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Institut ekonomických studií

Diplomová práce

2011 **Petr Málek**

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Improving Investment Timing

Diplomová práce

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ABSTRAKT

Časování investic

Tato diplomová práce se zabývá technickou analýzou finančních trhů neboli zkoumáním závislosti mezi aktuálním a minulým vývojem ceny, zejména konceptem „supportů" a „resistencí", tedy cenových hladin, na kterých se cena v minulosti zastavila. Nejprve je uveden výtah z nejdůležitější související literatury na téma technické analýzy, psychologie investování, behaviorálních financí a efektivity trhů. Následují teoretické argumenty ve prospěch možného fungování technických cenových hladin, stejně tak jako odpovědi na předpokládané námitky. Tato teorie je poté v podobě několika tisíc odlišných ale vzájemně podobných obchodních strategií testována na historických cenách několika nejdůležitějších finančních aktiv. Výsledky jsou porovnány s konzervativní buy-and-hold strategií a s náhodným obchodováním. Došli jsme k závěru, že obchodování na základě technických cenových hladin vede k pozitivním výsledkům s výhodou oproti náhodnému obchodování resp. buy-and-hold strategii. Parametry konkrétních strategií naše výsledy častěji ovlivňují očekávaným než neočekávaným způsobem.

ABSTRACT

Improving Investment Timing

This master's thesis is based on study of technical analysis of financial markets, i.e. analysis of dependencies between past and present price data, especially when it comes to "supports" and "resistances" or historical price levels where price recently tended to stop and reverse. First of all, summary of the most relevant literature on technical analysis is presented, together with literature on psychology of investing, behavioral finance and market efficiency. Following that, theoretical arguments in favor of possible edge in trading of technical levels are introduced and possible objections are addressed. This theory – in the form of several thousands of unique but similar trading strategies – is then tested on historical data of the most important financial assets. Results are compared to those of conservative buy-and-hold strategy and random trading. We reached the conclusion that trading based on technical price levels brings positive capital gains which are better than those achieved by random trading and buy-and-hold strategy. Parameters of our strategies influence the results in expectable manner more often than not.

KLÍČOVÁ SLOVA

finanční trhy, psychologie investování, technická analýza

KEYWORDS

financial markets, psychology of investing, technical analysis

ROZSAH PRÁCE

137 880 znaků s mezerami včetně poznámek pod čarou

131 800 znaků s mezerami bez poznámek pod čarou

Prohlášení

Prohlašuji, že jsem diplomovou práci vypracoval samostatně a použil pouze uvedené prameny a literaturu. Práce nebyla využita k získání stejného ani jiného titulu. Souhlasím se zapůjčováním práce a s jejím zveřejňováním pro účely výzkumu a studia.

V Plzni dne 18. května 2011

Petr Málek

Poděkování

Rád bych poděkoval Jiřímu Novákovi, Ph.D. za poskytnutí podnětných rad a připomínek, které přispěly k vytvoření této práce.

Master Thesis Proposal

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Specialization:	Economics & Finance	Defense Planned:	June 2011

Proposed Topic:

Improving investment timing

Topic Characteristics:

There is an ongoing academic debate about the efficiency of financial markets, about the usefulness of fundamental analysis, technical analysis, behavioral finance and many other means of finding an edge in trading which could lead to significant outperformance of stock markets. There is evidence that it is possible to find certain trading rules which systematically provide better results than those that would have been attained without these rules. Most often, they are of fundamental nature. This thesis should investigate if it's possible to combine these rules and further improve the results by addition of a few logical and theoretically justifiable technical rules.

Hypotheses:

1. There is a way to algorithmically detect technical support/resistance levels in stock market charts.
2. There is a way to improve investment timing using technical levels.
3. Different signals for closing out positions are needed, as opposed to entering positions.

Methodology:

First of all, trading rules would be outlined and theoretically justified. There are several means of detecting support/resistance levels and trading ranges – by price calculations, by volume, by statistics such as Bollinger Bands, or by a combination thereof. After that, these entry and exit concepts would be tested and optimized separately – entry according to the rules with random exit and vice versa. Then they would be combined into a complete strategy which would be tested and evaluated while taking into account risk and also results of buy-and-hold strategy. Either S&P 500 or Dow Jones Industrial Average stocks would be used because there is a good history of both prices and financial ratios.

In addition to that, this concept would also be tested in a combination with proven fundamental rules as outlined in the literature review. These rules seem to lack proper timing of entries and exits which can be a significant burden; addition of sound technical rules could improve the timing.

Outline:

1. Introduction
2. Literature review
3. Technical levels
   a. Theory behind technical levels
   b. Means of algorithmic detection
4. Empirics
   a. Testing usefulness of technical levels for entering a position
   b. Testing usefulness of technical levels for closing out a position
5. Conclusion

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Author

Supervisor

CONTENTS

I. INTRODUCTION

In the world of finance and investing, most people are familiar with the concept of technical analysis which is a discipline that tries to analyze historical price data, find repetitive patterns (using either visual observation or mathematical/statistical calculations) in them and use these findings for prediction of future price movement with some positive edge for capital gain. There are two popular views: (1) that market prices follow random walk which would mean it is impossible to make abnormal returns using technical analysis, and (2) that market prices are not completely random, are biased and therefore predictable with some positive edge at certain times under certain circumstances. Either way, technical analysis continues to receive much attention in practice. Financial newspapers often quote technical analysts, and some academic researchers have found empirical support for its usefulness both in long term trading and in intraday price charts (Brock, Lakonishok and LeBaron, 1992, Hudson, Dempsey and Keasey, 1996, Olster, 2000).

The aim of this work is to construct a trading strategy based on recent technical price supports and resistances, test its usefulness on historical data, determine if obtained results are robust or rather product of chance, and allow for further research in technical analysis and investment timing of similar nature. Testing for market efficiency using statistical tools is not within our scope.

Support is defined as price level below the current market price where the price recently stopped and reversed one or more times and thus signals where selling pressure was overcome by buying pressure enough for the price to turn around. Analogically, resistance is price level above the current market price where the price recently stopped and reversed one or more times signaling that buying pressure was overpowered by selling pressure enough for the price to turn around.

It is reasonable to expect that profit opportunities in financial markets exist because of conclusions of academic research in the field of behavioral finance. Investors are susceptible to emotional behavior and other biases which can cause mispricing and profit opportunity for others (Shiller, 2003, Barberis and Thaler, 2003). Trends are possible to occur and last sufficiently long because of natural tendency of humans to engage in herd behavior (Scharfstein and Stein, 1990, Cipriani and Guarino, 2008, 2009) instead of relying on their own research of undervalued stocks. Furthermore, it is reasonable to expect that technical price supports and resistances can be useful for finding some profit opportunities because these technical levels are visible on price charts and attract attention in the media which makes them psychologically important and likely to serve as triggers for timing investors' engagement in herd behavior and following the trend. While it is true that in short trading time frames (such as in intraday trading), these profit opportunities are probably exploited very quickly by sophisticated automated trading and pattern recognition, market participants with trading equipment of this quality due to high barriers of entry do not necessarily have to be numerous enough to exploit all profit opportunities in the long time frames where non-professional, emotionally vulnerable investment public is likely to be most active. Furthermore, it is sometimes rational for even informed investors to follow the lead of some irrational and uninformed investors over some limited period of time in order to make money (De Long, Shleifer, Summers and Waldman, 1990, Barberis and Shleifer, 2000). All these arguments are developed into more detail in chapters two and three.

It is reasonable to expect that technical supports and resistances will be a useful tool for timing trades. Emotions which we described in the previous paragraph are by their nature repetitive which means they are likely to transform into repetitive price patterns – the very definition of what is subject to technical analysis. More specifically, support and resistances show extreme levels where sellers got exhausted and were overcome by buyers and vice versa. This makes them psychological reference points which are likely to attract conscious or subconscious attention of traders and affect their decision making. They are also by definition record prices in some time frame and therefore they may also attract attention of media. Breakout of such level signals there was enough interest in pushing the price through a recent record low or high and overcome the pressure which was previously there to reverse the price. This gives traders the feeling of beginning of new trend and according to the herd behavior phenomenon, these traders will want to replicate this behavior and join the trend. Plus it causes the traders who were responsible for the prior reversal which formed the level to feel emotional pain and resign on their positions in an attempt to limit their losses. (For example, a resistance was formed by bears overcoming bulls. When this resistance is broken, it means these bears are now in a losing position and will be forced to close these positions (i.e. become bulls) and provide additional buying orders.) The result will be pressure for trading in the established direction which will drive the momentum of the move. The main cornerstone of each strategy we are going to investigate in this thesis is therefore the breakout of support or resistance.

After going through available literature and providing some arguments to be the above claims the objective of this thesis will be pursued by taking three steps. First, supports and resistances will be defined in an exact way which we can transform into a computer algorithm and test on real price data. Exact definition is required because otherwise the determination of technical levels would be biased by the observer's judgment. To make our results more robust, there will be several versions of this simple pattern recognition algorithm with some variable parameters; we will test a number of their combinations leading to roughly thousands of unique trading strategies based on one cornerstone concept. Second, we will run these strategies on historical data of four liquid assets (S&P 500 stock index, 10-Year Treasury Note yields, spot gold, and The Coca Cola Company shares (KO)). Third, we will calculate return on investment as compared to a benchmark (conservative buy-and-hold strategy) together with other useful evaluation statistics such as risk, win ratio, average profit, return on investment etc. Also, we will test for the strategies' robustness using random trading. We will try to test its profitability on the same historical price data and compare them to the real technical strategies. The outcome of this comparison will enable us to judge whether the obtained results for technical strategies are robust or merely a product of chance.

The main contribution of this work is that it should be a step toward understanding of reasons for and demonstrations of possible biased behavior in financial markets. This understanding is necessary if it is the aim of developed society to have quickly adjusting financial markets which in turn is essential for their smooth functioning and serving their purpose of correctly pricing assets at all times so that their price can be considered a good signal about their economic aspects. As opposed to earlier studies on usefulness of support and resistances which tested strategies which were very simplistic, in this work we will test more sophisticated strategies which better reflect functioning of financial markets and their participants. We will test several thousands of unique strategies based on the same concept in order to discover potential relationships between their settings and results. Also, this thesis deals with the theoretical justification of technical analysis as opposed to most previous studies which usually only engage in empirical testing of whatever strategy comes to authors' minds.

This thesis is structured the following way. First, in chapter two, relevant literature is overviewed and discussed. Relevant literature includes both sides of literature on market efficiency – its support and its counterevidence (documented anomalies). We then move to research in behavioral finance because it emerged as an attempt to address these and other anomalies in financial markets. Conclusions in behavioral finance are very important starting point in our argumentation regarding theoretical reasoning of the occurrence of mispricing and its possible detection by certain technical patterns. Next we review empirical studies on technical analysis. This is the other of the two most important sections in literature overview as this is our main topic and one of possible tools for detecting some sorts of inefficiencies. Our own empirical analysis will be partly inspired by these preceding studies. Finally we review studies on the phenomenon of round numbers because it serves as further evidence that whenever a price level is psychologically important and traders place orders at it, it will affect behavior of price in the future.

In chapter three, theoretical reasoning is presented as to why we should reasonably expect technical analysis to work as expected. Besides discussing macroeconomic implication and usefulness of our investigation, we start by arguments why we should expect some profit opportunities in general. Later, we move on to how it is connected with technical analysis, core topic of this work. We address the argument of quick exploitation of all possible market inefficiencies by sophisticated automated trading. Findings from overview of literature on technical analysis are summarized and interpreted. Improvements to methods used in this literature are suggested.

In chapter four, methodology is discussed in detail. Supports and resistances are properly defined, as well as several possible trading strategies based thereon. These strategies are also described in the form of simplified source code so as to present their exact definition free of any human judgment. Model of evaluation of the strategies' results is presented, methodology for determining the strategies' robustness is introduced and practical aspects such as data set, method of computation and software are discussed.

In chapter five, we review results and discuss them. We try to reveal how different combinations of entry and exit methods and their settings determine trading results as well as compare these results to random trading and buy and hold strategy in order to see if our strategies are fundamentally sound.

Chapter six summarizes and concludes.

In the appendix, detailed results of our empirical tests in form of tables and graphs are presented. Because of limited space, other detailed results as well as source codes of the algorithms used for our testing can be found on the enclosed CD.

II. LITERATURE REVIEW

Prediction of Price Movement

Let us begin with the theory of efficiency of financial markets in general. Market efficiency has three basic definitions: *weak efficiency* (inability to make predictions regarding price movement based on time series of historical prices alone; this logically includes all technical analysis), *semi-strong form efficiency* (inability to make such predictions based on historical prices or publicly available fundamental information about the security; i.e. this further includes fundamental analysis), and *strong form efficiency* (inability to make predictions based on any kind of information, including insider information) (Fama, 1970).

The efficient market hypothesis finds its support across many researchers. To name but one work, Michaely, Thaler and Womack (1993) investigated how stock markets behave after a positive or negative dividend announcement. Consistent with other studies named in that paper, they came to conclude that in the short run, markets react rationally, i.e. they tend to go up when a dividend is announced to be initiated and they go down when it is to be omitted. In the long run however, the results are similar, which means that it takes some time (up to months) for the market to adjust to the change in the intrinsic value of the stock indicated by the change in dividend policy. This may be considered a kind of underreaction. Another potentially mysterious phenomenon found by Michaely, Thaler and Womack (1993) is that there is a discrepancy between the market reactions after a negative dividend announcement, i.e. the dividends were cut or completely abolished and positive announcement when dividends were increased. Initiation reactions were about one half the magnitude of omission reactions, while the change in yield was about seven times larger for the omission announcements.

Documented Anomalies

However, there were other researchers who found profitable trading strategies which made abnormal profits when applied to real prices of liquid securities. If the markets were efficient, this would not have been possible as all publicly known information is always incorporated in the price at any given time and therefore cannot be capitalized on. Following are examples of those profitable edges: *Size effect* which means that empirically, smaller companies have higher returns than larger companies even after adjusting the returns for risk (Banz, 1981). *Price-earnings effect* shows that markets do not fully incorporate superiority of stocks with low price/earnings ratio (P/E ratio) (Basu, 1977) even after adjusting for risk and tax issues. When the transaction costs were introduced, the conclusions differed according to the frequency of trading. Frequent traders and speculators would have seen the profits vanish due to transaction costs; however, when the aim is simply reallocate portfolio, then doing it according to the P/E approach would make the investor significantly better off. By the same token, the *book-to-market effect* demonstrates that stocks of companies which have a higher book/market ratio tend to outperform those of the ones with low book/market ratio (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985). All of the above mentioned effects are possible demonstrations either of market inefficiency or of flawed asset pricing model (i.e. missing of some variable for which the ratios happen to serve as a proxy).

The effects have been investigated even in more recent papers. Today, the size effect seems to have disappeared after it received attention of the public. Schwert (2003) documents that in 1981, a mutual fund was established which closely mimicked the portfolio on which Banz (1981) based his research. Abnormal returns turned out to be merely insignificantly different from zero. Griffin and Lemmon (2002) focused on the book-to-market effect. The results showed that regardless of risk of distress, higher book-to-market ratio, on average, brings additional returns. The conclusion of the paper is, among others, that the book-to-market effect was still present and that it could not be sufficiently explained by the three-factor model (as described by Fama and French (1993)) or by differences in fundamentals, e.g. by the higher risk of bankruptcy possibly associated with the companies which have high book-to-market ratio.

Schiller (2003) points out the fact that there is too much unexplained volatility in the markets. If for each year in S&P 500 stock market history one computes present value of resulting dividends paid out the year after that and compares volatility of this time series with volatility of the stock market index (which, under efficiency, should be the future dividends' best possible estimate at each point in time), it becomes evident that the latter is significantly higher than the former. Schiller (2003) further argues that prediction technique which produces predictions much more volatile than the predicted variable itself must be flawed because result of such poor quality must imply making some serious errors.

Behavioral Finance

These findings have caused many economists to doubt the efficiency of financial markets which eventually led to the emergence of a new economic field: *behavioral finance*. Behavioral finance started to deal with financial markets behavior in connection to known features of human psychology and its imperfectness because there were too many anomalies insufficiently explained by the conventional theoretical models (Shiller, 2003). A useful summary of the theory, empirical evidence, and practical application of behavioral finance can be found in Barberis and Thaler (2003). In this work, we can find the summary of the main arguments in favor of behavioral finance:

(1) Limits to arbitrage. The arbitrage opportunities which are supposed to ensure correct pricing cannot be used to their fullest extent because they are not risk free. There is risk that the price will continue to deviate even more from the fair price, bringing serious losses. There are also commission fees and bid/ask spread working against the arbitrageur's favor, making part of the arbitrage opportunities unprofitable or at least more risky. There have been some examples of situations which almost certainly showed mispricing and unexploited arbitrage opportunities – for example the *twin shares* case study comprising stocks of two companies which remained separate entities but agreed to split all their combined cash flow according to a fixed ratio. Therefore, their stocks should theoretically trade at the exact same ratio to one another all the time which was however not the case in reality.

(2) Psychology. Cognitive psychologists have shown that when people have beliefs, they are susceptible to biased behavior. These beliefs come from several documented phenomena of human mind. They include for example overconfidence in one's judgment and abilities; for example, 90% of people think they are above average drivers. Another phenomenon is failure to have a representative sample when making conclusions about relationships of subjects or objects in universe – people tend to choose too small sample sizes relative to complexness of their deductions. Belief perseverance means that people often form a belief and because of pride and social pressure are not willing to change it much in the future

although the reality is proving them wrong. People also form beliefs based on their memories. The following example is often presented: those who have been mugged in the past are much more careful for their belongings than those who have not been mugged despite the fact the odds of getting mugged are equal and known for both individuals.

Behavioral finance also deals with explanation of stock market bubbles which seem to occur frequently. The most popular explanation is herd behavior which means that rather their own privately acquired information investors rely on actions taken by others. Instead of doing what they think is right they simply replicate behavior of others. This can lead to self-perpetuated buying or selling activity; causing bubbles and other, smaller forms of mispricing. Scharfstein and Stein (1990) and Cipriani and Guarino (2008, 2009) found evidence of herd behavior in financial markets. When price is moving in one direction, it means that buyers are outnumbering sellers – many more people are buying than selling. Following the principle of herd behavior, other investors will tend to replicate this behavior and become buyers as well, fueling the further price increase. Schiller (2003) quotes an unpublished paper by Andreassen and Kraus (1988) showing an experiment where people were shown stock prices in sequences and were told to trade according to them. It was revealed that these people tended to extrapolate those price sequences to future and disregard any fundamental analysis of the market which further makes the case for herding-driven stock market bubbles. Same conclusions were reached in similar studies by Smith, Suchanek and Williams (1988) and Marimon, Spear and Sunder (1993).

Schiller (2003) also addresses the popular claim: should markets be inclined to self-perpetuated buying or selling activity, this fact should be demonstrated by large daily momentum of prices which is not the case because prices statistically tend to follow random walk. Schiller (2003) points to a “distributed lag” model which does not generate time series with large day-to-day momentum and still sometimes gets caught up in a self-perpetuated one-directional activity.

One of the reasons for market efficiency is that whenever a detectable mispricing occurs, rational investors will exploit it and drive the price back to its fair level. It is not necessary for all investors to have rational expectations; whenever there are irrational investors, their irrational actions are offset by the rational ones. However, De Long, Shleifer, Summers and Waldman (1990) provide a theoretical model where it makes sense for rational investors to drive incorrectly situated price further away from the fair level in anticipation of more uninformed investors coming in to the market in a herd-like behavior. They point out to similarities between their conclusions and actual behavior of some successful fund managers.

Barberis and Shleifer (2000) showed another theoretical model coming to similar conclusions. The theory behind that model is that investors select their investment “styles” according to distributed lag of past returns.

Schiller (2003) claims that in general, there is no proof that “smart money” will always be powerful enough to offset all irrational behavior in markets as is assumed by efficient market hypothesis.

Technical Analysis

All of the above mentioned trading strategies were based on fundamental information about the companies. However, there have also been a number of papers focusing on technical analysis and how it can predict future market behavior. Technical analysis has much in common with behavioral finance because many technical patterns are aggregate manifestations of emotionally driven traders' behavior (e.g., historical price high can be a psychological barrier for many traders). There are many approaches one can take when it comes to trading by technical analysis: support and resistance levels, Fibonacci retracements, price patterns, moving averages, oscillators with different formulas, etc. (a list with detailed description of each technical tool can be found in Murphy (1999)) and virtually all of them have been subject of scientific research at some point in time. However, we will only mention research focused on support and resistance levels and trading range breakouts as these will be the main subject of this work. This specific category of technical analysis tools has been picked because it is one of the oldest. Also, it is easiest to find theoretical support for why it should have predictive capabilities, as will be seen later.

Brock, Lakonishok and LeBaron (1992) tested simple technical trading rules for (among others) local minimum or maximum breakouts on the historical data of the Dow Jones Industrial Average over the period from 1897 to 1986. They figured that the test is strongly supportive of the usefulness of technical analysis and that the abnormal returns made cannot be sufficiently attributed to additional risk. They tested the breakouts the following way: The range was defined by determining the local minimum and maximum which was the minimum or maximum of the last N days as of each trading day on the record. The tests were conducted based on $N = \{50; 150; 200\}$. According to technical analysts, these local minimums and maximums are important psychological barriers and they function as supports (when below the current market price) or resistances (when above the market price). They are supposed to be difficult to break but once the price does break through them, it is supposed to continue in the established direction for some significant amount of time; i.e. a new trend should be under way. The breakout rule was triggered when the price crossed the support/resistance level at least by an equivalent of 1% of the index's value. An alternative to this definition was the price exceeding (falling below) the resistance (support), i.e. without the 1% confirmation band. Either way, the position was held for 10 days after the breakout, after which the asset was sold (in case of a long position) or bought back (for short positions) at the current market price. All of the different combinations of the breakout rule were then applied to the historical data. Probabilities of success for both buy and sell signals for every set of rules were calculated as well as the difference between mean return after a buy signal and mean return after a sell signal. Additionally, t-statistics were calculated for each of the differences in order to be able to reject or not reject the hypothesis of the difference being equal to zero. Zero difference between mean buy return and mean sell return is what we would expect in an efficient market. The results show that this difference was positive for all 6 arbitrary trading strategies (the exact figure was in the range between 0.49% and 1.20% with the average at 0.87%) and all these figures were significant at the 0.05 level. They are to be compared to the mean 10-day return of buying and holding the Dow Jones index as it is: 0.17%. However, it needs to be tested whether these results are not obtained by coincidence or by data mining. Therefore, Brock, Lakonishok and LeBaron (1992) subjected them to a bootstrap test of robustness. Using the random walk process, AR(1) process, GARCH-M process, and EGARCH process, they randomly generated hundreds of alternative time series with the same or similar mean and variance like the original Dow Jones series. They applied the same trading rules to these hypothetical historical data, calculated the results in a fashion similar to the previous test and figured that the majority of random hypothetical scenarios showed worse results than the real scenario. For the GARCH-M process, the average result of the real scenario was in the upper 10-percent bound of the range of the average results of the hypothetical scenarios. For the other processes, the real scenario came out at an even higher position within the range, virtually at the top bound. This indicates that the achieved results are not likely to be attained by data mining or coincidence. However, it needs to be admitted that transaction costs might wipe out significant portion of these returns but it still holds that if the costs are reasonably low, the returns should remain abnormal, thereby violating the joint hypothesis of weak market efficiency and correctness of asset pricing model.

A similar approach has been applied to stocks in the United Kingdom by Hudson, Dempsey and Keasey (1996) who came to similar conclusions. They found similar biases in the British stock market but they also noticed that their significance deteriorates over time (probably due to increasing liquidity and thus also efficiency of the stock markets in general). They also tried to implement transaction costs into their model which led to conclusion that transaction costs make it impossible to make abnormal returns above the conservative buy-and-hold strategy and the U.K. market can therefore be considered efficient.

The concept of support and resistance levels was tested also on the intraday basis in the foreign exchange market. Olster (2000) examined important support and resistance levels in spot markets of U.S. Dollar against British Pound, German Mark and Japanese Yen. They used the technical levels published by six major foreign exchange trading companies at the beginning of each trading day from January 1996 through March 1998 and found evidence that intraday exchange rate trends were interrupted at the published technical levels. As opposed to Brock, Lakonishok and LeBaron (1992) and Hudson, Depsey and Keasey (1996), he investigated the supports and resistances as trend reversal patterns rather than trend continuation patterns. He first defined what a trend reversal was: the situation when the price came to within a 1% band around the published level and stayed above (below) the support (resistance) for some arbitrarily chosen time period which was 15 and 30 minutes. Then, the he calculated how many times in each month the price really bounced off the level and how many times it continued through the level. These figures were later compared to random data: hypothetical technical levels were calculated using random generation and the respective percentages of bouncing were calculated. If markets were truly random the number of months when the true technical levels beat the random levels at predicting market turns should be about half of the total number of months. However, the comparison showed that all six publishing companies beat the average success rate of the random predictions. Most of the figures are significant at the 0.05 level. However, they vary considerably both across the companies and across currencies studied. Also, the success rate depends strongly on whether the market is in a trend or in a trading range. Not surprisingly, when in trend, the success rate of technical levels drops. It is still positive but statistically less significant. Olster (2000) did not investigate the magnitude of returns which could have been made by trading this strategy, nor did he evaluate the consequences of risk adjustment, nor did he take into account the negative effect of transaction costs.

However, Curcio, Goodhart, Guillaume and Payne (1997) conducted a research focused on similar concept and their conclusions are different. The tested foreign exchange markets were the same; however the periods were different (April through June 1989 and February through June 1994), and also the trading rules were somewhat different – patterns were aimed at predicting trend continuation instead of trend reversals. They took the anticipated support and resistance figures, tested how the intraday foreign exchange markets reacted to them, and concluded that while there were some time periods when these levels provided profitable trading signals (mainly during trends – not surprisingly), the results are not profitable on average when all time periods are taken into account. Several sources for the technical levels were used in the test: intraday range predictions published by Reuters, previous day's high and low, the combination of the two (taking always the levels farthest apart), and the approach by Brock, Lakonishok and LeBaron (1992), i.e. local minimum and maximum (this time calculated over the past hour of trading). The possibility of a 0.1% band around each level was investigated as well. The results differed across the currency pairs and investigated periods. There were times when about one half of all the investigated rules made significant profits but there were other times when the results were mixed or where the profits turned negative, sometimes significantly negative. These results are even more significant when transaction costs are included as this wiped out virtually all profits and made the results significantly negative for most of the investigated periods and currency pairs.

We can see that the existing research on the usefulness of technical analysis seems to have been coming to differing conclusions. Brock, Lakonishok and LeBaron (1992), Hudson, Dempsey and Keasey (1996) and Olster (2000) found technical analysis useful but only in the absence of transaction costs, while Curcio, Goodhart, Guillaume and Payne (1997) did not find any merit to technical analysis. At the first glance, it is evident that the evidence supporting technical analysis is rather weak. On the other hand, the way of determination of technical levels was rather simplistic so it is not really a surprise that only limited functionality has been found. Also, transaction costs alone should not be the sole reason for rejection of trading strategy as the strategy might not be used by itself but rather as timing tool in combination with some other, more traditional valuation technique for buy or sell recommendations. These facts will be addressed in more detail later in chapter three.

Round Numbers

The concept of support and resistance has also been investigated in connection with the natural tendency of humans to stick to round numbers. The idea is that traders tend to make stop and/or limit orders rounded to integers or even multiples of five, ten, hundred etc. for two main reasons: first, it is observable in everyday life that people for some psychological reasons find round numbers more important (Mitchell, 2001). Second, round numbers are easier to communicate when giving trading orders to the broker; this is known as the *communication efficiency theory* (Grossman et al., 1997). The large multiples are especially important as they also receive attention even in the media which are sure to have some influence on individual traders' behavior. Thus, this concept is very similar to supports and resistances which are just other kinds of psychological levels.

The phenomenon of large numbers is documented by Osler (2003) who based his research on information from the book of orders provided to him by a broker. He studied the dollar-yen, dollar-pound and euro-dollar spot markets during the time period from August 1999 to April 2000. When the orders were divided into groups according to the last two digits, it was clear that the orders ending with 0 or 5 were much more numerous than all others. The null hypothesis of the distribution of orders being uniform can be rejected at the significance level of 0.01.

These findings were confirmed by Schwartz, Ness and Ness (2004) who found evidence of round numbers (x.00 and x.50) phenomenon in intraday trading of the S&P 500 futures for the years 1999 and 2000. Although the x.00 and x.50 prices cover only 20% of all possible prices, these clusters contain 40% to 60% of the real order prices. When one considers the opening and closing prices for each day, the clustering effect is even more evident: the x.00 and x.50 clusters account for about 85% to 90% of closing prices or opening prices, respectively. However, no test of significance was performed.

Aggarwal and Lucey (2007) focused on multiples of ten and one hundred in the gold market. London AM gold fixes (1980 through 2000), daily data of COMEX gold in both spot and futures markets (1982 through 2002), and intraday gold market data supplied by UBS London (September 2001 through December 2002) were used as datasets. Since the market stayed below the price of $1000 per troy ounce, testing of the multiples of one thousand would have been redundant. Among others, the test for uniformity of price distribution was conducted and it turns out that concentration of prices around the round number levels does not correspond to what we would expect from a uniform distribution with the p-value as low as 0.00 for all four datasets.

Sonnemans (2006) took advantage of the opportunity provided by the Netherlands migrating to euro in 1999 and investigated how placed trading orders changed because of the migration. Historical data of stocks quoted at the Amsterdam stock exchange for the years 1990 to 2001 were taken and for each company and each year, the amount of round number *crossings* was calculated. A crossing of a round number was defined as the situation when the closing prices for two successive days were apart with the round number between them. The results clearly show that multiples of ten attracted significantly more prices than integers, and that integers have attracted significantly more prices than fractions. They also show that zeroes and fives have significantly less crossings than other numbers, meaning that they serve as supports and resistances which, once broken, keep the price from crossing back over. When the same tests were conducted for the time after the migration to euro, the stock market has virtually instantly started to follow the same ‘rules’ in euro-prices. The clusters of prices in euro were not simple recalculation of the old orders according to the exchange rate. Rather, the new orders were again rounded to round numbers in terms of euro.

Another experiment has been done by Ikenberry and Weston (2003): in 2001, many U.S. equity markets transitioned from quoting price in eighths and sixteenths of a dollar to decimal format with tick size of one U.S. cent. Again, it was observed that immediately after the decimalization, traders started using round numbers of the decimal system. Nearly half of all orders were situated on prices ending with a nickel or a dime.

