on((Dempster and Jones, 2001), (Boboc and Dinica, 2013), (Wiles and Enke, 2015)). On the other hand, information other than closing prices is used in constructing new technical indicators. For example, volumes of stocks are leveraged to form the indicator VRSI (Volume Relative Strength Index). Standard deviations of returns of stocks are important inputs of the indicator Bollinger Band.

The majority of this literature is performed on S&P and Dow Jones stock indices. During the early periods, Alexander (1961) tests some ‘filter rules’ and finds that positive excess returns over buy-and-hold are achievable, but the outperformance vanishes when trading costs are taken into consideration. Alexander (1961) proposes an x-percent filter based on daily closing prices of securities in S&P Industrials and Dow Jones Industrials to test whether stock prices can incorporate new information on a gradually basis. The results of his experiments show that this proposition is valid for x ranging from 5 percent to 30 percent. However, Alexander (1964) find that when considering commissions of 2% for each round-trip, only the largest filter (45.6%) beat the buy-and-hold by a great margin while others cannot outperform the buy-and-hold after costs. Smidt (1965) tests 40 filter rules on May soybean future contracts and finds that 70% of tested rules are able to bring positive returns after commissions. Fama and Blume (1966) extend the work of Alexander (1964) by testing 24 filter rules with parameters ranging from 0.5% to 50% on 30 individual stocks of the DJIA but only to find 4 of 30 stocks can deliver average positive returns after costs per filter. Besides, most of the filter rules are not superior to the buy-and-hold strategy before commission. Namely, Fama and Blume (1966) fail to identify any profitable trading rules on 30 Dow Jones stocks. Xiao-Ming Li and Kong-Jun Chen (2006) used eight years' daily stock price and trading volume data of 39 corporations listed on the Shenzhen Stock exchange, but only to find extremely weak evidence for the predictability of technical analysis in China's stock market.

On the other hand, there still are some support for technical analysis. William, Josef and Blake (1992) test two of the simplest filter rules (moving average and trading range break) on Dow Jones Index from 1897 to 1986 and provide strong support for technical analysis. Choi et al. (1995) ended up generating predictions of 62.5% accuracy for in-sample data and 63.8% for the entire data set. Levy (1966) reports testing results of 68 filter rules with few of them based only on past prices and finds that all of them are able to provide higher returns than buy-and-hold strategy. Van Horne and Parker (1967), James (1968), test the filter rules in the form of moving averages of previous prices but still fail to discover any rule beating buy-and-hold in terms of profitability. Sullivan, Timmermann and White (1999) test filter rules in the form of support and resistance level, channel breakout and on-balance volume (OBV) on Dow Jones Industrial Average and S&P 500 index futures and give affirmative conclusions about tested filter rules outperforming buy-and-hold strategy. Michael (1999) used filter rules on lagged return and lagged volume data of large-capitalization listed securities on NYSE and AMEX and found that stocks with decreasing volumes experience greater reversals than stocks with increasing volumes. In later period of time, by revealing information from some technical indicators, for example, RSI (relative strength index) and ROC (rate of change) and closing price, low, high, moving average, Wong, Manzur and Chew (2003) test Relative Strength Index (RSI) on Singapore Straits Times Industrial Index and find that RSI rules produce statistically significant returns over all three sub-periods.

2.3 Genetic Algorithm

As the earliest computer scientists, Alan Turing, Norbert Weiner, John Von NeuMann and others aim to create artificial intelligence and entitle computer programs with life-like abilities to learn and adapt to the environment. The ultimate goal of artificial intelligence is for computers to model human brains and mimic human learnings. Mitchell (1995) mentions that studies on computer artificial intelligence has grown into three fields, namely neural networks, machine learning and evolutionary computations with GA being the most prominent example in evolutionary computations. GA was first discovered by John Holland in the 1960s to mimic the biological evolution in addressing computational problems. Later on, Holland and his students made further progression on GA in the 1970s. In Holland's GA, solutions are presented in the form of bit-strings made up by "chromosomes" and the biological evolution proceeds by transferring "chromosomes" from previous generations to following ones. The evolution is implemented by crossovers and mutations of the bit-strings. Specifically, each crossover works by cutting two bit-strings into two pieces and exchanging one subpart, which imitates the procedure of biological recombination of genes from chromosomes. Mutations change values of certain bits in the strings and these processes are similar to the gene mutations of human. However, the way crossovers and mutations happen to bit-strings is not random. Instead, there is a mechanism in place to assure "strong genes" are kept and passed over to subsequent generations while "bad genes" are discarded. Over the years, the GA has been utilized on various kinds of aspects. For example, the GA has been used in optimization problems such as circuit layout and job-shop scheduling. Besides, we can also see the appearance of GA in machine-learning tasks such as weather predictions. However, it was not until 1999 did the GA extend its adaptive ability to trading. In financial markets, the price is the most important metric for any asset and market participants fulfill trading according to certain prices. One logic of a trader in trading is to buy certain asset whenever its quoted price is lower than the fair value and sell certain asset whenever its quoted price is higher than its fair value. Therefore, the rationale of trading in this case is based on the relationships between quoted prices and fair values and this kind of relationships can be turned into the form of bit-strings. To be more precise, each trading strategy can be transformed into a bit-string, and correspondingly each bit-string can be interpreted into one trading strategy. This fact makes it possible to using the GA to refine trading strategies since, during the evolution, only "good genes" of strategies are maintained to form subsequent generations of trading strategies.

As a result of the lack of consensus on effective “filter rules”, over the years there has been an increasing amount of studies aimed at addressing this problem. Within those studies, Genetic Algorithm (GA) has be became one of the most important approach to discover profitable trading strategies for investment purpose. As an important part of machine learning, Genetic Algorithm has been used for various kinds of purposes and nowadays, and there is an increasing utilization of Genetic Algorithm in stock trading. One motivation to take advantage of Genetic Algorithm when trading stocks is, to spare investors the necessity to perform technical analysis manually, which could even be possibly incorrect and conveys misleading signals, especially when considering the ability of GA to explore the entire solution space to an extent that is also not achievable manually. The second merit of GA is about its covered breadth and deepness in learning and the reason why GA can accomplish this goal is because it can incorporate not only any mix of technical indicators but also diversified fundamental factors, which is extremely important for equity investment decision making. Also, GA is able to take various constrains into its framework and to address multi-parameter problems, which led it to the widely application in stock trading. Despite these merits of GA, the way how it is applied and connected to practice is essential to eventual investment results. Actually, there has been an inconsistency, according to the literature on this topic so far, about the effectiveness of leveraging GA on enhancing investment results. By making GA a part of the investment process, some researchers are able to consistently achieve outperformance in out-of-sample with cost taken into consideration while others are not. Specifically, most failures up to now are considered as the results of using daily data instead of trading on a monthly basis. Furthermore, another controversy on this topic is about the kind and complexity of technical indicators to use in order to achieve success.

As the pioneer in applying Genetic Programming (GP) to find trading strategies, Allen and Karjalainen (1999) use S&P 500 index daily price data from 1928 through 1995, but the rules found cannot beat the buy-and–hold strategy with one-way trading costs of 0.25% accounted in the out-of- sample data set. In their work, there are two kinds of functions: real functions and Boolean functions. Real functions are those used to derive moving average and local extrema of prices as well as arithmetic operators. Boolean functions include logical functions defining the relationship between two real numbers.

Dempster and Jones (2001) come up with a GA-based technical trading rules developed system, from which the best rule found achieve significantly modest profit on trading US Dollar/British Pound. The first major change they make when compared to the work of A&K (1999) is that, instead of relying on the simplest filter rules like closing price and moving averages, they utilize a combination of broad range of more refined technical indicators. For example, technical indicators listed within their work include but are not limited to CCI, MACD, MA Crossover, RSI and AMA. Besides, another modification from previous literature in their work that is directly associated with the consistent outperformance in out-of-sample is the adaption system. Specifically, this system works by generating technical trading rules by GA at regular intervals to have a feedback on the performance of existing rules. Namely trading rules are updated on a continuous basis and underperformed rules will be discarded or replaced by newly generated rules that deliver better performances. The Dempster and Jones approach breaks the previous routine in using GA to discover one fixed technical trading rules to apply in the entire out-of-sample test period and reach the conclusion of performance based on it. For the first time different trading rules are utilized during the tests of GA-based strategies in one out-of-sample test period, the implication of this modification is that trading rules in effect adapt to the market climates from which they are generated.

Becker and Seshadri (2003) make some modifications including adopting monthly instead of daily trading, and introducing a complexity-penalizing factor to the work of Allen and Karjalainen (1999) and presented GP-evolved technical trading rules that outperformed buy-and-hold strategy on the S&P 500. Even though those two modifications are considered essential to acquire trading rules with outperformances over buy-and-hold, there still are some other differences between experiment details. In the work of Becker and Seshadri (2003), the data used include not only closing prices but also openings, highs and lows of each month. In addition, they also introduce two price resistance markers which are respectively two previous 3-month moving average minima and two previous 3-month moving average maxima, which do not exist in the work of Allen and Karjalainen (1999).

Xue-Zhong He et al (2007) make further innovation on the kind of filter rules to be considered in GA. While Dempster and Jones (2001) extend technical trading rules to a broader range including many complicated technical indicators like MACD, RSI, AMA and so on, He et al (2007) come up with classified rules in five groups including fundamental value, technical rules, recent changes in quotes, bid-ask spread, order book depth imbalance and the last trade sign. This adjustment puts new elements into the solution space and additionally absorbs market information other than price and volume data. By adding fundamental values and information from limit order book into the solution space where GA explore, the results show that generated trading rules become more well-rounded and applicable. Furthermore, Lohpetch and Corne (2009) display that additional modification on the work of Becker and Seshadri (2003) led to strategies enjoying consistent excess return over the buy-and-hold strategy for monthly trading, which is, however, relatively rare for daily trading and situation for weekly trading is in between. They conclude that the Becker and Seshadri (2003) approach is able to generate trading rules outperforming the buy-and-hold strategy.

However, the outperformance is sensitive to data splits, especially when moving from monthly to daily trading. A majority of early research conducted on this topic end up with performance discrepancy between in-sample data and out-of-sample data. One of the explanation is that, being one of the machine learning method, GA is not able to avoid the data-mining problem. As a result, many studies come up with some methods to relieve, if couldn't avoid completely, the data-mining problem. For instance, Allen and Karjalainen (1999), instead of working on some certain technical indicators, let GA to reveal the best form of rules in addition to refine parameters. Another mechanism they have to deal with the data-mining problem is to split the entire data into 3 parts – training, evaluation and testing periods. In this framework, the best trading rules filtered by GA is not only purely based on the data GA work with, the evaluation period plays an essential role in reliving over-fitting problem in training period and leads to a more consistent result in different data set. However, they still fail in achieving consistent outperformance relative to the buy-and-hold strategy in the out-of-sample periods. Similarly, Tina Yu, Shu-Heng Chen and Tzu-Wen Kuo (2005) utilize the same data-mining alleviation mechanism as the work of Allen and Karjalainen (1999). However, by combining GA with lambda abstraction, eventually they succeed in finding profitable trading rules regardless of the market climate. In this thesis, we also apply this method in addressing data-mining problem.

Another example to alleviate data over-fitting problem can be seen in the work of Becker and Seshadri (2003), where they impose a complexity penalizing factor on the fitness function to come up with a bias toward simplicity. As a result, this penalty mechanism greatly contributes to, if not determine directly, the improvement on the work of Allen and Karjalainen (1999).

In addition to help beating buy-and-hold on equity trading, genetic algorithm has also been used in many other aspects of investment management. Mahfoud and Mani (1995) use the genetic algorithm to select stocks while Kindom and Feldman (1995) try to predict bankruptcy, Walker (1995) uses the GA to evaluate credits. Some other applications involve that Zhou and Dunis (1998) find the optimal parameter for an important technical indicator RSI using GA in their research of a FX trading system and that Packard (1990) applies the GA into budget allocation. Potvin et al (2004) prove that Genetic Programming-evolved rules worked well in markets that are either stable or falling. With increasing number of research covering this topic, the GA has extended its content and versatile classified metrics has been put into the process to investigate some previously unknown area and try to generate potentially beneficial strategies. For instance, Marney et al. (2001) introduce some risk measures while Khai and Cheng (2002) draw on modified sterling metric, to favor those rules with lower risk.

2.4 Regime Switching

Financial markets are not permanently stable, instead some abrupt changes take place now and then. These changes may give rise to extended periods with differences between behaviors or dynamics of financial series. Therefore, because of the significant variations in asset pricing across periods of time, those certain periods are distinguished and defined as corresponding regimes. For instance, stock return patterns with regard to mean, volatility and correlation have experienced significant variation through the global financial crisis happened in 2008. In fact, some previous studies on GA-based trading rules give rise to the concern that it is not optimal applying one fixed strategy all the time regardless of the market climates.

Pereira (1999) investigate GA-based technical trading rules and evaluate the single optimal rule in the out-of-sample from 1990 to 1997. The results show that the rule cannot beat the benchmark over the entire out-of-sample period. In fact, when examining the strategy performances in sub-periods, Pereira finds that excess returns are positive first but decline over time and end up being negative during the last couple of years. In other word, the best trading rule from the GA works well at first but becomes inferior gradually. Dempster and Jones (2001) realize that GA-based strategies may not persistently deliver superior performances as the market changes its dynamics. Thus they introduce an adaptive system to make the strategies in effect more adaptive to the market. The adaptive system works by leveraging the GA to generate trading strategies at regular interval, trading rules in effect are discarded when becoming losers or replaced when better rules have been generated. Besides, Potvin, Soriano and Vallee (2004) target 14 Canadian listed companies on TSX and acquire GA-based technical trading rules that can be beneficial when the market is stable or in downward trends. From these three studies, we find that, even if GA-based trading rules can deliver superior performances than the benchmark, the rules cannot handle every market climate and their outperformances may not be extended to a long period of time. Thus we are motivated to make GA-based trading rules more adaptive to the market in this thesis.

Among the early studies covering regime switching, Quandt (1958) estimates the parameters of a linear regression system experiencing two separate regimes and implies that the first necessary step is to identify the position of point in time when the switching takes place. In his study, economic variables are linearly connected to some factors with the parameters of the relationship are subject to discontinuous changes. Namely, in addition to the factors enjoying a linear relationship with economic variables, there are still other factors in place that non-linearly explain them as well. Goldfeld and Quandt (1973) come up with an influential model which is known as Markov-switching model to capture the occurrence of regime switching. Ang and Bekaert (1999) conclude that two regimes exist in equity market. The first regime are the periods when stock returns are more volatile while the second regime stands for relatively flat periods of time. Besides, stock return correlations are different between two regimes. Ang and Timmermann (2011) come up with 3 advantages of regime switching models. First, regime switching is natural and intuitive, therefore the application of regime switching models is able to help capturing business activity cycles over a long-term trend. Second, regime switching models are able to identify stylized dynamics of financial assets including skewness, fat tails, time-varying correlations and so on. Finally, regime switching models are capable of capturing non-linear behaviors of financial asset returns with linear specification to make asset pricing under regime switching tractable. However, different metrics are used to define regimes for different categories of financial assets. In terms of equity, one way to distinguish regimes is to identify bull and bearish market periods. In addition, another conventional approach fulfilling the same goal is to measure volatilities in the periods. Buren (2012) studies two prominent stock market cycles 1998-2005 and 2006-2011 and connected financial market changes, especially financial crisis, with volatility regime switch. The conclusion of this research includes that the extent of association between financial market changes and volatility regime switching varies over cycles. Maringer and Ramtohul (2012) present regime-switching recurrent reinforcement learning (RSRRL) model and apply it to investment problems. In fact, the RSRRL model is formed by connecting regime switching to the recurrent reinforcement learning (RRL) algorithm. In the work of Maringer and Ramtohul (2012), the volatility is used to switch between regimes and the RSRRL model is demonstrated to be better than the RRL model in addressing investment problems.

2.5 Identify the Gap

From the work of Allen and Karjalainen (1999), many studies investigate the effectiveness of the GA in filtering technical trading rules. In fact, most of the studies target S&P 500 index or Dow Jones Industrial Average index as the data set. However, the consensus on the profitability of GA-based trading rules is not reached yet. Therefore, based on the Chinese stock market, this thesis is aimed to join this debate by providing an out-of-sample test to verify whether the GA can discover trading rules that consistently beat the benchmarks.

Second, although some of the studies covering GA-based trading rules achieve consistent outperformances, the statistical significance of those profitable strategies is not demonstrated. In other words, it still remains as a question why certain trading strategies are selected by the GA as the best ones while others are not. Therefore, this thesis attempts to open up the black box of the GA by testing the statistical significance of the profitable GA-based trading rules through the Fama-MacBeth regressions (Fama and MacBeth, 1973).

Another contribution of this thesis to the academic literature is that we combine regime switching with the genetic algorithm and find that, trading rules from the regime-switching GA model outperform those from the GA model. Most of the previous studies on this topic use the genetic algorithm to work out one single strategy in each test and to apply it across the entire data set. Nevertheless, it is not optimal to rely on technical indicators in a fixed manner all the time regardless of market climates, especially when different market regimes are in place. Dempster and Jones (2001) introduce an adaptive system in the process the GA refine trading rules. In the adaptive system, trading rules are discarded once they become losers or better strategies are presented. Maringer and Ramtohul (2012) combine regime-switching model with the recurrent reinforcement learning (RRL) algorithm to generate the regime-switching recurrent reinforcement learning (RSRRL) model and apply it to investment problems. In the work of Maringer and Ramtohul (2012), the volatility is used to switch between regimes and the RSRRL model is demonstrated to be better than the RRL model in finding profitable trading strategies. Thus, in this thesis, we combine the literature on the GA-based trading rules and that on the regime switching to form the regime-switching Genetic Algorithm (RSGA) model. The results show that, trading strategies generated from the RSGA model are more profitable and adaptive to the market than those from the GA model.

Overall, the contributions of this thesis to the literature is as follows. First, we provide an out-of-sample test on the effectiveness of the GA in finding profitable trading rules by using data in the Chinese stock market. Second, we open up the black box of the GA from a statistical approach and explain why certain strategies are chosen by the GA as the best ones. Finally, we connect the literature on regime switching and that on the GA-based trading rules and demonstrate that the regime-switching GA beat the GA in seeking profitable trading rules.