Summing up the overview of literature on round numbers, it can be said that there is quite strong support of the thesis that markets do not behave completely rationally in this respect; if they did, the importance of round numbers would not be so high. As we see, investors really tend to assign increased importance to psychologically appealing levels for no other rational reason. And if round numbers are psychologically appealing to them, there is no reason to believe that technical supports and resistances, which are in essence visible and memorable recent extremes, should be any different in this respect.

III. HYPOTHESES

Motivation

Why Should We Care?

From a macroeconomic point of view, inefficiency is a negative thing because it is responsible for the fact that prices do not correctly reflect the true fundamental situation of particular asset. In a free market environment, price is usually the only signal economic agents have in order to be able to spontaneously determine the correct allocation of all resources which satisfies their and societal needs the best way. When these signals are distorted, the allocation of resources will be sub-optimal and there will be an unnecessary loss to the society or part of it. Put simple, free and efficient price mechanism is a good way for a society to transmit dispersed knowledge among economic agents (Hayek, 1945). It is thus in the best interest of any society to have efficient markets (including markets for financial assets) where everything is priced correctly at all times and any changes in supply or demand are translated into a corresponding change in price very quickly so that related economic behavior will be changed in line with the change of supply and/or demand. Speaking of financial markets, it would mean prices of all securities would correctly reflect present value of the security's future cash flows, liquidation value of the assets behind that security, risk of default, counterparty risk, liquidity risk, currency exchange rate risk, inflation premium, etc.

If successful, further research in financial market inefficiencies would be economically beneficial because it would give economic agents a potential for profit. By self-correcting market mechanism, arbitrage, this would lead to attempts to exploit those inefficiencies and resulting elimination of the bias. Society would thus have financial markets which are less susceptible to emotional behavior of investors and reflect fundamental state of the world in a more accurate and up-to-date way.

Reasons for Mispricing

Theory of market efficiency is built on the assumption that economic agents have rational expectations, i.e. they are on average as right about the future as is possible given the information available *ex ante*, and they update their information and correct their behavior accordingly as new developments arise. However, these assumptions do not seem to hold in practice for two main reasons. First, information travels slowly. It is true that in times of computers and internet, any information can be shared worldwide within seconds; on the other hand, this leads to the situation when everyone is exposed to extreme load of unstructured and often conflicting information, analyses and opinions from different sources which have different interests. Information flow can be further distorted by unpredictable governmental policies. It thus takes long time and effort for anyone to analyze this large amount of information which not everyone is willing and able to do. Taking a recent example, there were many economists and financial advisors who predicted the subprime mortgage crisis of 2007 and the resulting financial meltdown in fall of 2008; one of them being Schiff (2007). Before the crisis hit, he described its causes and predicted the development which really happened, together with arguments why it would happen. It suggests that people who are willing and able to make a detailed research taking into account all and not just some variables, who are able to question dogmas, and who are able to separate themselves from the crowds, do have better information and can find underpriced and overpriced assets much (even years) sooner than average investors; and it is not till the average investors discover the mispricing that the correcting move occurs and profits can be enjoyed. The bottom line is that some people have better information than others and some people have poor quality information (or none at all). The former will have a competitive advantage and make money and the latter will be at a disadvantage and lose money. When both groups are aggregated into one, the outcome could be zero (or slightly positive with the premium attributable to inflation and volatility) and the markets could look random and unbeatable for an average observer, even when it is not necessarily the case.

The second reason is the existence of emotions, resulting failure of economic agents to behave rationally, and failure of rationally acting individuals to offset the irrational behavior as assumed by the efficient market hypothesis – given that rationality means taking steps which will result in the best combination of return on capital and individual level of risk tolerance. As indicated by the research in the field of behavioral finance, prices tend to follow psychological rather than economic laws in the short to middle run before finally adjusting to the true fundamental state of the world. Many psychological and behavioral aspects of human nature are responsible for this. In addition to those mentioned in the chapter on behavioral finance (mostly summarized by Barberis and Thaler, 2003 and Shiller, 2003), namely beliefs, memories and herd behavior, there are also other phenomena like fear, greed, the need to be right, the comfort of having a leader, herd behavior, failure to recognize that financial market environment is a zero sum game, failure to recognize that experience gained in other parts of person’s life will not help succeed in financial markets, and many others. For comprehensive guide and supporting literature on this topic, see this work’s author’s bachelor thesis (Malek, 2009). We will not further elaborate on this topic at this point as it was covered earlier during the overview of literature on behavioral finance.

Why Technical Analysis Could Help

We will now focus on the latter of the two possible reasons of market inefficiency – emotions – because it is the main motive why it is reasonable to consider technical analysis relevant for academic research. Emotional behavior is by its nature repetitive and therefore causes patterns, which are thus likely to transform into repetitive price patterns with some predictive capability. Two examples of such patterns are support and resistance. Support is a low price level where prices recently tended to stop one or more times; resistance is a high price level where prices recently tended to stop one or more times. In other words, they show the extreme psychological levels within the observer's time frame where out of the two groups of buyers and sellers one got exhausted, resigned on its view of the market and was outnumbered and eventually overpowered by the other; and vice versa. As such, these levels are likely to be important for investors and speculators (whether consciously or subconsciously). It is probably safe to say that extremes of any sort attract at least attention of mass media which is likely to affect investors' behavior – i.e. it is likely to affect their buying and selling and thus also future development of the price time series. Whether price should be expected to bounce off the support/resistance or break out and continue with an explosive move remains to be seen later when we get to testing and tweaking. It could also happen that both scenarios are possible with some other, yet untold variable giving indications early enough. It will also be discussed later that even if this is not the case, profit still can be made in the markets by speculating for example on volatility.

Out of the two possible ways of trading supports and resistances – breakouts and bouncing off – especially the breakouts (i.e. support and resistances taken as trend continuation patterns) have a potential because of the phenomenon called herd behavior and buying or selling mania which we thoroughly described in literature overview in chapter two. If we take breakouts as trend continuation patterns, we are basically describing exactly that kind of situation where market is moving in one direction and where herd behavior is likely to bring in new trend followers who will drive the price further by their action. And these trend followers should be most numerous immediately after the breakout of an important level because that is the level which has the largest psychological value among the largest portion of investor public. Also, that is what receives the attention in mass media, and that is where most market participants will enter the trend following position. Another argument in favor of breakouts is that when they occur, all investors who sold their shares (or even went short) around the top and were thus responsible for the reversal which created the resistance find themselves missing out on a move (or even in a losing position, respectively). Because of natural tendency to emotional behavior, it is likely that at least part of these weak investors will be emotionally pressured to cover shorts and go long. These buying orders will push the price upward, causing even more emotional pain to those who have not covered and bought yet, causing more investors to cover and buy, etc. Again, reverse applies for bottoms and their breakouts where it is the people who caused the bottom reversal by their short covering and buying and are emotionally pressured to sell their losing position after the breakout of the low.

However, reversals are a reasonable strategy too. When price decreases to levels which are low by recently historical standards (support), it means that *ceteris paribus* price deviated below the fair value area and is likely to bounce back because of investors perceiving it as historically underpriced, “cheap” etc. and buying it. Reverse is applicable to price having risen to high levels (resistances).

Also, combination of both approaches can be considered. One could search for long term trends and rely on their continuation (due to herd behavior). During that trend, one could wait for a short term pullback to support (for long term uptrends) or, respectively, resistance (for long term downtrends). Therefore, two edges would be combined: long term trend with good momentum driven by herd behavior and short term attractive pullback away from what has recently been perceived as fair value. In this work, the scope needs to be limited and we will thus focus on the breakouts; other uses of supports and resistance could be subject to further interesting research.

We must also not forget about self-fulfilling prophecies. Since technical levels attract attention in the media and since it is safe to say that some portion of investors is familiar with basics of technical analysis, their trading orders might make the preceding trading signals work. Profit opportunity for average investor would then be a function of the speed at which others execute these trading orders and resulting liquidity of markets at the time of the breakout or bounce-off. Theoretically, all investors will do their action at the same time and therefore price should react by a sudden and immediate gap to the new ground. There would be no continuation of prices between the two points in time and the profit opportunity would be non-tradable. However, in practice, all investors are not alike; they have different risk tolerance, level of emotional pain, level of confidence, trading time frames etc. As a result, if self-fulfilling prophecy is really the case for technical analysis, they will enter at slightly different times, making the breakout continuous and tradable. Those who will come first – at the breakout or shortly after it – will profit and those who will come late will merely provide the profits for the former group and break even or lose themselves. What it means "shortly after the breakout" and "late" will be revealed by the empirical research later.

Empirical research is also needed to answer the question if the mere fact that one level is important, is really sufficient to form a significantly profitable trading strategy at all. However, even if we discover it is not, it should not be thrown away completely before a more detailed investigation is done. First of all, as will be discussed below, two separate edges might be too small to bring significant profits but the same two edges combined could still be significantly profitable. Second of all, a profitable trading strategy does not necessarily equal a way of predicting the next move with some good probability. There are other things on which one can speculate besides prices: one example is volatility. If we were provided with a strategy which cannot anticipate direction of market moves but can anticipate their size (i.e. market volatility), it is a profitable strategy because even volatility can be traded (through straddle/strangle stop order combinations, through coin tosses with stop losses and targets adjusted for a risk-reward ratio larger than 1:1, through certain option combinations, through entering directional trades in volatility indexes such as VIX (CBOE S&P Volatility Index) etc.).

More Sophisticated Algorithmic Trading

It is a common knowledge that thanks to evolution of computers and internet, large portion of daily volume in financial markets is generated by automated trading. Designers of these automated trading systems use more sophisticated and very expensive methods of pattern recognition like neural networks. It is therefore possible to object validity of arguments presented in this thesis on the ground that if technical inefficiencies were really present in financial markets, these sophisticated algorithms would easily reveal them and exploit any advantage they might offer, leaving no profit potential for average investors who do not possess the resources and equipment necessary to engage in this form of trading.

There is every reason to believe this is true for extremely short term trading timeframes such as day trading (exiting a trade on the same day it was entered; holding it for hours, minutes or even seconds) or trading very short term swings (several days in length). In such short periods of time, price movement is small in magnitude and it thus takes smaller amount of buying or selling orders to affect the market price. Thus, whenever mispricing is found by one of these sophisticated strategies and acted upon, it is likely to be exploited very quickly because it is comparatively small. But if we take the other extreme – say, investment time frame of several years – it is difficult to find analogical theoretical support for this hypothesis. In these extremely long time frames, it takes incomparably more money and more orders to affect price movement. If mispricing (be it driven by emotions or by lack of relevant information) occurs, more investors have to detect it and act upon it in order to fully exploit it, avoiding any emotionally driven mistakes. Since emotion-free, rational trading is something very difficult to achieve (experiments in behavioral finance confirm it) and since algorithmic trading has high barriers of entry preventing the majority of investors from benefiting from it, it is challenging to imply that there is enough automated trading in the world to exploit all existing inefficiencies. The sophisticated traders who are able to determine mispricing will probably be small in number compared to uninformed public comprising up to billions of people who account for most of the trading volume (either by trading on their own account or by investing in pension funds and mutual funds which execute the trades for them). The argument of automated trading therefore does not seem to be sufficient to reject the hypothesis that long time frame repetitive inefficiencies occur in financial markets. This theory is in agreement with De Long, Shleifer, Summers and Waldman (1990) and Barberis and Shleifer (2000).

Existing Research and Its Consequences

Let us move from theoretical thoughts on technical analysis to empirical research. At the first glance, some conclusions from the literature overview above suggest that markets price the assets perfectly, there is no profit opportunity, and therefore it is worthless to spend any time with this way of market analysis. The crucial point was that although financial markets alone are not fully efficient and do allow people to make abnormal profits by trading certain strategies, any such profits would have been wiped out by transaction costs which makes the strategies obsolete.

However, investors do not necessarily have to use the investigated analyses for deciding whether to trade or not; instead, they might as well use them for mere timing of their investments which they already decided to make. They might use some other, more sophisticated valuation analysis of a stock to come to the decision to enter a long position in the foreseeable future (a position which is likely to be significantly profitable even after subtracting the transaction costs) and then use one of the presented biases to get better timing. Thus, two biases would be combined and transaction costs would only be paid once. For example, they might use standard fundamental analysis and valuation techniques to estimate future cash flows based on their expertise and discount them to present value, arrive at the conclusion that particular stock is significantly undervalued even after accounting for all necessary transaction costs, and thus decide to invest in it. At this point, the question is not *if* a trade will be made but *when* it will be made. Transaction costs are not an issue anymore because they are going to have to be paid either way. Now, if there is a technique to answer the *when* question and we are to test its reliability based on its expected return adjusted to risk, and we do not have to take into consideration transaction costs, many trading strategies from the empirical research which looked unprofitable or barely profitable can now turn into significantly profitable strategies. As was seen above, transaction costs were, most of the time, the sole reason for rejection of a trading strategy's usefulness.

We should also explain in more detail what the *when* question is and why it is important. We have already discussed the notion that if we are to buy an undervalued asset with the anticipation of making an abnormal return on it, it can and usually does happen that the price remains at the same level for an extended period of time and that it can take long before it finally starts moving and provides the abnormal return expected. Size of the mispricing can even increase for that matter, as was shown above when speaking of limits to arbitrage in the discussion on behavioral finance (Barberis and Thaler, 2003). Usefulness of traditional fundamental analysis which only cares about the *if* and not the *when* is thus influenced by the fact that investment timing is done randomly and that it would be very useful to have a strategy for investment timing. Better buying and selling prices could be attained. Also, it would be possible to shorten the time in position (thus improving the time performance of capital – 1-percent appreciation over six months is for obvious reasons better than 1-percent appreciation over a year). It can also lead to better likelihood of the trade being successful because two favorable edges are being put together. It should be stressed again that transaction costs are not an issue in this situation because they would have had to be paid anyway – due to the primary (e.g. fundamental) reasons that the trader decided to enter the trade in the first place. Even if it was only a question of one trade for entering a buy-and-hold strategy designed for long term protection of savings against inflation and collecting dividends, there are times when it could be statistically better to do the buying and there are times when it is statistically worse.

Possible Improvements to the Studied Technical Strategies

In literature overview, we came to conclude that most technical strategies which were subject to the studies showed some positive expectancy but this was gone once we subtracted the necessary transaction costs. We made a point that this is not an issue if we plan to use the strategy in combination with another rather than by itself. We also showed why it is logical to expect mispricing and why it is logical to assume that technical analysis could reveal mispricing in certain situations.

Another point to be made is that it is apparent there are some possible improvements to the way technical analysis was tested in the above studies. Certainly the trading rules could be improved. Basically the only trading rule these studies used to algorithmically test for the usefulness of support (resistance) levels was taking the lowest (highest) price for past *N* days and trading the breakout of or bounce from this level, sometimes with or without an allowance band around it.

However, at least when speaking of the breakouts, for large *N*s, the breakout level can be very far from the current price, which means the price will have to travel a long distance before it breaks out. Trends do not last forever – before a trend can continue, a correction usually has to happen due to the need for profit taking, and the longer the uninterrupted trend, the more likely the profit taking correction or sideways consolidation. When price goes a long distance and the trade is entered late, the chance of correction is very high and this poses a risk of losing. On the other hand, when the technical level is close to the recent price action, no trend has happened yet, less traders are in position (lower likelihood of profit taking), more traders are out of positions (more potential buyers (sellers) who will push the price further up (down) by their buying (selling)). It is thus reasonable to trade only those breakouts where the price has not traveled a long distance when they happened. This is the first improvement we can make to the existing trading strategies.

Additionally, when we just take the highest or lowest price of the last N days as the breakout level, there is no guarantee that this level is really psychologically important for traders. What makes the technical levels potentially important is that they serve as important psychological barriers – they show historical maximums or minimums and as such are attractive to media and thus to many traders, probably. However, the highest price of last, say, 50 days is not necessarily a maximum visible on the historical price chart. Suppose that the maximum price of the last 50 days occurred on the day T-50 (i.e., the earliest day of our time window). Now, if the price on day T-51 is higher than that of T-50, the price on T-50 will still be recognized as a local maximum by the algorithm although it is obvious that it is not really a local maximum. Entering a trade at this price is no longer strategic; it is rather random price level with no psychological implications for the public. The reasons why the chance of the trade working out should be in the trader's favor are gone and he is left with nothing but a gamble. This can distort the results of the earlier studies. This makes the second possible improvement to be pursued in this thesis.

If we could find a way to change the rules so that they are a better reflection of how the markets operate, it is possible that the tests would yield better results. This would be beneficial in two possible ways: (1) we might find a profitable trading strategy which any investor could use to make abnormal return on their capital, whether by trading solely this one strategy or by trading this strategy only at times when his capital is not invested in something else, or (2) the strategy could be used in combination with some other strategy and its purpose would be to add additional edge, improve the timing of the investment, and thus improve time performance of invested capital. For example, an investor might perform a value analysis of a stock, learn that this stock is underpriced, and instead of buying it immediately, he could wait for a technical signal which would trigger the anticipated uptrend. Even if this meant buying the stock for the same price (or even slightly worse price), it might still be a good and economical decision if it kept the investor away during a long period of sideways movement. Speaking in terms of time performance of capital, it is – for example – economical to keep out of a stock which is expected to go up by 1% over the following 1 year because 1% annual return on a risky asset is far less attractive than similar or even higher return on index (less risky than one stock) or riskless asset.

Hypothesis

- **Hypothesis 1: There is a positive association between using breakouts of technical levels (which are price levels where price tended to stop and reverse in prior weeks) for investment timing and risk adjusted returns on investment.**

Summing up this chapter, (1) we are interested in possible market inefficiencies because we want to have efficient markets for good allocation of resources by economic agents, (2) imperfect information, susceptibility to emotional behavior among investors and herding can and probably does cloud investors' judgment and cause them to misprice securities at times, (3) technical analysis investigates repetitive patterns in price series and is thus a good tool for identifying some sorts of repetitive irrational behavior, (4) automated trading does not necessarily exploit all detectable repetitive patterns in the higher trading time frames (weeks, months, years as opposed to minutes or seconds) because of large barriers of entry and possibilities of speculation on continuation of uninformed traders' irrational behavior, and (5) existing research which usually does not find any significant profit opportunity in technical analysis can be improved both in methodology (investigation of more sophisticated and logical trading strategies) and in evaluation of results (usefulness of any strategy should not be dismissed solely because of relatively large transaction costs).

Technical analysis (more precisely supports and resistances) demonstrates patterns of psychological behavior of other investors and therefore could help us either find a way to make abnormal returns in the market, or at least improve returns of already existing fundamental trading strategies by improving investment timing – i.e. by keeping the investor away during the consolidation periods and making them enter their positions at times when the markets are likely to move in the desired direction.

IV. METHODOLOGY

First of all, it is necessary to define what *support* and *resistance* mean, how their usefulness will be tested and what dataset will be used.

Definition of Support and Resistance

There are many definitions of support and resistance. Olster (2000) gathered some quick research. It seems reasonable to say that "support is a level or area on the chart under the market where buying interest is sufficiently strong to overcome selling pressure. As a result, a decline is halted and prices turn back again. ... Resistance is the opposite of support."

In other words, if we visually checked a historical price chart, support would be demonstrated by a significant trough where the price had been going down, this trend was interrupted, and the price reversed to make significant, although maybe temporary, move to the upside. If there are several such reversals lined up horizontally at similar level (i.e. we can draw a horizontal line approximately connecting the troughs), the support level is of higher significance. Also, interruptions of trends which are larger in time and/or magnitude are of higher significance than interruptions of smaller trends.

Resistance is a peak where price, after moving upwards, was stopped and reversed to make a significant downside reaction. Several such peaks at similar prices form a resistance of higher importance.

Pattern Recognition Algorithm

In order to test the hypothesis of technical pattern usefulness, we need to find a way to algorithmically define these patterns. Otherwise we would not have their clear definition and we could not use any reliable method for testing and risk-return evaluation. We will start with Entry Method 1 which builds on the approach taken by Brock, Lakonishok and LeBaron (1992) and Hudson, Dempsey and Keasey (1996) and aims to improve it.

Entry Method 1: Maximum/Minimum Price of Last N Days

There are several approaches to recognition of supports and resistances. Support is basically a price level at which price has stopped and reversed in recent past – either once or multiple times. One way to identify such support is take the minimum price for past *N* days and trade on their breakouts. If we were to put this into a simple sketch of algorithm, we would arrive at something like this (note that this is just for entering positions; liquidating will be covered later):

```
For i = 1 To i = TotalTradingDays
      Support = MinPrice(i – N, i - 1)
      Resistance = MaxPrice(I – N, i - 1)
      If Price(i) > Resistance + Allowance And Price(i - 1) < Resistance +
            Allowance Then BuyMarket
      If Price(i) < Support - Allowance And Price(i - 1) > Support –
            Allowance Then SellMarket
End For
```

Code 1: Maximum/Minimum Price of Last N Days

Note that in order to save space, this and all following codes are not complete and only serve to demonstrate the basic idea. Complete source codes which were really used for testing can be found on the enclosed CD.

However, we have seen earlier that this approach might not be as reliable as one might think at the first glance. If the market is trending, it might easily happen that the minimum price of last *N* days occurred at time *T*-*N*, with the price at *T*-*N*-1, *T*-*N*-2 etc. even lower than at *T*-*N*. *T*-*N*, would have been recognized as market turning point, although it was not a market turning point at all. This is going to have to be fixed by an additional requirement which will make sure the market is not in a trend.

This can be done quite easily. First, we need to realize we want to have price in a range before we attempt to find support/resistance levels using the method we have just outlined. When prices are in a range, it means they are not moving very much – the volatility is low for a significantly long period of time. On the other hand, when prices are trending, the volatility is by definition high. Volatility can be measured for example by sample standard deviation. An easy way of trading range detection is comparing sample standard deviation of past *N* days to some reference level (either calculated level such as *N*-day average of the standard deviation or an arbitrarily chosen level). The trading rule would be to wait for the standard deviation to drop below the reference level, meaning a trading range has probably been established. At this point, an *N*-day minimum and maximum price would be determined and these numbers would serve as significant technical levels to be traded on their breakout – with or without an allowance band. This would change the above code the following way:

```
For i = 1 To i = TotalTradingDays
      Support = MinPrice(i – N, i - 1)
      Resistance = MaxPrice(I – N, i - 1)
      If PriceStdDev(i – N, i) < VolatilityThreshold Then
            If Price(i) > Resistance + Allowance And Price(i - 1) <
                  Resistance + Allowance Then BuyMarket
            If Price(i) < Support - Allowance And Price(i - 1) >
                  Support – Allowance Then SellMarket
      End If
End For
```

Code 2: Maximum/Minimum Price of Last N Days, Improved

Entry Method 2: Point and Figure Method

In technical analysis, *point and figure* charts refer to charts which are constructed based on some minimal fluctuation. If we set the minimum fluctuation to, say, 5 points and the price time series starts at 100, it means that next reading of this chart will be either 95 or 105, depending on which one of these prices was hit first in reality. Let's say this next price was 105. Now, the same procedure is repeated. Next reading will be either 100 or 110; again depending on which number was hit first in the time following after the price touched 105. In other words, point and figure chart shows us that price moved first from 100 to 105 and then from 105 to the next price (100 or 110) etc. It shows us the series of prices rounded to the nearest fives or tens as they really happened in reality. The main difference as opposed to ordinary price chart is that point and figure chart smoothes all noise in between these round numbers – all noise of size less than 5 points. The trend, or any price movement larger than 5 points in size, is kept. The threshold of 5 points can be set to any other number based on our purposes, of course. The algorithm for constructing the point and figure chart would look something like this:

```
Points = Array(TotalTradingDays,2)
Point(1,1) = Price(1)
Point(1,2) = 1
LastPointIndex = 1
For i = 2 To i = TotalTradingDays
	If Price(i) >= Point(LastPointIndex,1) + Threshold Then
		Point(LastPointIndex+1,1) = Point(LastPointIndex,1) + Threshold
		Point(LastPointIndex+1,2) = i
		LastPointIndex = LastPointIndex + 1
	End If
	If Price(i) <= Point(LastPointIndex,1) - Threshold Then
		Point(LastPointIndex+1,1) = Point(LastPointIndex,1) - Threshold
		Point(LastPointIndex+1,2) = i
		LastPointIndex = LastPointIndex + 1
	End If
End For
```

Code 3: Point and Figure Method, Calculation

Here, `Points` is a two-dimensional array. Each row represents one record of point and figure chart. The first column contains price and the second column contains time (trading day number).

This chart type will be useful for support/resistance testing because if we set the threshold high enough, each peak of the point and figure chart will represent a point where a significant price reversal occurred. And that is definition of support/resistance.

As for calculation of the correct support/resistance levels to be traded on breakout, one way to do it is go back in time and find the most recent low which is below the current market price, and by the same token find the most recent high which lies above the current market price. Buy orders will be placed above the high and sell orders below the low. Again, some allowance can be used. See below for a sketch of such algorithm.

```
For i = 1 To i = TotalTradingDays
      For j = TotalPoints To j = 1
            If Points(j,2) < i And Points(j,1) > Price(i) Then
                  If Points(j-1,1) < Points(j,1) Then
                        If Points(j+1,1) < Points(j,1) Then
                              Resistance = Points(j,1)
                              Exit For
                        End if
                  End If
            End If
      End For
      For j = TotalPoints To j = 1
            If Points(j,2) < i And Points(j,1) < Price(i) Then
                  If Points(j-1,1) > Points(j,1) Then
                        If Points(j+1,1) > Points(j,1) Then
                              Support = Points(j,1)
                              Exit For
                        End if
                  End If
            End If
      End For
      If Price(i) > Resistance + Allowance And Price(i - 1) < Resistance +
            Allowance Then BuyMarket
      If Price(i) < Support - Allowance And Price(i - 1) > Support -
            Allowance Then SellMarket
End For
```

Code 4: Point and Figure Method, Trading

Entry Improvement 1: Time Duration of Supports/Resistances

Either of the two methods could be further improved by measuring significance of detected supports or resistances. One good way of doing that would be measuring their "width" (i.e. time duration) relative the "height" of the price action contained above (below) them. Those levels which were "wide" relative to their "height" would be of higher importance because it would mean that a long time period of consolidation occurred recently with relatively small movements in price. Generally speaking, it is reasonable to assume that these consolidations offer good chances of sustainable trend because, as was already noted above, it means that few trend followers are in position – meaning low risk of profit taking and high chance of out-of-position trend followers taking a late position, thus pushing the price further in the established direction.

In practice, the time duration measurement could be achieved by first determining the nearest support and resistance level. Subsequently, we would find out how long the price has been strangled between these two levels and divide this by price difference between the two levels. That way we would have a kind of *time duration ratio*. We would require this ratio to be higher than some predetermined threshold (which we consider a variable in our testing). Sketch of algorithm is as follows:

```
For i = 1 To i = TotalTradingDays
      Support = (SeeAbove)
      Resistance = (SeeAbove)
      For j = i - 1 To j = 1
            If Price(j) > Resistance + Allowance Then Exit For
            If Price(j) < Support - Allowance Then Exit For
      End For
      TimeDurationRatio = (i - j) / (Resistance - Support)
      If TimeDurationRatio > DurationThreshold Then
            If Price(i) > Resistance + Allowance And Price(i - 1) <
                  Resistance + Allowance Then BuyMarket
            If Price(i) < Support - Allowance And Price(i - 1) >
```

```
                 Support - Allowance Then SellMarket
      End if
End For
```

Code 5: Time Duration of Supports/Resistances

Entry Improvement 2: Trend Following

In the chapter on motivation and hypothesis, we claimed that due to the natural tendency of humans to herding, markets will tend to trend over the long run. When they do, it is not worth trading against the prevailing trend because the odds of success are against us. Also the profit potential is very limited. (For example, it is common to see situations when there is public consensus that prices are too high and yet money managers continue to buy because they do not want to miss the move. Should prices fall, they will not be blamed for the losses because they will not be the only ones who lost money and therefore their reputation as measured by performance against broad benchmarks will not suffer (Scharfstein and Stein, 1990).)

Therefore, the above methods could be further improved by applying a trend following filter – buy only when the overall trend is up and sell short only when it is going down. The easiest and most popular way of doing that is probably comparing price to a moving average. If price is above moving average, we consider the trend to be to the upside and only take long signals, and vice versa. It is necessary to set the period of moving average long enough so that temporary pullbacks within a trend do not cross that moving average and cause us to mistakenly consider the trend reversed when it is not. On the other hand, we cannot use too long periods because it would make the moving average lagging and less responsive to new developments in the market. Therefore, moving average period will be a variable in our strategy. The sketch of source code for trend following is as follows:

```
For i = 1 To i = TotalTradingDays
      Support = (SeeAbove)
      Resistance = (SeeAbove)
      SumCloses = 0
      For j = i – MAPeriod To i = 1
            SumCloses = SumCloses + Price(j)
      End For
      MovingAverage = SumCloses / MAPeriod
      If Price(i) > MovingAverage And Price(i) > Resistance + Allowance And
            Price(i - 1) < Resistance + Allowance Then BuyMarket
      If Price(i) < MovingAverage And Price(i) < Support - Allowance And
            Price(i - 1) > Support – Allowance Then SellMarket
End For
```

Code 6: Filtering According to Trend

Exit Method 1: Reverse Signal

First exit method which will probably come to mind is using the same rules as for the entry methods. That would mean the investor would be exposed to the market one hundred percent of time. He would get a long signal, go long, and hold that position until he gets a valid short signal. When that happens, he liquidates the long and immediately sells short. When he gets a long signal again, he covers his shorts and immediately goes long again, etc.

The source code is not disclosed as it would be identical to each entry method introduced above, except that on each signal, double order would be entered – one for liquidating the existing position and the other for establishing a new one in opposite direction.

However, if we apply either or both of the improvements to our entry methods, the position reversal rules would perhaps get too conservative. Conservativeness is good for fresh entries but when it comes to exiting an established position, it does not make sense to wait too long for the clearest reversal signs. Markets can and do reverse even without any clear signs. Conservative rules might increase a chance of a reversal to occur after a signal shows up; however, it does not mean that reversal signal will show up before every reversal. As a result, closing out must be much less restricted than entering. Therefore, besides this traditional approach, we will consider an alternative to this exit method as well:

Exit Method 2: Trailing Stop Loss

Stop loss order is a stop order placed at certain price which we consider crucial to a trade – either because we want to limit risk, or because we consider occurrence of that price as a signal that reasons for entering the trade are nullified and it is thus logical to exit it, or both.