3. Methodology

The way we conduct the tests is also based on the framework of the Allen and Karjalainen (1999) approach with some adjustments on the details of experiments. Specifically, filter rules in the work of Allen and Karjalainen (1999) are in the forms of maximum, minimum and moving average of closing prices. However, in this thesis three popular technical indicators are utilized, which include RSI, MACD and Bollinger Band. Details of these three technical indicators can be found in Appendix A. The selections of filter rules in this thesis are similar to the work of Dempster and Jones (2001) except that they include a broader range of refined technical indicators. In addition, the depth of technical trading rules is fixed in the work of Allen and Karjalainen (1999) while we allow autonomy for GA to determine the best strategy depth.

Therefore, this thesis attempts to test whether, based on three well-known technical indicators – RSI, MACD and Bollinger Band, GA is able to help robustly acquiring better outcomes than the benchmark, which is normally buy-and-hold. In addition, another test in this thesis is that, we move one step forward by putting regime-switching into the framework of GA to generate trading strategies that are more flexible and dynamic. Previous literature has been focusing on developing and applying one single trading strategy from the GA. Then the conclusion of the effectiveness of the GA in finding profitable trading rules is based on the performance of the single strategy in the out-of-sample period. However, we assume that changed market regimes justify different applications of technical analysis and multiple trading strategies should be allowed to respond to regime changes. Thus, in this study, we also investigate the impact of adding regime-switching to the process of GA on investing results.

The content of this section is as follows. Section 3.1 explains why the GA has been popular in modeling the expectations in market. Section 3.2 shows the reason why in this thesis, we select those three technical indicators RSI, MACD and Bollinger Band as filter rules for the GA to explore. Section 3.3 illustrates the detailed procedure of GA. Section 3.4 reviews the fitness functions used in the evolution of GA. Section 3.5 illustrates the GA with regime switching, especially the difference between it and the GA without regime switching.

3.1 Why Genetic Algorithm

The process of learning and adaption in forming, testing and replacing forecasting models is time-consuming but crucial to inductive reasoning. In order to implement it in a more efficient manner, the Genetic Algorithm is introduced and verified as a perfect match with the purpose. The reasons why this is the case include that the GA works well with bit-strings since two core refining approach “crossover” and “mutation” can be easily fulfilled in the manner of bit-strings. When the GA is working on each “crossover”, some elements of two predicting models are exchanged. If the models come in the form of bit-strings, the whole process is, technically, cutting two bit-strings at one same position and exchange them. Similarly, each “mutation” is simply the modification of one random selected gene (bit). Besides, the GA is able to finish the learning and adaption in a significantly lower time scale because the magic of machine learning is that information is thoroughly investigated and significant patterns are discovered quickly. At the beginning, the GA randomly generate a large number of predicting models and test their performance using historical data. After that, good genes will be identified and used to create offspring generation by generation, promoting the average predicting ability of the hypotheses population. This feature makes the GA or other evolutionary optimization approach extremely applicable whenever the size of exploration space is too large for other optimization method to perform.

Second, another advantage over traditional optimization approaches the GA comes with is that, discontinuous and non-differentiable problems are within the working range of the GA, so is the case for problems with multiple optima. Third, the GA works with approximately the same logic with inductive reasoning. In the procedure of the GA, large number of forecasting hypotheses will be generated, tested in each generation with the gene (bit-strings) of those predicting well passed to next generation and non-performing ones being discarded, which is pretty similar to the learning and adaption in inductive reasoning.

Finally, the GA has a unique attribute that makes it a special and powerful approach. In addition to simply reserve good genes (bit-strings) and completely drop non-performing ones, the two phases in the GA "crossover" and "mutation" give rise to more potential desirable patterns. Rather than merely choose between retaining and discarding, there are many cases that a fraction or just one bit of the gene will be replaced, therefore we will end up with much more diversified predictors with at least some good genes to test. What's equivalently important is that the introduced probability mechanism prevents the temporarily underperforming forecasting models from being completely dropped, which still maintain the some potentially good piece of genes even though the bit-string in a whole in not a persuasive one.

In each period, the expectation model will come in the form of a combination of market condition and forecast. The market condition is a summary of the current phase of market while the forecast is a prediction of the following market movements. As each individual will hold many models available in each period and uses the most accurate ones to act upon, appropriate response will emerge in each of the scenarios recognized. For example, on the one hand, if we describe the market from 5 dimensions and conventionally use a bit-string of 5 bits to express the market condition, the bit on each position in the bit-string represents one dimension of the market. The first bit may mean that current price is higher than the 10-day average and second bit probably stands for the fact that current trading volume is the highest in 20 days. On the other hand, the forecast could be that price will increase (decrease) and corresponding action will be taking long (short) positions respectively. Specifically, suppose we use "1" on each position to stand for that certain status of market is in presence while "-1" means not. One additional possible case is that "0" will appear on some positions in the bit-string with corresponding dimensions of market are not considered before taking action. In fact, forecasting models considering more dimensions of market will give rise to bit-strings with more “1” or “-1” in them while the less sophisticated counterparts see more “0” in the bit-strings. Practically, each market participant will have finite predicting models and it is only when the current market conditions precisely match the ones in predicting models will the participant take actions – market condition “10010” will not trigger the action of recognized model condition “10001”.

By forming the expectation model in the architecture of bit-strings, some advantages can be noticed. First, there is a process of learning and adaption. Since forecasting models are recognizing pattern and base prediction on previous market movement under recognized pattern, generated appropriate response will not stay fixed as market changes – participants will update themselves with the most recent information and adjust the combination of market status and response in case of need. Second, there is a profound exploration of the market. Technically, the number of market dimensions considered (length of bit-string) is positively related to the number of market status recognized. If we still use “1”, “-1” and “0” as possible value for each bit, in terms of a bit-string of 5 bits, totally 243 (3^5) different market conditions will be recognized while models considering 7 dimensions of market will see 2187 (3^7) different patterns. Therefore, as more dimensions are put into consideration, market will be explored from a detailed perspective and theoretically, as many market conditions as possible could be distinguished. Finally, the nature of those predictors in the form of bit-strings allow individuals to categorize information important to themselves. Some participants believe in technical indicators and will use a lot of them while some others may add fundamentals as supplements. This attribute promotes different “type” of participants and a diversified market.

3.2 Technical Indicators

Since all the forecasting models generated by inductive reasoning using the Genetic Algorithm are based on the way we define the market, special efforts should be taken to guarantee that the bit-strings (market dimensions) are constructed in a manner that market conditions are clearly segregated and that market movements are predictable. In the experiments, we use three technical indicators Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and Bollinger Bands to recognize and distinguish market status. Of course, there should be a reason why, among a large number of technical indicators, we choose those three to recognize patterns and make predictions of market movements. First, RSI belongs to momentum indicators and is used to determine oversold and overbought conditions of market by comparing the magnitude of recent gains and recent losses. Second, MACD is a trend-following indicator that investigates the relationship between two moving average lines of different duration. Finally, Bollinger Bands are constructed with three bands – upper band, middle band and lower band. Current Market status can be identified by the relative location of updated price with regard to the three bands. Although those three indicators are among the most popular ones used by traders, we still want to get more insights into the effectiveness of them.

In order to confirm, whether RSI, MACD and Bollinger Band are able to work effectively and stably on judging market status and predict following movement, we perform some t-tests for each of them to show that, different market status reflected by the technical indicators are significantly associated with returns. In designing this experiment, we use RSI, MACD and Bollinger Band to categorize the market into 4 conditions respectively, which is consistent to our design in GA framework. Since our objective is to reveal whether some certain conditions are good predictors of price movements, take RSI for example, we perform a Fama-MacBeth regression (Fama and MacBeth, 1973) where the daily realized returns (returns of next trading day) of component stocks of CSI 300 Index are regressed against the 4 market conditions categorized by RSI. Namely, for each component stock, there is 4 independent variables to explain its next day's realized return, with the corresponding regressor matching its current status taking value 1 while others taking value of 0. Therefore, on a daily basis, the regression is of the following form:

$$\boldsymbol{R_i} = \boldsymbol{\beta_1} * \boldsymbol{RSI_{status_{i1}}} + \boldsymbol{\beta_2} * \boldsymbol{RSI_{status_{i2}}} + \boldsymbol{\beta_3} * \boldsymbol{RSI_{status_{i3}}} + \boldsymbol{\beta_4} * (1 - \boldsymbol{RSI_{status_{i1}}} - \boldsymbol{RSI_{status_{i2}}} - \boldsymbol{RSI_{status_{i3}}}) \qquad (1)$$

$\mathrm{R}_{\boldsymbol{i}}$ is the daily return of stock i while RSI_{status_i} stands for current status of RSI with regard to stock i. We use a random period of 120 days and perform this cross-sectional regression day by day. Namely we totally perform 120 OLS regressions and end up with 120 set of coefficients for each status defined for the technical indicator RSI. After that, t-test for the coefficients is implemented to verify the significances of associations between realized returns and each RSI status. According to the results, we can find that 2 out of 4 status categorized by RSI have significant relationship with returns during the testing period. Therefore, we can use RSI to predict price movements. Similar results are found for the other two technical indicators MACD (2 out of 4) and Bollinger Band (2 out of 4), which proves the effectiveness of technical indicators form the perspective of statistics and leads us to believe into the predicting power of them. Table 1 lists the detail of the Fama-MacBeth regressions for each of those three technical indicators.

[Please insert Table 1 here]

In addition to the statistical tests above, we also investigate the effectiveness of these three technical indicators from the practical point of view. In the daily practice, a trader will maintain a stock pool and construct the portfolio selecting stocks from it. We show here that depending on these three technical indicators, superior returns can be achieved. Similar to the steps we used in the t-tests of technical indicators, here we also conduct the Fama-MacBeth regressions with a rolling window of 75 days over the period from 2010.06 to 2015.10. On a daily basis, we use the average coefficients of each market status to forecasting stock returns of following days and rank them from the highest to the lowest. Then our portfolio is constructed by taking long positions of top 10% stocks and short positions of the bottom 10% stocks. This hedged position on each day is essentially, measuring the excess return between "strong" stocks and "weak" stocks on that day, which reflects technical indicators' ability in distinguishing them. In this experiment, we still use the data of component stocks of CSI 300 Index and verify the effectiveness of RSI, MACD and Bollinger Band both individually and altogether. The Figure 1, Figure 2, Figure 3 and Figure 4 in appendix are the plots of cumulated returns of the hedged position using only one technical indicator (RSI, MACD and Bollinger Band respectively) and these three indicators altogether.

[Please insert Figure 1 here]
[Please insert Figure 2 here]
[Please insert Figure 3 here]
[Please insert Figure 4 here]

Conclusively, regardless of whether the indicators are considered individually or together, the hedged position delivers significantly positive return with small drawdowns. This finding, persuades us that the technical indicators RSI, MACD and Bollinger Band are effective in segregating market statuses and predicting market movements. We are then confident in the GA utilizing these indicators to generate forecasting models.

3.3 Genetic Algorithm Procedure

Discovered by Holland (1962, 1975), the genetic algorithm (GA) is a kind of evolutionary algorithm and a process of search, iteration which ends up with robust near-optimal results. Being an evolutionary algorithm, first of all, the GA needs to know the environment to work with. Usually problems need to be addressed show up in certain forms, then a population of potential solutions will be kept and evaluated through a fitness function specific to the problem. GA works by picking better solutions on a relatively basis and evolve generation by generation to finally reach the near-optimal results. Beasley et al (1993) make a detailed description of genetic algorithm.

When using genetic algorithm, it is necessary to put the potential solutions in a structure GA could deal with, and the convention is to use bit strings with a mapping between the structure and original solutions. Usually GA starts working by randomly initializing the first population of certain size from the solution space, with each sample in the population being the potential candidate. On top of that, a fitness function fitting the problem must be defined to evaluate each candidate. For example, a route planning problem might have a fitness function to measure each solution from the respect of time spent or distance traveled. If instead, a portfolio management problem displays, the fitness function can take the form of realized investing returns or risks. Whenever both the fitness function and first population of solutions are ready, the next step is for GA to proceed in the evolution. The subsequent generations are created based on promising candidates through passing the elites, crossover and mutation according to certain probabilities. The probabilities assigned to each candidates are totally based on their corresponding performances measure by fitness function. Relatively better candidates will be favored and enjoy higher probabilities of being selected in "crossover" and "mutation". This mechanism will ensure that solutions are getting refined and optimized by generation and that candidates in subsequent generations will deliver better performance than the previous counterparts. Specifically, within the mechanism, there are three approaches that make it work as desired.

First, some of the samples with highest fitness values are called elites in generation and they will be directly passed to next generation. Second, in crossovers, 'parents' are chosen randomly with tilts towards those candidates with relatively better performance and then recombined to form the 'children' for next generation. As to the recombination, each time a pair of parents will be selected and cut their "genes" into two parts at a random location, exchanging a piece of which to form the 'children' in next generation. Third, in terms of the 'mutation', a parent is randomly chosen with probabilities in favor of high-strength candidates and one random "gene" of the parent is changed to generate one 'offspring' in next generation. This is repeated until the formation of next generation is completed.

With the same manner, following generations are created gradually in an identical way until one of predetermined terminating criteria has been met. Practically, there are two popular ways to define the criterion. The first one is to set a generation threshold (e.g. 50 generations) and the evolution stops when meeting predetermined threshold. The other one is to measure the degree of promotion in the performance of the best candidate in each generation, with the evolution finishes whenever there is no significant improvement in certain number of generations in a row. The final generation formed after all the evolution are left with superior candidates (genes) because the candidates of underperformance have been discarded in the evolution process. Then the top solutions in the final generation can be applied to the presented problem and normally, their performance will be near-optimal. However, due to the stochastic nature of GA, there is no guarantee for the convergence of the best solution from GA to the global optimal one.

Actually, for population size, there is a tradeoff between diversity and cost of computational resources. In other word, large population size can ensure better exploration of the solution space at the expense of being more time–consuming. This is not only the issue for genetic algorithm, similarly, brute-force method even more heavily relies on computational resources since each possible scenario will be tested in this approach. For the sake of this reason, GA is a more superior optimization method than brute-force. When looking at the market from the perspective of three technical indicators RSI, MACD and Bollinger Band, we transform the trading strategies into bit-strings, which is consistent to all the experiments in this thesis. If there are 10, 4 and 4 possible conditions for RSI, MACD and Bollinger Band respectively and each pair of indicators can be connected by "AND", "OR" or "XOR", overall there will be 34560 (10*4*4*3*3*3*2*2*2) different bit-strings represented through permutation and combination. In brute-force method, each of these 35460 scenario will be tested for performance to reveal the best one. However, when it comes to the

GA, with a generation size of 1000, after 10 generations we gain almost the same result. The explanation is that, the GA is able to retain those trading strategies that have superior "genes" and quickly recombine "strong genes" from kept trading strategies to finally approach the best one among all the scenarios, sparing the effort to test each of the scenario, especially the non-performing ones. In order to test the additional efficiency we are able to get switching from the method of exhaustion to GA, we have run two trials with everything in common except for the method and time, the conclusion is that, by using GA, we end up saving 65% of the time spent on exhaustion.

Although GA carries many merits, especially when compared to traditional optimization methods, we cannot ignore the limitation it comes with. In addition to the fact that, there is no guarantee for the convergence between GA's best solution to the essentially best one and the positive relationship between population size and execution time, the stochastic nature of GA can also be a weakness. Namely, if the initial population generated consists of no good "genes" because of the randomness, "Elite Passover" and "Crossover" will just picking relatively better member from a "bad" population and "Mutation" is left as the only way to come up with good "genes". Under this condition, it will be much more difficult to reach the near-optimal solution before the evolution meets predetermined stop point. Due to those limitations, the nature of problems to be solved should be considered first, and GA will be utilized only when its overall efficiency override those of other optimization methods. In fact, it will be more productive to be considered as a supplementary approach rather than replacing all of the traditional methods.

Genetic algorithm is a learning process including initialization, iteration and optimization. The detailed process of GA can be seen in previous content. After generating the first generation of potential solution, if we use holding period return as the fitness function, each candidate is evaluated in the form of excess return over buy-and-hold strategy and ranked accordingly. Then the evolution of trading tactics proceeds generation by generation to reach the near-optimal solution. Here we explain the two most important steps in the evolution- 'Crossover' and 'Mutation'.

Crossover

10100011101 Parent A

00110100110 Parent B

Offspring A: 10100000110 & Offspring B: 00110111101

Mutation

Parent: 10100011101

Offspring: 10100010101

Specifically, the trading strategies are randomly selected with probabilities in favor of those with better performances to perform the crossover and mutation and this is why the non-performing hypotheses are more likely to be discarded while models predicting well see more of their genes passed to the following generations. In the example above, a pair of parents (10100011101 and 00110100110) are chosen and cut at a randomly selected digit location (between sixth and seventh digit), then one piece of the bit string of each parent is exchanged to form two children (10100000110 &00110111101) in the next generation. As to one mutation, a parent (10100011101) is selected and the eighth digit is chosen to mutate, we end up with an offspring 10100010101 for next generation. After several rounds of crossover and mutation, when the number of offspring reaches the predetermined population size, the formation of a new generation is completed and each member in it is again, tested in the fitness function and ranked accordingly.

With sufficient iterations (generations), there will be a significant promotion in the performance of potential solutions since the "strong chromosomes" are reserved and passed along while the "weak chromosomes" are discarded. As the result, trading strategies making up the last population when the iterations end at are of high strength in training period.

However, we do not choose the best one of them as our optimal trading strategy. The reason why the best technical trading rule measured by the fitness function in the last population is not practically optimal is because of the data over-fitting problem. Namely, we expect the trading strategies selected by the GA to not only behave well in the training periods (in-sample) but also to deliver consistent performances in the testing periods (out-of-sample). Since we use one machine learning approach to optimize the solutions, the way experiments are designed is tightly related to the degree of over-fitting problem.

Previous literature has come up with several effective methods to alleviate this problem. In the work of Allen and Karjalainen (1999), the entire data is separated into three pieces as training, evaluation and testing periods respectively. In this case, the optimal trading rule is no longer equivalent to the best candidate in the last generation from GA. Instead, the best members from each generation are measured again in the evaluation period and the one delivering top performance in the evaluation period is instead considered as the final eventual trading rules to apply in the testing period. As a result, those trading strategies with significantly contrary performances between training and evaluation periods will be discarded and this is how the data over-fitting problem is relieved in the work of Allen and Karjalainen (1999). Ideally, the data over-fitting problem can be almost completely addressed if the data set is divided into infinite number of periods with periods other than the last one being evaluation periods. However, it is not reasonable and computational viable to implement this adjustment. In this thesis, we rely on the same approach in the work of Allen and Karjalainen (1999) to alleviate the data-mining problem. Actually, by splitting the data set into 3 pieces (training, evaluation and testing), the over-fitting problem is greatly relieved according to the results of experiments. In addition, in the work of Becker and Seshadri (2003), another method to solve the same problem is to modify the fitness function by imposing a penalty on complicated trading rules to favor relatively simple trading rules ones. The rationale behind is understandable because as more conditions or constraints are attached to a trading rule, the chance of only performing in certain periods of time increases. In this thesis, we do not apply this method and there in no penalty to favor any certain trading rule.

3.4 Fitness Function

As the evolution of GA proceeds, there should be a mechanism through which non-promising solution candidates are discarded and the “genes” are getting promoted by generation. The fitness function is then designed for this purpose. Technically, the fitness function can be of various forms and should be designed specifically to the presented problems. Since we are going to, taking advantage of GA, promote stock trading performances, a good choice for the fitness function in our tests is the excess return over certain benchmarks such as the buy-and-hold (pure indexing) strategy, with trading costs taken into consideration. Practically, the continuously compounding cumulative returns during the training period are computed, then trading costs and the corresponding buy-and-hold returns are subtracted to reach the excess returns. In our first experiment verifying the effectiveness of the GA on one stock index, short sale is not allowed and in each period of time, according to corresponding signals, our alternatives can be either taking long position of the index considered or maintaining an empty position. The daily realized returns are calculated whenever our position is not empty and cumulated over the entire period to reach the holding period return. Then the fitness function is to measure and rank the holding period returns of each strategy so that the evolution of GA can keep working. To imitate the reality as much as possible, trading costs are taken into account while working out the realized returns and in our experiments, the one-way trading expense has been set at 20bps, which is similar to the work of Allen and Karjalainen (1999). As a result, strategies involve frequent changes of position are easier to be knocked out if we set the trading cost at a relatively high level and vice versa. In other words, the trading costs act as a penalty on the frequent trading. Therefore, by controlling the level of trading expense, we are able to attain different strategies with desired trading frequency.

Similarly, if, instead of taking positions of only indices, we now need to consider large number of stocks to construct and maintain a portfolio, then the objective of fitness function will turn to the holding period of return of the portfolio as a whole. In this case, each of the stock in pool should be minded in the same manner as we do in experiment with only index. The daily continuously compounding return for stock i in day j (X_{ij}) can be computed as:

$$X_{ij} = Ln(P_{ij} - P_{ij-1}) \quad \text{IF stock i is in the portfolio in day j}$$

$$X_{ij} = 0 \text{ IF stock i is not in the portfolio in day j} \tag{2}$$

Therefore, the cumulative return for the portfolio (PR) during the training period is as follows. In the equation, W_{ij} is the weight of stock i on day j while X_{ij} stands for the return of stock i in day j.

$$PR = \sum_{j}^{i} w_{ij} x_{ij} \quad (3)$$

$W_{ij} = 0$ if stock i is not in the portfolio in day j

Finally, the excess return over buy-and-hold is worked out as:

$$ER = PR - R_{bh} - 0.002 * n \quad (4)$$

Where R_{bh} is the continuously compounding buy-and-hold return and n is the total number of transaction for the portfolio during the training period.

In addition to target holding period return, there are theoretically infinite ways to define the fitness function. In practice, the realized return is not the only criterion to select strategy and other aspects (e.g. risk) of a trading strategy should be viewed as well. Actually sometimes risk matters more than return. In order to reduce risk, some adjustments of the fitness function will be justified and we could introduce one of risk metrics as an additional part of the fitness function so that genetic algorithm will favor those strategies with lower risk. As risk comes in various kinds of form and different investors pay attention to different aspects, the way we modify the fitness function is supposed to match the purpose. For example, if an investor is not comfortable with large drawdown, he or she should utilize a fitness function which is able to filter out strategies with high drawdowns. To satisfy this goal, we should consider the maximum drawdown as the risk and the fitness function should incorporate a metric to reflect this risk. Practically, one option is to divide holding period return by the maximum drawdown during the period, then a penalty is introduced for those strategies with large drawdowns and they have to achieve even higher return to be able to end up with same fitness value as strategies with lower drawdowns. Actually, the ratio of the holding period return over the maximum drawdown during the same holding period is defined as the sterling ratio. In another situation, for example, if investors are concerned about volatility, then the Sharpe ratio which is the ratio of the difference between realized return and risk-free return over standard deviation of return during the whole period of time, could be the objective of fitness function. In this manner, strategies with high volatility are at a definite disadvantage and those with smooth cumulated return will be favored.

$$Sterling\ ratio = \frac{cumulative\ return}{Maximum\ drawdown} \tag{5}$$

$$Sharpe\ ratio = \frac{cumulative\ return - risk\ free\ return}{Standard\ deviation} \tag{6}$$

However, satisfying certain investment needs or preferences is not the only reason to modify the fitness function. Furthermore, the over-fitting problem may give rise to some necessary adjustment to the fitness function and the magnitude of adjustment varies according to some predetermined criterion. For instance, one of the criteria could be that, the more complex the trading strategy, the higher the penalty. Since complicated trading strategies in place after the evolution are more prone to be a result of data mining, we impose more difficulties on those complicated forecasting models in achieving superior outcomes, with other aspects being identical. Namely, when two strategies are totally same except that three classified rules are used in one while only two classified rules are considered in the other one, then the trading strategy using only two classified rules should be more likely to be selected than the strategy using three classified rules.

Then we illustrate the appearance of trading strategies appearing in the fitness function, namely, the approach through which we conduct the trading. In practice, portfolios are constructed by taking long and short positions according to certain rules. The trading strategies in our experiments are expressed in bit-strings and describe the conditions to be satisfied in order for long or short positions to be taken. Each trading strategy (bit-string) has four parts in total. The first one is the market conditions to be met in the form of classified rules, which include fundamental metrics, technical indicators and even limit book information, etc. For instance, one technical indicator rule based on Bollinger Bands might be expressed as:

$$P_{i-1} \leq \ Bollinger_{upper_{i-1}}\ \boldsymbol{AND}\ P_i > \ Bollinger_{upper_i} \tag{7}$$

Where P_i and $Bollinger_{upper_i}$ are the stock closing price and Bollinger upper band at day I respectively. Another technical indicator rule, for example, could be presented as

‘The short-term moving average crosses below the long-term moving average’, and equity investors will be more familiar with this condition by calling it ‘Death Cross’. The classified rules should be interpreted from the bit strings taking values from 0 and 1 to ensure that the GA can work with it. One example of categorized conditions for RSI, MACD and Bollinger Band can be found in the appendix as table 1. In table 1 we categorize RSI into 10 intervals with equal length, for MACD and Bollinger Band, 4 sections are defined for each. In this case, we are able to tell the current status for each of them according to the values of corresponding bits. Second, we need to consider the relationships among indicators and thus, there should be connections between each pair of rules. One approach is to let rules contained in the trading strategies linked by connectors in the form of Boolean functions, which might choose among ‘AND’, ‘OR’ and ‘XOR’ reflected respectively by ‘00’, ‘01’ and ‘10’ in bit-strings. Third, there is a ‘structure unit’ in the trading strategies that identify which classified rules should be considered. Suppose there are five potential classified rules, then the structure unit should be a bit string of five digits, with each digit taking 0 or 1. The indicators with “0” on their corresponding locations in the bit-string are ignored when generating the trading strategy. The last part of a trading strategy is the ‘action’ which can be taking long positions (“1”), taking short positions (“-1”) or keeping an empty position (“0”). Similarly, using binary numbers can accomplish this goal.

Overall, one example of the bit-string, based on three potential classified rules, could be ‘10120011101’ and this bit-string is interpreted as “if the RULE #1 is at status 1 or the RULE #2 is at status 2, then long positions of the target should be taken”.

10120011101 Classified Rules

10120011101 Connectors

10120011101 Structure Unit

10120011101 Action

3.5 Genetic Algorithm with Regime Switching

The behavior of financial market is not stable. Instead, both temporary and permanent changes will take place. In addition, those changes can also be categorized as recurring or unique ones. Whenever the market comes across such changes, financial instruments across sectors will experience significant impact as a result. For instance, during each global crisis, volatility of asset prices rises dramatically and return correlations among asset classes jump drastically. Since these changes will normally persist for extended period of time, trading strategies performing well previously may become losers for extended periods of time for the sake of market changes.

Therefore it is no longer to apply one fixed strategy all the time in case such major changes take place. Actually, among previous literature studying GA-based trading rules, Dempster and Jones (2001) introduce an adaptive system which enable multi-strategies to be in effect during one testing period. In their work, GA generate trading strategies at regular intervals and update current strategy in effect. Specifically, current strategy in effect will be discarded once it becomes loser or whenever better trading strategies are generated. This is the first research on GA-based trading strategies that allows updates of strategies to make trading rules more suitable to market climates. Overall, we agree that relying on one fixed trading rule all the time is not optimal and adaption to the market is necessary to further improvements on trading results. However, the way we make the trading strategies adaptive is different from the Dempster and Jones approach (2001).

There have been many researches covering market regimes and regime switching models have been developed and applied consequently. Market regimes are defined as certain periods of time according to their special dynamics. For different financial asset classes, different metrics are used to identify regimes. Specifically, in terms of stock market, a normal way is to identify certain regime by the level of volatility during the period. Actually when investing in equity markets, key issues to consider include volatilities, correlation among stocks expected return and so on. Ang and Bekaert (1999) conclude that two volatility regimes exist in stock market. Similarly, Buren (2012) also supports that volatility regimes are in place but their association with market changes vary across business cycles. In addition, another understanding of stock market regimes can be defined as bull and bear market periods. Due to different dynamics of assets upon regime change, the optimal investment choice justified in previous regime will not guarantee the transition of its performance into the new regime. For example, buy-and-hold strategy will end up with totally opposite results when applied to both bull and bear market. Besides, volatile markets favor strategies with higher trading frequency. Therefore, both our intent to discover the near-optimal strategy by GA and the corresponding design of experiment should take the issue of regime switching into consideration. In this thesis we pay attention to volatility regimes of equity and modify our experiments by admitting that one single strategy is not optimal for the sake of regime switching. Namely, rather than letting GA reveal only one unique pair of long-short signals, we now entitle the evolution autonomy to identify two market regimes and discover the best strategy specific to each of them. In order to take advantage of the regime switching model from the perspective of ex-ante forecasting, we use GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. Actually there have been many models predicting volatility, the major reason why we select GARCH model is because it is able to capture volatility clustering, which reflects the real market well. The following is a brief introduction of GARCH model and way we put GARCH into the evolution of GA.

First we also consider CSI 300 Index and P_t is the closing price series. Thus the daily corresponding continuously compounding return R_t is defined as:

$$R_t = Log(P_t) - Log(P_{t-1}) \tag{8}$$

Then the GARCH (1, 1) model based on daily continuously compounding return R_t will be of the following form:

$$R_t = \delta + \varepsilon_t = \delta + \mu_t \sqrt{h_t} \tag{9}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta h_{t-1} \tag{10}$$

Where α_0, $\alpha_1$and β are positive to guarantee that conditional variance is positive and the innovation is the product of an i.i.d process with zero mean and unit variance $\mu_t$and the square root of conditional variance.

Now we implement the modification on our experiment once getting predicted volatility from GARCH and we let GA divide the market into two regimes based on a threshold level of volatility. Then two pairs of strategies will be formed to suit each of the regimes, on a daily basis, our final strategy to time the market will switch between those two strategies and is totally dependent on the current regime displayed. In this experiment with regime switching, in order to be consistent and comparable, we also use the data of CSI 300 Index from January 2010 through November 2015 to be the out-of-sample. In terms of the details in our experiment design, everything is identical except that length “gene” for each candidate strategy are doubled to incorporate another pair of signals. With the same evolution process generation by generation, we end up with one outcome with two pair of signals after the training and evaluation. On top of that, we are also provided with the volatility threshold to tell the regimes apart and to identify which pair of signal to apply.

Strategy 1 applies IF:

Predicted volatility <= threshold volatility

Strategy 2 applies IF:

Predicted volatility > threshold volatility

As a comparison, the entire process of GA in generating optimal strategies with and without regime-switching is presented as follows. In this comparison, the procedure is targeting market with two regimes. Apparently, the main difference between is at the very beginning of procedure. In designing experiments considering regime-switching, the metrics market regimes are based on should be defined first. In addition, the structure of each candidate solution become more complex as another pair of trading strategy as well as a threshold are added.

Procedure of GA without regime-switching:

1. Initialize the solution population, with each candidate consists of one pair of trading signals. (Training)
2. Test each candidate in current solution by predetermined fitness function and make a ranking correspondingly. (Training)
3. Generate next solution population, by passing elites, crossover and mutation, from current generation until stopping criterion is met. (Training)
4. Repeat step 2 and 3. (Training)
5. Evaluate the best candidates in each generation to alleviate data over-fitting problem. (Evaluation)
6. Test the eventually optimal solution from evaluation in out-of-sample. (Testing)

Procedure of GA with regime-switching

1. Determine the way from which market regimes are defined. (Training)
2. Initialize the solution population, with each candidate consists of two pair of trading signals corresponding to each regime in addition to a threshold to tell regimes apart. (Training)
3. Test each candidate in current solution by predetermined fitness function and make a ranking correspondingly. (Training)
4. Generate next solution population, by passing elites, crossover and mutation, from current generation until stopping criterion is met. (Training)
5. Repeat step 3 and 4. (Training)
6. Evaluate the best candidates in each generation to alleviate data over-fitting problem. (Evaluation)
7. Test the eventually optimal solution from evaluation in out-of-sample. (Testing)

3.6 Constructing Equity Portfolios

When it comes to trading strategy, some traders rely more on market timing while others might prefer stock selection. One of the major difference between market timing and stock selection is that, market timing is to predict market movements from a macro perspective and gives little attention to individual stock, which is a top-down analysis. Ideally, a successful market-timing strategy will increase the exposure of portfolio to the market whenever market is in an upward trend and vice versa. However, stock selection starts from each individual stock and tries to identify the best ones from their peers. A superior stock-selection strategy will discover a pool of stocks outperforming market portfolio regardless of the market climate. According to the Capital Asset Pricing Model (CAPM) (William Sharpe, 1964), investors are compensated in two ways: time value of money and risk. The time value of money is represented by the risk-free return denoted as r_f in CAPM while the risk is reflected by "beta" in the formula, which is actually the focus of market-timing strategies.

$$\overline{R_a} = r_{rf} + \beta_a(r_m - r_f) \tag{11}$$

However, the realized return is not equal to the expected return from CAPM, instead there is one additional part called "alpha", which comes from stock selection and has nothing to do with market timing. To be more precise, investors will use technical analysis, fundamental analysis and so on to distinguish between "good" stocks and "bad" ones and put different weights on them from the benchmark. The excessive return achieved by this way is called the "alpha". Thus investors with superior investing ability are able to enjoy positive alpha while unexperienced traders may end up with negative alpha.

$$R_a = \overline{R_a} + \alpha_a \tag{12}$$

Since we are testing whether GA-based trading strategies can increase portfolio performances, there should be some benchmarks so that we can reach the conclusion.
In this paper, our first benchmark is the Index and we will show that, by using GA-based technical trading strategies in market timing, we are able to achieve significantly better returns than index return. The equity portfolio constructed in this way will have

instruments tracking the market index as its holdings. However, it will differentiate from pure indexing by the fact that both long and short positions can be taken. One conventional way to construct this kind of equity portfolios is to take long and short positions of the corresponding index ETF and use GA-based trading strategies in the entire construction of stock portfolio by taking long or short position of the index ETF according to the signals came up with by GA. On each trading day, the portfolio status will be one of the following three conditions: long position, short position and empty position. To achieve this, GA will explore historical market movements and provide us with a unique combination of long-short signals. Long and short positions will only be taken when corresponding signals are triggered, otherwise we maintain an empty position. As we know, there is neither market timing nor stock selection in the buy-and-hold strategy, therefore all the excess returns of the index ETF portfolios over pure indexing come in the form of market timing.

Besides, our second benchmark comes in the form of a portfolio constructed through stock selection. Namely this time we will compare three equity portfolios in total. In terms of the first portfolio which is still pure indexing, there will be neither market timing nor stock selection and this portfolio has a fixed exposure to the market, therefore the returns of this portfolio will be equal to the index return. In the second portfolio, we use another quantitative approach to fulfill stock selections through Fama-MacBeth regressions (Fama and MacBeth, 1973) on a daily basis. In the second portfolio, fixed exposure to the market is still in place. However, another resource of return in the form of stock selections is introduced into the portfolio. In other word, there are “alpha” and fixed “beta” in the second portfolio. When compared to the first portfolio based purely on indexing, the excess returns of the second portfolio are from stock selections. The third portfolio is where market timing and stock selection are combined. Specifically, not only “alpha” but also variable “beta” exist in this portfolio. The difference between the second and third portfolios is that there is only one resource of excess return over pure indexing in the second portfolio (stock selection) while additional returns come from two aspects in the third portfolio (market timing and stock selection).

Furthermore, when we conduct the experiments testing GA with regime switching, naturally the most direct benchmark is the portfolios constructed by GA without regime switching, with other things equal. Overall, by conducting our experiments in such sequence, we get to know where excess returns come from and reach conclusions based on that.

4. Data, Experiments and Results

When conducting our experiments, we use the data of CSI 300 index and its component stocks. First we also verify whether consistent superior daily trading rules on CSI 300 index can be revealed by GA. After that, we turn to demonstrate that market timing from technical trading strategies discovered by GA is able to provide another resource of return to both pure indexing and portfolio with stock selection. Moreover, at the same time we present generated trading rules and their corresponding performances, we also use an econometric way to show that trading strategies generated by GA are reasonable and statistically significantly correlated to achieved returns. Last but not least, we make a comparison between the performances of trading strategies from GA and GA with regime switching.