When entering a trade, the stop loss order would be placed below the nearest support (for long trades) or above the nearest resistance (for short trades). If the position goes in the desired direction and new supports (or resistances, respectively) are formed by the new price action, the stop loss order would be trailed so that it is always below/above the nearest support/resistance, locking in part of the unrealized profit at that point. Supports and resistance would be detected according to the same rules we described in Entry Method 1 and Entry Method 2, respectively.

This should be beneficial in two ways. First, losing trades would be exited quickly – as soon as reasons for entering it no longer exist. If support or resistance is broken in the direction opposite to our position, it is basically a countersignal. If we use one of the two Improvements, we might not necessarily go as far as establishing an opposite position but we should at least acquire neutral view on the market and thus flatten our positions. Should the trend continue, we can always reestablish our original position after the price breaks out the technical level which was created by the pullback that triggered our stop loss, as this situation qualifies as a new signal in that direction.

Second, trades which on the other hand go in our favor and which translate into trends would be ridden for as long as possible for highest possible profits. As soon as support or resistance is broken in the opposite direction, it is a countersignal to become at least neutral (or even – but not necessarily – establish opposite position) and, again, wait for further developments, based on which an opposite trade is made or position in the same direction is reestablished.

This way, the trading methodology would be summarized as entering a trade under *normal or restrictive* conditions (depending on whether or not we use one of the Improvements) and liquidating it under *just normal* conditions.

```
For i = 1 To i = TotalTradingDays
      Support = (SeeAbove)
      Resistance = (SeeAbove)
      If PriceStdDev(i – N, i) < VolatilityThreshold Then
            If LongPositions > 0 And Price(i) > Resistance + Allowance And
                  Price(i - 1) < Resistance + Allowance Then BuyMarket
            If ShortPositions > 0 And Price(i) < Support - Allowance And
                  Price(i - 1) > Support – Allowance Then SellMarket
      End If
End For
```

Code 7: Trailing Stop Loss

Although we used the term *stop loss*, this exit method will not be built using real stop orders. Rather, we will want to be consistent with the entry methods and wait for the price to close below that hypothetical sell stop order (or above hypothetical buy stop order, respectively). The exit would then be executed by a market order at the day’s close.

It should also be noted that by definition, Exit Method 2 is identical to Entry Method 1 and 2 without Improvements. Therefore the combination “Entry Method 1, No Improvement, Exit Method 1” will provide identical trades as the combination “Entry method 1, No Improvement, Exit Method 2”. Same will be true for “Entry Method 2, No Improvement, Exit

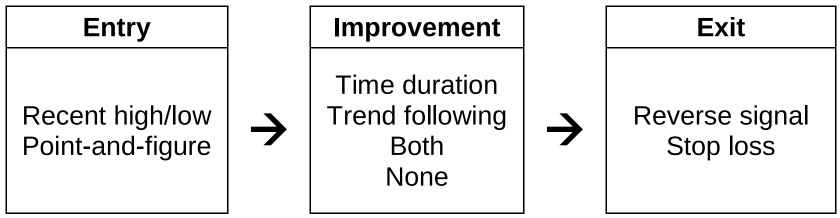
Method 1" and "Entry method 2, No Improvement, Exit Method 2". In order to avoid duplicities, we will not test Exit Method 2 in combination with Entry Method 1 and 2 without Improvement. However, in all other cases of Entry Methods (that is, both Entry Methods with either or both Improvements), the Exit Method will make a difference.

Another known way of exiting trades is the so called profit target, i.e. a predetermined point in the direction of the trade at which, if reached, the trade will be liquidated and profit will be taken. According to the arguments outlined above, the most logical place to put such profit target would be one of the resistances (for longs) or supports (for shorts) ahead because that is where reactions can be anticipated. Again, should the move continue in the original direction, it is always possible to reestablish the original position after the support/resistance breakout.

However, we will not test this kind of exits for the following reason: As will be seen later, most trades are long positions; it is logical because of the natural tendency of securities markets to rise in the long run thanks to inflationary pressures. Therefore – most of the time – these markets rise to all time highs, i.e. to levels previously unseen. If they rise to previously unseen levels, there is no historical price action at these levels which would form supports and resistances, and we thus have no means of determining profit targets using the sort of technical analysis under our investigation. At times, price action is there but is many years old and thus less likely to play significant role in mass psychology.

Summary of Entry and Exit Methods

Our entry and exit methods can be summarized into the following matrix from which all combinations of our interest should be clear:



We have two entry strategies, four possible ways to (not) improve them, and two ways of exiting – giving us the total of 16 combinations. When we correct for the duplicity of "Entry Method 1, No Improvement, Exit Method 1" versus "Entry Method 1, No Improvement, Exit Method 2" and "Entry Method 2, No Improvement, Exit Method 1" versus "Entry Method 2, No Improvement, Exit Method 2", we arrive at the final number of 14 combinations. Furthermore, each combination will break down into more sub-combinations based on different settings we will use. Entry Method 1 will have the `N`, `VolatilityThreshold` and `Allowance` variables adjustable. For Entry Method 2, it will be `Threshold` and `Allowance`. Improvements will have other variables added on top of that: for Time Improvement, `DurationThreshold` will be added and for Trend Improvement, it will be the moving average period, or `MAPeriod`. For their combination, both `DurationThreshold` and `MAPeriod` will be added.

In order to save computing time and avoid geometrical increase in the number of possible combinations for the more complex, improved strategies, we will fix the `Allowance` setting when testing the Improvements and not consider it a variable anymore (the value of the setting will be determined according to results of testing strategies without Improvements). By the same token, when testing the Trend and Time Improvement, we will limit the range of `DurationThreshold` and `MovingAverage` parameters according to earlier findings when these Improvements were investigated separately.

Model of Evaluation

Following Brock, Lakonishok and LeBaron (1992), we are going to measure performance of our strategies in a straightforward way: we will run each strategy on real historical data and calculate the basic statistics. These would include number of trades, share of buy signals and sell signals, average profit on each trade, average profit on each buy signal and each sell signal. Also, we will calculate average daily return as percentage (for buy signals, sell signals and both) as well as respective standard deviations of the cumulative profit curve. We are going to compare strategies to each other according to the ratio of annual return (360-times daily average return) over daily standard deviation of returns. This way, the return figure will be risk adjusted which is necessary for reasonable comparison.

We will also need to employ a test of each strategy's robustness to find out if it is really sound and reliable way of trading. We will simply enter and exit positions on each day on random basis and will calculate our profits and losses from real historical price data. Same statistics and tests will be obtained from them. This procedure will be repeated 2000 times. At the end, we will sort all these results of random trading plus results from the "real" trading from the best to the worst and see in which part of the list the real results happen to be. If they are close to the top, it is an indication of high chance of our strategies being fundamentally sound and predictive; if not, it indicates risk that their results are good out of luck.

Dataset and Software

The trading rules will be tested on a stock market index; the most liquid index in the world is the S&P 500. In order to make sure that we do not focus too much on one market, we will also perform the tests in the history of 10-year T-Notes yields, gold spot and shares of The Coca Cola Company (KO) (this company was selected because it is one of the largest companies within the non-cyclical group; we want a non-cyclical stock because it is less likely to be correlated with the market average which is already included in the sample). The data will be obtained from Yahoo Finance website where they are available for free download in the Excel format which can easily be converted to other suitable formats, if necessary. S&P 500 data history reaches back to 1950, 10-year T-Note yields go from the year 1962, gold is covered between 1968 and 2008, and KO from 1962. The data for KO were adjusted for several large and sudden jumps in price which happened probably due to occasional stock split.

Neither individual American stocks nor other stock market indexes such as the DAX, Nikkei and others will be tested because they are highly correlated with the American index due to global systemic risk and thus they would not yield any additional benefit when it comes to reliability of testing. Also, stock market indices, government bonds and gold are very popular and very liquid markets and we want to test our hypotheses on as liquid markets as possible because these markets are likely to be closest to 100% efficiency.

As for programming, the scope of this work is such that Microsoft Office Excel 2007 should meet all our requirements.

V. RESULTS

S&P 500

Discussion of Results

Entry Method 1 – No Improvement – Reverse Exit[1]

In this combination of entry and exit method, there are three variables: (1) `Period` or number of days for which we calculate maximum and minimum prices as supports and resistances, (2) `Allowance` or coefficient by which we multiply closing price of each day to arrive at the minimum distance by which the price has to cross a support or resistance in order to be considered a breakout, and (3) `VolatilityThreshold` or maximum allowed value of ratio of standard deviation over the `Period` divided by closing price for the trade to be entered. As explained in chapter four, low volatility as measured by `VolatilityThreshold` should ensure that price has moving sideways at the point when a trade is entered and we can thus be confident that the calculated minimum and maximum are really technical levels not distorted by a trend. Volatility is calculated as a ratio against closing price because we want to account for the fact that volatility naturally goes up over time as markets rise to new levels due to long term inflationary pressures.

Two main observations can be made from the summary table. First, the higher the `Period`, the higher the profits and losses are. Exact results strongly depend on the other settings but it is clear that generally speaking, profitable combinations get more profitable with increasing `Period` and unprofitable combinations get more unprofitable with increasing

[1] For detailed table, see the file Entry Method 1 - No Improvement - Reverse Exit.xls on the enclosed CD.

`Period`. Generally, results get more profitable with increasing `Period`. Second, the higher the `Allowance`, the less profitable the strategy is. The absolutely most successful `Allowance` is the smallest one: 0.001 or 0.1% of closing price. Impact of this variable is increasing with increasing `Period`. This relationship does not hold only for `VolatilityThreshold` of 0.0284.

Regarding `VolatilityThreshold`, no important relationships are visible from the table. The only point worth mentioning is that `VolatilityThreshold` of 0.001 does not produce any trades and `VolatilityThreshold` of 0.0147 is extremely unprofitable. All other values above 0.0147 produce stable results.

Entry Method 1 – Time Improvement – Reverse Exit[2]

In order to save computing time and simplify our deductions, we fix the `Allowance` variable for this combination according to the best value from the previous combination of methods which was clearly 0.001. Variables `Period` and `VolatilityThreshold` remain. New variable, `Dur/rng threshold`, is introduced; it is the ratio between time duration of support or resistance (number of days passed since the level was formed for the first time) and "height" of the trading range between support and resistance (price difference between the two levels). The higher this ratio is, the longer the support and resistance last relative to how far away they are, and the higher significance can be attributed to them because it means few trend followers are in position which means there are many potential trend followers who will drive the trend further once it is established by breaking out of this tight price range.

[2] For detailed table, see the file Entry Method 1 - Time Improvement - Reverse Exit.xls on the enclosed CD.

Looking at the summarizing table, we discover that there are very little differences between different values of `VolatilityThreshold` except for 0.0147 which is less profitable than settings higher than that. However, there is observable effect of the `Period` setting because most profitable combinations are concentrated in the 70-100 area whereas the 10-60 area produces merely mediocre results. Other than that, there are not many differences between unique values of `Period` variable except for the value of 10 which is extremely unprofitable. Furthermore, the `Dur/rng threshold` setting seems to be making a great deal of difference. In all instances are the most profitable setups concentrated towards the upper side of the range, namely 922 and 1037.

Looking at the numerical values of profit and loss in general, it is evident that Time Improvement makes a positive difference.

Entry Method 1 – Time Improvement – Stop Loss[3]

Here we are investigating a method combination which is essentially equal to the previous one with the only difference that we are not in position all the time; we use a trailing stop loss at the nearest technical level and if it gets us out of position, we do not reenter until a new legitimate signal occurs.

In line with findings regarding previous combinations, `VolatilityThreshold` setting does not make much difference except the 0.0147 setting which is somewhat worse than the others. The best performing settings seem to be concentrated in the upper right-hand side of each segment of the summary table, i.e. for `Dur/rng threshold` equal to 2-347 and `Period` equal to 50-100. Generally speaking, using stop loss makes the results far worse for this

[3] For detailed table, see the file Entry Method 1 - Time Improvement – Stop Loss.xls on the enclosed CD.

method combination than not using it; two exceptions are durations of 922 and 1037 combined with period 10 which are however clear outliers.

Entry Method 1 – Trend Improvement – Reverse Exit[4]

For the sake of simplification, again, we fix the `Allowance` variable at 0.001. Variables `Period` and `VolatilityThreshold` remain and new variable, `MAPeriod`, is introduced. It is simply the time period over which we calculate the moving average for determination of trend.

Here, again, `VolatilityThreshold` is rather unimportant parameter except the low values around 0.0147 which provide comparatively worse and more volatile results. As far as `Period` and `MAPeriod`, there is no significant trend in either of them. However, taking these two in combination, it is observable that better results are obtained when `Period` goes down and `MAPeriod` goes up. Best results are associated with the former setting around 30-50 and the latter around 250-300.

It is also evident that Trend improvement brings better results than the original combination without improvement.

Entry Method 1 – Trend Improvement – Stop Loss[5]

Here, results indicate strong influence of `Period`. Especially the 70-100 range is significantly better than the other tested values. `VolatilityThreshold`, again, does not make much difference except the poorly performing and volatile 0.0147 setting. `MAPeriod` performs best around 250-300 days; in line with results of this method combination without stop loss.

[4] For detailed table, see the file Entry Method 1 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[5] For detailed table, see the file Entry Method 1 - Trend Improvement - Stop Loss.xls on the enclosed CD.

Comparing the results in general, it can be concluded that neither in this case does using stop loss lead to better results.

Entry Method 1 – Trend and Time Improvement – Reverse Exit[6]

In order to save computing time, `Allowance` will be fixed again at 0.001. `Dur/rng threshold` and `MAPeriod` will be tested only for the three best values from previous separate tests which is 807-1037 and 250-350, respectively. If combination of both improvements is used each of the possible settings produces either one or zero trades over the entire testing time period which is roughly 60 years. Plus, profits are generally not much larger for this combination than for each improvement taken separately. It is therefore reasonable to exclude this from our investigation.

Entry Method 1 – Trend and Time Improvement – Stop Loss[7]

Again, in order to save computing time, `Allowance` will be fixed at 0.001. `Dur/rng threshold` and `MAPeriod` will be tested for ranges 2-232 and 200-300, respectively. Using stop loss produces much more trades as opposed to the previous method combination. Most profitable `Period` is 80-100; `VolatilityThreshold` does not matter except the somewhat poorer results for 0.0147. `Dur/rng threshold` is definitely better when it gets lower and `MAPeriod` is better when it gets larger.

[6] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.
[7] For detailed table, see the file Entry Method 1 - Trend and Time Improvement – Stop Loss.xls on the enclosed CD.

Entry Method 2 – No Improvement – Reverse Exit[8]

This time we only have two variables: (1) `Period` or coefficient by which we multiply current closing price in order to get the minimum size of two one-directional price movements forming a support or resistance, and (2) `Allowance` which has the same meaning as above. The summary table demonstrates that the best range for `Period` is definitely 0.048-0.124. Higher values get much worse in terms of results. As far as `Allowance` is confirmed, lower values are better, thereby confirming findings from investigation of the previous method combinations.

Entry Method 2 – Time Improvement – Reverse Exit[9]

Fixing `Allowance` again at 0.001 and adding `Dur/rng threshold` (idea behind this indicator is identical to the above), we find that while different `Dur/rng threshold` settings do not seem to influence results to a larger extent, `Period` is definitely better at settings above 0.105 with the peak at 0.124-0.143. As opposed to combinations involving Entry Method 1, in this case the Time improvement does not lead to obtaining better results compared to the original strategy without improvement.

Entry Method 2 – Time Improvement – Stop Loss[10]

Using stop loss for this combination does improve results as opposed to Time improvement with reverse exit but it is still not better than Entry Method 2 without

[8] For detailed table, see the file Entry Method 2 - No Improvement - Reverse Exit.xls on the enclosed CD.
[9] For detailed table, see the file Entry Method 2 - Time Improvement - Reverse Exit.xls on the enclosed CD.
[10] For detailed table, see the file Entry Method 2 - Time Improvement - Stop Loss.xls on the enclosed CD.

improvements. Here, best results are obtained when `Dur/rng threshold` goes up above 577 and `Period` goes down below 0.143.

Entry Method 2 – Trend Improvement – Reverse Exit[11]

In this combination, `Allowance` is fixed again at 0.001 and `MAPeriod` (idea behind this indicator is identical to the above) is added. Here, too, `MAPeriod` setting does not play a significant role in determining results; the most important setting is `Period` which provides best results between 0.048-0.124. Trend improvement does not lead to better results compared to the original strategy without improvement.

Entry Method 2 – Trend Improvement – Stop Loss[12]

In line with what has been observed about most combinations involving Entry Method 2 so far, best results are obtained in the lower part of the `Period` range, namely between 0.01 and 0.086. `MAPeriod` filter is best for larger values like 1040-2000. Here, too, the improvement does not bring better results than the respective method combinations without improvement.

Entry Method 2 – Trend and Time Improvement – Reverse Exit[13]

Following the same principles as in the case of Entry Method 1, we limited the range of tested values for `MAPeriod` and `Dur/rng threshold` to the best three values (1200-1520

[11] For detailed table, see the file Entry Method 2 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[12] For detailed table, see the file Entry Method 2 - Trend Improvement - Stop Loss.xls on the enclosed CD.
[13] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.

and 117-347, respectively). However, as was the case of Entry Method 1 with both Improvements and reverse exit, we only have either one or zero trades for each possible setting which makes our samples not representative enough and it is pointless to discuss them.

Entry Method 2 – Trend and Time Improvement – Stop Loss[14]

Even here, lower settings of `Period` provide good results while higher settings provide no results because they do not produce any trades over the tested time period. `MAPeriod` and `Dur/rng threshold` do not pose a significant effect. This is the first and only combination of Entry Method 2 and some Improvements which leads to better results than versions without Improvement.

Summary

For combinations based on Entry Method 1, in all but one case ("Entry Method 1, Trend Improvement, Reverse Exit") the `Period` variable positively influenced results; i.e. the higher it was the better results were obtained. Higher `Period` probably means we are trading more visible supports and resistances which will attract more attention and will work out best. `VolatilityThreshold` does not have much effect on results in any of the cases, except that the lowest values around 0.147 always performed very poorly as compared to the others, which is to say it is contrary to what we would logically expect (lower volatility means more pronounced trading range with more potential of breaking out and making a big move). Either the logic is flawed or volatility as measured by standard deviation is not a good measure of

[14] For detailed table, see the file Entry Method 2 – Trend and Time Improvement - Stop Loss.xls on the enclosed CD.

how a trading range is developed. `Dur/rng threshold` does not show any consistent direction of influence. If stop loss is not used, higher values bring better results, which is expectable (for the same reason why we would expect low `VolatilityThreshold` to have positive influence) but with the use of stop loss it goes the opposite direction both in the case of Trend Improvement alone and in Trend and Time Improvement. `MAPeriod` consistently influences the result in a positive manner for all instances of Trend Improvement applied to Entry Method 1 which is in line with our theory because the higher the variable, the larger the trend according to which we trade and the more momentum it will have; it will also lead to fewer whipsaws.

In case of combinations based on Entry Method 2, `Period` behaves contrary to what we found in case of Entry Method 1 because lower values consistently offer better results. This shows there is a limit to how significant supports and resistances should be traded. `Dur/rng threshold` generally affects results either in no particular direction or slightly positively when it gets larger which is logical because it signals increased importance of consolidation and the following move. The same applies to `MAPeriod` which is, too, logical.

Improvements generally worked very well for Entry Method 1 unless they were protected by stop loss. For Entry Method 2, only the combination of both improvements led to better results although stop loss was used. It is evident that both Improvements and stop loss are not consistent concepts and in some cases they are beneficial while in other cases they are not, depending on the exact strategy used.

`Allowance` was generally better at small values, which is expectable. Larger values would mean we would have to wait till long after the breakout before establishing the correct position, i.e. we would miss part of the move. This finding is confirmatory for our theory that supports and resistances are psychologically relevant points where supply can overcome demand very quickly (or vice versa) and price can move very quickly as the trend attracts public following.

See Table 1 in the appendix for summary of these findings in tabular form. For each strategy combination which was tested and produced more than one or two trades, a number between zero and three was entered: number three means positive influence (the higher the parameter gets, the better the results), one means negative influence, two means that best results were found in the middle of the tested range, and zero means there was no visible relationship.

Comparison to Random Trading

Graphs 1 to 14 show distribution of risk adjusted returns for each of our method combinations in comparison to random trading. Each chart is constructed as follows. The non-random trading sample is made of risk adjusted annual returns of all possible combinations of settings we tested above for the method combination investigated in that particular chart. The random trading sample is made of risk adjusted annual returns for 2000 series of random entries and exits. These two samples are put together, maximum and minimum risk adjusted return is calculated and the range between them is divided in 10 equal intervals. The chart shows how many combinations of settings produced a result which falls into each interval. It does the same for random trading. Since there are incomparably more instances of random strategies than non-random ones, the non-random distribution curve is multiplied by a convenient coefficient in order to make the two curves similar in vertical size.

It is observable that without optimizing the parameter settings, in all but one case ("Entry Method 1, Time Improvement, Stop Loss", Graph 3) the non-random trading distribution curve is shifted to the right relative to one of random trading, meaning that non-random trading generally produced higher risk adjusted returns than random trading. Logically, if we decided to optimize parameters of our strategies according to our findings above, the advantage would widen even more.

Comparison to Buy and Hold

Graphs 15 to 28 use the same methodology to compare our strategies' results to those of simple buy and hold strategy. In order to maintain consistency, only long positions will be taken into account when evaluating our strategies.

As far as combinations including Entry Method 1, there are four instances where our strategies are superior ("No Improvement, Reverse Exit", "Trend Improvement, Reverse Exit", "Trend Improvement, Stop Loss", and "Trend and Time Improvement, Stop Loss"), two where they are of comparable quality ("Time Improvement, Reverse Exit" and "Time Improvement, Stop Loss"), and one where buy and hold is superior ("Trend and Time Improvement, Reverse Exit"). In other words, Entry Method 1 generally seems to be superior to buy and hold, although the difference is not as pronounced as was the case when we were comparing it to random trading.

Entry Method 2 is generally comparable to buy and hold in terms of risk adjusted results. Three strategy combinations are superior ("Time Improvement, Stop Loss", "Trend and Time Improvement, Reverse Exit", "Trend and Time Improvement, Stop Loss"), one is comparable ("Time Improvement, Reverse Exit"), and three are inferior ("No Improvement, Reverse Exit", "Trend Improvement, Reverse Exit", "Trend Improvement, Stop Loss").

10-Year Treasury Note Yields

Discussion of Results

Entry Method 1 – No Improvement – Reverse Exit[15]

The lower the `Period`, the higher the profits and losses are, although the relationship is not very strong. Regarding the variable `VolatilityThreshold`, no important relationships are visible from the table again, except for the lowest values which are somewhat better. `Allowance` is, as usual, better at the lower values of the range.

Entry Method 1 – Time Improvement – Reverse Exit[16]

`Allowance` is fixed again at 0.001. Looking at the results, there are again little differences between different values of `VolatilityThreshold` and `Dur/rng threshold`. Effect of the `Period` setting is small yet visible. Smaller values provide somewhat better results. Generally speaking, this Time Improvement does not bring any significant edge beyond the "No Improvement" version of this method combination.

[15] For detailed table, see the file Entry Method 1 - No Improvement - Reverse Exit.xls on the enclosed CD.
[16] For detailed table, see the file Entry Method 1 - Time Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 1 – Time Improvement – Stop Loss[17]

`VolatilityThreshold` setting does not make much difference except the 0.00206 setting which is somewhat worse than the others. `Dur/rng threshold` is best at the higher values (3920-6532) and `Period` between 50 and 80 (disregarding the value 10 which seems to be an outlier). Using stop loss improves the results significantly as opposed to the previous combination.

Entry Method 1 – Trend Improvement – Reverse Exit[18]

`Allowance` variable is fixed at 0.001. `VolatilityThreshold` remains rather insignificant except for the lowest value which performs worse. `Period` does not influence results very much either. `MAPeriod` is definitely best within the lower half of the range, namely 50-250. Trend Improvement brings better results than the original combination without improvement.

Entry Method 1 – Trend Improvement – Stop Loss[19]

Here, the lower the `Period`, the better the results are. `VolatilityThreshold` is insignificant. `MAPeriod` provides best results when it is lower. Comparing the results in general, it can be concluded that even here, using stop loss led to further improvement in performance.

[17] For detailed table, see the file Entry Method 1 - Time Improvement - Stop Loss.xls on the enclosed CD.
[18] For detailed table, see the file Entry Method 1 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[19] For detailed table, see the file Entry Method 1 - Trend Improvement - Stop Loss.xls on the enclosed CD.

Entry Method 1 – Trend and Time Improvement – Reverse Exit[20]

`Allowance` is fixed again at 0.001. `Dur/rng threshold` and `MAPeriod` will be tested for values 2-1961 and 50-150, respectively. `Dur/rng threshold` is best for the lowest value of 2. There are not many differences between different `MAPeriod` settings; the same applies for `VolatilityThreshold`. `Period`, again, slightly improves performance the lower it gets. There is no significant additional edge as compared to trading Entry Method 1 without Improvement.

Entry Method 1 – Trend and Time Improvement – Stop Loss[21]

Too few trades were generated by this method combination and we will therefore disregard the results.

Entry Method 2 – No Improvement – Reverse Exit[22]

The table demonstrates that `Period` works best in the lower range of 0.01-0.048. `Allowance` produces better results, the smaller it gets.

Entry Method 2 – Time Improvement – Reverse Exit[23]

`Allowance` is fixed at 0.001. `Dur/rng threshold` produces better towards the lower end of the range (around 2-1961), as well as `Period` which works best between 0.01 and

[20] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.
[21] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.
[22] For detailed table, see the file Entry Method 2 - No Improvement - Reverse Exit.xls on the enclosed CD.
[23] For detailed table, see the file Entry Method 2 - Time Improvement - Reverse Exit.xls on the enclosed CD.

0.086. Empirics show that Time Improvement does not improve Entry Method 2 with Reverse Exit.

Entry Method 2 – Time Improvement – Stop Loss[24]

However, using stop loss for this combination does improve results as opposed to the previous two combinations. Best results are obtained when `Dur/rng threshold` goes up above 2614 and `Period` goes down below 0.086 with the exception of 0.01.

Entry Method 2 – Trend Improvement – Reverse Exit[25]

`Allowance` is fixed again at 0.001. Influence of `MAPeriod` and `Period` is mutual; `MAPeriod` performs best when it goes above 27 and `Period` does so when it is at or below 0.048. This Improvement does bring better results than the combination without Improvement.

Entry Method 2 – Trend Improvement – Stop Loss[26]

`Period` makes the best performance around the lowest values of 0.01-0.048. `MAPeriod` shows a slightly positive improvement the higher it gets. Here, too, the Improvement does bring better results than the respective method combinations without Improvement.

[24] For detailed table, see the file Entry Method 2 - Time Improvement - Stop Loss.xls on the enclosed CD.
[25] For detailed table, see the file Entry Method 2 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[26] For detailed table, see the file Entry Method 2 - Trend Improvement - Stop Loss.xls on the enclosed CD.

Entry Method 2 – Trend and Time Improvement – Reverse Exit[27]

Range of tested values for `MAPeriod` and `Dur/rng threshold` is limited to the best three values (1680-2000 and 2-1308, respectively). However, these combinations did not obtain enough trading signals to be representative.

Entry Method 2 – Trend and Time Improvement – Stop Loss[28]

The same applies to the version with both Improvements and Stop Loss exit. Here, the investigated parameters were 1680-2000 for `MAPeriod` and 2614-4573 for `Dur/rng threshold`.

Summary

When we look at Entry Method 1, we find that usually, the `Period` variable produces better performance when it is lower. This is true except for "Entry Method 1, Time Improvement, Stop Loss" where best results occur between values of 50 and 80. Higher `Period` means we are trading more important supports and resistances with more public following, on the other hand there is a downside to it: some sudden moves might be missed. As was the case in testing on S&P 500 historical data, `VolatilityThreshold` does not have much effect on results, except the poorly performing lowest values. `Dur/rng threshold`, again, does not show any consistent direction of influence. `MAPeriod` most of the time influences the result in such a way that lower values bring better results.

[27] For detailed table, see the file Entry Method 2 – Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.
[28] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.

Taking a look at combinations based on Entry Method 2, `Period` behaves consistently with what we found about Entry Method 1; lower values bring better results. `Dur/rng threshold` generally improves results slightly when it gets lower and is used without Stop Loss. With Stop Loss, the relationship goes the other direction – higher threshold, better returns. This is probably due to the fact that high threshold makes exits too restrictive and causes them to be late. However, when it is used purely for entries and when exits are handled by stop losses which are less restrictive, the advantage is magnified while the disadvantage is diminished. `MAPeriod` improves performance of the strategies as it increases.

For Entry Method 1, Improvements usually worked when they were coupled with using Stop Loss. Otherwise, no consistent advantage is found in them. For Entry Method 2, these findings apply, too.

`Allowance` was generally better at small values, which is in line with previous findings.

See Table 2 for overview of our findings.

Comparison to Random Trading

Graphs 29 to 42 show distribution of risk adjusted returns for each of our method combinations in comparison to random trading of Treasury Notes. The way these charts are constructed is identical to the case of S&P 500. Even in here, it is observable that disregarding the possibility of parameter optimization, in all cases did the non-random trading turn out to be either comparable or superior to random entries and exits in this market.

Comparison to Buy and Hold

As opposed to S&P 500, this comparison will not be done in case of Treasury Notes. While S&P 500 is expected to generally rise in price over the long run because of long term economic growth and because of long term inflationary pressures, prices of Treasury Notes are mostly determined by interest rates as set by central banks (in this instance, the Federal reserve). There have been periods when interest rates were rising a bond prices falling (the era of Fed chairman Volcker) as well as periods when rates were falling and bond prices climbing (the era of "easy money" policy after chairman Volcker). Therefore, it does not necessarily follow that buy-and-hold is a conservative long term strategy for the bond market, as opposed to other assets like stocks or gold.

Gold

Discussion of Results

Entry Method 1 – No Improvement – Reverse Exit[29]

In the gold market, `Period` has a positive effect on obtained results, especially in the 80-100 area. `VolatilityThreshold` shows no consistent relationship. There are not many differences between different values of `Allowance` but the lowest value of 0.001 seems to be most consistent.