Specifically, section 4.1 reviews some basic facts of the data we used in these experiments and the reason why we target CSI 300 index as our data set. Section 4.2 presents the experiments aiming at verify the effectiveness of GA in finding superior technical trading rules. Section 4.3 presents some experiment results to demonstrate how pure indexing strategy can benefit from the trading rules generated by GA. Section 4.4 shows some other experiments to illustrate the way portfolio based on stock selection can also benefit from trading rules from GA. Section 4.5 reviews the experiments and results of technical trading rules generated by GA with regime switching.

4.1 Data

In this thesis, the data set to be used for tests is the CSI 300 index, which was constructed on 04.08.2005. CSI 300 index is a capitalization-weighted index with free-float adjustments constructed by including 300 sample stocks in Shanghai equity market and Shenzheng equity market according to certain criteria. The component stocks in CSI 300 index account for 60% of the total capitalization of Shanghai equity market and Shenzheng equity market. In addition, the way component stocks are selected accurately reflects the industry structure. We acquire the data of CSI 300 index from CSMAR database and use the daily closing price data of CSI 300 Index and its component stocks from April 2005 through October 2015 in our experiments. Figure 5 is the plot of CSI 300 index from 2005.04 to 2015.11.

[Please insert Figure 5 here]

Due to the fact that CSI 300 Index is not stationary in this period, I normalize the data by taking the log difference of closing prices. This will transform the closing prices into continuously compounding return and spare us the issue of magnitude, promoting comparability. Figure 6 is the plot of cumulatively continuously compounding return of CSI 300 index from 2005.04 to 2015.11.

[Please insert Figure 6 here]

According to the transformed data, we can identify three distinct phases. Namely, the index boomed and increased from 1000 points to 5700 points during October 2005 through December 2007, which is followed by a sharp drop (from 5700 points to 1800 points) lasting approximately one year (January 2008 – December 2008). The index is relatively stable during October 2009 through October 2010. As a fact of this diversity of market condition during 2005.04 – 2010.10, we have chosen the data set of this time period as our training sample (in-sample) for verifying GA-generated strategies while 2010.11 – 2015.11 is defined as the out-of-sample. Table 2 contains some basic facts of CSI 300 index during the period from 2005.04 through 2015.11 including number of days, average daily return, cumulative return, return volatility, maximum drawdown and Sharpe ratio.

[Please insert Table 2 here]

The unique characteristics of Chinese stock market make it difficult to achieve outstanding performances by technical analysis. First, since the constructions of the two exchanges in 1990 (Shanghai Stock Exchange and Shenzheng Stock Exchange), China's stock market has experienced significant higher growth than Japan's Nikkei 225, Hong Kong's Hang Seng Index, the Dow Jones STOXX 600 covering Europe and the Dow Jones World Emerging Markets Index which covers 11 major emerging markets all over the world. Second, China's stock market is greatly influenced by the government. In fact, up to now the China's government still imposes a tight control on the issuance of IPOs. Besides, a lot of listed companies in China have low free-float ratios for the sake of widespread holdings of the government. Meanwhile, market speculations and manipulations are common in China's stock market as a result of the unusual market structure. Third, China's stock market is volatile and has gone through various kinds of market climates. For example, the Dow Jones China Index ends up with an average annualized volatility of 51.10% during the period from 1994 to 2001. In the same period of time, the Dow Jones Industrial Average achieves an average annualized volatility of 15.8%. Besides, if a bear market is defined as 20% drop from the previous peak, then China's stock market has experienced more than 15 bear markets since its commencement, which is more frequent than the Dow Jones Industrial Average. Fourth, China's stock market is slightly correlated to other stock markets all over the world such as Dow Jones Industrial Average, Nikkei 225, Hang Seng Index and STOXX. For example, political issues have great impacts on Chinese stock markets.

Therefore, it can shed new lights into the application of the GA on trading strategies if we are able to find superior technical trading rules by the GA in such a complicated market environment. In other word, by testing the GA's ability to filter trading strategies in such a complex environment, we are capable of deciding whether strategies revealed are able to adapt to and handle complex market sentiments and preferences. Namely, we avoid generating strategies that perform well in flat markets but fail to deliver similar performance in complicated ones, which is reasonable and meaningful to both academy and practice. Second, although the GA has been widely used in investing process, few of application is targeting Chinese stock market and this is definitely, a gap to bridge. By taking on this study with Chinese stock market, we are going to fill this breach and verify whether there will be differences between the effectiveness of the GA in discovering strategies among different markets.

4.2 Verification of Genetic Algorithm

Since we have demonstrated in previous content that, from the perspective of predicting returns, that those three technical indicators (RSI, MACD and Bollinger band) we pick are effective on trading within CSI 300 Index to make sure there are potentially superior strategies available to be discovered by GA. In this section, we conduct several experiments to verify whether GA is effective in filtering strategies and trading rules generated are able to consistently beat buy-and-hold after transaction costs. In designing our experiments, we use daily data from 2005.04 through 2015.11 of CSI 300 index and use similar framework in the work of A&K (1999) except for the modifications we list before.

With a population size of 500, ten experiments are performed on the in-sample data (2005.04 – 2010.10) and the generated trading strategies vary in term of the level of complexity, with the depth of strategies being at most three levels. For example, one simple strategy could be:

IF RULE #1 IS TRUE, THEN LONG POSITION IF RULE #1 IS FALSE, THEN SHORT POSITION

As a comparison, one complex rule could be in the following form:

IF RULE #1 IS FALSE AND (RULE #2 IS TRUE OR RULE #3 IS TRUE), THEN LONG THE POSITION

IF RULE #1 IS TRUE OR (RULE #2 IS FALSE AND RULE #3 IS FALSE), THEN SHORT THE POSITION

The corresponding Buy-and-Hold return during this period is 48.97% and the in-sample performance of each of the 10 GA-generated strategies is in Figure 7.

[Please insert Figure 7 here]

According to the results, for the training data set, GA-generated strategies outperform Buy-and-Hold, with the mean excess return being 54.96% during April 2005 through October 2010.

Although satisfying outcomes are gained on the in-sample data, when these strategies are utilized in the out-of-sample (November 2011 – October 2015), half of these strategies are not able to beat Buy-and-Hold, which indicates the existence of data over-fitting problem. Namely, we can't take it for granted that each strategy recommended by genetic algorithm is profitable and supposed to apply in the market. However, based on the fact that some of the GA-based strategies do perform well in the out-of-sample, one approach addressing this over-fitting problem and telling us, among all the strategies generated by genetic algorithm, which strategies should be relied on, is needed. Figure 8 is out-of-sample performance of each of the 10 GA-generated strategies while Figure 9 is the plot of the cumulative return of one of the 10 generated strategies in the out-of-sample period.

[Please insert Figure 8 here]

[Please insert Figure 9 here]

As we know, every predicting model with parameters generated from certain period of time may suffer from data mining. We definitely cannot suppose that strategies filtered by GA are able to avoid this problem. The fact that majority of the 10 experiments we performed on CSI 300 index end up with inconsistent performances between in-sample and out-of-sample exactly justifies this concern. Thus, in order to relieve data mining to some extent, if impossible to completely avoid, and for the selected strategies to not only perform well on the in-sample but also outperform Buy-and-Hold strategy on the out-of-sample, we take on the data over-fitting alleviation mechanism used in the work of A&K (1999). Specifically, the data set is the core of this adjustment and now the entire data set is further organized to check on the strategies recommended by genetic algorithm on the in-sample. Specifically, instead of dividing data into in-sample and out-of-sample, out-of-sample are further separated into selection and testing period, thus the whole data set is consisting of training, selection, and testing data. Strategies generated in the training period are evaluated in selection period to check their usefulness in out-of-sample. After that, only those strategies with consistent performances between training and selection period will be utilized in the testing period, which is of course, also an out-of-sample.

Specifically, the best-performing predicting model in each generation from training will be tested by the same criterion but instead, on the data set in evaluation period. The most crucial change we make here is that, rather than simply taking the best member in last generation, a new criterion is used – we narrow the candidates down to the best member in each generation and finally select the one that ranks first in the selection (evaluation) period. Take CSI 300 Index for example, April 2005 – October 2010 is chosen again as the training period as a result of the market diversity of this period. November 2010- October 2014 is the selection period while October 2014 – October 2015 is the testing period. To test the effectiveness of this over-fitting alleviation system, we conduct another experiment by taking the 10 trading strategies from previous 10 experiments and measure their performances in the new defined training, evaluation and testing periods respectively. Not surprisingly, since the training period remains the same, all of the generated strategies outperform Buy-and-Hold strategy by a significant amount.

Figure 10 is the performances of these 10 trading strategies in the training period.

[Please insert Figure 10 here]

However, when these 10 strategies are utilized in the selection period, not all strategies work well as they do in the training period. Half of these 10 strategies cannot beat buy-and-hold in the evaluation period. The rationale of this data over-fitting alleviation system is to identify those strategies with significantly contrary performances between different periods and discard them for the sake of this discrepancy. Therefore, this is a way to further filter the trading strategies. By measure their performances in training, evaluation and testing periods respectively, we can test the assumption that strategies performing in not only training period but also evaluation period will end up being the top strategies as well in testing period. Figure 11 presents the performances of these 10 trading strategies in the evaluation period while Figure 12 presents the performances of these 10 trading strategies in the testing period. In Figure 13, the comparison among the performances, in terms of cumulative return, of buy-and-hold and the three top trading rules from evaluation period in testing period is presented.

[Please insert Figure 11 here]
[Please insert Figure 12 here]
[Please insert Figure 13 here]

In fact, top three strategies measured in the selection period are still the best three strategies in the testing period. Therefore, we are confident about this data over-fitting alleviation system in terms of its ability to address data over-fitting problem by some extent.

The outcomes above are based on the fact that fitness function in genetic algorithm is the holding period return (HPR). Practically, sometimes risk-adjusted return is preferred as a way to reduce risk and maximum drawdown is a typical and popular metric to represent risk. Therefore, as a comparison, the entire process before is repeated except that fitness function is adjusted sterling ratio, rather than holding-period return (HPR). By using adjusted Sterling ratio as the fitness function, we literally attach a penalty to those strategies with large volatility and, as a result of this, strategies standing out are able to maintain a lower level of risk.

This time, twenty experiments are performed on the training period (2005.04-2010.10) and strategies are evaluated over selection period (2010.11-2014.10). Finally, testing period is used to check whether those strategies enjoy consistent performance in both selection and testing period (2014.10-2015.10). Totally 18 different strategies are generated from the twenty trials and their performances in each of three periods are displayed as following. One issue worth mentioning is that it is useless to measure risk-adjusted return when return is negative. Thus we only calculate the adjusted sterling ratio for those strategies with positive return.

$$Adjusted\ Sterling\ ratio = \frac{cumulative\ return}{1+Maximum\ drawdown} \tag{13}$$

We find that, due to the market downward movement during the selection period, only two strategies end up with positive return and these two strategies are accidentally the top 2 strategies recommended by GA on training period, which is rather rare in our experiments. According to previous experience, we transfer those 18 trading strategies to testing period and find that top strategies in the evaluation period still maintain their rankings in the testing period. Figure 14 is the scatter plot of the performances of these 18 trading strategies in the training period. Figure 15 is the comparison between the performances, in terms of cumulative return, of buy-and-hold and the best trading rule from evaluation period in testing period.

[Please insert Figure 14 here]

[Please insert Figure 15 here]

Consequently, the strategy recommended by genetic algorithm is more or less similar to that when fitness function is HPR. The reason why this is the case is because China's stock market has experienced a lasting sharp drawdown since June 2015 and strategy that is supposed to maximize sterling ratio is able to escape from the drawdown before its commencement.

Overall, so far we have demonstrated that as long as the data over-fitting alleviation system is in place, trading strategies generated after the evolution will not deliver significantly contrary between in-sample periods and out-of-sample periods. Besides, all of the technical trading rules generated this way in our experiments are able to beat buy-and-hold in the out-of-sample period. According to the results of experiments so far, we have two conclusions about the GA-based technical trading rules. First, based on CSI 300 index and the framework of the work of A&K (1999), GA is able to help generating superior technical trading rules that consistently beat buy-and-hold after considering trading expenses on a daily basis. Second, the data over-fitting alleviation mechanism is essential in achieving consistent outperformances for strategies generated by GA in the out-of-sample periods.

Since we have gained empirical results and demonstrated the effectiveness of the GA, more tests are performed to show that the GA is capable of enhancing the portfolio performances from the perspective of higher returns and lower risks. In the following section, we present the performance of four kinds of equity portfolios with the returns attributed respectively to pure indexing, market timing, stock selection and market timing with stock selection.

4.3 Pure Indexing

In this section, we perform another several comparisons to show that, GA-based strategies can provide equity portfolios with another resource of returns by timing the market. The data we use in these experiments include daily closing prices of CSI 300 index and its component stocks from 2005 through 2015. due to the fact that GA asks for some data to do the training before it can provide us with the performances of trading strategies in our-of-sample periods, the real comparison will be over 5 years from 2010.01 through 2015.12. First, we present the performance of buy-and-hold strategy. Since there is no market timing or stock selection in this passive portfolio and we assume taking long position of the index all the way during these 5 years without any adjustment, namely pure indexing. The Figure 16 is the plot of historical closing points and Figure 17 displays the corresponding cumulative continuously compounding returns of this passive portfolio – pure indexing. We can see that buy-and-hold strategy achieves a return of 6.12% with a Sharpe ratio of 0.0024 during this period of time from 2010.01-2015.12.

[Please insert Figure 16 here]

[Please insert Figure 17 here]

4.4 Market Timing

In order to show that performances of pure indexing can be promoted by the ability of GA-based technical trading rules to time the market, we still do not consider stock selection and only long or short positions of CSI 300 Index can be taken if our position is not empty. The reason we allow short positions is that the costs of taking short positions of index will be much lower than those of shorting individual stocks. Besides, the flexibility and smartness of GA can be tested if we not only permit long positions, but also short positions. As we explained in previous sections, there will be data over-fitting problems for every machine learning method and GA suffers from it as well. In order to relieve this problem to some extent, we reserve some data as the evaluation period. To be more precise, the daily prices of CSI 300 Index from 2005 January through 2008 April are used by GA to do the training, and the evaluation is performed during the period from 2008 May to 2009 December. After the training and evaluation, GA provides us with one unique set of long-short trading rules and we apply them in the testing period (out-of-sample) between 2010.01 through 2015.12. With the same design of experiment, we perform 10 experiments to get 10 different market timing strategies. The Table 3 contains key aspects of the gained strategies in the out-of-sample.

[Please insert Table 3 here]

Since GA works with bit-strings, we interpret gained results and take strategy 1 in table above from the perspective of GA for example and make a detailed explanation. Within this certain strategy, the trading rules for taking positions are as following:

Taking long position IF:
DIFF>DEA & difference between DIFF and DEA increasing (MACD) OR
Closing price cross above upper band (Bollinger) XOR RSI>75 (RSI)

Taking short position IF:
Closing price cross below lower band (Bollinger Band) OR
25<=RSI<50 (RSI)

Taking empty position IF: Otherwise

When we investigate this trading strategy discovered by GA, we find that one of the long signals is purely based on MACD while short position signals rely on RSI and Bollinger Band. Consequently, there will be 4 potential different signals to be released:

1. Only long position signal is released.
2. Only short position signal is released.
3. Neither long nor short position signal is released.
4. Both long and short position signals are released.

According to the strategy, long position signals and short position signals are not mutually exclusive and theoretically, there is contradiction when both long and short signals are conveyed, therefore we should consider whether this GA-generated strategy is practically reasonable and we eventually reach an affirmative conclusion. As we know, the technical indicator MACD is based on moving average of closing prices with different durations and whenever the condition for taking long positions "DIFF>DEA&DIFF>0" is met, the market has been in an upward trend for a while. In this case, recent closing price has been rising for some periods of time so that it is impossible for closing to be below the lower band of Bollinger Band. Similarly, whenever RSI takes value between 25 and 50, market is considered as relatively weak and it is not likely to see MACD in the phase "DIFF>DEA&DIFF>0" simultaneously. Therefore, although the signals for taking opposite positions are not theoretically mutually exclusive, practically, they will not display at the same time.

We also check the details of our experiment results and find no co-existence of contrary signals in any period of time. Besides, the meaning of this strategy is logical and match our understanding of the market. In terms of the first signal for long position considering only MACD, we have explained that market is keep being strong and recent closings are getting higher recently and it will be good buy points then. The other buying signal rely on two technical indicators – RSI and Bollinger Band. RSI is known as an approach to judge the section market has moved into and a value above 75 for RSI is normally reflect that market has been in overbought sector while values below 25 stand for the opposite. Bollinger Band is used to measure the deviation of closing prices to its moving average on a daily basis in our experiments, the common sense is to consider both upper and lower band as important points where breakings are going to release particular signals. However, the exact signals from breaking upper or lower band vary to different participants or different stocks. Take the breaking above the higher band for example, this phenomenon appears to some equity traders as good buying point for the sake of penetration of a resistant level. Whereas, the same situation might convey exactly opposite signals for others because stocks with prices jumping above the higher band is also considered as being overbought and reverse is expected. When investigating the second signal (closing price cross above upper band XOR RSI>75) for taking long position of this strategy, we surprisingly find that dilemma is addressed wisely. As we know, RSI is another technical indicator tracking momentum of the target. When RSI is put into consideration with Bollinger Band in the manner of the strategy, they are able to confirm each other and a clearer picture is presented to us. Precisely, the strategy tells us whenever closing price jumps above the higher band of Bollinger with a corresponding value of RSI below 75, it should be considered as a breaking. However, when RSI rises above 75 at the same time, overbought market is more likely presenting instead and therefore, a buying signal is not appropriate in this situation.

With one-way trading cost of 20bps, by using strategy 1 in the training period, we are able to end up with a holding period return (HPR) of 216%, which exceeds the return of indexing by 97% after cost. Most importantly, in the testing period of 5 years, which is totally out-of-sample, we are able to enjoy a HPR of 134% with a Sharpe ratio of 0.94, when passive investing ends up with return of only 6% over 5 years. We pay special attention to the period from June 2015 through September 2015 when CSI 300 Index plummets by near 50% (5380 to 2900) over 3 months. According to the strategy 1, our position spends more than 90% of the time shorting the index during this period, not only avoid suffering from this crisis but also making some profits from it. Figure 18 and Figure 19 are the comparisons between strategy 1 and buy-and-hold strategy in the form of cumulative returns in training and testing periods respectively.