[29] For detailed table, see the file Entry Method 1 - No Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 1 – Time Improvement – Reverse Exit[30]

`Allowance` is fixed at 0.001. Looking at the results, there are again little differences between different values of `VolatilityThreshold` and `Dur/rng threshold`. Effect of the `Period` setting is, too, very small. It is difficult to draw any conclusions here because most of the settings provided very few trades. Basically the only settings with many trades are those with `Dur/rng threshold` equal to zero which is equivalent to not using the Time Improvement at all.

Entry Method 1 – Time Improvement – Stop Loss[31]

Findings about this method combination applied to the gold market are analogical to the previous combination with Reverse Exit.

Entry Method 1 – Trend Improvement – Reverse Exit[32]

`Allowance` variable is fixed at 0.001. `VolatilityThreshold` is again not very influential except the lower part of the range with somewhat better results. `Period` improves our results when it gets bigger, namely in the upper half of the range. `MAPeriod` definitely works best toward the upper half of the range, too. Trend Improvement brings much better results than the “No Improvement” version.

[30] For detailed table, see the file Entry Method 1 - Time Improvement - Reverse Exit.xls on the enclosed CD.
[31] For detailed table, see the file Entry Method 1 - Time Improvement - Stop Loss.xls on the enclosed CD.
[32] For detailed table, see the file Entry Method 1 - Trend Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 1 – Trend Improvement – Stop Loss[33]

In this version, `Period` has slightly positive effect while `VolatilityThreshold` is insignificant. `MAPeriod` is the most important parameter here; it provides best results when it is higher. In general, it can be said that using Stop Loss partly diminishes the advantage brought by Trend Improvement.

Entry Method 1 – Trend and Time Improvement – Reverse Exit[34]

`Allowance` is fixed at 0.001. `Dur/rng threshold` and `MAPeriod` is tested for the best values previously found which is 0-4658 and 250-400, respectively. `Dur/rng threshold` is best for the lowest value of 0 (identical to not using this improvement at all) because higher settings produce too few trading signals which follows logically from findings on Time Improvement earlier. There are not many differences between different `MAPeriod` settings; the same applies for `VolatilityThreshold`. `Period`, again, improves performance the higher it gets, if we only take into account cells with `Dur/rng threshold` equal to zero which are the settings that produce enough trades to draw conclusions. Apparently, there is a small but positive effect when we compare this set of results to that for the "No Improvement" combination.

[33] For detailed table, see the file Entry Method 1 - Trend Improvement - Stop Loss.xls on the enclosed CD.

[34] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 1 – Trend and Time Improvement – Stop Loss[35]

These results are further improved with the introduction of Stop Loss; other conclusions are identical to those in the previous paragraph.

Entry Method 2 – No Improvement – Reverse Exit[36]

Entry Method 2 without improvement has `Period` work best in the middle of the range, namely 0.067-0.105. Interestingly, `Allowance` brings best returns when it is high (0.019) but the difference is not very large.

Entry Method 2 – Time Improvement – Reverse Exit[37]

`Allowance` is fixed at 0.001. As was already observed, `Dur/rng threshold` settings above 0 do not produce enough trading signals to be of any significance. `Period` works well for rather higher settings (above 0.067). Time Improvement with Reverse Exit clearly does not bring better results than the corresponding version without Improvement.

Entry Method 2 – Time Improvement – Stop Loss[38]

After implementing Stop Loss to "Entry Method 2, Time Improvement", our conclusions remain. Results are somewhat better but still not as good as those obtained without Improvement.

[35] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.
[36] For detailed table, see the file Entry Method 2 - No Improvement - Reverse Exit.xls on the enclosed CD.
[37] For detailed table, see the file Entry Method 2 - Time Improvement - Reverse Exit.xls on the enclosed CD.
[38] For detailed table, see the file Entry Method 2 - Time Improvement - Stop Loss.xls on the enclosed CD.

Entry Method 2 – Trend Improvement – Reverse Exit[39]

`Allowance` is fixed again at 0.001. Here, parameters have quite a strong effect. `MAPeriod` brings much better results for settings at or above 1360 while `Period` works best for values at or below 0.086. As opposed to the previous case, this Improvement does bring better results than the combination without Improvement.

Entry Method 2 – Trend Improvement – Stop Loss[40]

These results are further improved by the use of Stop Loss. In that case, `Period` still makes the best performance below 0.124 and `MAPeriod` shows positive improvement when it gets higher above 1200.

Entry Method 2 – Trend and Time Improvement – Reverse Exit[41]

The values tested for `MAPeriod` and `Dur/rng threshold` are 1680-2000 and 0-4658. Again, these combinations did not obtain enough signals to be worthy of analysis.

Entry Method 2 – Trend and Time Improvement – Stop Loss[42]

The same applies to the version with Stop Loss exit. The investigated parameters were 1680-2000 for `MAPeriod` and 0-4658 for `Dur/rng threshold`.

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[39] For detailed table, see the file Entry Method 2 - Trend Improvement - Reverse Exit.xls on the enclosed CD.

[40] For detailed table, see the file Entry Method 2 - Trend Improvement - Stop Loss.xls on the enclosed CD.

[41] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.

[42] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.

Summary

Summing up our findings regarding method combinations based on Entry Method 1, we see that there is a quite consistent influence of `Period` which produces better signals when it is higher. `VolatilityThreshold` continues to have virtually no effect on results, except the lowest values which tend to deviate somewhat. `Dur/rng threshold`, when significantly higher than zero, produces no trading signals, it is therefore better not to use it at all. However, `MAPeriod` positively affects the results when it gets higher.

As far as Entry Method 2 is concerned, `Period` does not show any consistent direction of influence. `Dur/rng threshold` has to be disregarded because usually when this restriction was used, there were not enough signals generated to draw any conclusions. `MAPeriod` improves performance of the strategies as it increases.

For both entry methods, Trend Improvement significantly improved the final results; on the other hand, Time Improvement either was counterproductive or did not produce enough trading signals to make any judgments.

`Allowance` was generally better at small values for Entry Method 1 which is expectable; however, for Entry Method 2, the larger values brought better results, although the difference was not very large.

For summary, see Table 3.

Comparison to Random Trading

Graphs 43 to 56 show distribution of risk adjusted returns for each of our method combinations in comparison to random trading of gold. It is evident that in all cases, non-random trading performed better than random trading.

Comparison to Buy and Hold

Graphs 57 to 70 have been constructed the same way as in the case of S&P 500 and they show comparison of our method combinations with long trades only against buy and hold strategy applied to the gold market in terms of risk adjusted returns. In all but four cases, it is clearly observable that trading according to support and resistances offers an advantage.

The Coca Cola Company Shares (KO)

Discussion of Results

Entry Method 1 – No Improvement – Reverse Exit[43]

In this case, `Period` influences results positively, namely in the upper half of the range. `VolatilityThreshold`, as usual, shows no consistent relationship except for the lowest values which are worse. Not surprisingly, `Allowance` should be set to the lowest value of 0.001 to bring the best results; otherwise the anticipated moves will be missed.

Entry Method 1 – Time Improvement – Reverse Exit[44]

Given the findings above, `Allowance` is fixed at 0.001. There are negligible differences between results for different values of `VolatilityThreshold` while `Dur/rng threshold` is most efficient for the values in the lower half of the range. Effect of the `Period` setting is significantly positive. However, there is not much improvement as compared to the combination without Improvement.

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[43] For detailed table, see the file Entry Method 1 - No Improvement - Reverse Exit.xls on the enclosed CD.
[44] For detailed table, see the file Entry Method 1 - Time Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 1 – Time Improvement – Stop Loss[45]

Findings about this method combination are analogical to the previous combination with Reverse Exit. In some ranges of the parameters, results were improved but only at the expense of other ranges where results deteriorated.

Entry Method 1 – Trend Improvement – Reverse Exit[46]

`Allowance` variable is fixed at 0.001. `VolatilityThreshold` is not important for the most part, `Period` has positive influence and so does `MAPeriod`. This case of Improvement brings distinctly better results than not using it at all.

Entry Method 1 – Trend Improvement – Stop Loss[47]

`VolatilityThreshold` remains insignificant, `Period` has clearly positive effect and so does `MAPeriod`, although not as much. In general, Trend Improvement with Stop Loss brings better results than the version without Improvement but worse than that with Trend Improvement and Reverse Exit.

Entry Method 1 – Trend and Time Improvement – Reverse Exit[48]

`Allowance` is fixed at 0.001. The parameters `Dur/rng threshold` and `MAPeriod` are tested for ranges of 0-794 and 400-500, respectively. `Dur/rng threshold` and `VolatilityThreshold` show no consistent direction of influence. `MAPeriod` clearly improves

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[45] For detailed table, see the file Entry Method 1 - Time Improvement - Stop Loss.xls on the enclosed CD.
[46] For detailed table, see the file Entry Method 1 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[47] For detailed table, see the file Entry Method 1 - Trend Improvement - Stop Loss.xls on the enclosed CD.
[48] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.

the obtained results when it gets higher; the same applies for `Period`. Apparently, this type of Improvement has positive effect.

Entry Method 1 – Trend and Time Improvement – Stop Loss[49]

`Period` provides best signals when in the upper half of the range (50-100) and so does `MAPeriod` (best settings are 450 and 500). `Dur/rng threshold` is clearly better at the lowest value of zero and `VolatilityThreshold` shows no consistent effect. Again, this Improvement is beneficial but not as much as in the version without Stop Loss.

Entry Method 2 – No Improvement – Reverse Exit[50]

For this method combination, `Period` works best in the middle of the range, namely 0.124-0.143. Surprisingly, there is not very strong influence of the `Allowance` parameter. For further testing, we will arbitrarily choose 0.001 again.

Entry Method 2 – Time Improvement – Reverse Exit[51]

`Dur/rng threshold` settings are superior for the lower values, namely 0-3434. Beyond that, not only are the results worse but too few trades are triggered, too. No clear pattern is observable in the investigated `Period` settings. This Improvement does not seem to improve results of the version without Improvement.

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[49] For detailed table, see the file Entry Method 1 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.
[50] For detailed table, see the file Entry Method 2 - No Improvement - Reverse Exit.xls on the enclosed CD.
[51] For detailed table, see the file Entry Method 2 - Time Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 2 – Time Improvement – Stop Loss[52]

The very same conclusions apply to Time Improvement with Stop Loss.

Entry Method 2 – Trend Improvement – Reverse Exit[53]

No conclusions can be drawn in this instance because none of possible combinations signals more than one trade.

Entry Method 2 – Trend Improvement – Stop Loss[54]

`MAPeriod` has positive influence in the upper half of its range and `Period` performs best in the lower half of its range. Generally, this type of Improvement brings significantly better results; it needs to be born in mind however that neither of these settings produced more than 10 signals over the investigated period.

Entry Method 2 – Trend and Time Improvement – Reverse Exit[55]

The values tested for `MAPeriod` and `Dur/rng threshold` are 400-1040 and 1717-5151. These combinations did not obtain enough signals.

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[52] For detailed table, see the file Entry Method 2 - Time Improvement - Stop Loss.xls on the enclosed CD.
[53] For detailed table, see the file Entry Method 2 - Trend Improvement - Reverse Exit.xls on the enclosed CD.
[54] For detailed table, see the file Entry Method 2 - Trend Improvement - Stop Loss.xls on the enclosed CD.
[55] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Reverse Exit.xls on the enclosed CD.

Entry Method 2 – Trend and Time Improvement – Stop Loss[56]

The same applies to the version with Stop Loss exit. The parameter settings were the same as in the previous case.

Summary

For Entry Method 1, we see that the influence of `Period` is very significantly positive, i.e. better results are obtained for higher values of the parameter. `VolatilityThreshold`, as is usual, does not have any detectable effect except the lowest and poorly performing values. `Dur/rng threshold` restriction is not beneficial for trading and tends to make strategies work better when it is rather lower. On the other hand, `MAPeriod` affects the results very positively.

Moving on to combinations based on Entry Method 2, `Period` does not show any consistent direction of influence. `Dur/rng threshold` was better at the lower values and `MAPeriod` at the higher values although for these two parameters the evidence is not as strong because only part of the combinations had enough sample trades to be considered seriously.

For Entry Method 1, Trend Improvement significantly improved the final results, whether it was applied alone or in combination with Time Improvement. The best versions were those without Stop Loss. Entry Method 2 brings us to similar conclusions but fewer signals were generated and thus the evidence is not as strong.

For Entry Method 1, `Allowance` was better at small values; in the case of Entry Method 2, these results were mixed and no conclusion could be drawn.

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[56] For detailed table, see the file Entry Method 2 - Trend and Time Improvement - Stop Loss.xls on the enclosed CD.

For summary, see Table 4.

Comparison to Random Trading

Graphs 71 to 84 show that in line with our previous findings, technical level trading outperforms random trading on risk adjusted basis.

Comparison to Buy and Hold

Graphs 85 to 98 show the comparison to buy and hold strategy. It is observable that except for "Entry Method 2, Time Improvement" (in both versions) and "Entry Method 2, Trend and Time Improvement, Stop Loss", technical level trading outperforms buy and hold.

VI. CONCLUSION

In this thesis, we tried to build several combinations of trading strategies with adjustable parameters. These strategies were based on the phenomenon of breakout of supports and resistances, i.e. visible price levels where price recently stopped and reversed. Later, we tested these strategies on historical data and judged their usefulness and robustness. We used a limited number of markets because of limited computer time and limited space.

Our expectations that this approach would work stemmed from earlier research in the field of behavioral finance and technical analysis. We presented several arguments, out which the most important are: indications of emotional behavior and herding for which evidence has been found in financial markets, and limitations of rational investors' ability to outweigh the influence of irrational investors.

We presented several ways of detecting supports and resistances and laid forward several possible ways of trading them. Later, we tested several thousands of different combinations on historical price data, investigated relationships between input parameters and risk adjusted results, as well as compared them to the benchmark (conservative buy and hold strategy) and to random trading with the aim of helping us determine whether or not obtained results are merely a product of chance.

Our findings regarding all tested markets (S&P 500, 10-year Treasury Note yields, gold and The Coca Cola Company shares) can be summarized as rather positive. If we look at Tables 1 through 4, we find that except T-Notes, the `Period` parameter always influenced our results positively which would be in line with theoretical expectations (larger `Period` means we are trading based on larger and longer supports and resistances). By the same token, we would expect trend following based on moving average with longer period to be more profitable; our results indicate that (`MAPeriod` most of the time brings better results when it gets larger). As far as the `Allowance` parameter is concerned, more profitable risk adjusted results are obtained for lower values which is an argument in favor of technical analysis because it indicates that when a technical level is broken, it is better to enter a position sooner rather than later. If there was not any meaning to technical levels, it should not matter how long one waits before establishing a position after the breakout. `VolatilityThreshold` does not seem to play a significant role. `Dur/rng threshold` is clearly making results worse more often than better; it is best when this value is low or even equal to zero which is equivalent to not using Time Improvement at all. If we sum up these partial conclusions, we can say that out of five investigated parameters, three behaved in line with our theory, one behaved neutrally and one behaved contrary to our expectations.

In all four markets, when compared to random trading, our strategies show clear superiority regardless of their settings. When compared to buy and hold, the results of comparison are a little bit more mixed but still favor our technical strategies significantly. This would be further magnified if we only used those settings which came out to be most profitable. That would obviously expose us to the problem of "over-fitting" and data mining because regardless of what price series we test, it is always possible to find *ex post* some way of trading them very profitably on that particular sample; it does not however mean that this success will be repeated when traded on fresh data which was not part of the sample on which the strategy was optimized. Therefore we do not attempt to make such comparison.

However, it needs to be noted that, looking back at the pivot tables summarizing performance of different combinations of parameter settings, the visual layout of colors in these tables does not look random. If those settings did not have any fundamental influence on the results and therefore carried the danger of over-fitting, they should not form any visual patterns in the pivot table and should rather be random. But if we look at the colors, we usually find continuous areas, shapes and clusters which should not occur in random environment. And since we saw that these areas, shapes and clusters are slightly more often than not in accordance with our theoretical expectations, there is a reason to interpret this as something not of pure chance but rather of more fundamental nature. Therefore, we should not consider the danger of parameter over-fitting as high as we usually do.

As was explained in previous chapters, we did not take transaction costs in consideration because we think of our strategies not in terms of being traded by themselves but in terms of being used for timing of trades being made for other reasons (the simplest example would be timing of entry into a buy and hold position). Our conviction is that all strategies subject to academic study generally should not always be investigated under the influence of transaction costs because we never know if the edge will be used by itself or if several independent edges will be put together to provide edge of multiple size, although transaction costs will only have to paid once.

Our final conclusion is that although research in this field is far from complete, there are indications that besides the theoretical justification, empirical testing shows the technical concept of supports and resistances does have some predictive capability which can be used to, at least, improvement of investment timing.

There are certainly many ways this research could be extended. Most importantly of all, there are better ways of support and resistance detection. Sophisticated algorithms for pattern recognition could be used to measure their horizontal and vertical sizes and character of trading in between them (volatile or calm and directionless). It could measure how many times the levels were touched by price because the more times it is touched, the higher significance it will have. Furthermore, some levels are not exactly horizontal; that is another barrier in detection by the means we introduced above and the research would certainly be more reliable if adequate algorithms would be created which are not susceptible to these and other imperfections. Also, the testing sample could be extended to include more markets and lower time frames.

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LIST OF APPENDICIES

APPENDICIES

		Reverse Exit					Stop Loss				
		Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod	Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod
Entry Method 1	No Impr.	3	1	0							
	Time Impr.	3		0	3		3		0	1	
	Trend Impr.	1		0		3	3		0		3
	Trend and Time Impr.						3		0	1	3
Entry Method 2	No Impr.	1	1								
	Time Impr.	3			0		1			3	
	Trend Impr.	2				0	1				3
	Trend and Time Impr.						1			0	0

Table 1: Influence of Parameters (S&P 500)

		Reverse Exit					Stop Loss				
		Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod	Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod
Entry Method 1	No Impr.	1	1	0							
	Time Impr.	1		0	0		3		0	3	
	Trend Impr.	0		0		1	1		0		1
	Trend and Time Impr.	1		0	1	0					
Entry Method 2	No Impr.	1	1								
	Time Impr.	1			1		1			3	
	Trend Impr.	1				3	1				3
	Trend and Time Impr.										

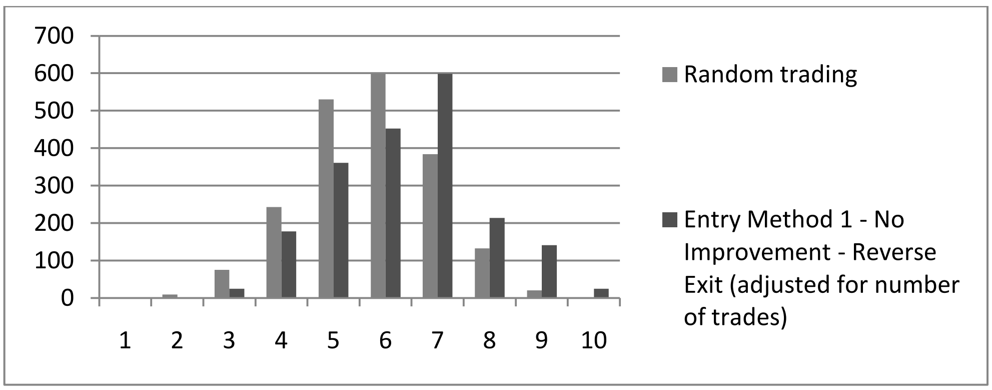
Table 2: Influence of Parameters (T-Notes)

		Reverse Exit					Stop Loss				
		Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod	Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod
Entry Method 1	No Impr.	3	0	0							
	Time Impr.	0		0	1		0		0	0	
	Trend Impr.	3		0		3	3		0		3
	Trend and Time Impr.	3		0	1	0	3		0	1	0
Entry Method 2	No Impr.	2	3								
	Time Impr.	3			1		3			1	
	Trend Impr.	1				3	1				3
	Trend and Time Impr.										

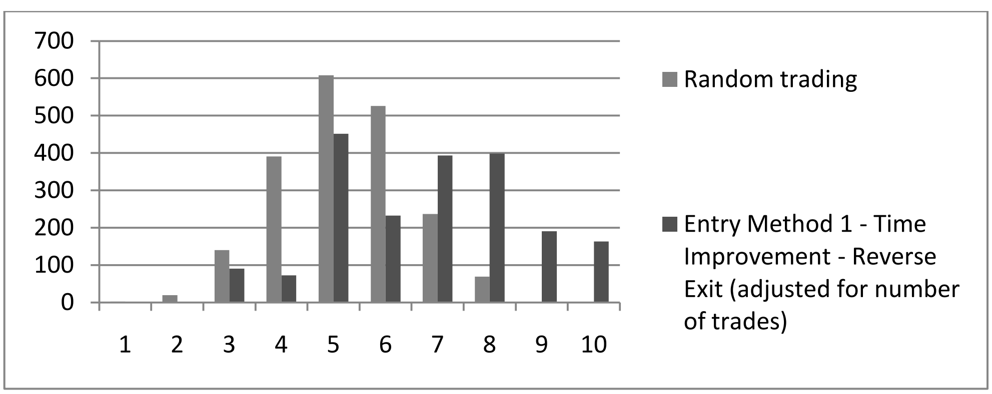
Table 3: Influence of Parameters (Gold)

		Reverse Exit					Stop Loss				
		Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod	Period	Allowance	VolatilityThreshold	Dur/rng threshold	MAPeriod
Entry Method 1	No Impr.	3	1	0							
	Time Impr.	3		0	1		3		0	1	
	Trend Impr.	3		0		3	3		0		3
	Trend and Time Impr.	3		0	0	3	3		0	1	0
Entry Method 2	No Impr.	2	0								
	Time Impr.	0			1		0			1	
	Trend Impr.						1				3
	Trend and Time Impr.										

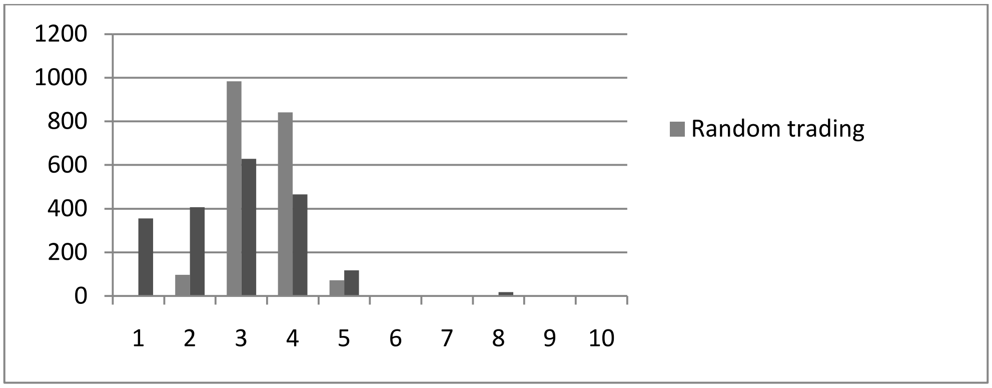
Table 4: Influence of Parameters (KO)



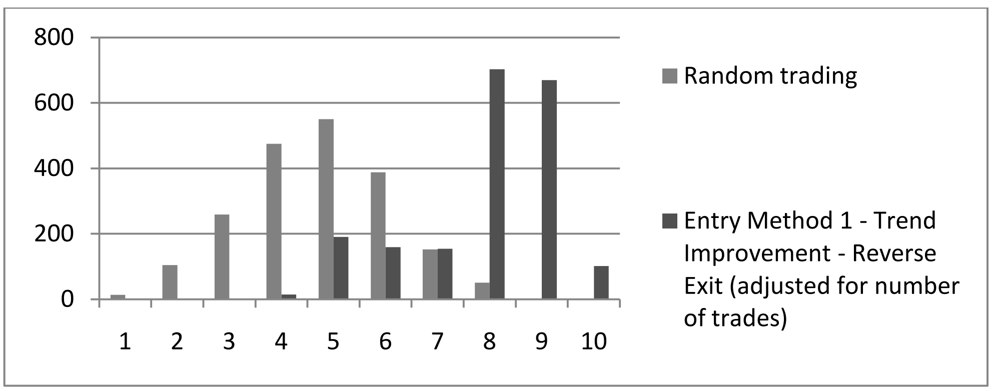
Graph 1: Random Trading and Entry Method 1, No Impr., Reverse Exit (S&P 500)



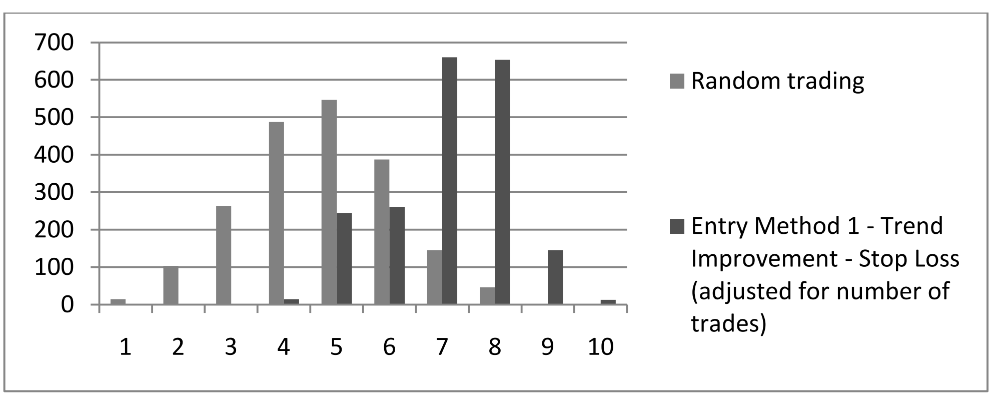
Graph 2: Random Trading and Entry Method 1, Time Impr., Reverse Exit (S&P 500)



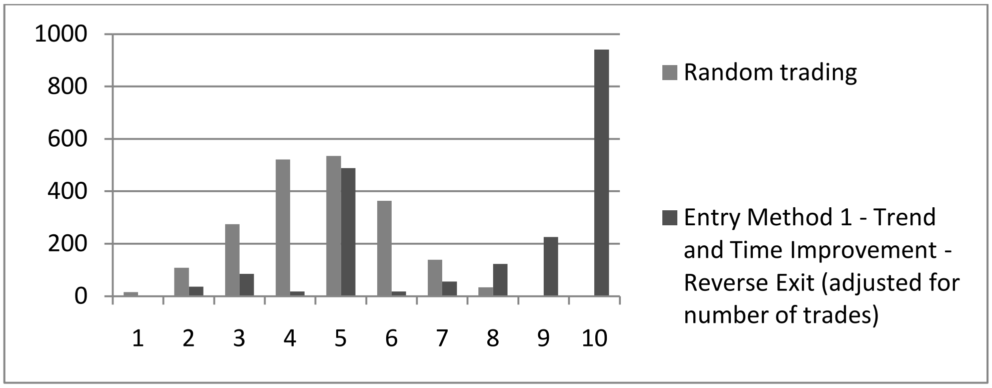
Graph 3: Random Trading and Entry Method 1, Time Impr., Stop Loss (S&P 500)



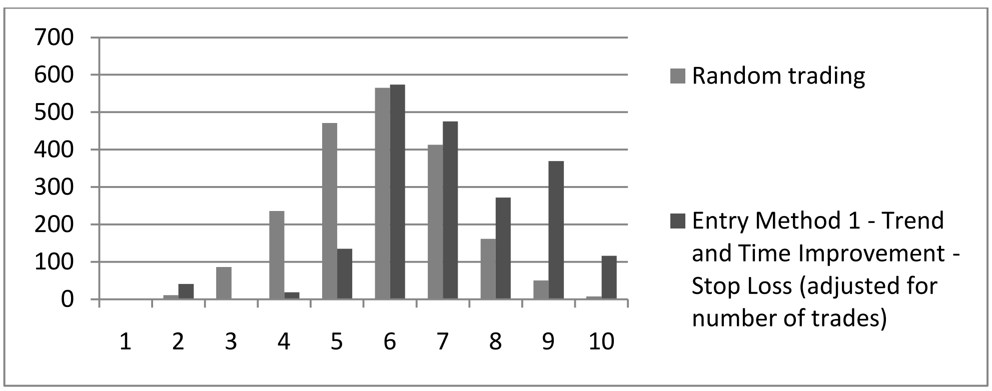
Graph 4: Random Trading and Entry Method 1, Trend Impr., Reverse Exit (S&P 500)



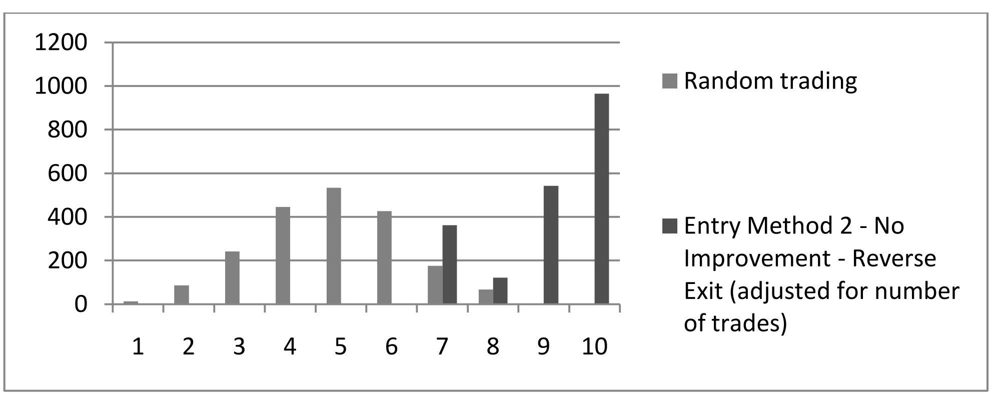
Graph 5: Random Trading and Entry Method 1, Trend Impr., Stop Loss (S&P 500)