[Please insert Figure 18 here]

[Please insert Figure 19 here]

In order to show that GA is able to enhance portfolio performance by discovering underlying effective application of technical indicators, we conduct a statistical test on the indicators GA leverages on. Similar to previous experiment we have verifying the effectiveness of technical indicators, here we utilize approximately the same design.

Namely, we run a regression of daily return of CSI 300 Index on an exhaustive and mutually exclusive set of factors standing for possible scenarios of technical indicators over both the training period (2005.01 - 2008.04) and evaluation period (2008.05 - 2009.12).

$$\begin{gathered} R_i = \beta_1 RSI_1 + \beta_2 RSI_2 + \beta_3 RSI_3 + \beta_4(1 - RSI_1 - RSI_2 - RSI_3) \\ +\beta_5 MACD_1 + \beta_6 MACD_2 + \beta_7 MACD_3 + \beta_8(1 - MACD_1 - MACD_2 - MACD_3) \\ +\beta_9 Bollinger_1 + \beta_{10} Bollinger_2 + \beta_{11} Bollinger_3 + \beta_{12}(1 - Bollinger_1 - Bollinger_2 - Bollinger_3) \end{gathered} \tag{14}$$

Where R_i is the daily continuously compounding return of CSI 300 Index. RSI_i, $MACD_i$ and $Bollinger_i$ are regressors standing for scenario of those three indicators. In fact, according to this regression, we have categorized RSI, MACD and Bollinger into 4 scenarios respectively. The Table 4 contains detailed information of the categorization and t-stats for each of the regressors in regression above.

[Please insert Table 4 here]

Based on the regression, we are able to find indicator scenarios that are significantly associated with positive and negative index returns and open the black box where GA generate strategies for us. One of signals for long position in strategy one exactly matches the scenario of MACD that accurately predicts upward market. The same situation can be found for one of the signals for taking short positions as well.

Overall, the 10 experiments we perform on timing CSI 300 Index provide us with 10 different strategies enjoying superior performances compared to indexing. Thus we have successfully demonstrated that pure indexing can benefit from GA-based technical trading rules with regard to timing the market and changing exposures to the market correspondingly. In next section, we will present the performance of the active portfolio with stock selection and the difference when market timing from GA-based technical trading rule is added in.

4.5 Stock selection with market timing

In addition to pure indexing, here we prove that actively managed portfolios can also benefit from GA. In terms of the actively managed portfolio involving stock selection, we take advantage of Fama-MacBeth regression (Fama and MacBeth, 1973) in making stock return forecasts on a daily basis. Details of Fama-MacBeth regression can be found in previous chapter and in this experiment we also use the three technical indicators (RSI, MACD and Bollinger Band) to explain realized returns. Within the regressions, the dependent variable is the daily realized return of 300 component stocks, which is calculated as the log-difference of daily closing prices. On the other side of regressions, there are 12 regressors, which exhaustively reflect each possible condition of each technical indicator we considered. For example, among the 12 regressors explaining the realized return of one stock, only 3 regressors will take the value “1” while other regressors are valued “0”. With a rolling-window of 75 days, this approach continuingly informs us, based on recent market movements, the indicator status significantly associated with positive and negative returns and essentially, the best way we utilize those three technical indicators in making predictions. We then construct and adjust this portfolio according to the ranking of stocks by predictions. In the experiment, we construct two portfolios through this method. The first one is made up of long positions in the top 5% component stocks while the second one consists of short positions in the bottom 5% component stocks from the ranking on a daily basis. The following Figure is the cumulated log-return of these two portfolios over 5 years.

The short-position portfolio enjoys a HPR of 150% with a Sharpe ratio of 1.96 while the long-position portfolio ends up with a HPR of 135% with a Sharpe ratio of 1.7. Those two actively managed portfolios beat the passive indexing. Figure 20 displays the performances of both the long-position portfolio and the short-position portfolio in terms of cumulative returns.

[Please insert Figure 20 here]

Since we have verified GA’s market-timing ability before, here we also test if the GA still work well within actively managed portfolio. Because we are testing the performances of different strategies on the same period of time, we transfer the previous GA-generated long-short signals to actively managed portfolios. Specifically, long signal generated by the GA represent an upward trend of market while the short signal conveys the opposite meaning. Therefore, it is reasonable to assume long positions portfolio will beat the short one in upward trends and this relationship will reverse when market plummets. Thus, when we bring the GA in to the portfolio construction, the outcome can be even better off by taking the long positions when GA-generated positive signal is triggered and taking short positions when the negative one shows up. The Figure 21 will give us a big picture of GA's judgment on the market movements, we use "100" to represent long signals and "-100" to stand for short signals.

[Please insert Figure 21 here]

So the refined actively managed portfolio is constructed in this way: when the long signals or empty signals are released, our refined portfolio takes the top 5% component stocks as its holding, which is same as the long position portfolio. When short signals show up, our refined portfolio will experience same daily returns as those for short position portfolio. The refined portfolio sees a growth of 261% with a Sharpe ratio of 2.54, which is apparently, better than both the long-position portfolio and the short-position portfolio defined before. The following is a summary of the three portfolios in comparison and the Figure of cumulative returns for each of them.

Portfolio 1: Long positions of top 5% CSI 300 Index component stocks after ranking.
Portfolio 2: Short positions of bottom 5% CSI 300 Index component stocks after ranking.
Portfolio 3: Switch between Portfolio 1 and Portfolio 2 based on market timing of GA strategy.

In fact, we provide the Figure 22 to show the comparison among these 3 portfolios and Table 5 containing details of each portfolio we considered in this comparison to prove that GA is able to add value to not only pure indexing, but also actively managed portfolios from the perspectives of both higher return and lower risk.

[Please insert Figure 22 here]
[Please insert Table 5 here]

Overall, according to our experiments measuring the benefit GA brings to portfolios, the results show that originally passively managed portfolio (pure indexing) is able to end up with a return of at least 106% with a Sharpe ratio close to 1 over the period from 2010.01 through 2015.12. In the same period of time, buy-and-hold strategy achieves a return of 6.12% with a Sharpe ratio of 0.0024. With regard to the kind of actively managed portfolio with returns attributed to stock selection, originally it is able to achieve returns of 135% and 150% by taking long and short positions respectively from

2010.06 to 2015.12. However, a significantly higher return of 261% is achievable during the same period of time when GA is applied in the investing process. Also, there is a promoted Sharpe ratio associated with the actively managed portfolio for the sake of market-timing ability provided by GA-based technical trading rules.

4.6 GA with regime switching

So far, we have conducted several experiments to show GA is able to filter strategies and to narrow those to superior ones still performing well in out-of-sample periods as long as some mechanism is in place to alleviate data over-fitting problem Next, in this section we are going to verify and illustrate that, GA can adjust to and incorporate regime switching into its working environment. Namely, comparison between investing results from trading strategies generated from GA only and those from GA and regime-switching together are presented to justify our assumption that even better performances can be fulfilled when regime-switching is put into consideration of GA.

In the new experiments to generate technical trading rules from GA with regime switching taken into consideration, we are going to provide GA with discretion in identifying market regimes with regard to volatility. In this thesis, we only consider the situation where GA segregates the market into two regimes and generate trading strategies for each of them correspondingly. The only difference between our new experiments and previous ones is that, instead of only one, now two pairs of long-short signals are generated with a threshold point to separate regimes. Therefore, in applying technical trading rules generated from GA, we should first judge the market regime we are currently in.

The Figure 23 shows the forecasted volatility based on GARCH model in the out-of-sample period and the corresponding threshold point GA select from one experiment to differentiate the market regimes. Figure 24 illustrates the percentages of each regime in the form of a pie chart.

[Please insert Figure 23 here]

[Please insert Figure 24 here]

Based on this categorization, with a threshold volatility of 0.0253, regime 1 accounts for 95% of the entire period from 2010 through 2015. Regime 2 is defined as the periods with a relatively high volatility (when daily volatility is higher than 0.0253). In other

word, in this experiment, we end up with two strategies after all the evolution and apply one of them in 95% of the time, with the other one used during the rest 5% period.
With the market regimes taken into consideration, we can easily find that, in the periods defined as regime with high volatility, strategy 2 markedly beats strategy 1 and our final strategy has taken advantage of the outperformance of strategy 2 over that period. Specifically, strategy considering regime switching achieves a holding period return of 168% with a Sharpe ratio of 1.17. As a comparison, regime 1 strategy which is the best in two strategies filtered by GA, underperforms by 57% in HPR with a Sharpe ratio of 0.77. It is noticeable that neither of the 2 strategies specific to regimes is able to beat strategies we attain in previous experiments when regime switching is not considered in its framework. However, the final regime-switching strategy based on two strategies specific to regimes achieve better performance instead. Figure 25 reviews the plots of the trading rules specific to each regime and the final strategy as well in the form of cumulative returns in the out-of-sample.

[Please insert Figure 25 here]

The rationale behind this phenomenon is that, on the one hand, when regime switching is not taken into consideration, the entire time window in test is used to filter trading strategies, regardless of the market regimes. Thus optimal strategy gained by this way has already gauged its performance in each period of time and achieved a balance between different market regimes. In other word, strategies that deliver significantly contrary performances will not achieve superior ranking from fitness function that measure both return and risk. On the other hand, when regimes are clearly defined to generate corresponding suitable strategies, each strategy generated is aiming at achieving the best performance in certain regime instead of the whole time window. Therefore, when these strategies are applied all the time, chances are that they perform well in regime where they are generated and lose in other regimes.

To verify our conclusion, another 9 experiments are conducted with regime switching in consideration and the Table 6 contains outcomes of these 9 experiments. All the results are based on the period of time from 2010.01 through 2015.12 and identical test design.

[Please insert Table 6 here]

Overall, according to the experiment results, regime switching being part of the evolution of GA enables us to consistently acquire better results than any single strategy applied all the time. The reason why this is the case is because regime switching is practical and indeed take place in equity market, thus reasonable investors should not stick with one single trading rule across every period of time. Instead, there are optimal investment strategies for each market regime and when market is clearly segregated into regimes and generate strategies based upon, we are able to end up with better results.

5. Conclusion and Implication

In this thesis, we verify the effectiveness of the Genetic Algorithm (GA) in discovering profitable trading rules by providing an out-of-sample test in Chinese stock market. The framework of our testes follows the Allen and Karjalainen (1999) approach. However, while the trading rules in the work of Allen and Karjalainen (1999) are based on closing prices, moving averages and local extrema of closing prices, we utilize three refined technical indicators (RSI, MACD and Bollinger Band) to construct the filter rules in our tests. In fact, the appearance of the filter rules to be refined by the GA in this thesis is similar to that in the work of Dempster and Jones (2001).

The results show that, based on data of daily closing prices of CSI 300 index and its component stocks, technical trading rules generated from the GA can consistently deliver outperformances over the buy-and-hold strategy by providing an additional return resource in the form of timing the market. This finding clearly stands for our answer to the question whether GA-based technical trading rules are able to consistently beat buy-and-hold in daily trading. Besides, we find that the market timing ability of GA-based technical trading rules is portable to benefit active equity portfolios based on stock selection as well. Meanwhile, by conducting statistical tests, we open the black box of GA and verify the effectiveness of technical trading rules selected by GA.

Furthermore, we introduce regime switching into the framework of the GA and come up with one regime-switching genetic algorithm (RSGA). The trading strategies from the RSGA model consistently achieve even better results than those from the GA model. Since most previous studies in this field stick with taking advantage of the GA to, in each test, discover and apply one single trading strategy and reach the conclusion based on gained strategy performance. This modification makes a methodological progress on leveraging the GA to generate trading strategies.

Overall, the GA is a powerful tool when it comes to investment problems because it enables us to efficiently investigate the solution space and reveal satisfying strategies in a quick manner. As a result, market participants can benefit from this tool from various kinds of perspectives. First, by changing the objective of fitness function, strategies meeting different investing preferences or requirements will be acquired. Second, in addition to equity investments, trading of fixed income instruments, foreign exchange and other financial assets can also promote its performance from GA.

However, as a machine learning method, the GA suffers from data over-fitting problem, even though some alleviation mechanism is in place already. Thus future studies on this topic should pay special attention to further refinements on the design of experiments to address this problem. Besides, among previous studies, experiment designs are different from various aspects but there is no conclusion on whether the design of tests is directly associated with the outcomes. Also, there is no comments on the optimal design of tests on using the GA to discover profitable trading rules. Thus, subsequent studies can also be aimed to answer this question.

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Appendix A – RSI, MACD and Bollinger Band

RSI

Relative Strength Index (RSI) is one kind of momentum indicators developed by J. Welles Wilder. This technical indicator is used to measure the changes of price movements. RSI ranges from 0 to 100 and the formula to calculate RSI is as follows.

$$\mathrm{RSI} = 100 - \frac{100}{1 + RS}$$

$$\mathrm{RS} = \frac{\text{Average gain}}{\text{Average loss}}$$

When working out RSI, the duration which are the periods of time all the calculations are based on should be defined first. Take a duration of 14 days for example, the first average gain and average loss are calculated as following.

First average gain = Sum of the gains over past 14 days / 14
First average loss = Sum of the losses over past 14 days / 14

The second, and subsequent calculations are based on the prior averages and the current gain and loss:

Average Gain = [(previous Average Gain) x 13 + current Gain] / 14
Average Loss = [(previous Average Loss) x 13 + current Loss] / 14

Conventionally, market is considered overbought when RSI rises above 70 and oversold when RSI drops below 30. Signals can also be generated by looking for divergences, failure swings and centerline crossovers.

MACD

The Moving Average Convergence/Divergence oscillator (MACD) is another momentum indicator that turns two moving averages into an indicator. The values of MACD can be both positive and negative because it is calculated by subtracting the moving average with longer duration from the shorter one. For example, two moving averages with duration of 12 and 24 respectively are used to make the MACD line.

MACD line = 12-day exponential moving average – 24-day exponential moving average

Besides, there is a signal line that is a moving average of the MACD Line itself and the MACD histogram is the difference between MACD Line and Signal Line. Take a duration of 9 days for instance.

Signal Line = 9-day exponential moving average of MACD Line

MACD Histogram = MACD Line – Signal Line

Positive MACD indicates that the shorter EMA is above the longer EMA. Positive values increase as the shorter EMA diverges further from the longer EMA and the upside momentum is increasing. Negative MACD values indicated that the shorter EMA is below Longer EMA. Negative values increase as the shorter EMA diverges further below the longer EMA and the downside momentum is increasing.

Besides, traders also look for signal line crossovers, centerline crossovers and divergences to generate signals.

Bollinger Band

Bollinger bands are constructed based on moving averages and standard deviations of prices. The upper band is constructed by adding certain standard deviation to the middle band while the lower band is constructed by subtracting certain standard deviation from the middle band. The middle band is the moving averages. Therefore, the appearance of Bollinger bands varies according to the standard deviations.

Suppose the Bollinger Band is constructed based on a duration of 20 days and 2 standard deviations.

Middle Band = 20-day simple moving average

Higher Band = 20-day simple moving average + 2 * 20-day standard deviation

Lower Band = 20-day simple moving average - 2 * 20-day standard deviation

According to Bollinger, the bands should contain 88-89% of price action, which makes a move outside the bands significant. Thus, the higher band and lower band are often considered as important supporting or resisting levels.

Appendix B – Figures

Figure 1: Cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10.

Figure 1 presents, by Excel software, the plot of cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator RSI on a daily basis.

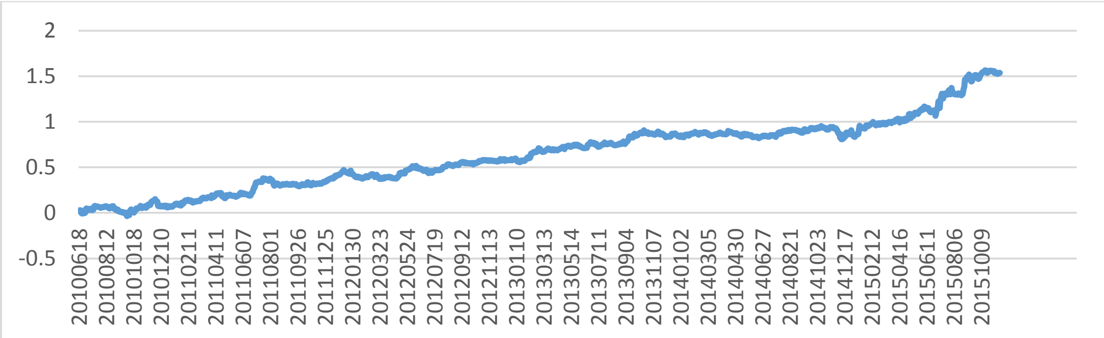


Figure 2: Cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator MACD.

Figure 2 presents, by Excel software, the plot of cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator MACD on a daily basis.

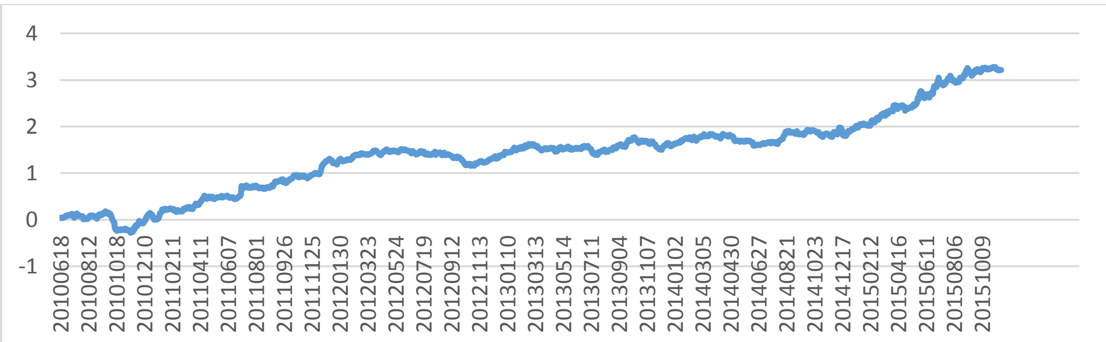


Figure 3: Cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator Bollinger Band.

Figure 3 presents, by Excel software, the plot of cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator Bollinger Band on a daily basis.