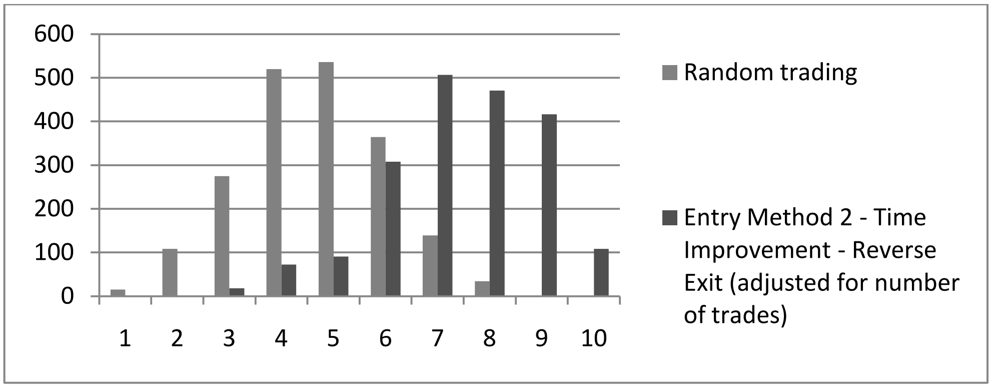
Graph 6: Random Trading and Entry Method 1, Trend and Time Impr., Reverse Exit (S&P 500)



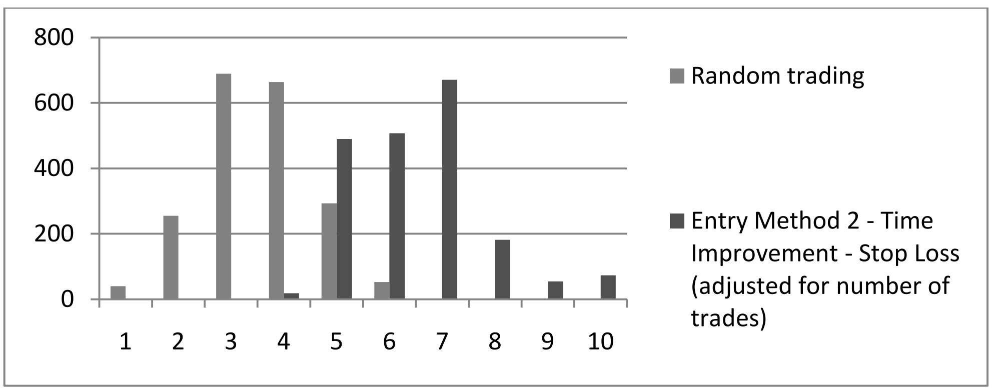
Graph 7: Random Trading and Entry Method 1, Trend and Time Impr., Stop Loss (S&P 500)



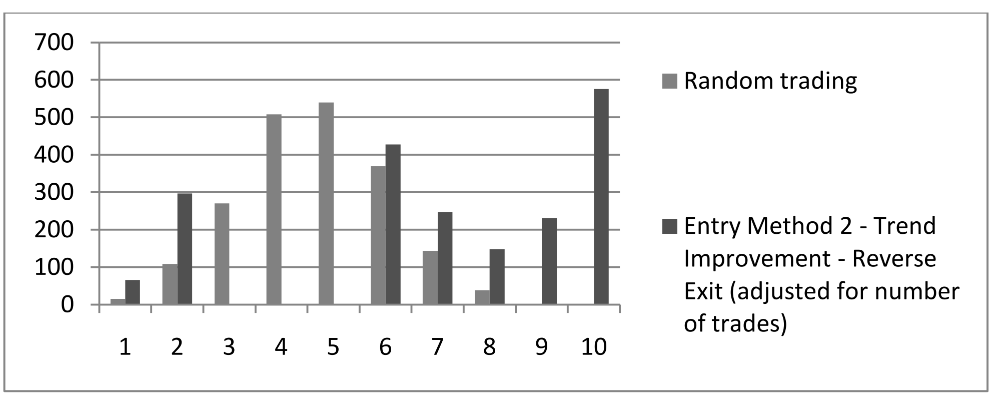
Graph 8: Random Trading and Entry Method 2, No Impr., Reverse Exit (S&P 500)



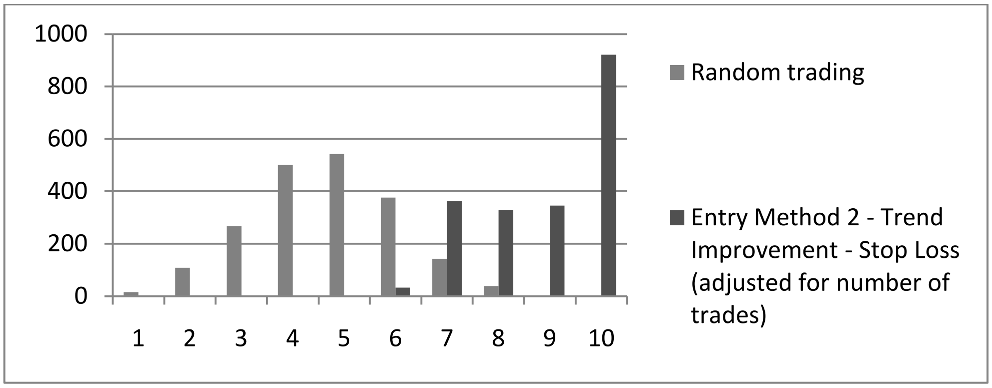
Graph 9: Random Trading and Entry Method 2, Time Impr., Reverse Exit (S&P 500)



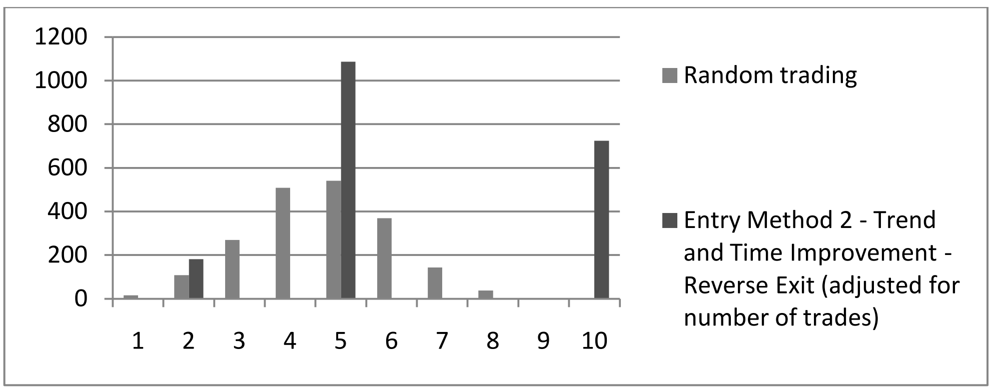
Graph 10: Random Trading and for Entry Method 2, Time Impr., Stop Loss (S&P 500)



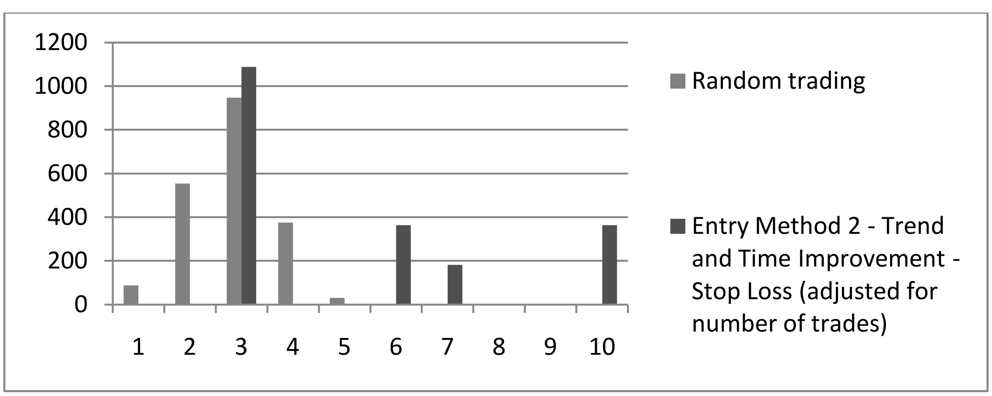
Graph 11: Random Trading and Entry Method 2, Trend Impr., Reverse Exit (S&P 500)



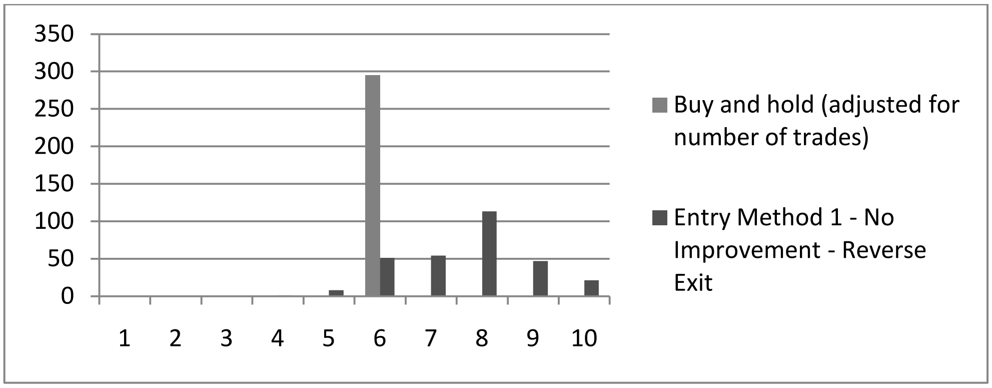
Graph 12: Random Trading and Entry Method 2, Trend Impr., Stop Loss (S&P 500)



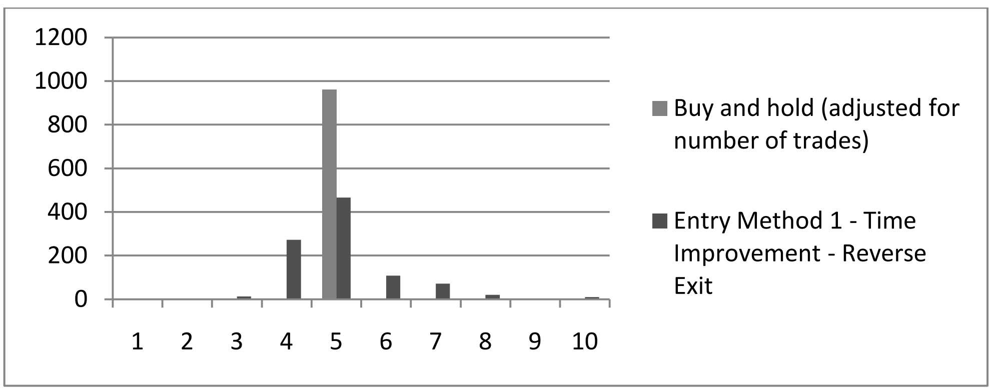
Graph 13: Random Trading and Entry Method 2, Trend and Time Impr., Reverse Exit (S&P 500)



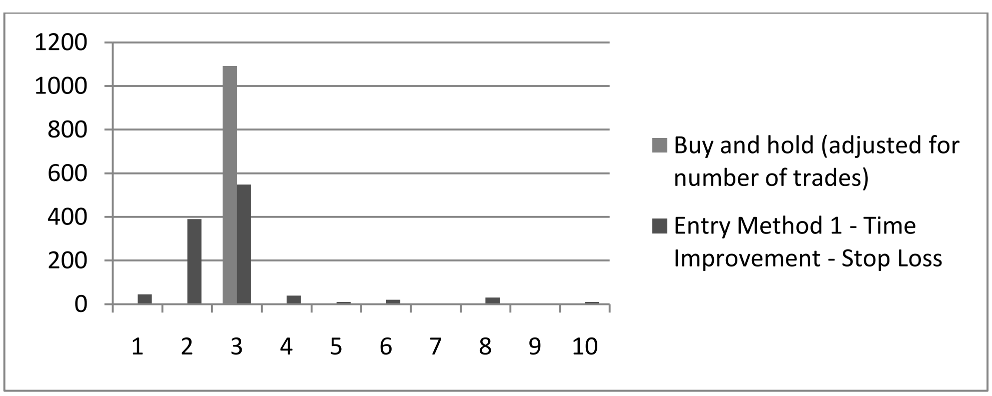
Graph 14: Random Trading and Entry Method 2, Trend and Time Impr., Stop Loss (S&P 500)



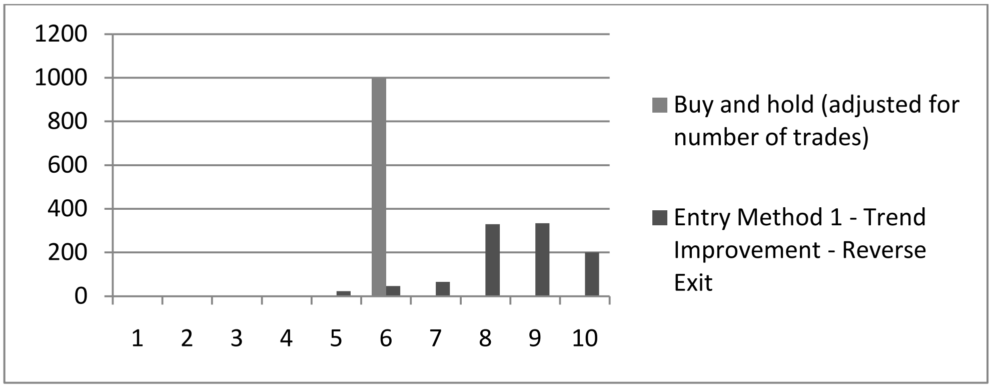
Graph 15: Buy and Hold and Entry Method 1, No Impr., Reverse Exit (S&P 500)



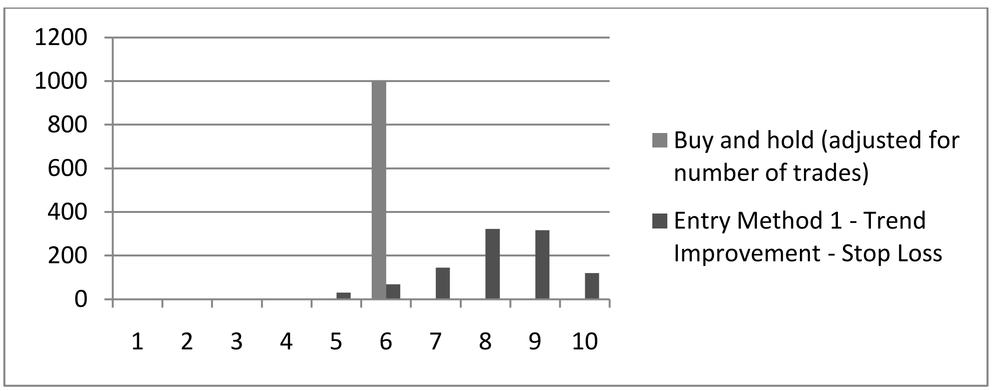
Graph 16: Buy and Hold and Entry Method 1, Time Impr., Reverse Exit (S&P 500)



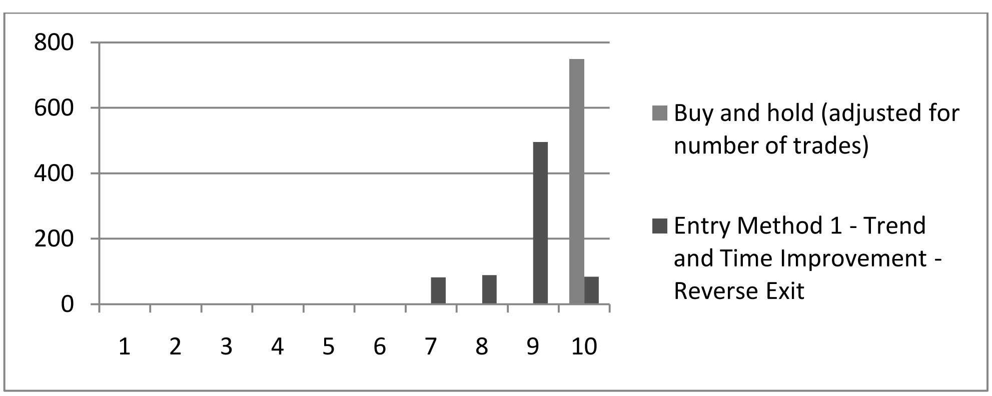
Graph 17: Buy and Hold and Entry Method 1, Time Impr., Stop Loss (S&P 500)



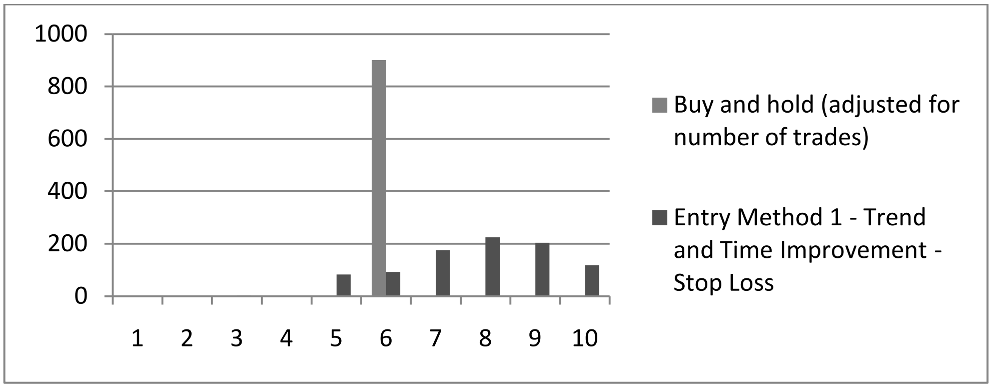
Graph 18: Buy and Hold and Entry Method 1, Trend Impr., Reverse Exit (S&P 500)



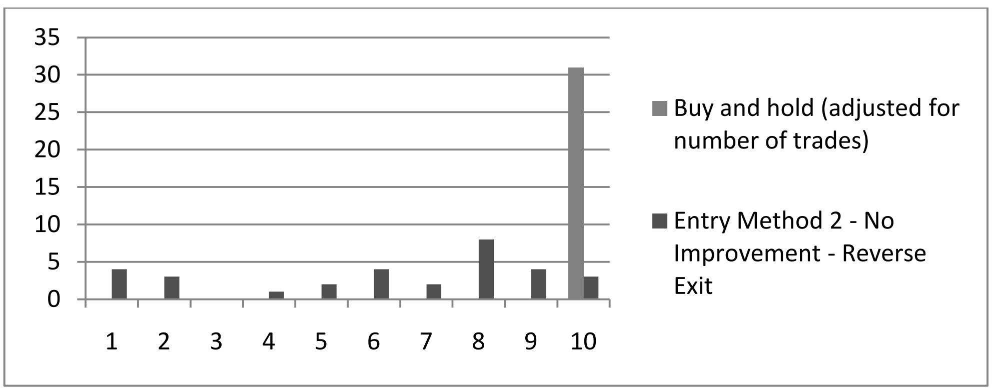
Graph 19: Buy and Hold and Entry Method 1, Trend Impr., Stop Loss (S&P 500)



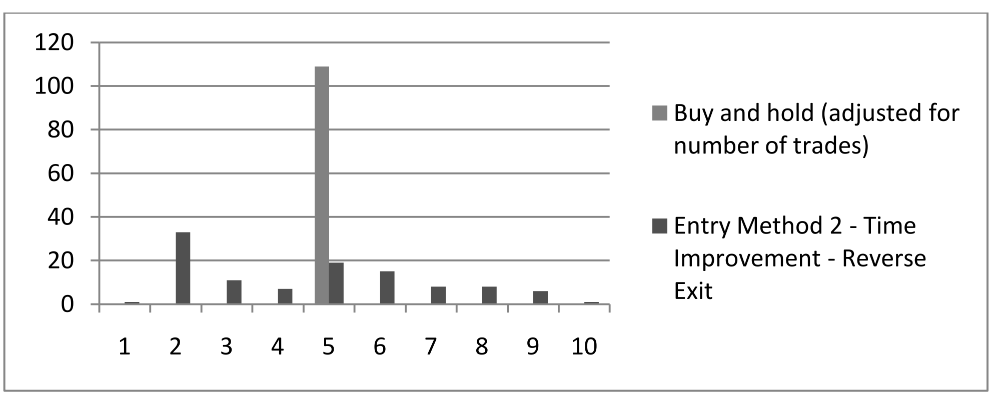
Graph 20: Buy and Hold and Entry Method 1, Trend and Time Impr., Reverse Exit (S&P 500)



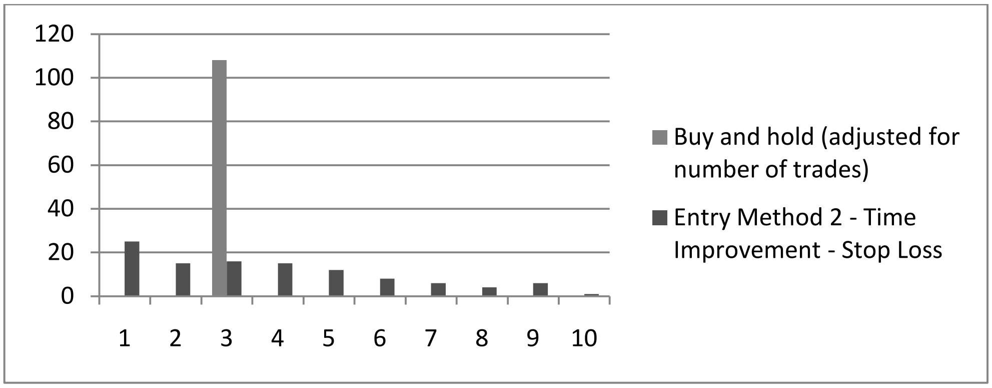
Graph 21: Buy and Hold and Entry Method 1, Trend and Time Impr., Stop Loss (S&P 500)



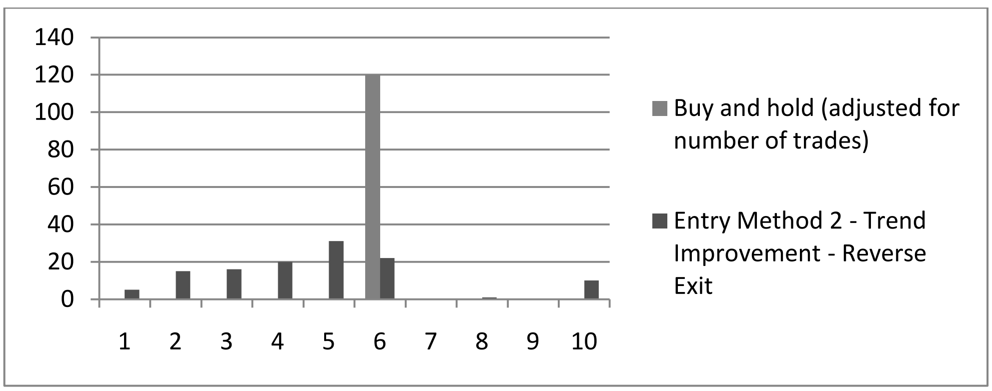
Graph 22: Buy and Hold and Entry Method 2, No Impr., Reverse Exit (S&P 500)



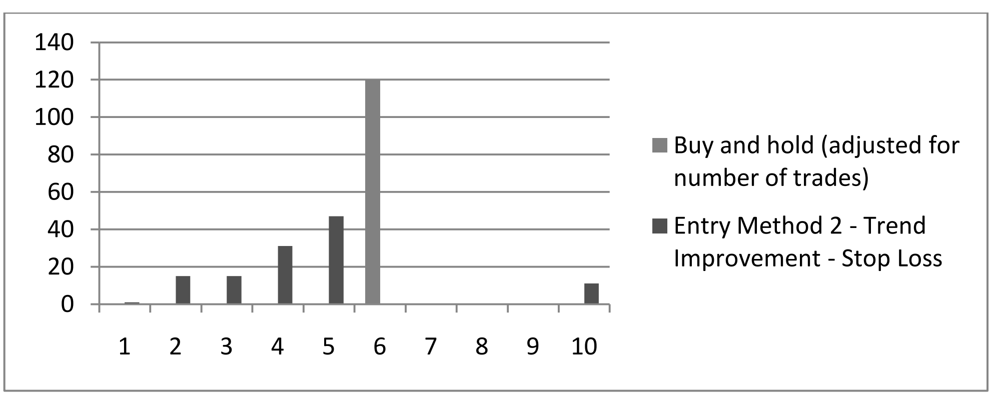
Graph 23: Buy and Hold and Entry Method 2, Time Impr., Reverse Exit (S&P 500)



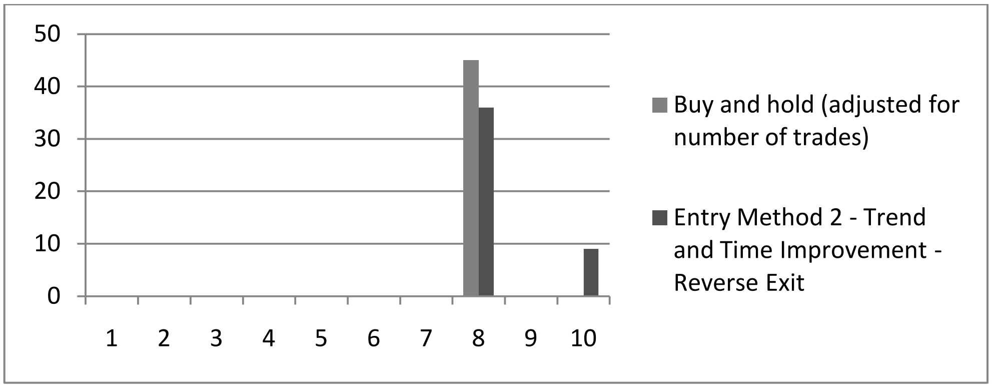
Graph 24: Buy and Hold and Entry Method 2, Time Impr., Stop Loss (S&P 500)



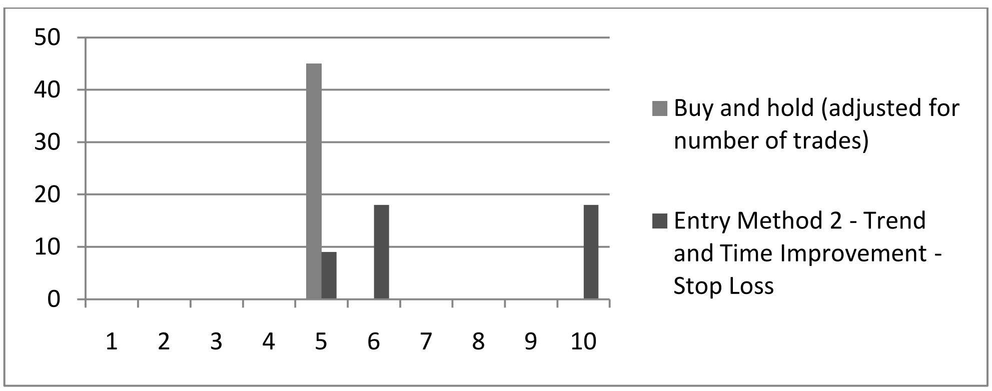
Graph 25: Buy and Hold and Entry Method 2, Trend Impr., Reverse Exit (S&P 500)



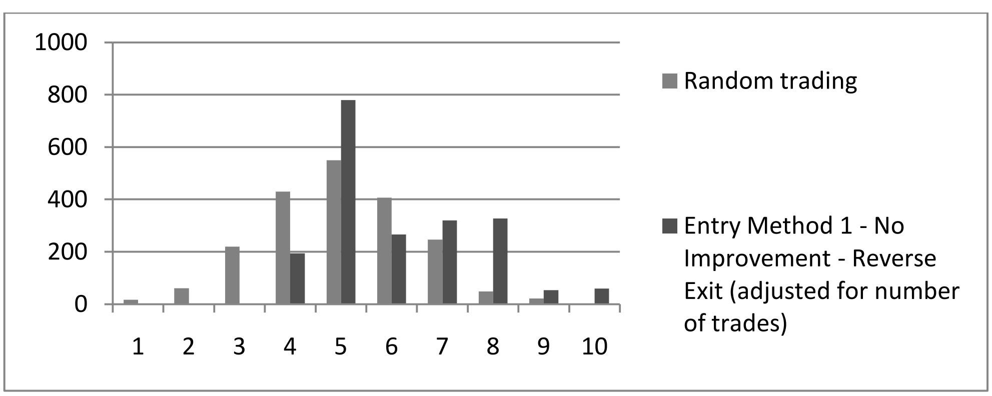
Graph 26: Buy and Hold and Entry Method 2, Trend Impr., Stop Loss (S&P 500)



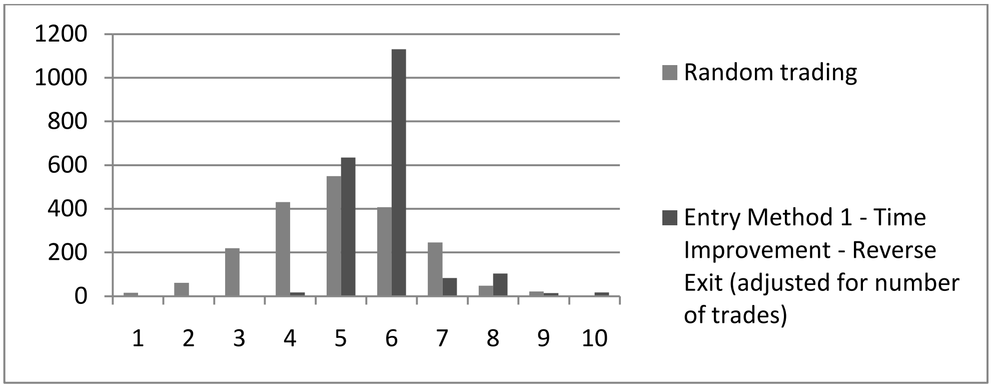
Graph 27: Buy and Hold and Entry Method 2, Trend and Time Impr., Reverse Exit (S&P 500)



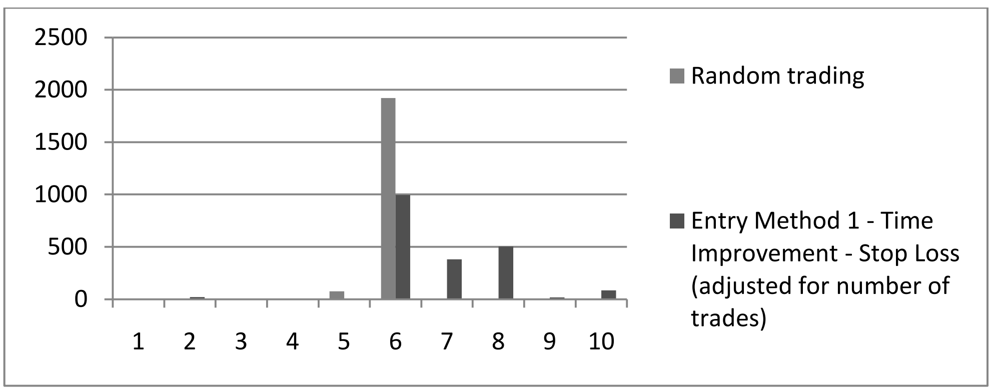
Graph 28: Buy and Hold and Entry Method 2, Trend and Time Impr., Stop Loss (S&P 500)



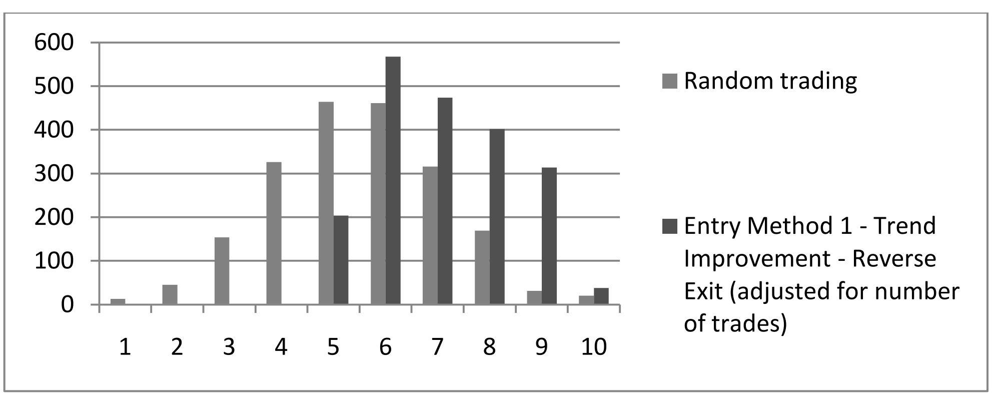
Graph 29: Random Trading and Entry Method 1, No Impr., Reverse Exit (T-Notes)



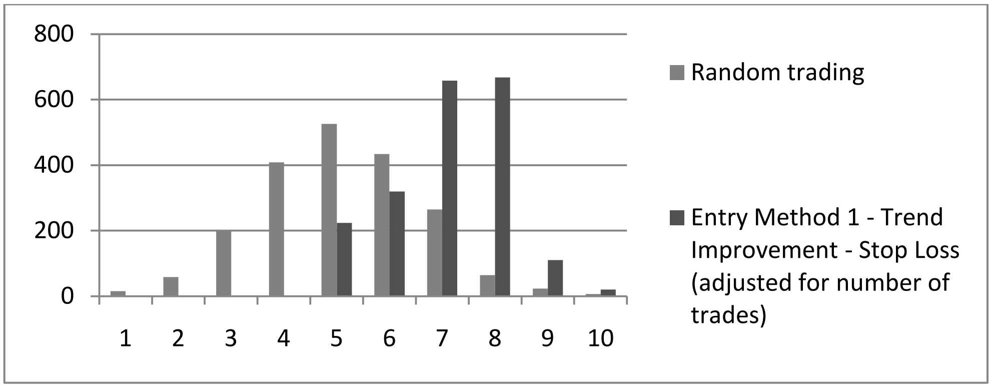
Graph 30: Random Trading and Entry Method 1, Time Impr., Reverse Exit (T-Notes)



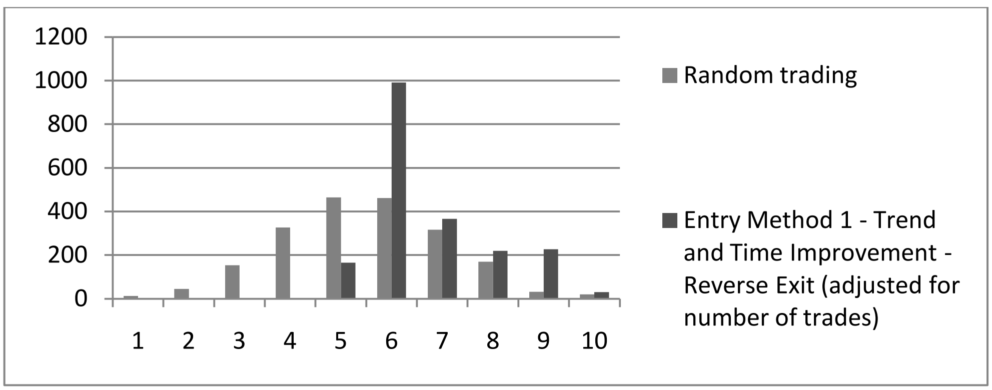
Graph 31: Random Trading and Entry Method 1, Time Impr., Stop Loss (T-Notes)



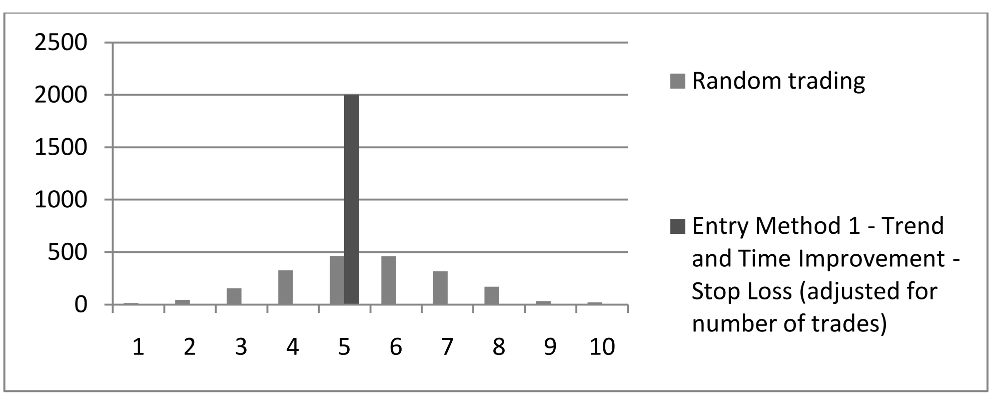
Graph 32: Random Trading and Entry Method 1, Trend Impr., Reverse Exit (T-Notes)



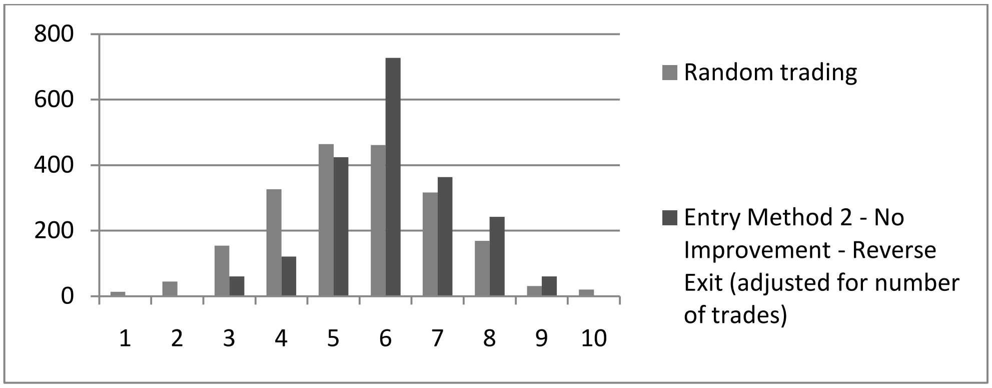
Graph 33: Random Trading and Entry Method 1, Trend Impr., Stop Loss (T-Notes)



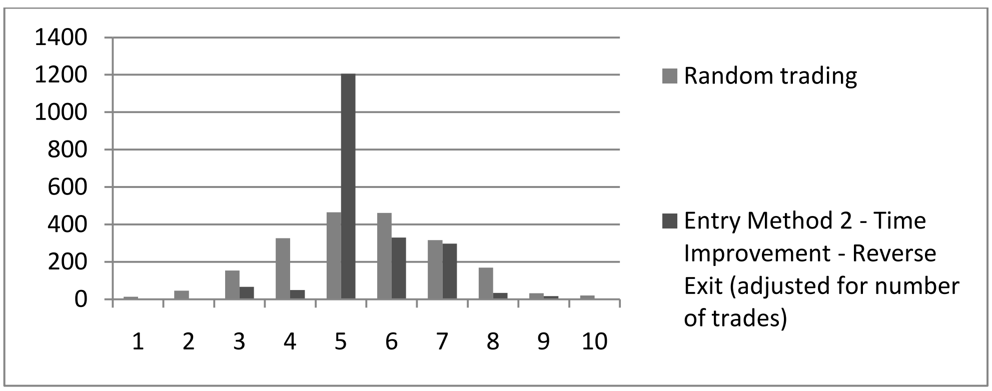
Graph 34: Random Trading and Entry Method 1, Trend and Time Impr., Reverse Exit (T-Notes)



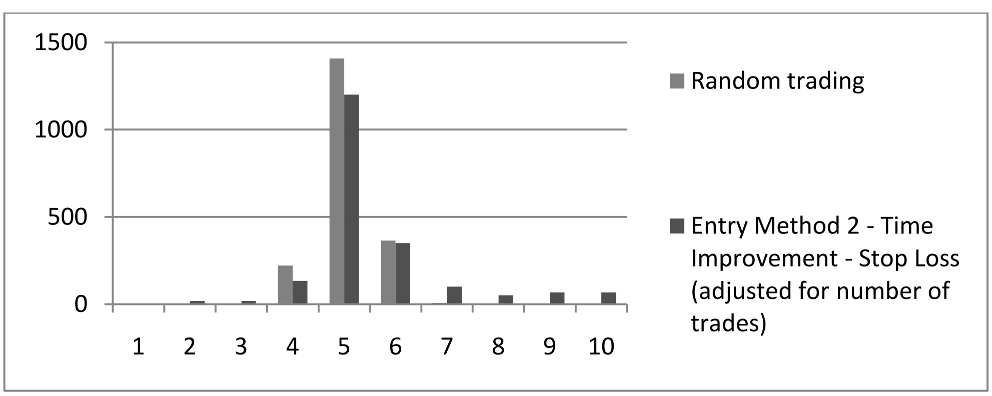
Graph 35: Random Trading and Entry Method 1, Trend and Time Impr., Stop Loss (T-Notes)



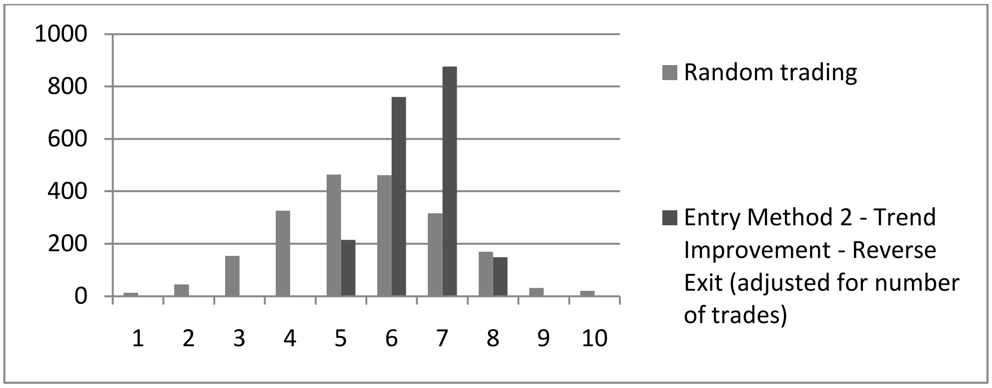
Graph 36: Random Trading and Entry Method 2, No Impr., Reverse Exit (T-Notes)



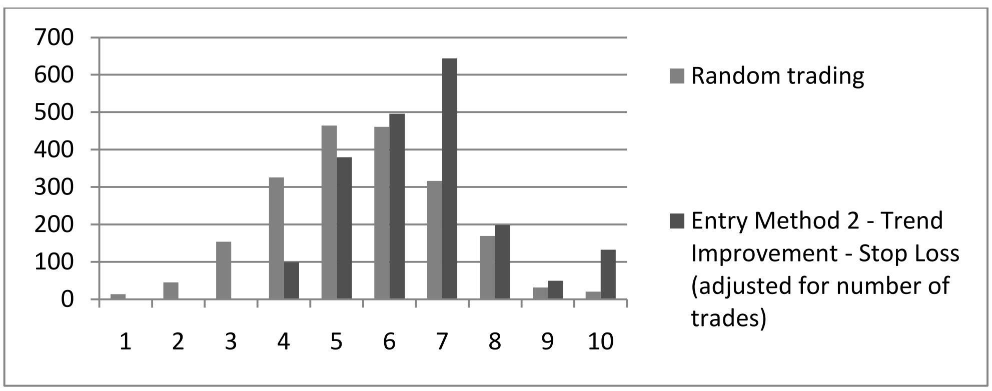
Graph 37: Random Trading and Entry Method 2, Time Impr., Reverse Exit (T-Notes)



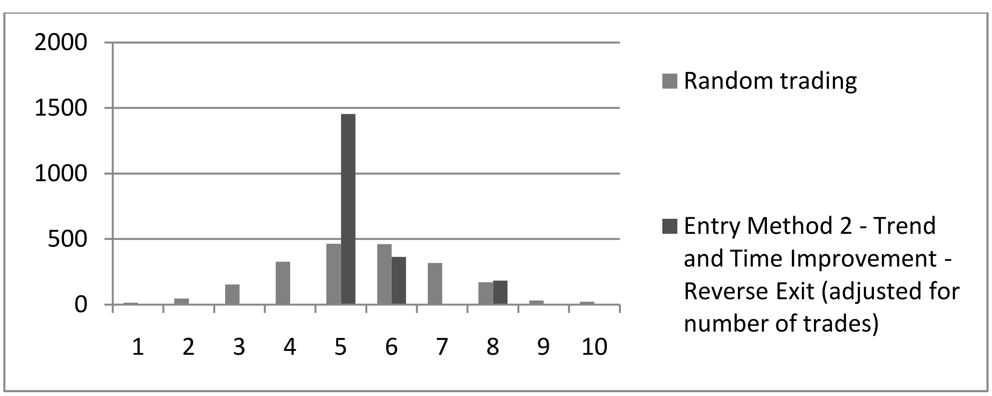
Graph 38: Random Trading and for Entry Method 2, Time Impr., Stop Loss (T-Notes)



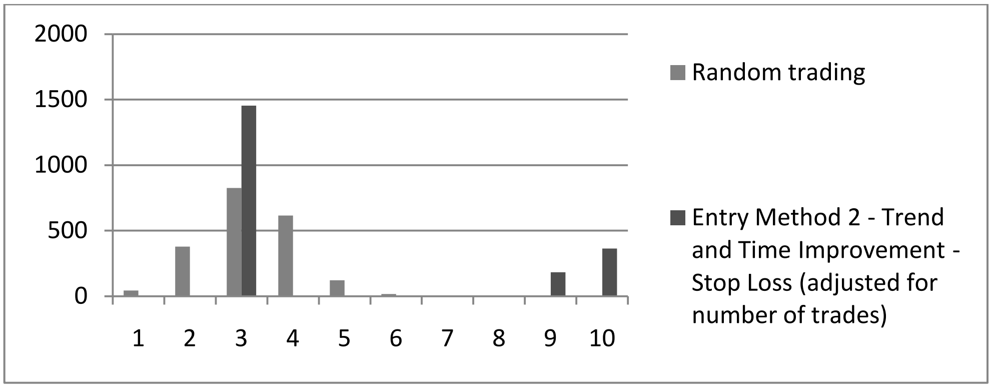
Graph 39: Random Trading and Entry Method 2, Trend Impr., Reverse Exit (T-Notes)



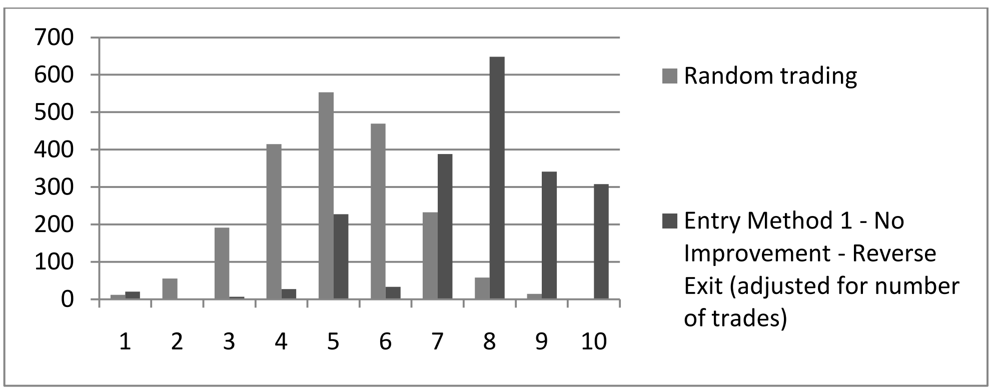
Graph 40: Random Trading and Entry Method 2, Trend Impr., Stop Loss (T-Notes)



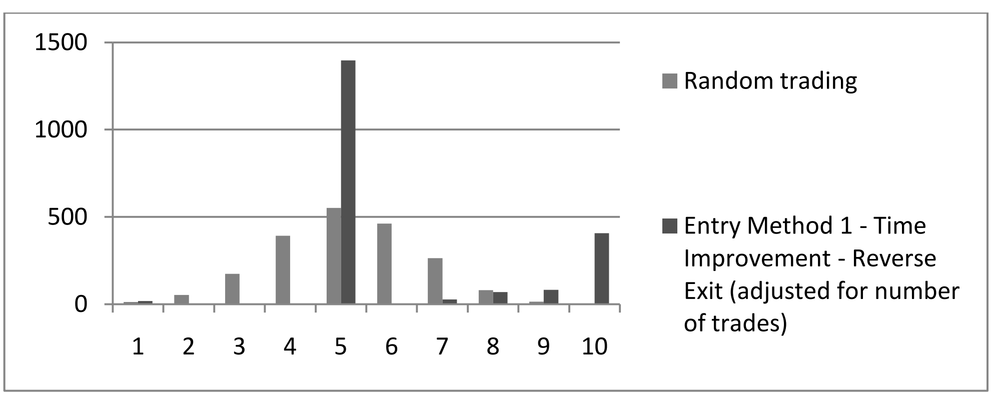
Graph 41: Random Trading and Entry Method 2, Trend and Time Impr., Reverse Exit (T-Notes)



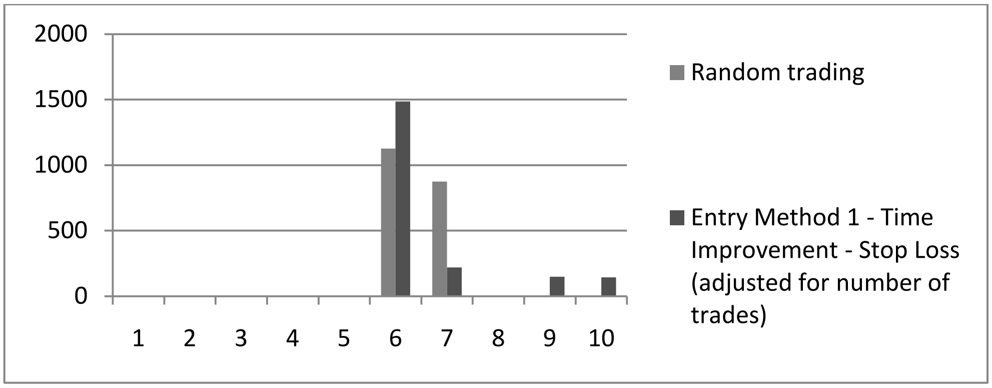
Graph 42: Random Trading and Entry Method 2, Trend and Time Impr., Stop Loss (T-Notes)



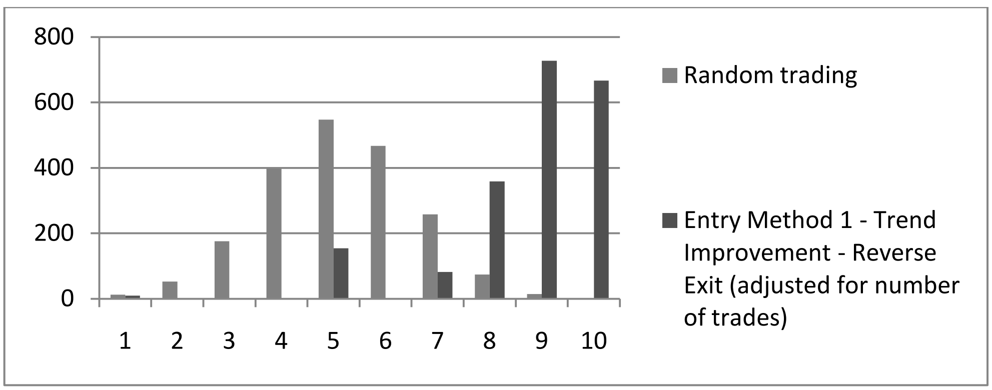
Graph 43: Random Trading and Entry Method 1, No Impr., Reverse Exit (Gold)



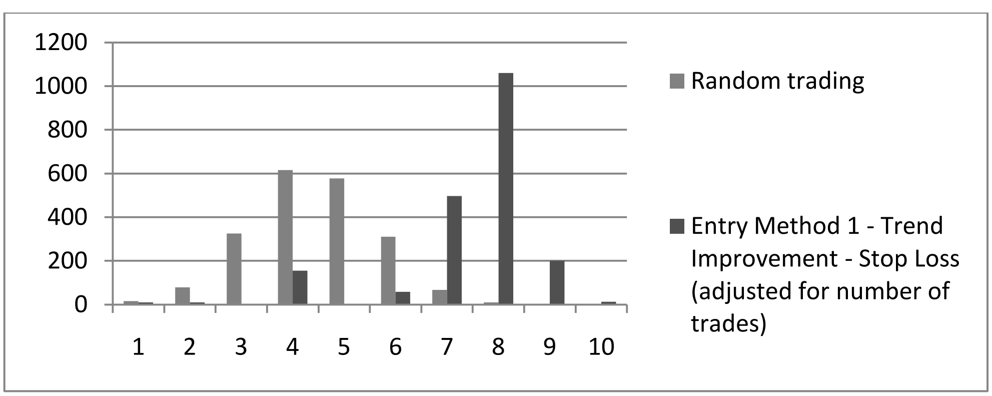
Graph 44: Random Trading and Entry Method 1, Time Impr., Reverse Exit (Gold)



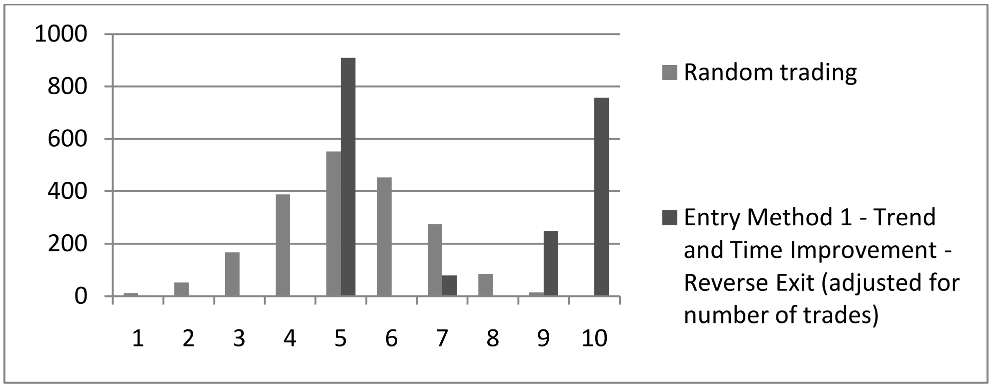
Graph 45: Random Trading and Entry Method 1, Time Impr., Stop Loss (Gold)



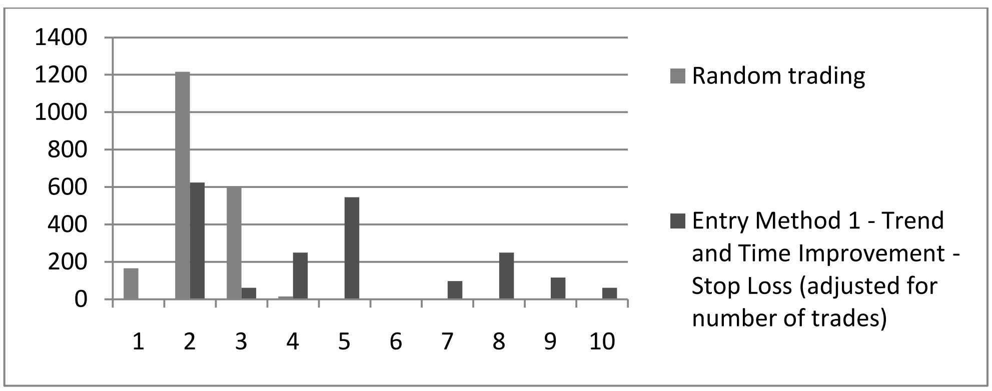
Graph 46: Random Trading and Entry Method 1, Trend Impr., Reverse Exit (Gold)



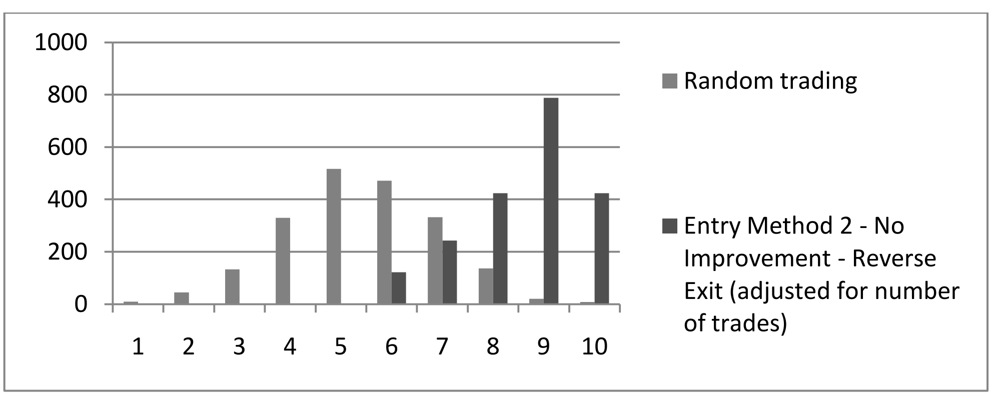
Graph 47: Random Trading and Entry Method 1, Trend Impr., Stop Loss (Gold)



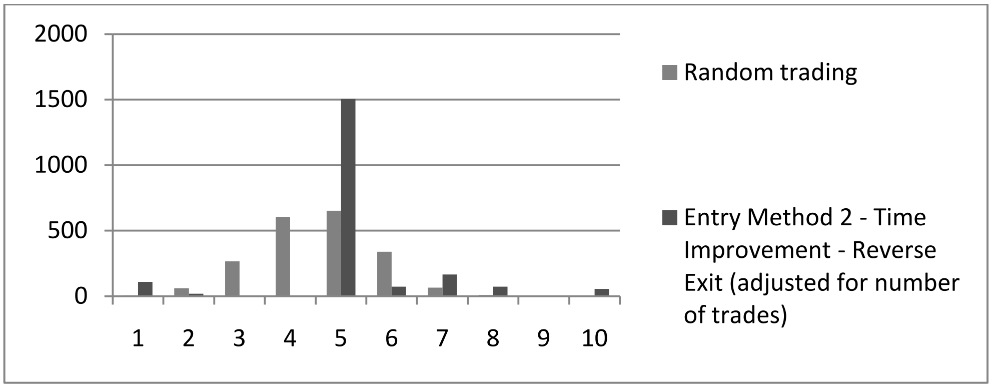
Graph 48: Random Trading and Entry Method 1, Trend and Time Impr., Reverse Exit (Gold)



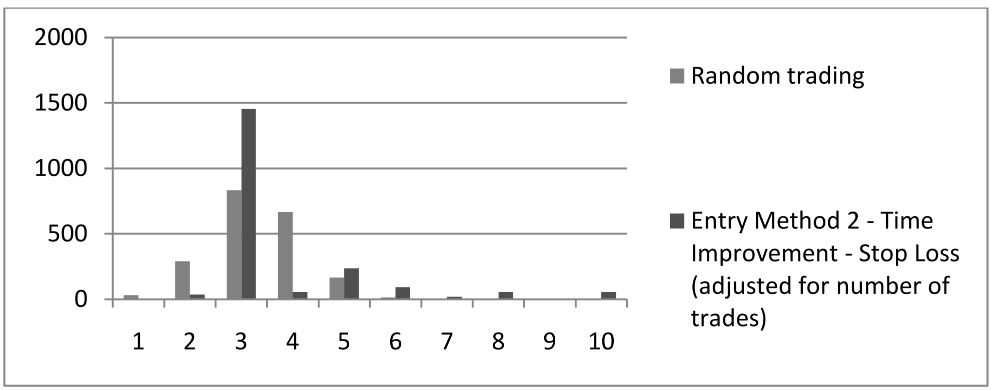
Graph 49: Random Trading and Entry Method 1, Trend and Time Impr., Stop Loss (Gold)



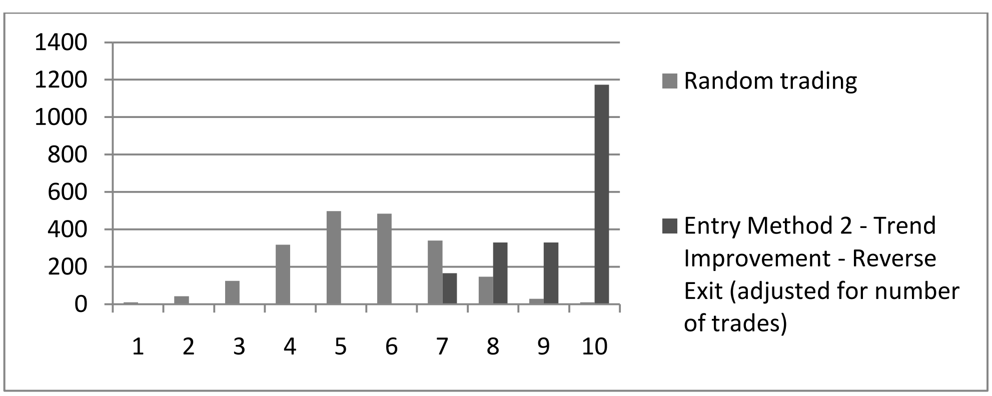
Graph 50: Random Trading and Entry Method 2, No Impr., Reverse Exit (Gold)