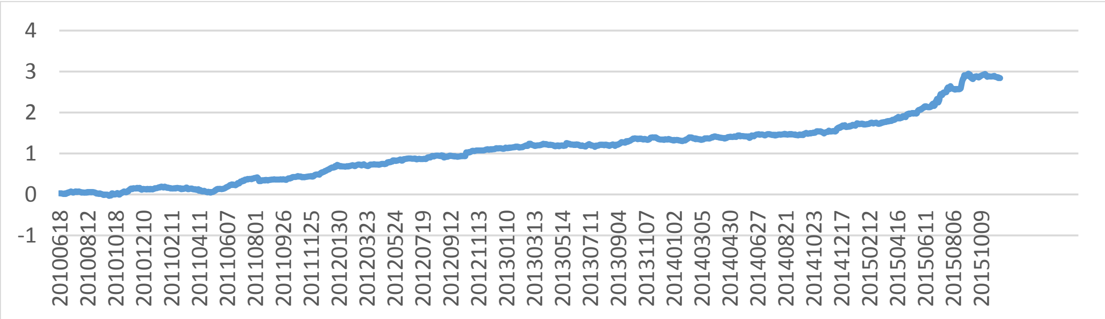


Figure 4: Cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator RSI MACD and Bollinger Band together.

Figure 4 presents, by Excel software, the plot of cumulative returns of the hedged portfolio constructed by taking long positions of the top 10% CSI 300 index component stocks and short positions of the bottom 10% CSI 300 index component stocks over the period from 2010.06 to 2015.10. Stocks are ranked and selected by Fama-MacBeth regressions with the technical indicator RSI, MACD and Bollinger Band on a daily basis.

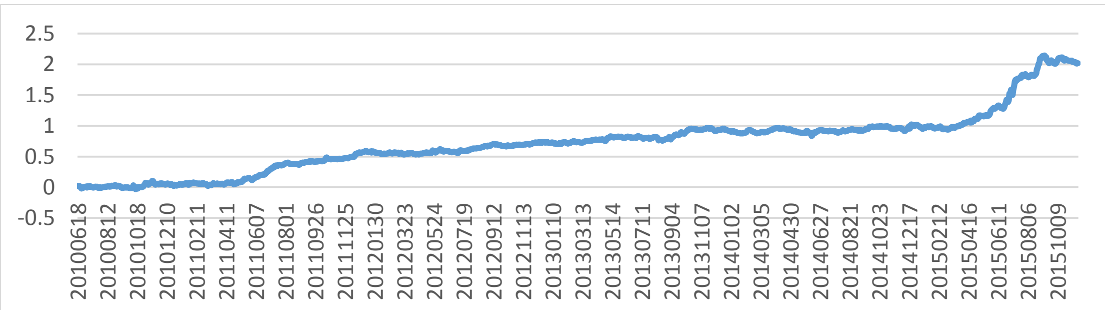


Figure 5: CSI 300 index from 2005.04 to 2015.11

Figure 5 is the original plot of the CSI 300 index from 2005.04 to 2015.11 from Excel software.

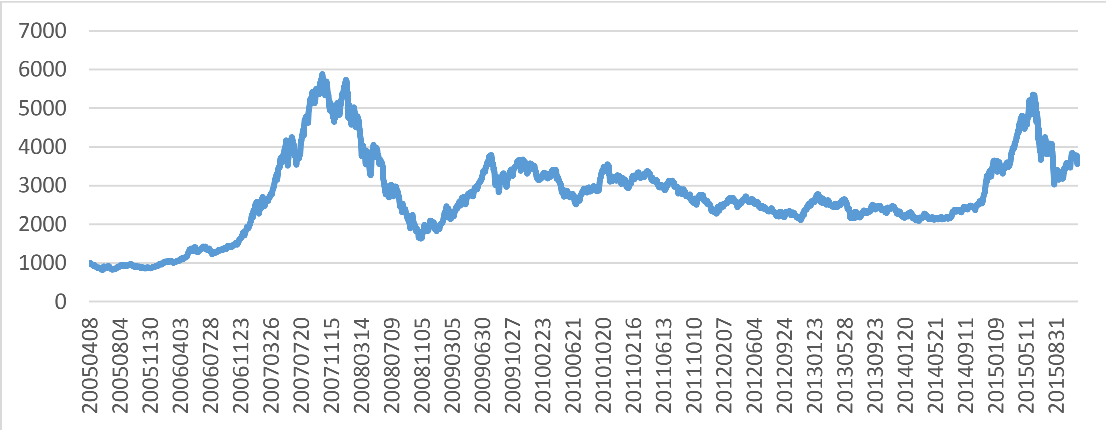


Figure 6: Cumulative continuously compounding returns of buy-and-hold strategy of CSI 300 index from 2005.04 to 2015.11.

Figure 6 displays the cumulative continuously compounding returns of buy-and-hold strategy of CSI 300 index from 2005.04 to 2015.11. This strategy assumes taking long position of the CSI 300 index from 2005.04 all the way up to 2015.11 without any change in between. The cumulative continuously compounding returns are calculated as the sum of the daily continuously compounding returns, which are the log-differences of the closing prices in two consecutive days.

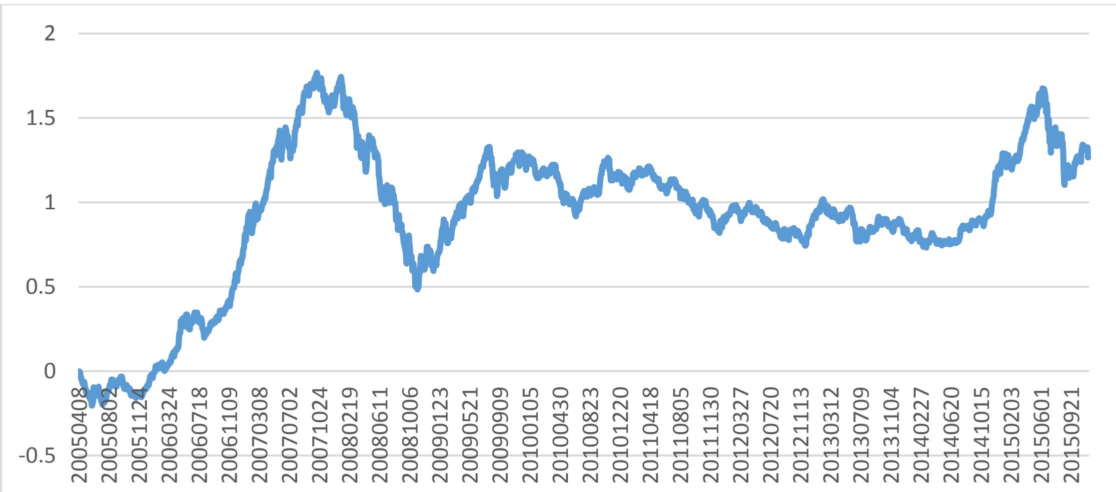


Figure 7: In-sample performances of 10 GA-based technical trading rules in terms of excess returns over buy-and-hold and the number of transactions for each strategy over the period from 2005.04 to 2010.10.

Figure 7 is the in-sample performances of 10 GA-based technical trading rules on CSI 300 index over the period from 2005.04 to 2010.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented.

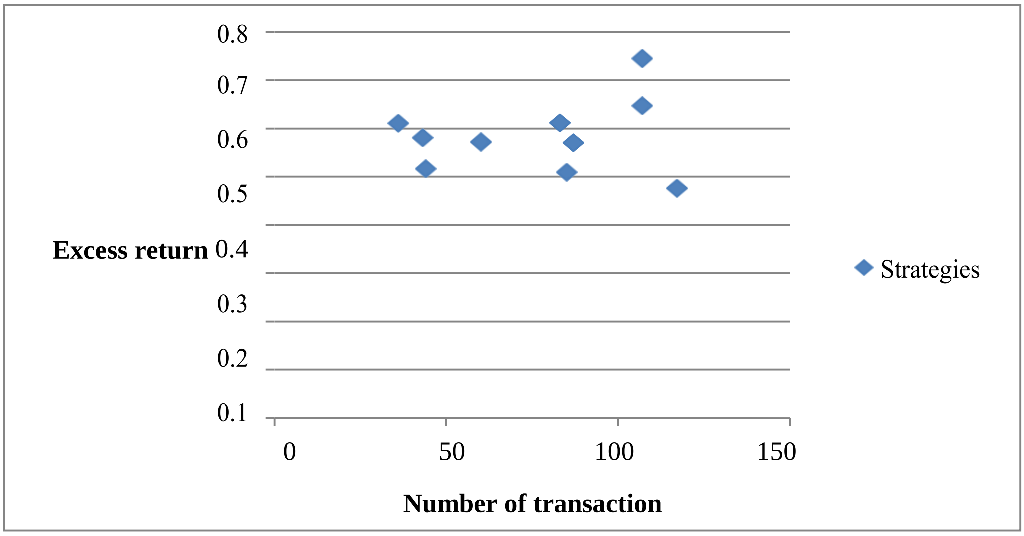


Figure 8: Out-of-sample performances of 10 GA-based technical trading rules in terms of excess returns over buy-and-hold and the number of transactions for each strategy over the period from 2010.11 to 2015.10.

Figure 8 is the out-of-sample performances of 10 GA-based technical trading rules on CSI 300 index over the period from 2010.11 to 2015.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented.

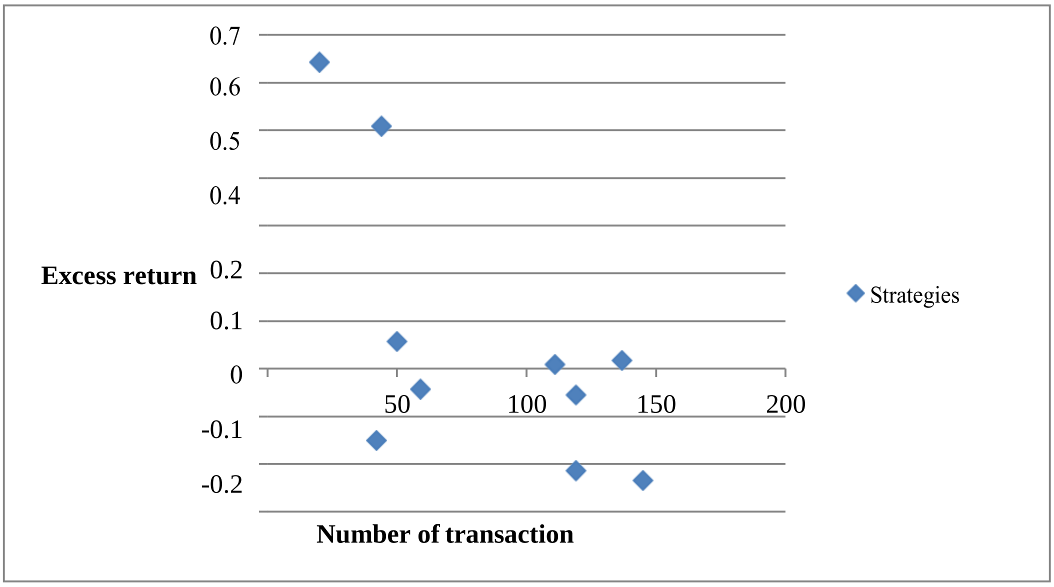


Figure 9: Comparison between one GA-based strategy and buy-and-hold strategy in terms of cumulative returns in the out-of-sample period from 2010.11 to 2015.10.

Figure 9 present the performances of one GA-based strategy and the buy-and-hold strategy on CSI 300 index from 2010.11 to 2015.10. Performances of strategies are presented in the form of cumulative returns.

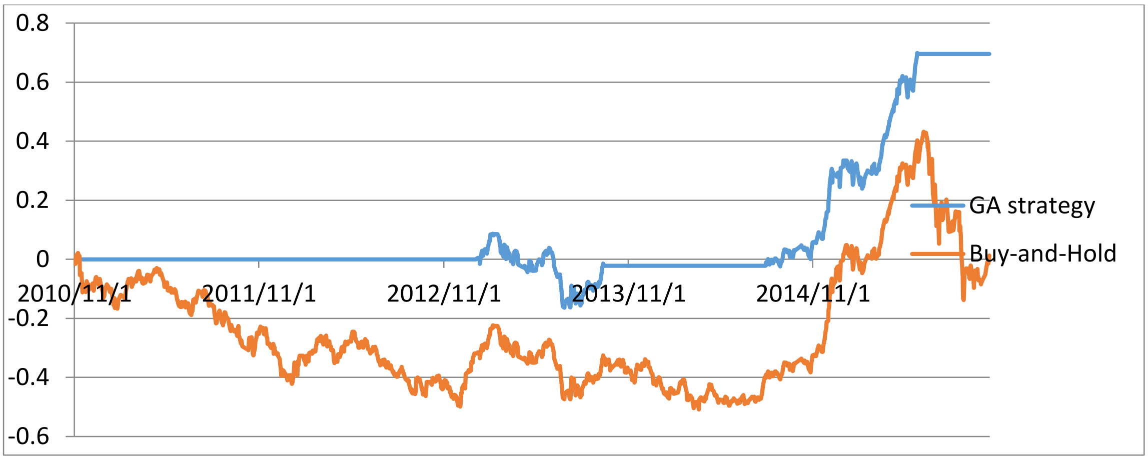


Figure 10: Training period performances of 10 GA-based technical trading rules with data over-fitting alleviation system in place in terms of excess returns over buy-and-hold and the number of transactions for each strategy over the period from 2005.04 to 2010.10.

Figure 10 is the in-sample performances of 10 GA-based technical trading rules on CSI 300 index over the period from 2005.04 to 2010.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented. These 10 strategies are gained with the data over-fitting alleviation system in place.

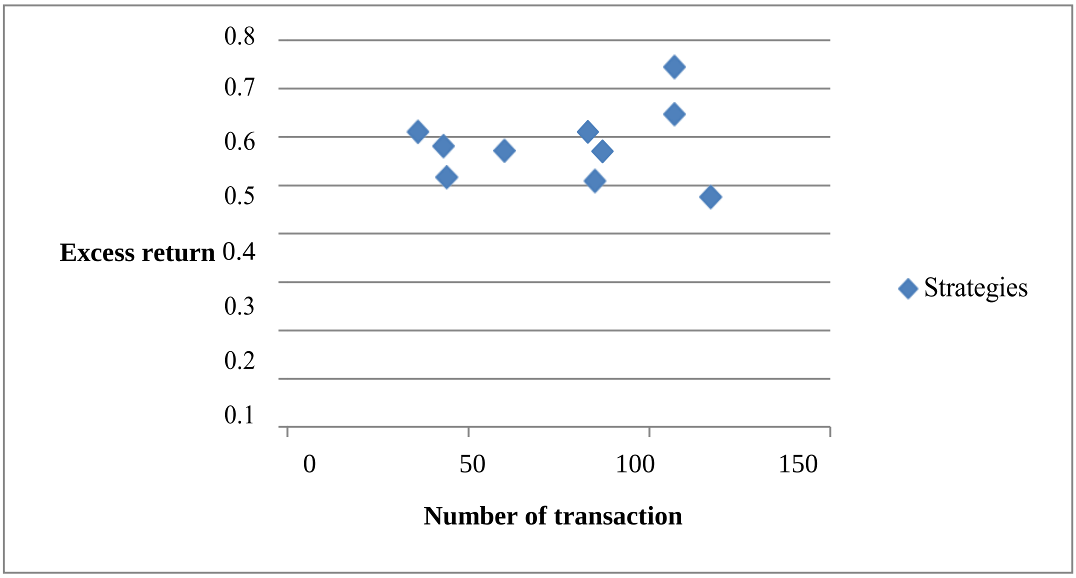


Figure 11: Evaluation period performances of 10 GA-based technical trading rules with data over-fitting alleviation system in place in terms of excess returns over buy-and-hold and the number of transactions for each strategy over the period from 2010.11 to 2014.10.

Figure 11 is the evaluation-period performances of 10 GA-based technical trading rules on CSI 300 index over the period from 2010.11 to 2014.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented. These 10 strategies are gained with the data over-fitting alleviation system in place.

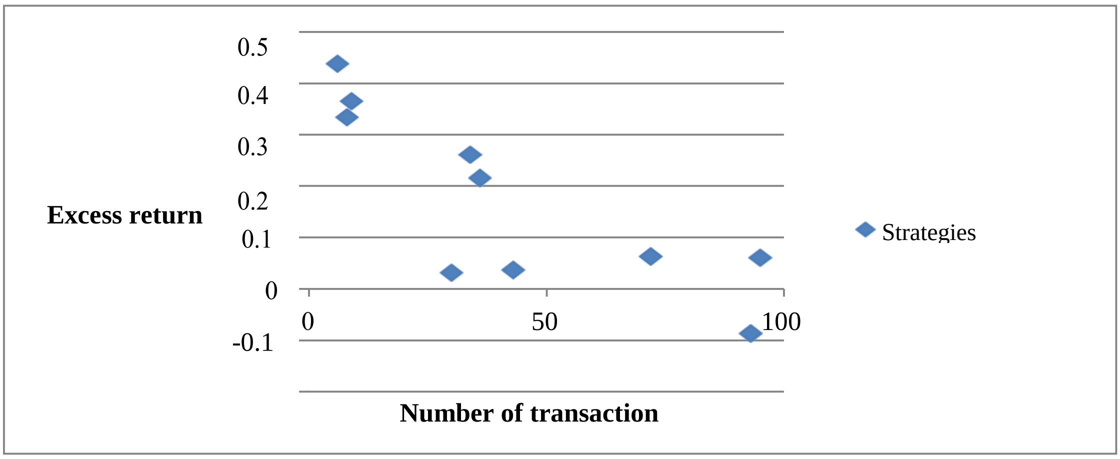


Figure 12: Testing period performances of 10 GA-based technical trading rules with data over-fitting alleviation system in place in terms of excess returns over buy-and-hold and the number of transactions for each strategy over the period from 2014.11 to 2015.10.

Figure 12 is the testing-period performances of 10 GA-based technical trading rules on CSI 300 index over the period from 2014.11 to 2015.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented. These 10 strategies are gained with the data over-fitting alleviation system in place.