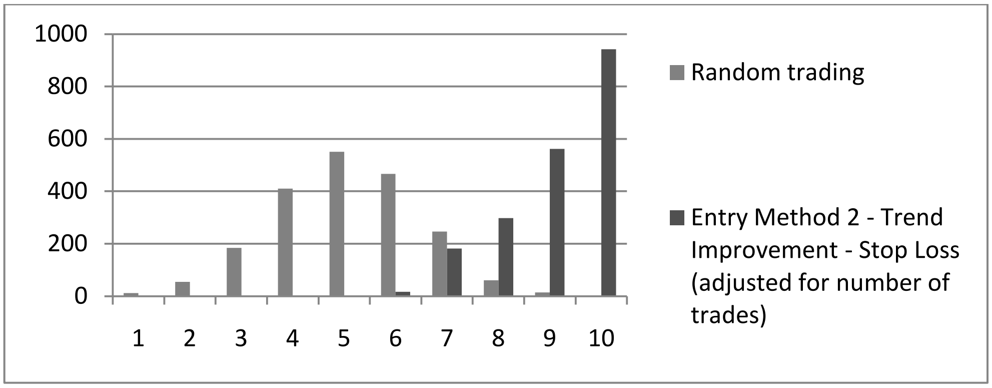
Graph 51: Random Trading and Entry Method 2, Time Impr., Reverse Exit (Gold)



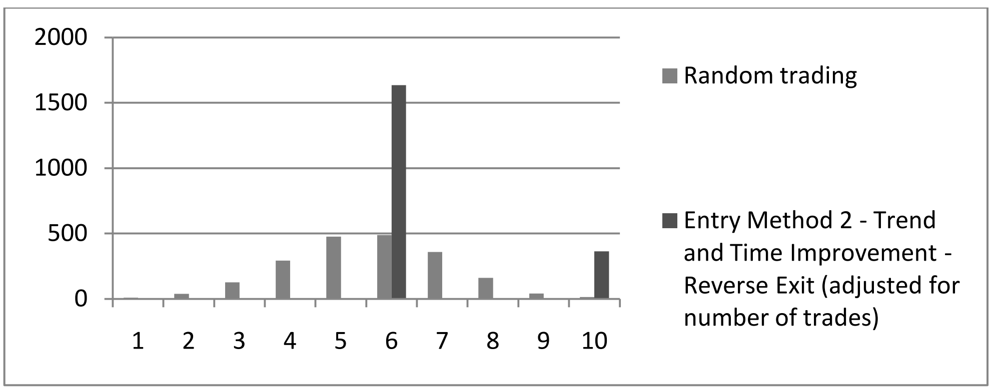
Graph 52: Random Trading and for Entry Method 2, Time Impr., Stop Loss (Gold)



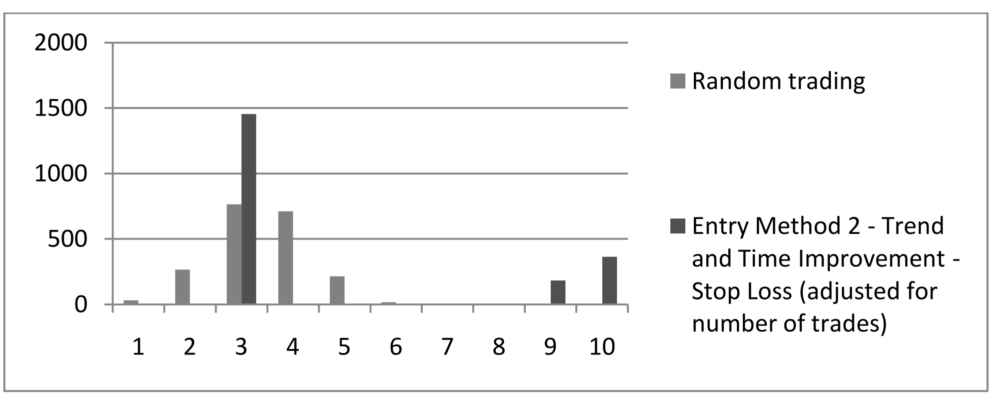
Graph 53: Random Trading and Entry Method 2, Trend Impr., Reverse Exit (Gold)



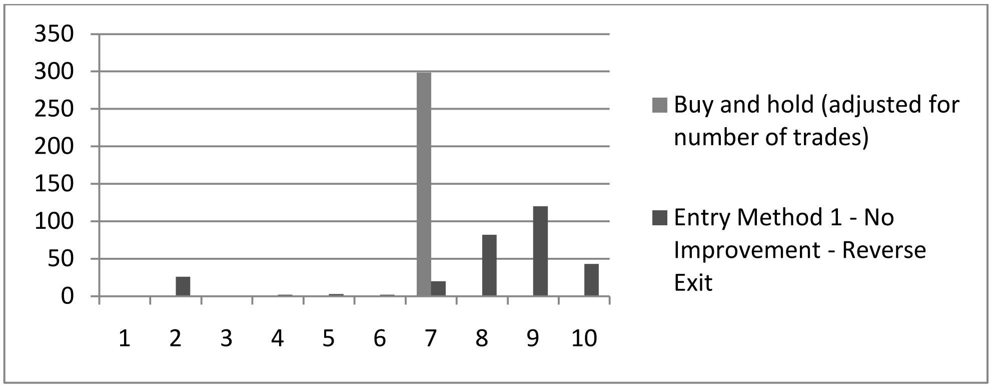
Graph 54: Random Trading and Entry Method 2, Trend Impr., Stop Loss (Gold)



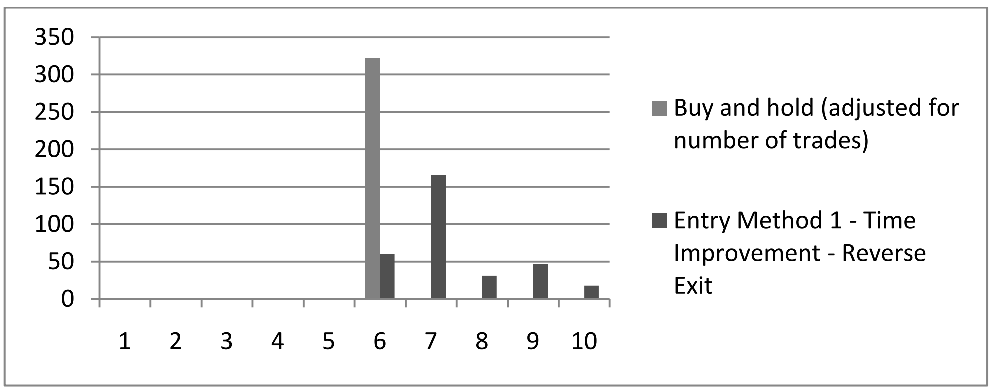
Graph 55: Random Trading and Entry Method 2, Trend and Time Impr., Reverse Exit (Gold)



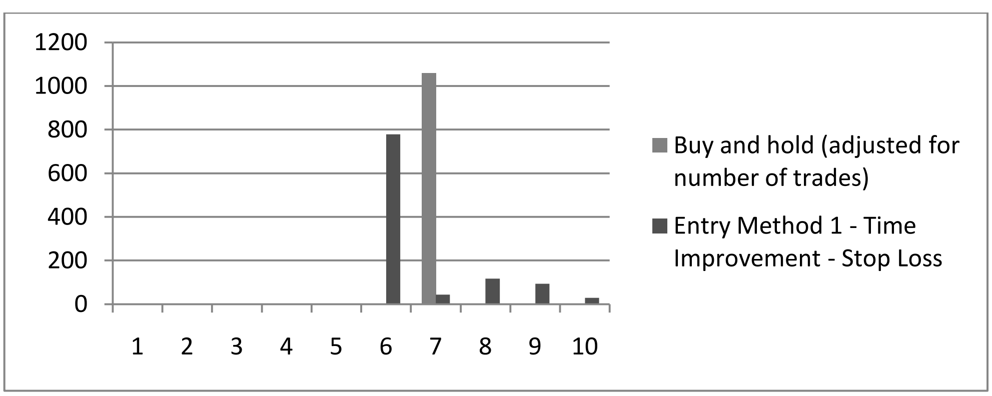
Graph 56: Random Trading and Entry Method 2, Trend and Time Impr., Stop Loss (Gold)



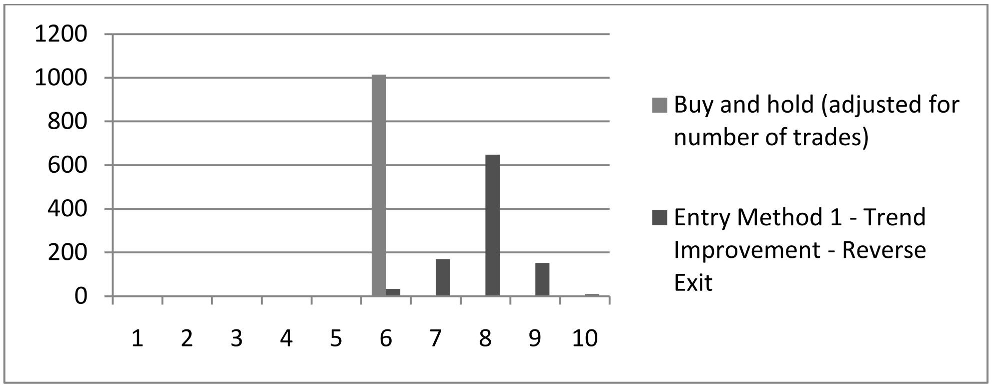
Graph 57: Buy and Hold and Entry Method 1, No Impr., Reverse Exit (Gold)



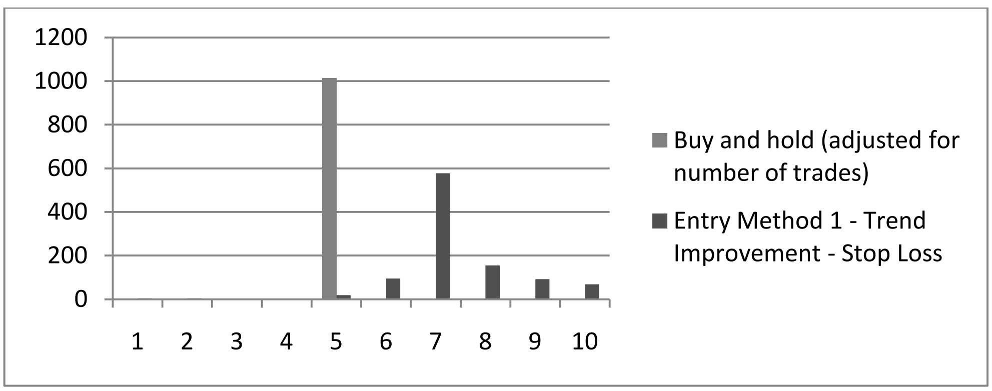
Graph 58: Buy and Hold and Entry Method 1, Time Impr., Reverse Exit (Gold)



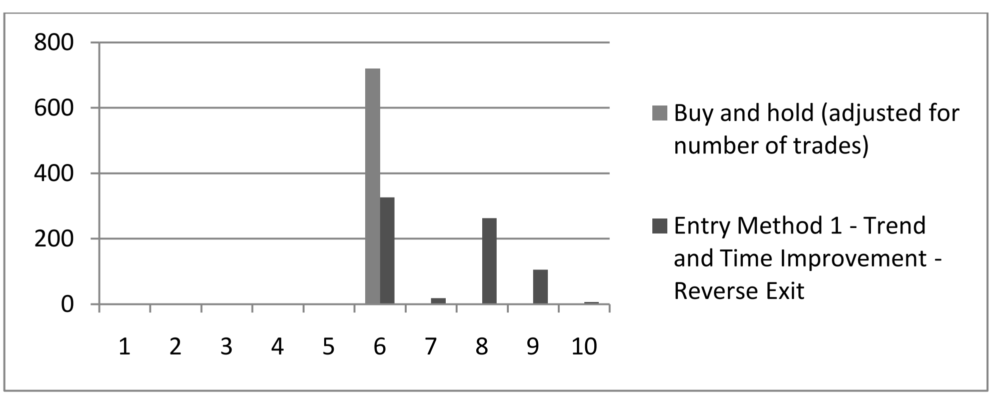
Graph 59: Buy and Hold and Entry Method 1, Time Impr., Stop Loss (Gold)



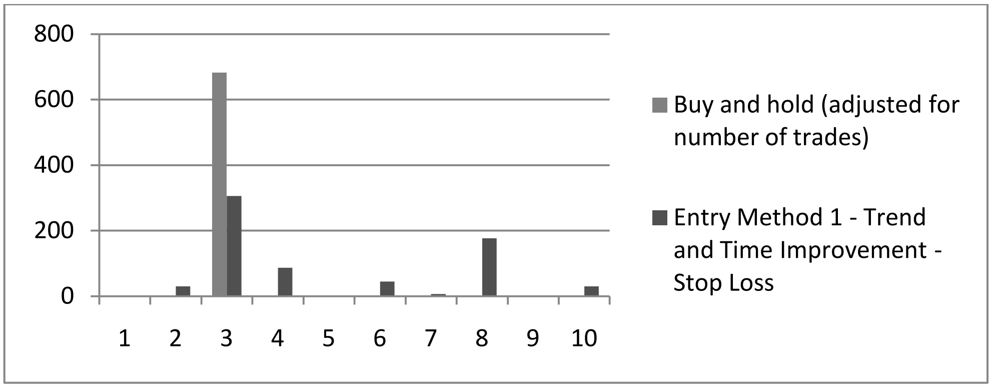
Graph 60: Buy and Hold and Entry Method 1, Trend Impr., Reverse Exit (Gold)



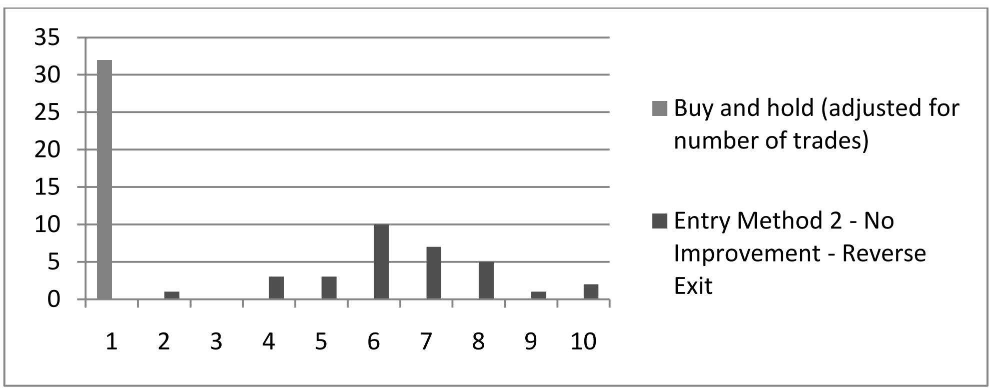
Graph 61: Buy and Hold and Entry Method 1, Trend Impr., Stop Loss (Gold)



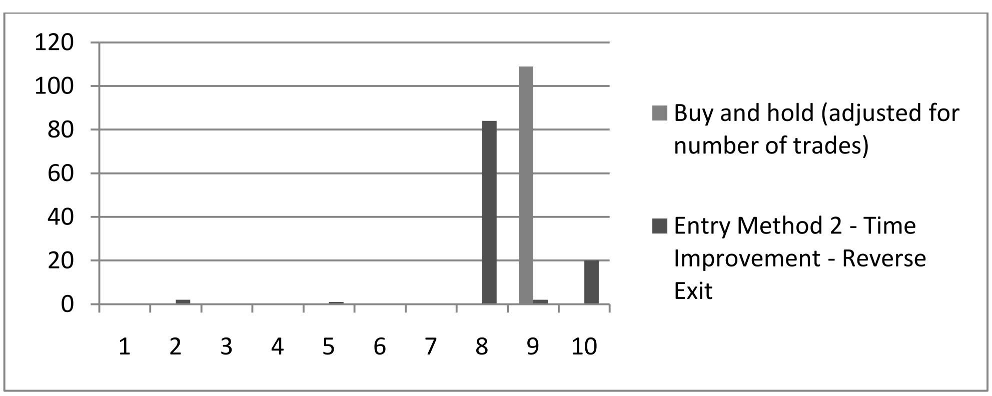
Graph 62: Buy and Hold and Entry Method 1, Trend and Time Impr., Reverse Exit (Gold)



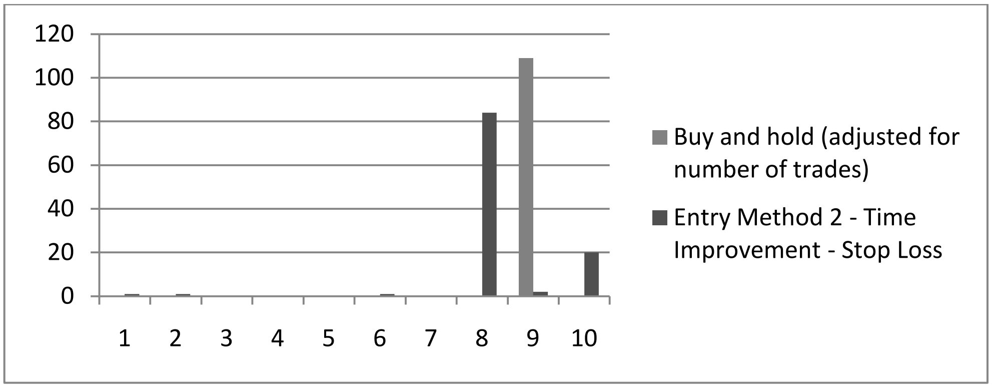
Graph 63: Buy and Hold and Entry Method 1, Trend and Time Impr., Stop Loss (Gold)



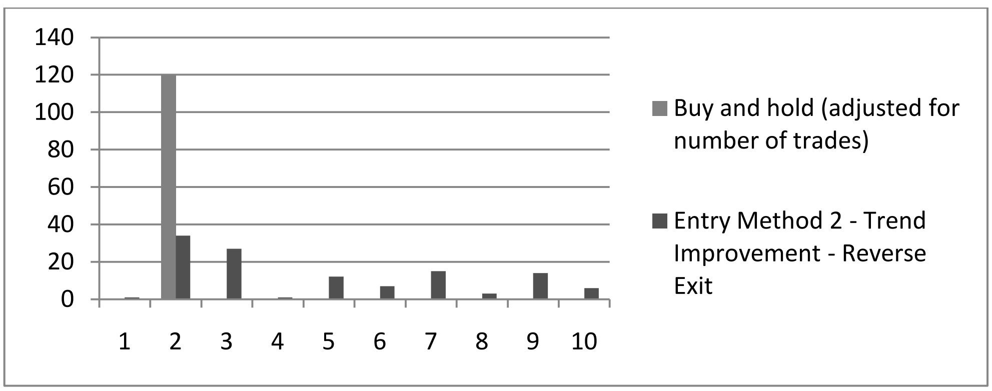
Graph 64: Buy and Hold and Entry Method 2, No Impr., Reverse Exit (Gold)



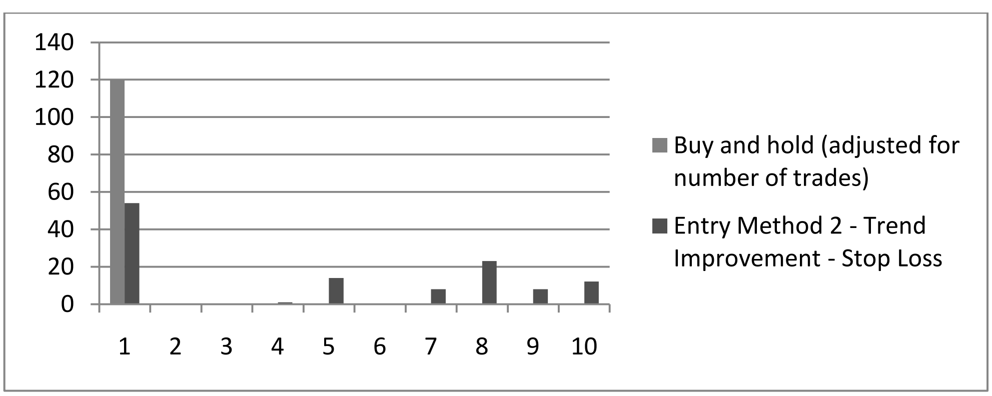
Graph 65: Buy and Hold and Entry Method 2, Time Impr., Reverse Exit (Gold)



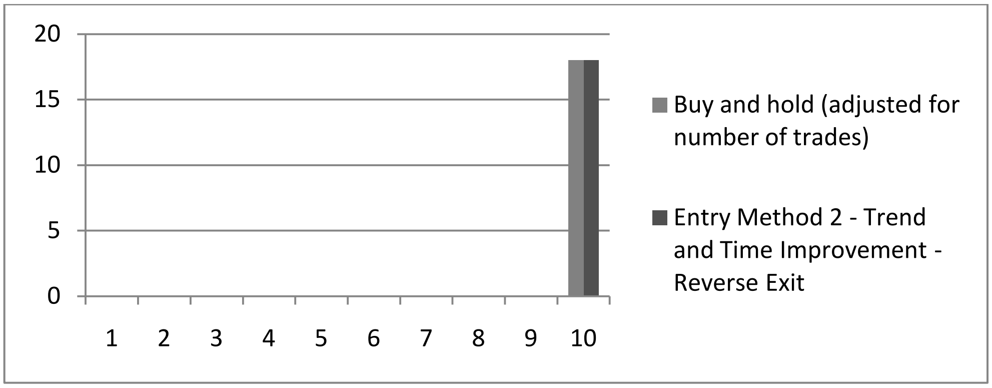
Graph 66: Buy and Hold and Entry Method 2, Time Impr., Stop Loss (Gold)



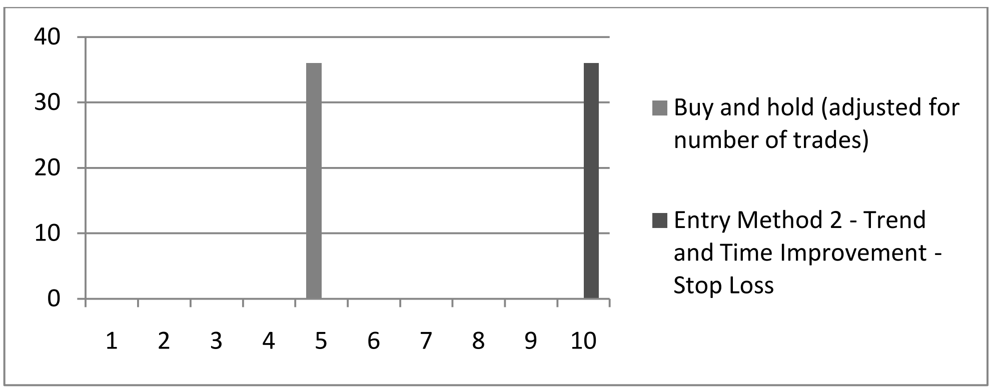
Graph 67: Buy and Hold and Entry Method 2, Trend Impr., Reverse Exit (Gold)



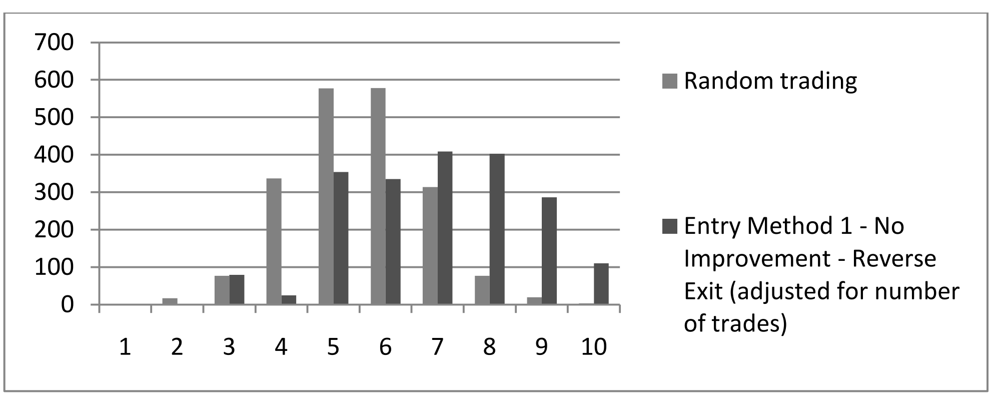
Graph 68: Buy and Hold and Entry Method 2, Trend Impr., Stop Loss (Gold)



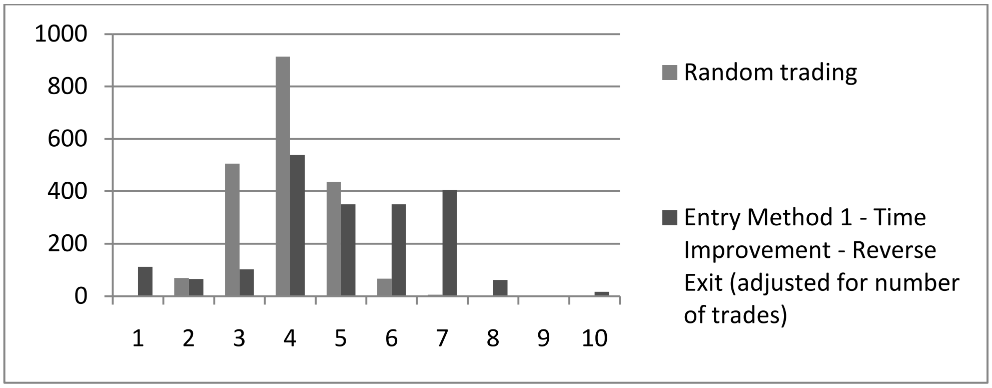
Graph 69: Buy and Hold and Entry Method 2, Trend and Time Impr., Reverse Exit (Gold)



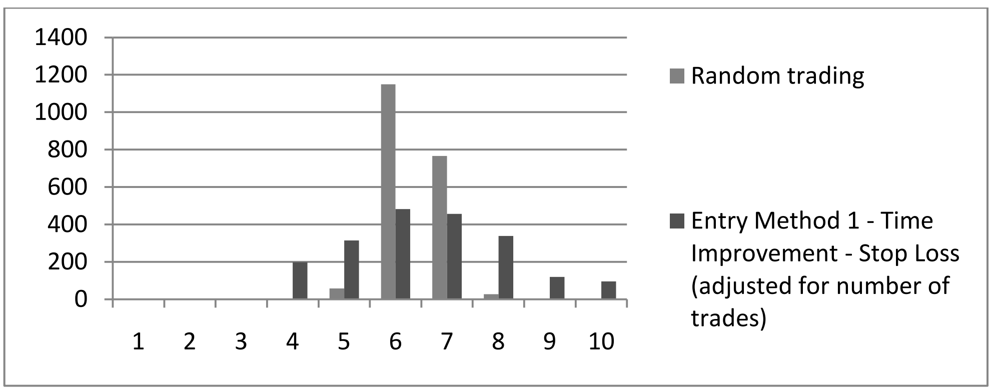
Graph 70: Buy and Hold and Entry Method 2, Trend and Time Impr., Stop Loss (Gold)



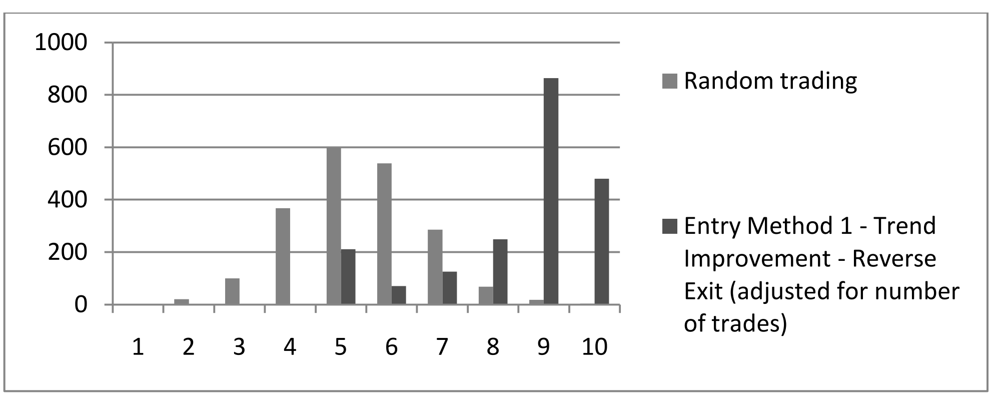
Graph 71: Random Trading and Entry Method 1, No Impr., Reverse Exit (KO)



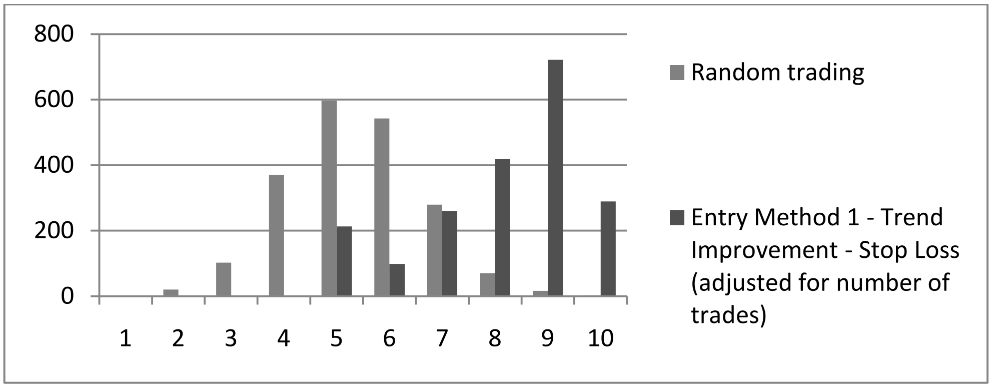
Graph 72: Random Trading and Entry Method 1, Time Impr., Reverse Exit (KO)



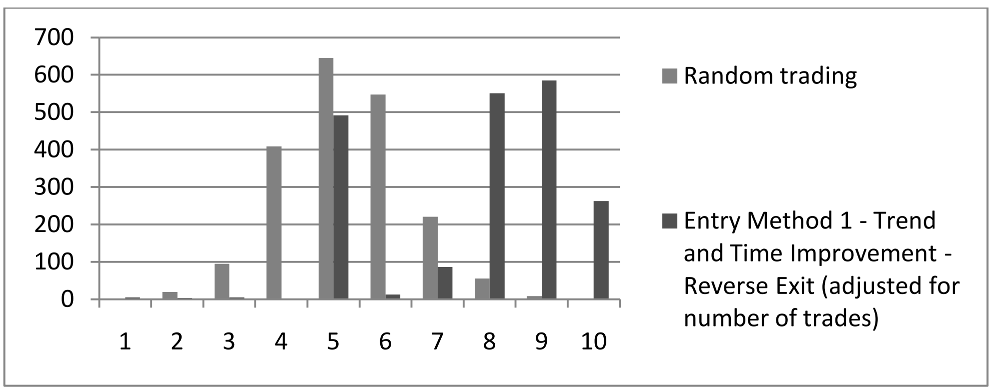
Graph 73: Random Trading and Entry Method 1, Time Impr., Stop Loss (KO)



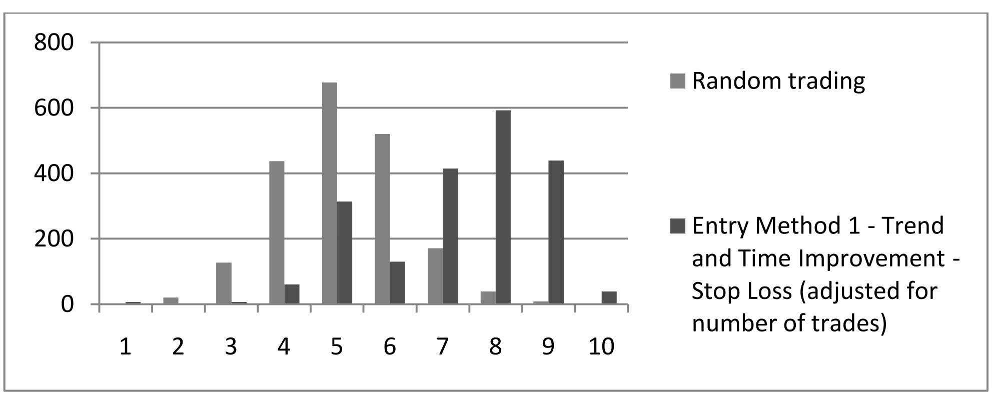
Graph 74: Random Trading and Entry Method 1, Trend Impr., Reverse Exit (KO)



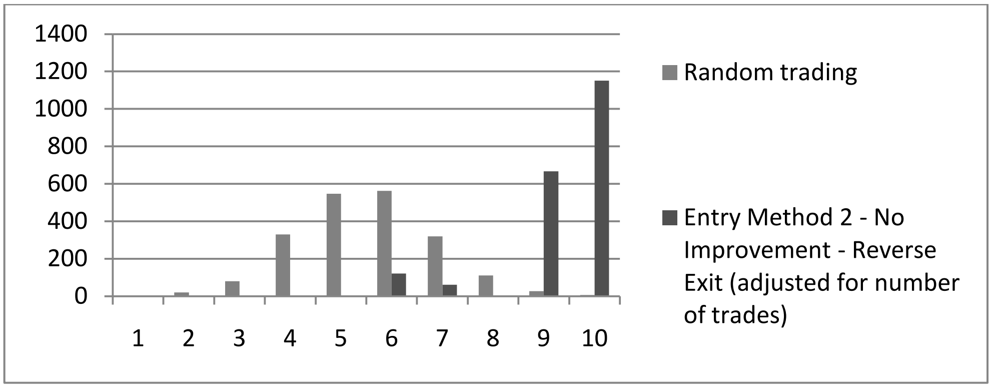
Graph 75: Random Trading and Entry Method 1, Trend Impr., Stop Loss (KO)



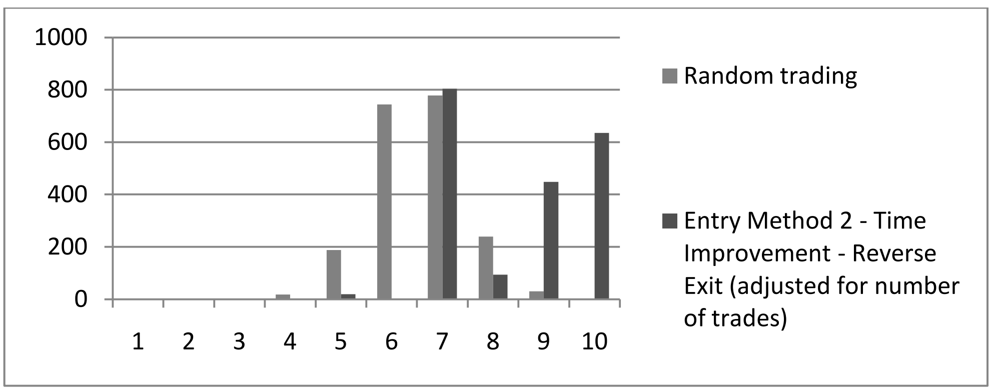
Graph 76: Random Trading and Entry Method 1, Trend and Time Impr., Reverse Exit (KO)



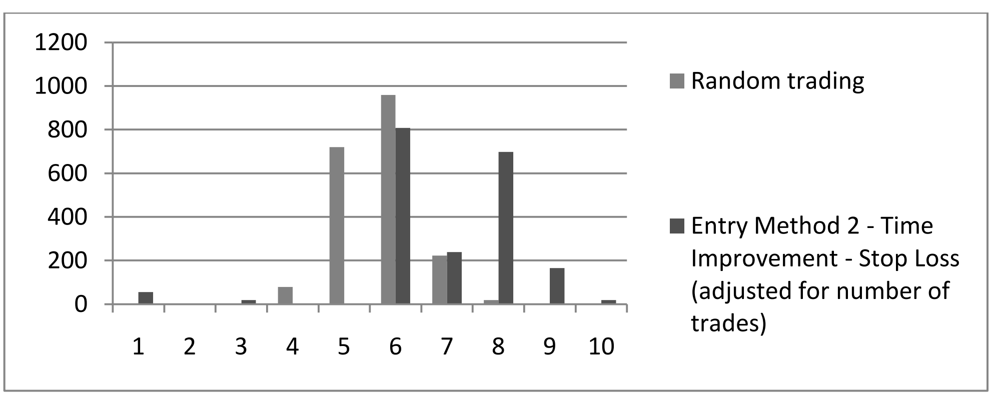
Graph 77: Random Trading and Entry Method 1, Trend and Time Impr., Stop Loss (KO)



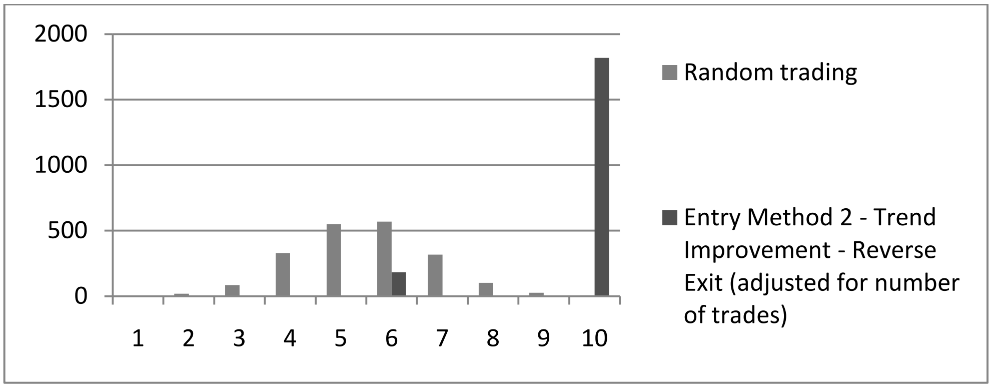
Graph 78: Random Trading and Entry Method 2, No Impr., Reverse Exit (KO)



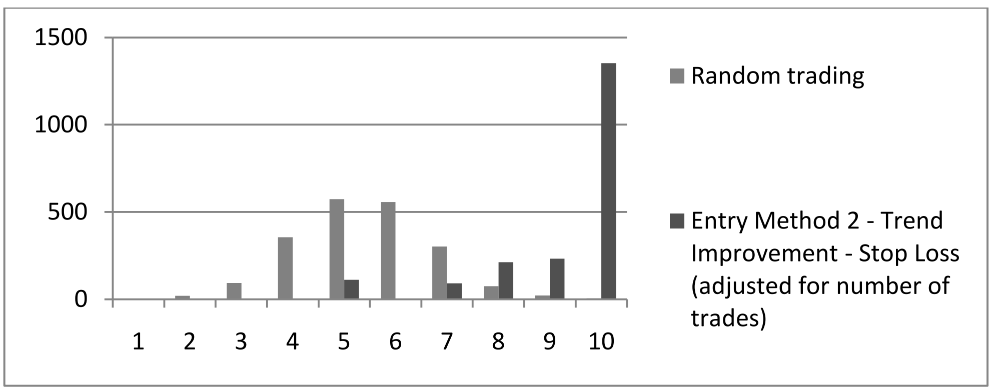
Graph 79: Random Trading and Entry Method 2, Time Impr., Reverse Exit (KO)



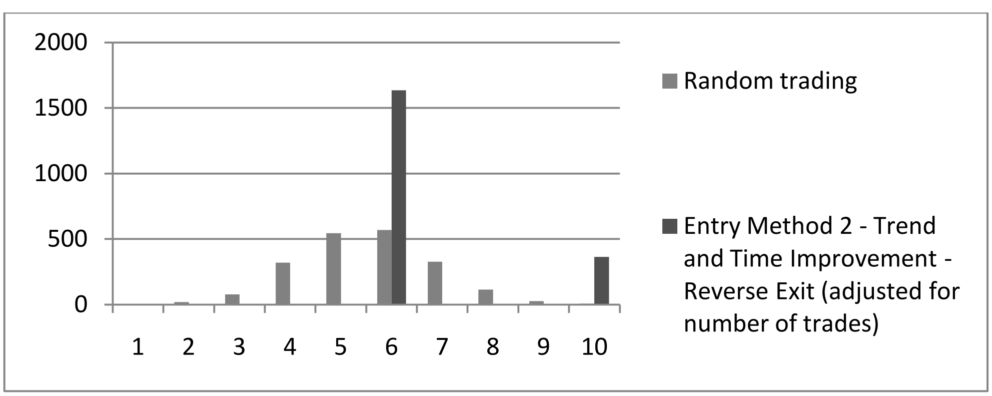
Graph 80: Random Trading and for Entry Method 2, Time Impr., Stop Loss (KO)



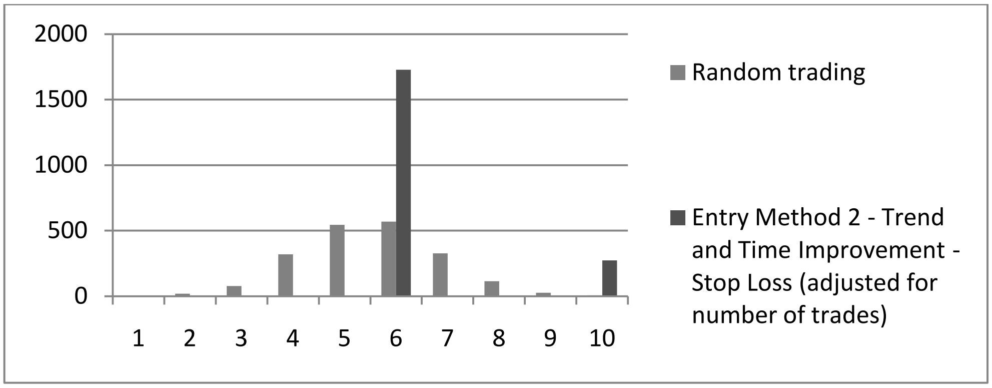
Graph 81: Random Trading and Entry Method 2, Trend Impr., Reverse Exit (KO)



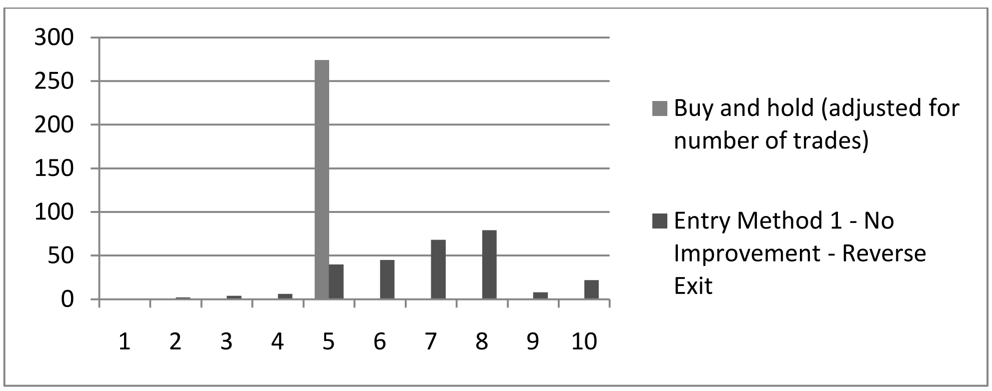
Graph 82: Random Trading and Entry Method 2, Trend Impr., Stop Loss (KO)



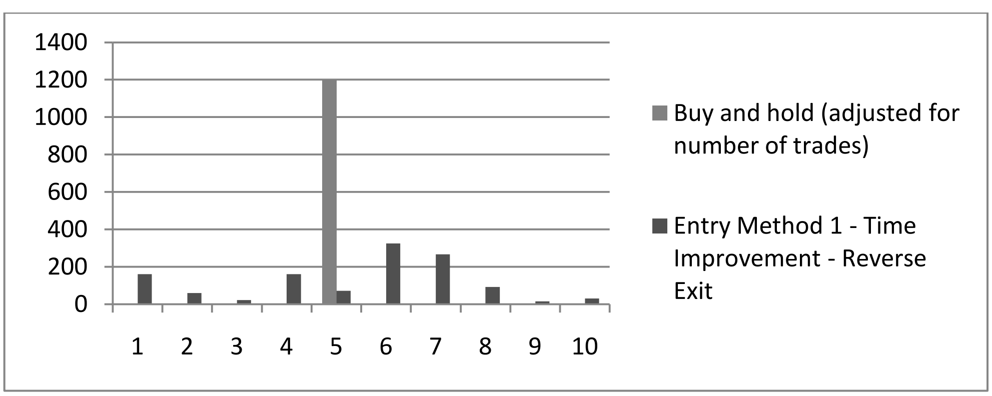
Graph 83: Random Trading and Entry Method 2, Trend and Time Impr., Reverse Exit (KO)



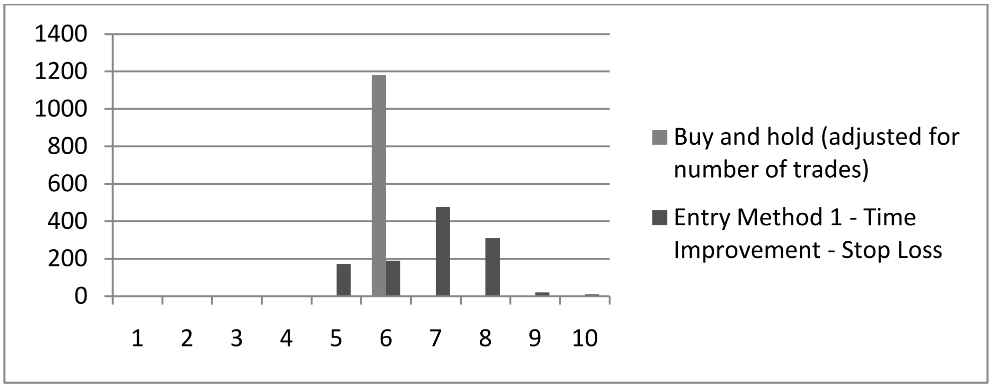
Graph 84: Random Trading and Entry Method 2, Trend and Time Impr., Stop Loss (KO)



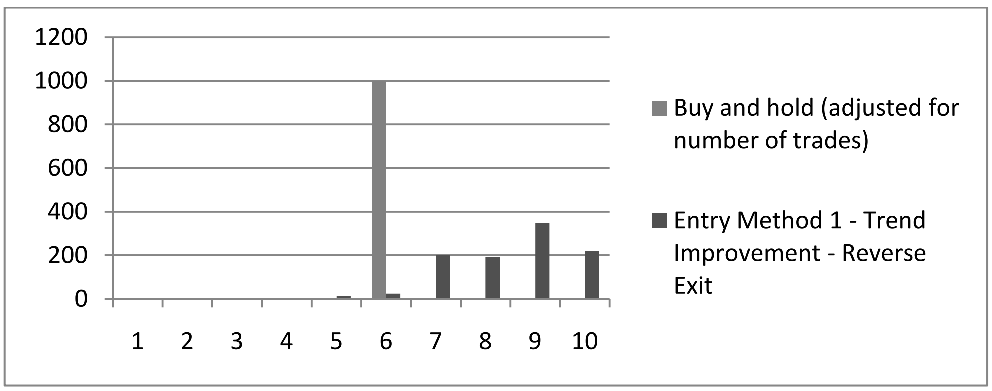
Graph 85: Buy and Hold and Entry Method 1, No Impr., Reverse Exit (KO)



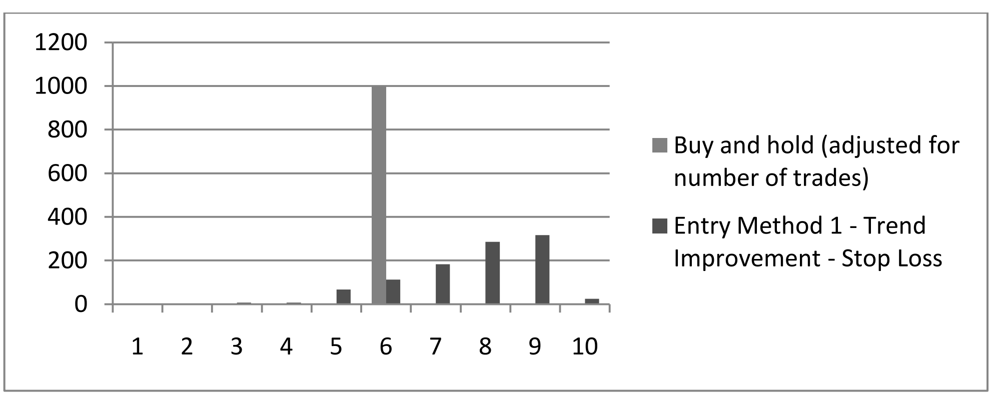
Graph 86: Buy and Hold and Entry Method 1, Time Impr., Reverse Exit (KO)



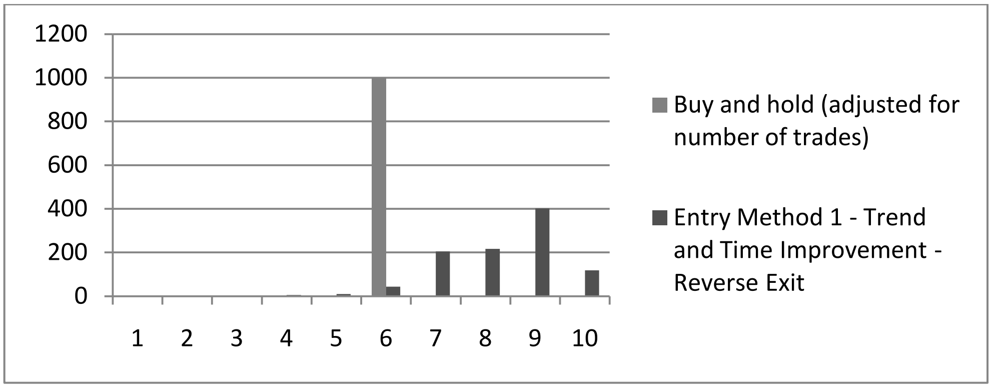
Graph 87: Buy and Hold and Entry Method 1, Time Impr., Stop Loss (KO)



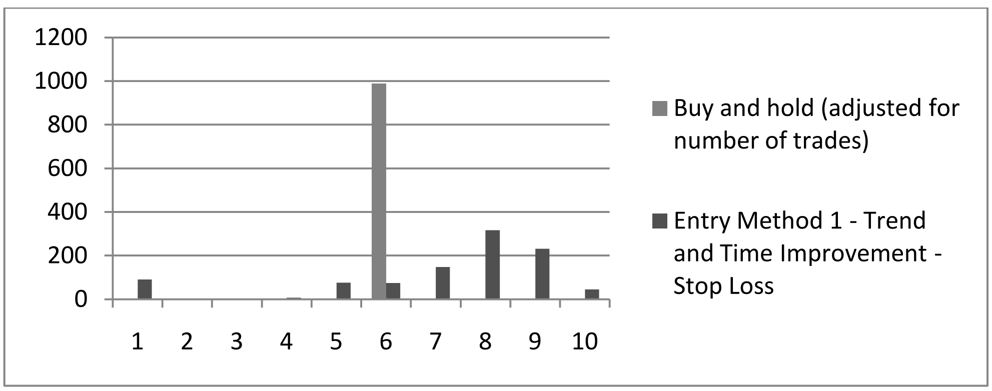
Graph 88: Buy and Hold and Entry Method 1, Trend Impr., Reverse Exit (KO)



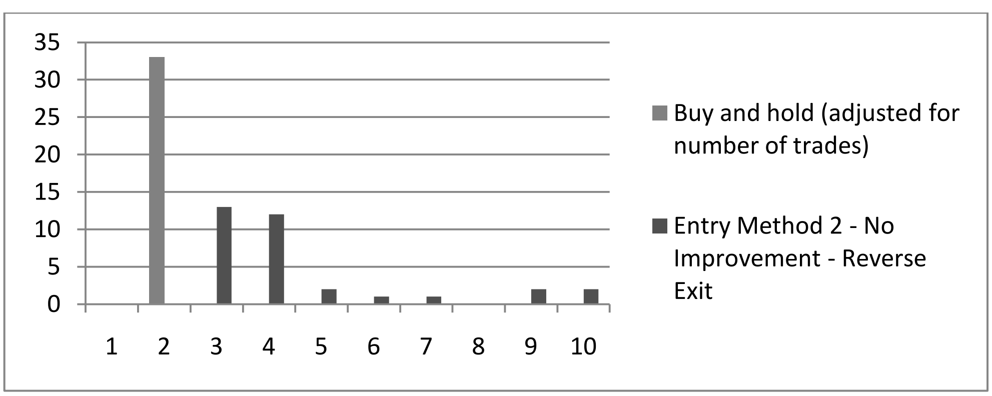
Graph 89: Buy and Hold and Entry Method 1, Trend Impr., Stop Loss (KO)



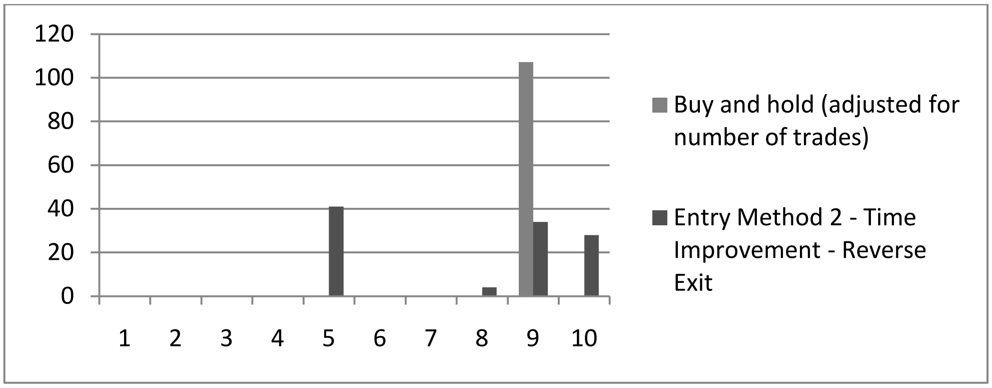
Graph 90: Buy and Hold and Entry Method 1, Trend and Time Impr., Reverse Exit (KO)



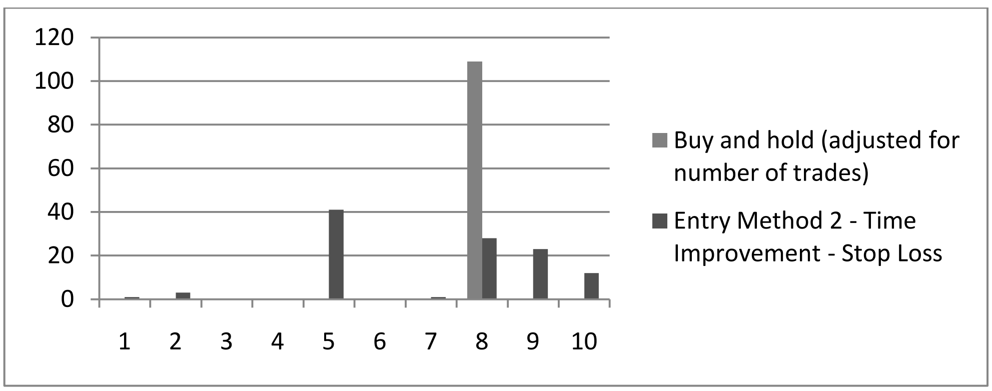
Graph 91: Buy and Hold and Entry Method 1, Trend and Time Impr., Stop Loss (KO)



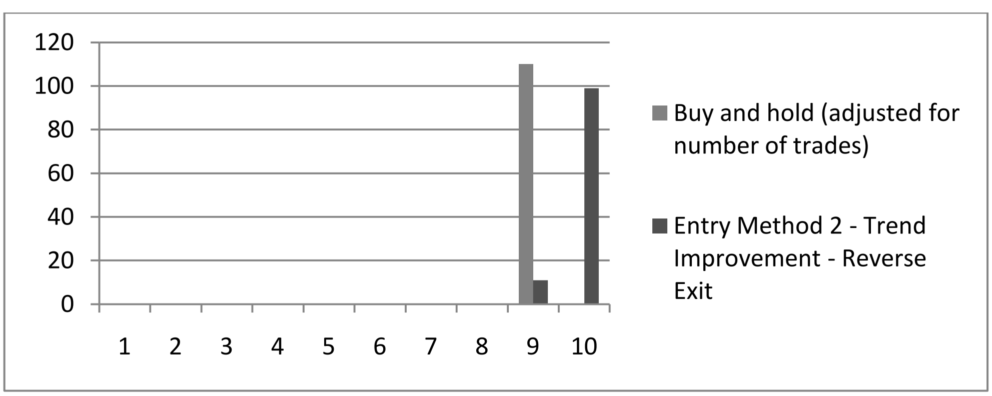
Graph 92: Buy and Hold and Entry Method 2, No Impr., Reverse Exit (KO)



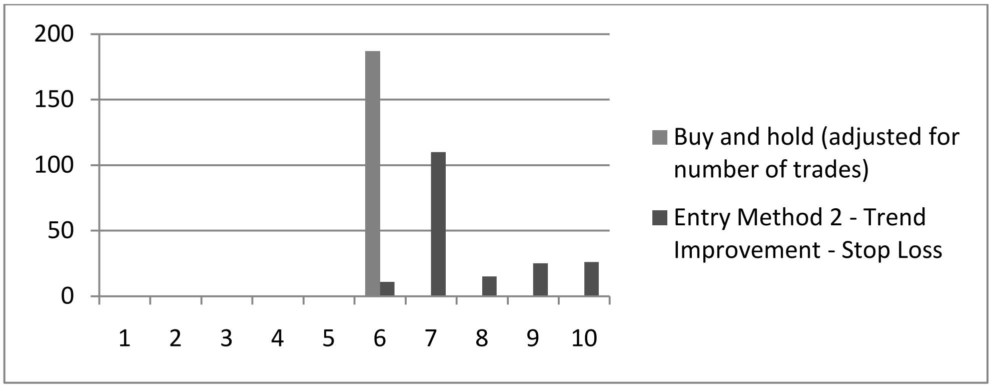
Graph 93: Buy and Hold and Entry Method 2, Time Impr., Reverse Exit (KO)



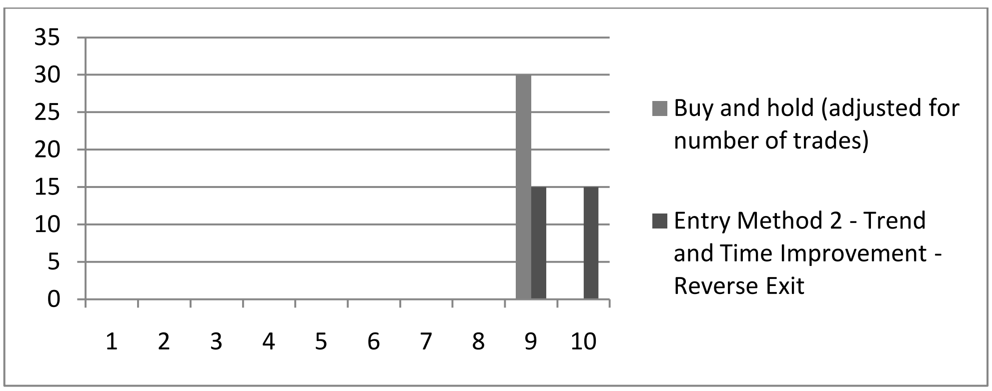
Graph 94: Buy and Hold and Entry Method 2, Time Impr., Stop Loss (KO)



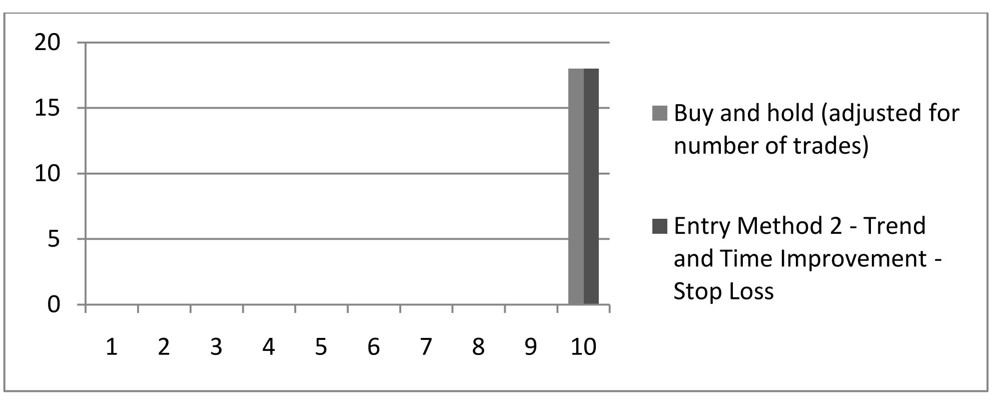
Graph 95: Buy and Hold and Entry Method 2, Trend Impr., Reverse Exit (KO)



Graph 96: Buy and Hold and Entry Method 2, Trend Impr., Stop Loss (KO)



Graph 97: Buy and Hold and Entry Method 2, Trend and Time Impr., Reverse Exit (KO)



Graph 98: Buy and Hold and Entry Method 2, Trend and Time Impr., Stop Loss (KO)