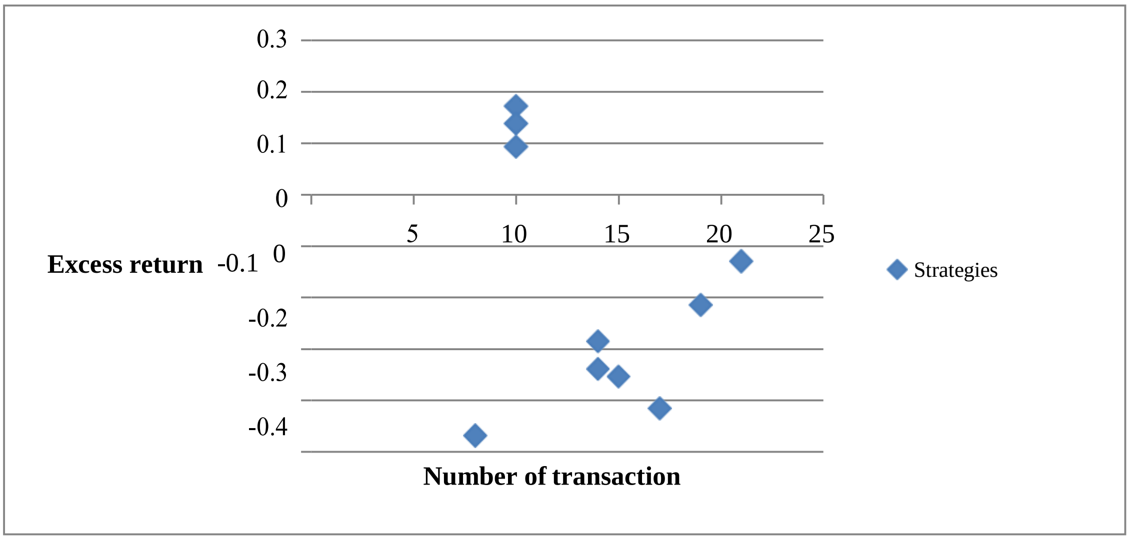


Figure 13: Comparison between the cumulative returns of the top three GA-based technical trading strategies and buy-and-hold over testing period from 2014.11 to 2015.10.

Figure 13 presents the performances, in the form of cumulative returns, of the top 3 technical trading strategies from the Figure 12 and the buy-and-hold strategy on CSI 300 index from 2014.11 to 2015.10.

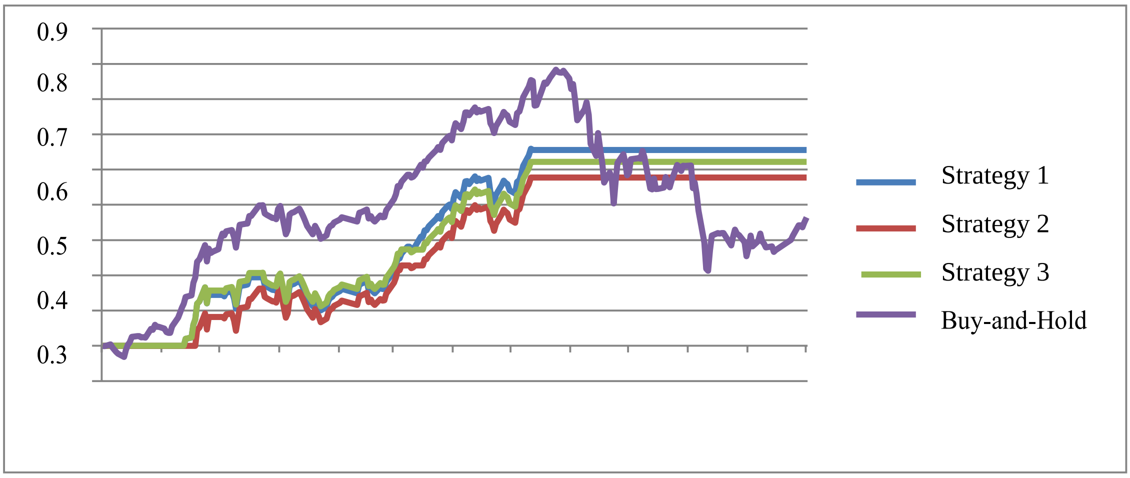


Figure 14: scatter plot of the performances of these 18 GA-based technical trading strategies in terms of excess return over buy-and-hold and adjusted Sterling ratio in the training period from 2005.04 to 2010.10

Figure 14 is the in-sample performances of 18 GA-based technical trading rules on CSI 300 index over the period from 2005.04 to 2010.10. For each strategy, the excess return over the buy-and-hold strategy and the number of transaction are presented. These 18 strategies are gained with the Sterling Ratio as the fitness function of the GA evolution process.

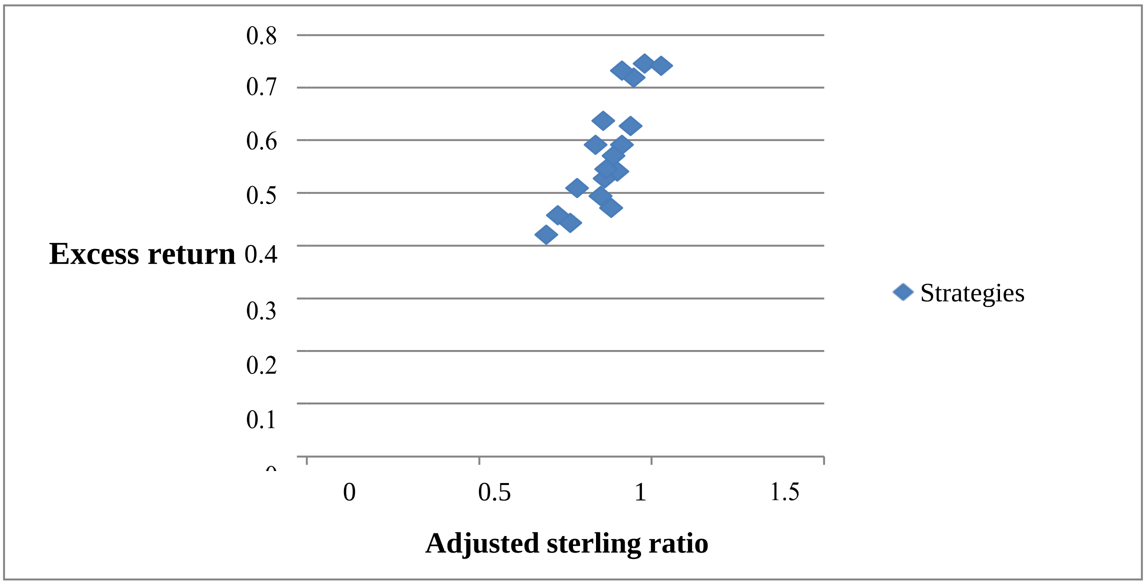


Figure 15: The comparison between the cumulative returns of buy-and-hold and best trading strategies from evaluation period in testing period (2014.10-2015.10)

Figure 15 presents the performances, in the form of cumulative returns, of the top technical trading strategy from the Figure 14 and the buy-and-hold strategy on CSI 300 index from 2014.11 to 2015.10.

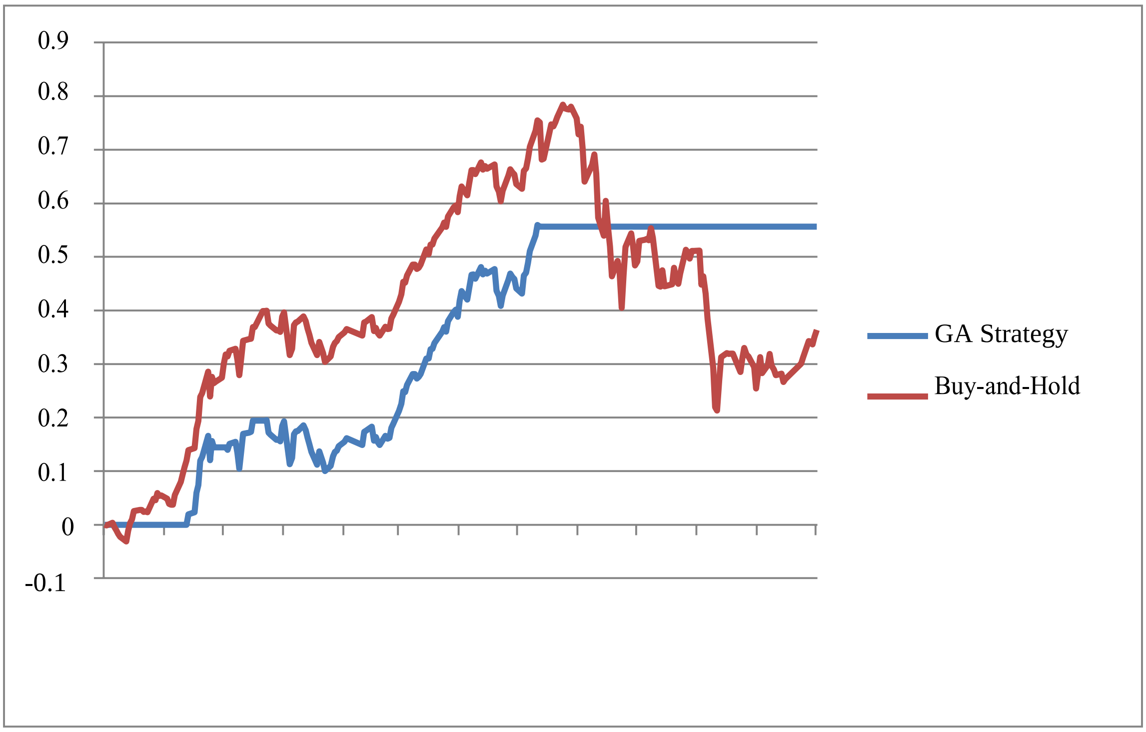


Figure 16: CSI 300 index from 2010.01 to 2015.12

Figure 16 is the original plot of the CSI 300 index from 2010.01 to 2015.12 from Excel software.

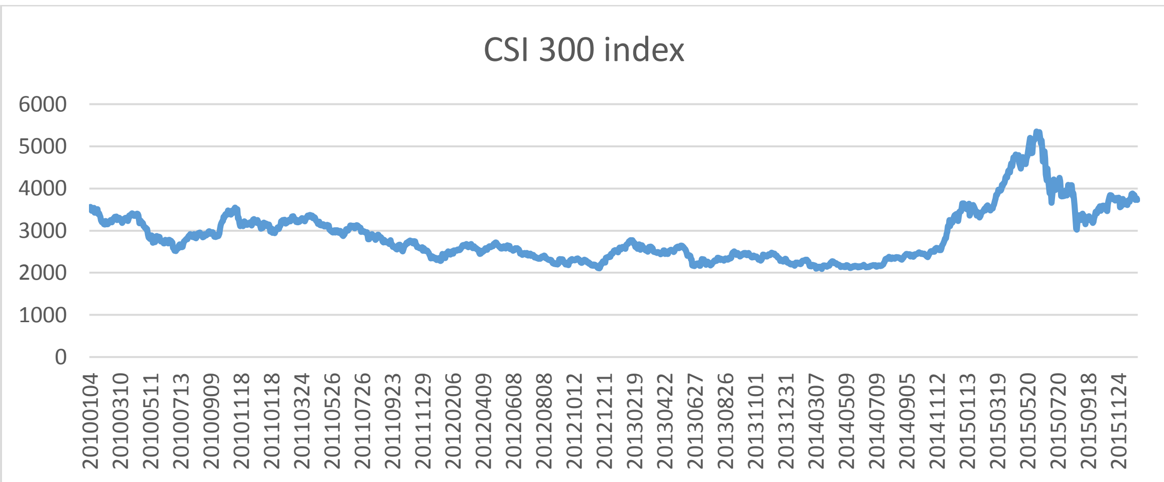


Figure 17: Cumulative return of buy-and-hold strategy on CSI 300 index from 2010.01 to 2015.12

Figure 17 displays the cumulative continuously compounding returns of buy-and-hold strategy of CSI 300 index from 2010.01 to 2015.12. This strategy assumes taking long position of the CSI 300 index from 2010.01 all the way up to 2015.12 without any change in between. The cumulative continuously compounding returns are calculated as the sum of the daily continuously compounding returns, which are the log-differences of the closing prices in two consecutive days.

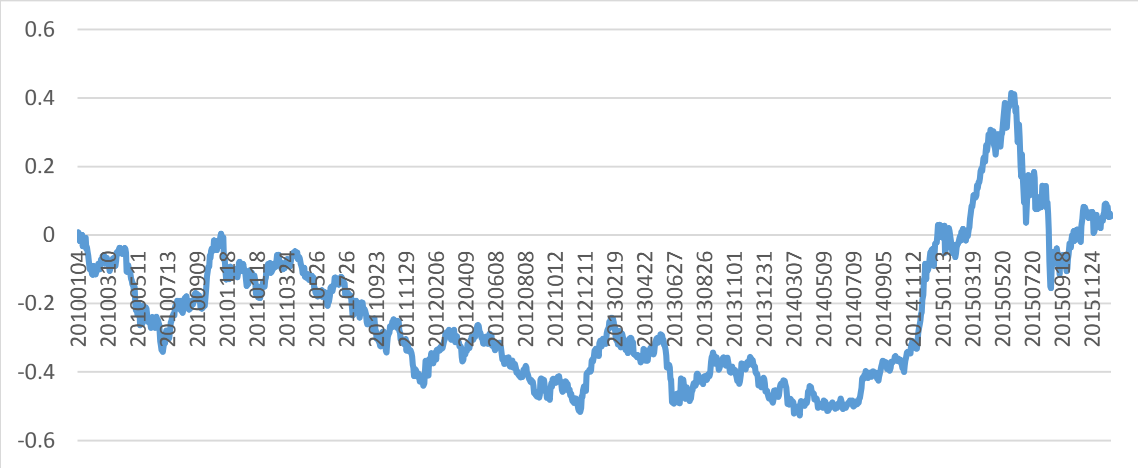


Figure 18: Comparisons between strategy 1 and buy-and-hold strategy in the form of cumulative returns in training period from 2005.01 to 2008.04.

Figure 18 presents the training-period performances, in the form of cumulative returns, of the trading strategy 1 and the buy-and-hold strategy on CSI 300 index from 2005.01 to 2008.04. Strategy 1 releases buy-signals when the condition "DIFF>DEA & difference between DIFF and DEA increasing (MACD) OR Closing price cross above upper band (Bollinger) XOR RSI>75 (RSI)" is met. Strategy 1 releases sell-signals when the condition "Closing price cross below lower band (Bollinger Band) OR 25<=RSI<50 (RSI)" is met. The signals maintain their status until the opposite signal is released.

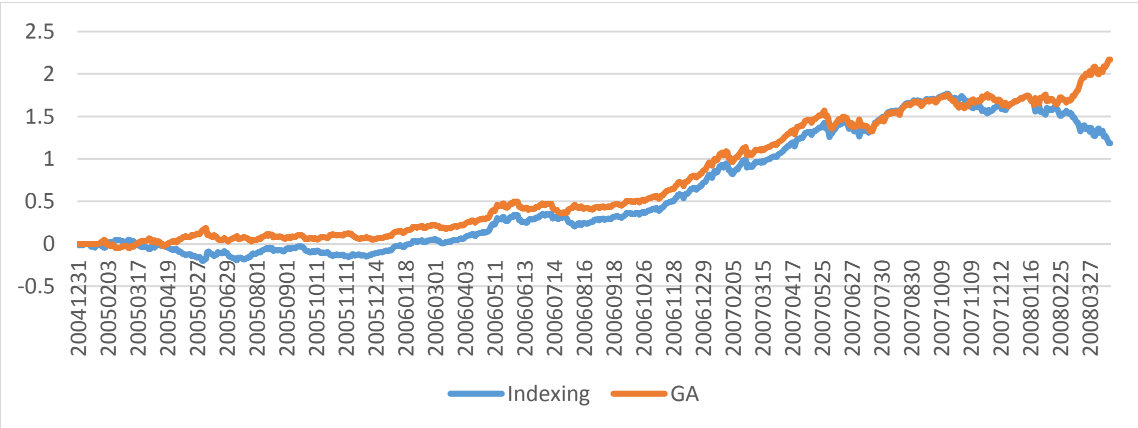


Figure 19: comparisons between strategy 1 and buy-and-hold strategy in the form of cumulative returns in testing period from 2010.01 to 2015.12.

Figure 19 presents the testing-period performances, in the form of cumulative returns, of the trading strategy 1 and the buy-and-hold strategy on CSI 300 index from 2010.01 to 2015.12. Strategy 1 releases buy-signals when the condition "DIFF>DEA & difference between DIFF and DEA increasing (MACD) OR Closing price cross above upper band (Bollinger) XOR RSI>75 (RSI)" is met. Strategy 1 releases sell-signals when the condition "Closing price cross below lower band (Bollinger Band) OR 25<=RSI<50 (RSI)" is met. The signals maintain their status until the opposite signal is released.

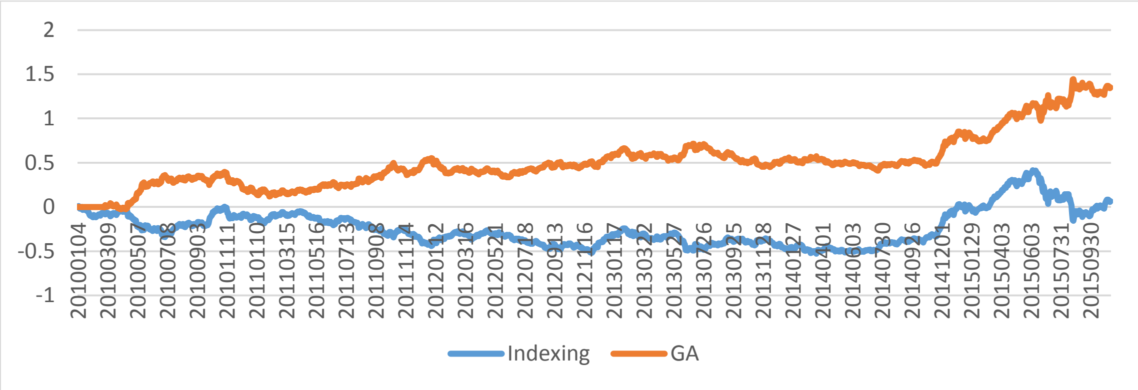


Figure 20: Cumulative returns of the long-position portfolio constructed by taking long positions of the top 5% component stocks in CSI 300 index and the short-position portfolio constructed by taking short positions of the bottom 5% component stocks in CSI 300 index during the period from 2010.01 to 2015.06.

Figure 20 presents the performances, in the form of cumulative returns, of two actively managed portfolio from 2010.01 to 2015.06. One is constructed by taking long positions of the top 5% component stocks in CSI 300 index while the other one is constructed by taking short positions of the bottom 5% component stocks in CSI 300 index. Component stocks of CSI 300 index are ranked by predicted returns through Fama-MacBeth regressions.

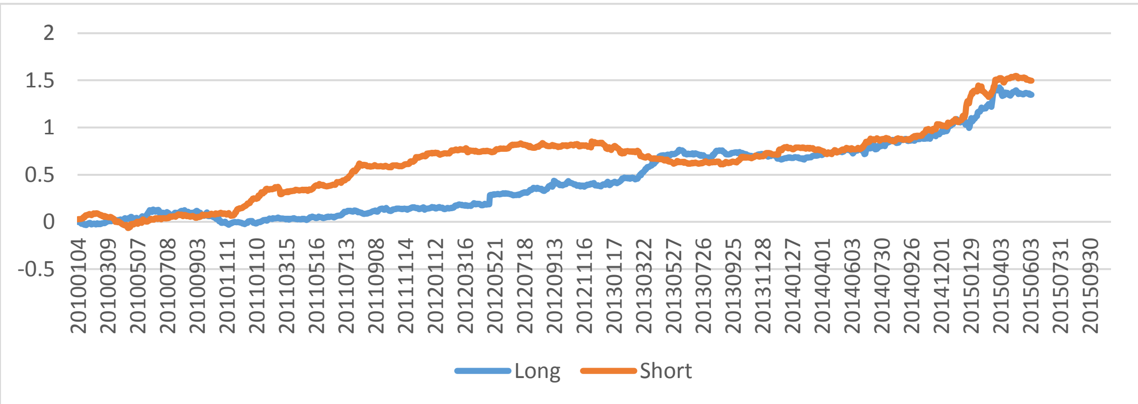


Figure 21: Long-short signals released by one GA-based technical trading strategy with “100” stands for taking long positions and “-100” for taking short positions from 2010.04 to 2015.12.

Figure 21 presents the signals of one GA-based strategy over the period from 2010.04 to 2015.12. Signals are used to guide the position of stock portfolio. While “100” stands for taking long positions of the top 5% component stocks in CSI 300 index, “-100” stands for taking short positions of the bottom 5% component stocks in CSI 300 index. Component stocks of CSI 300 index are ranked by predicted returns through Fama-MacBeth regressions.

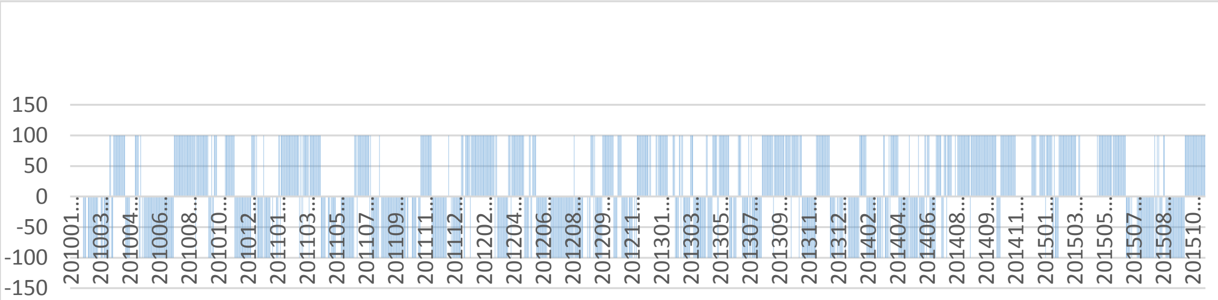


Figure 22: Comparison between the long-position portfolio, short-position portfolio and the combined portfolio according to GA-based technical trading rules from 2010.01 to 2015.11.

Figure 22 presents the performances, in the form of cumulative returns, of three actively managed portfolio from 2010.01 to 2015.06. The first portfolio is constructed by taking long positions of the top 5% component stocks in CSI 300 index while the second portfolio is constructed by taking short positions of the bottom 5% component stocks in CSI 300 index. Component stocks of CSI 300 index are ranked by predicted returns through Fama-MacBeth regressions. The third portfolio switches between the first and the second portfolios according to the long-short signals in Figure 21.

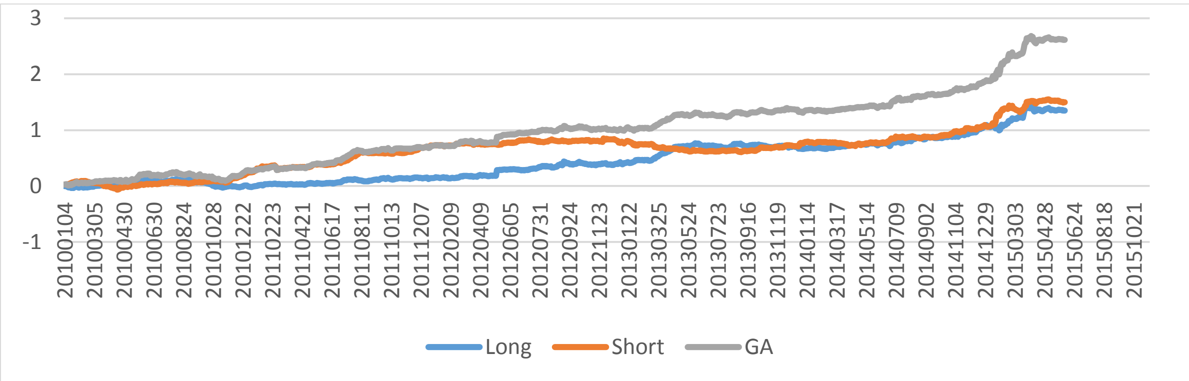


Figure 23: Forecasted volatility of the CSI 300 index based on GARCH model in the out-of-sample period from 2010.01 to 2015.11 and the corresponding threshold point GA select from one experiment to differentiate the market regimes.

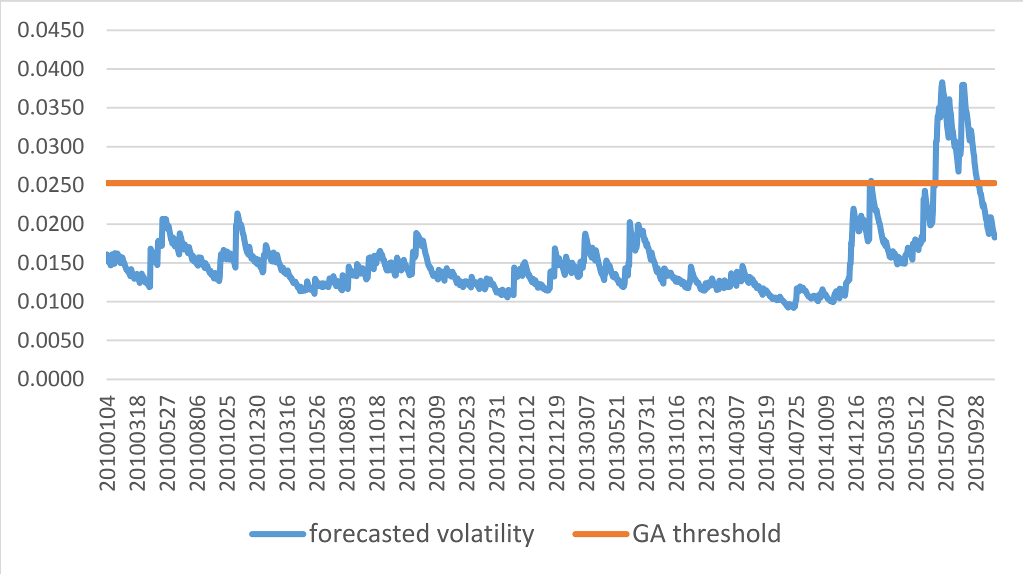


Figure 24: Percentage of each regime from one GA-based technical trading rule with regime switching taken into consideration.

Figure 24 describes the percentage of time, from a pie chart, in regime 1 and regime 2 according to the segregation from one GA-based trading rule in Figure 23.

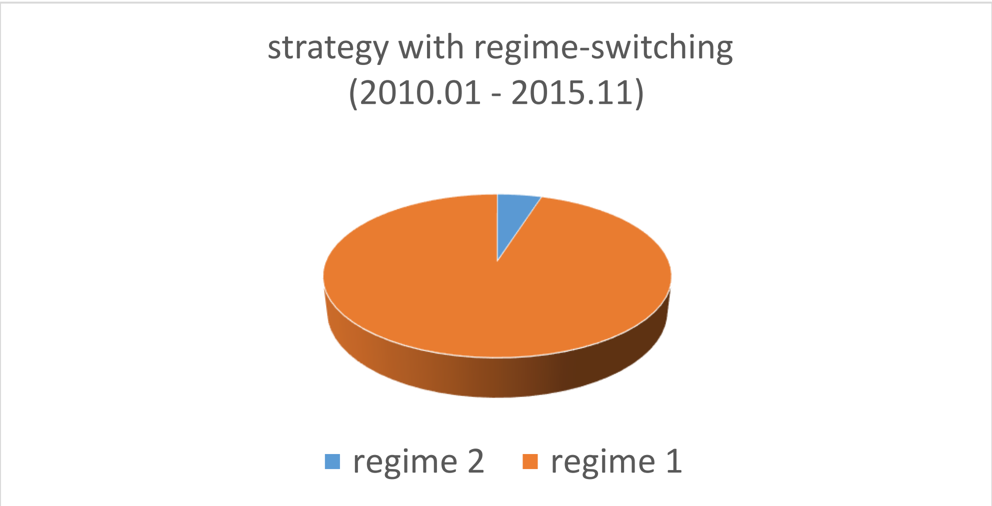
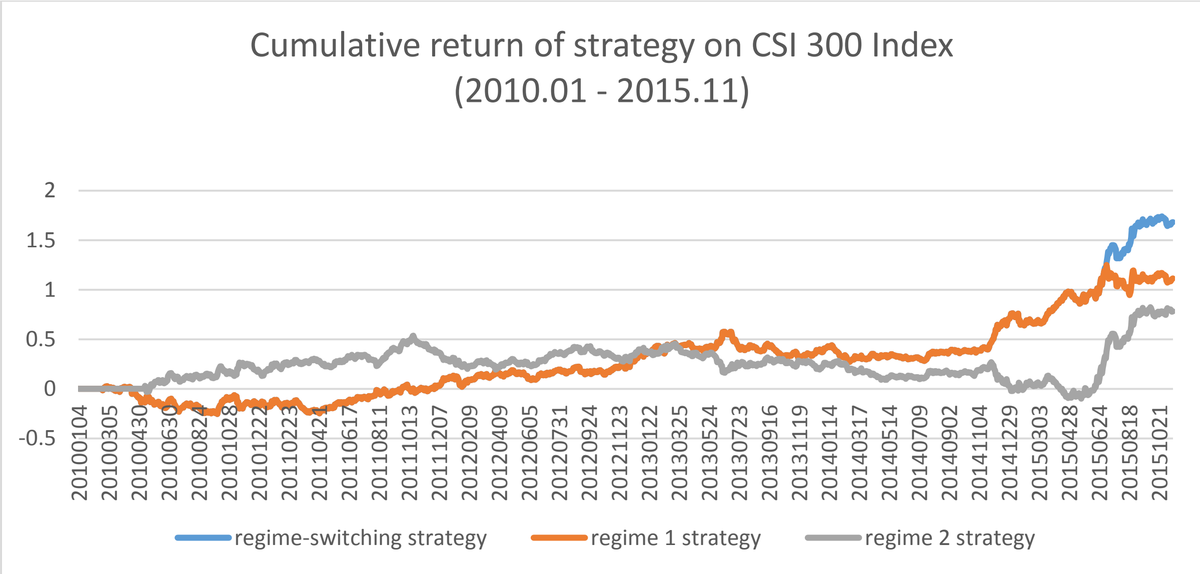


Figure 25: Cumulative returns of technical trading strategies specific to regime 1, regime 2 and the final trading strategy from one experiment.

Figure 25 presents the cumulative returns of 3 trading strategies. The first and the second strategies are generated by the genetic algorithm specifically to regime 1 and regime 2. The regime-switching strategy combines the regime 1- strategy and the regime 2-strategy according to the GARCH volatilities in each period of time and the volatility threshold.



Appendix C -- Tables

Table 1: Detail of Fama-MacBeth regressions on technical indicators RSI, MACD and Bollinger Band to identify statuses significantly associated with positive and negative returns over 120 days from 2013.03 to 2013. 06. Significance at 5% significance level is indicated by *.

Relative Strength Index (RSI)		
Status	**Scenario**	**T-stat**
1	100>=RSI>75	-3.04*
2	75>=RSI>50	-0.84
3	50>=RSI>25	-0.77
4	25>=RSI	2.82*
Moving Average Convergence Divergence (MACD)		
Status	**Scenario**	**T-stat**
1	$MACD\_DIFF_i \geq MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i \geq MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	2.03*
2	$MACD\_DIFF_i \geq MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i < MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	1.36
3	$MACD\_DIFF_i < MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i \geq MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	-1.58
4	$MACD\_DIFF_i < MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i < MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	-2.47*
Bollinger Band		
Status	**Scenario**	**T-stat**
1	closing$_i$ <= lower band$_i$	-2.45*
2	middle band$_i$ >= closing$_i$ > lower band$_i$	-1.77
3	higher band$_i$ >= closing$_i$ > middle band$_i$	0.98
4	closing$_i$ >= higher band$_i$	2.63*

Table 2: Basic facts of CSI 300 index over the period from 2005.04 to 2015.11 including number of days, average daily return, cumulative return, return volatility, maximum drawdown and Sharpe ratio.

CSI 300 Index from 2005.04 to 2015.11	
Number of trading days	2640
Average daily return	$3.7*10^{-3}$%
Cumulative return	5.39%
Volatility of return	1.61%
Maximum drawdown	57.07%
Sharpe ratio	0.036

Table 3: Key facts of the 10 GA-based technical trading strategies on CSI 300 index in out-of-sample period from 2010.01 to 2015.12. Information contained includes return attribution, holding period return, number of transaction, maximum drawdown and Sharpe ratio for each strategy.

Strategy performances in out-of-sample (2010.01 – 2015.12)					
	Return attribution	HPR	Number of transaction	Maximum drawdown	Sharpe ratio
Strategy 1	Market timing	136%	150	30%	1.01
Strategy 2	Market timing	128%	104	35.8%	1.03
Strategy 3	Market timing	123%	107	30.6%	0.98
Strategy 4	Market timing	118%	174	31.5%	0.87
Strategy 5	Market timing	112%	113	27.5%	0.95
Strategy 6	Market timing	130%	116	26.6%	1.06
Strategy 7	Market timing	118%	106	21.15%	1.02
Strategy 8	Market timing	129%	155	24.9%	1.08
Strategy 9	Market timing	106%	150	26.4%	1..00
Strategy 10	Market timing	133%	118	26%	1.03
Benchmark	Pure indexing	6.12%	1	57%	0.00024

Table 4: Categorization of the statuses for RSI, MACD and Bollinger Band and t-stats for each of the statuses with regard to returns. Significance at 5% significance level is indicated by *.

Relative Strength Index (RSI)		
Status	**Scenario**	**T-stat**
1	100>=RSI>75	-3.23*
2	75>=RSI>50	-1.06
3	50>=RSI>25	-2.43*
4	25>=RSI	2.56*
Moving Average Convergence Divergence (MACD)		
Status	**Scenario**	**T-stat**
1	$MACD\_DIFF_i \geq MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i \geq MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	2.25*
2	$MACD\_DIFF_i \geq MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i < MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	-2.44*
3	$MACD\_DIFF_i < MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i \geq MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	0.86
4	$MACD\_DIFF_i < MACD\_DEA_i$ **AND** $MACD\_DIFF_i - MACD\_DEA_i < MACD\_DIFF_{i-1} - MACD\_DEA_{i-1}$	-1.98*
Bollinger Band		
Status	**Scenario**	**T-stat**
1	$closing_i$ <= lower $band_i$	-3.03*
2	middle $band_i$ >= $closing_i$ > lower $band_i$	-1.35
3	higher $band_i$ >= $closing_i$ > middle $band_i$	-2.43*
4	$closing_i$ >= higher $band_i$	2.58*

Table 5: Key facts of portfolio 1, portfolio 2 and portfolio 3. Information contained includes return attribution, holding period return, maximum drawdown and Sharpe ratio.

Portfolio performances over 5 years (2010.06 – 2015.11)					
	Return attribution	GA	HPR	Maximum drawdown	Sharpe ratio
Portfolio 1	Stock selection	NO	135%	16.04%	1.70
Portfolio 2	Stock selection	NO	150%	24.56%	1.96
Portfolio 3	Stock selection Market timing	YES	261%	16.23%	2.54

Table 6: Key facts of the 10 experiments with regime-switching considered. Information contained includes holding period return, maximum drawdown and Sharpe ratio.

Experiment		**HPR**	**Sharpe ratio**	**Maximum drawdown**
Experiment 1	Regime 1 strategy	126%	0.85	32%
	Regime 2 strategy	62%	0.64	43%
	Final strategy	158%	1.10	32%
Experiment 2	Regime 1 strategy	114%	0.92	33%
	Regime 2 strategy	56%	0.45	29%
	Final strategy	162%	1.12	33%
Experiment 3	Regime 1 strategy	108%	0.86	26%
	Regime 2 strategy	77%	0.49	38%
	Final strategy	149%	1.16	26%
	Regime 1 strategy	119%	0.75	35%

Experiment 4	Regime 2 strategy	85%	0.52	49%
	Final strategy	160%	1.18	35%
Experiment 5	Regime 1 strategy	120%	0.83	29%
	Regime 2 strategy	53%	0.48	38%
	Final strategy	145%	1.15	29%
Experiment 6	Regime 1 strategy	119%	0.69	33%
	Regime 2 strategy	65%	0.38	24%
	Final strategy	138%	1.12	33%
Experiment 7	Regime 1 strategy	121%	0.77	38%
	Regime 2 strategy	78%	0.33	32%
	Final strategy	140%	1.14	38%
Experiment 8	Regime 1 strategy	111%	0.81	35%
	Regime 2 strategy	80%	0.56	42%
	Final strategy	139%	1.09	35%
Experiment 9	Regime 1 strategy	125%	0.73	31%
	Regime 2 strategy	86%	0.53	33%
	Final strategy	154%	1.16	31%