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MASTER THESIS

An Investigation into the Profitability of Technical Analysis in Equity Markets

Techninės analizės prognozavimo galios akcijų rinkose tyrimas

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Introduction

Technical analysis is the process of analyzing historical price data of equity products, bonds, commodities, forex and crypto and predicting the future price of that or another product solely based on that analyzed data. In 2022, with the surge in popularity of trading and the recent ease of access to trading apps and websites, technical analysis is being sold online as a sure-fire way to predict the market, however academicians are unsure as to the validity of technical analysis. There is both empirical scientific evidence that technical analysis is effective at producing excess return (Park & Irwin 2006, Brock et al 1992) and evidence from professional traders that use technical analysis successfully (Taylor & Allen 1992, Menkoff 2010). On the opposing side, there is dominant academic theory that states that due to the nature of the financial markets it is not possible to gain an alpha by analyzing the historical price data (Fama 1970, Maikiel 1996) as well as a plethora of empirical studies that denounce the efficacy of technical analysis. (Sullivan et al. 1999, LeBaron 2000)

Within technical analysis there are a variety of ways in which to make sense of the historical data and several levels of difficulty and complexity in which to do so. At the simpler end of the spectrum exists Japanese candlestick charting, originating in mid-18th century Japan by Japanese businessman, Munehisa Homma (*Pring 2002, Marshall, Young & Rose 2006, Hutton 2015)* who applied the technique at his local rice exchange. Technical Analysis evolved to another branch beginning with Charles Dow and his 'Dow Theory' in the late 1900s. The late 20th century has added neural networks and computer technology to the tool basket of technical analysts, which is performing strongly.

These systems and strategies continue to be developed with research and methods being reported with significant promises of potential returns although these promises may be specious (Harvey 2017). Most of the strategies used are out of the reach of the retail investor since it requires significant human capital and technical expertise to operate, inconveniently, the methods available to the retail investor are also the least profitable ones. The sophisticated and complex algorithms are confined to the large institutional banks who have the resources to develop, run and manage them.

The research conducted in this paper aims to illuminate further the ability of technical analysis to accurately predict future stock prices in equity markets. In doing so, if technical analysis strategies, especially on the less complex end of the spectrum, are found to be unsuccessful it would prompt retail investors to simple use a buy and hold strategy or a dollar cost averaging approach and save themselves the transaction costs of trading, at a minimum, and at a maximum, the significant risks that accompany speculation

The topic of technical analysis in equity markets has been thoroughly and repeatedly researched and tested, yet no final determination has been reached. Both academically and in professional circles, intense debates are ongoing. Previous papers have studied and tested both the very simple technical analysis strategies and the very complex. Study on the subject exploded in the early 1990s after a landmark paper by Brock et al. found significant profits in their method of technical analysis. Over the next decade many academics attempted to recreate their profits with mixed results. Park and Irwin in 2004 delivered a since influential paper that analyzed ninety-two modern papers with fifty-eight of those finding results in favor of technical analysis. In the last decade there has been a significant increase in the focus of machine learning based techniques which have shown strong results. The performance of technical analysis does not exist in a vacuum solely dependent on its own design and settings, the efficiency of the stock and of the market that that stock is in, plays a key role in its success and studies are being performed to test the efficiency of different markets.

The problem this thesis aims to address is the lack of consensus and clarity of the efficacy of technical analysis in equity markets. Is technical analysis wholly ineffective and, as many have stated, exists as astrology for men, or is the answer more nuanced? Does the question of technical analysis exist more analogous to the question does medicine work. Given the right medicine, at the right time for the right condition, medicine is effective but give chemotherapy to a patient with a broken finger and note the results. Perhaps using historical price data to forecast future price data has the possibility to succeed but one might need the right model, for the right market sentiment, in a stock and market with the right efficiency. The aim of this thesis is to test that hypothesis, how does the profitability of technical analysis change given different market conditions, stock efficiency levels and market efficiency levels. The results will be deeply analyzed and any results significantly deviating from the mean will be analyzed to determine the cause.

To achieve this, firstly a literature review must be conducted to determine what strategies are effective or ineffective, and what markets are inefficient or efficient. In doing so, the most optimal parameters will be identified in which to perform the test and reduce the risk of performing research which has already been conducted. Secondly, a model will be developed of multiple indicators which have shown promise in the literature review. This model will then be tested on the historical price data of stocks of different efficiency levels in multiple markets.

1. THEORETICAL KNOWLEDGE AND LITERATURE REVIEW OF TECHNICAL ANALYSIS

1.1 Literature Review Introduction

The topic of the profitability of technical analysis has been examined to a significant extent since the early 1990s. In this review, technical analysis will be divided into four categories, candlestick patterns, chart patterns, technical indicators, and machine learning techniques. Relevant scientific studies will be presented and summarized. A table for each category will be included to provide a quickly understood consensus of the sentiment toward technical analysis for the category. The review will include the key details of the study, particularly those which are relevant to this paper. There is no time period excluded in selection are no geographic location excluded. Studies must only be specific to equity markets and be in the English language. Studies were found using MDPI, ScienceDirect, SemanticScholar, SSRN, JSTOR, ResearchGate, and the Vilnius University Library online catalogue search function and database. A systematic review was performed to extract relevant information regarding testing methodology, markets tested, results etc. A summary was included at the end of the chapter to present the main findings of the literature review.

A systematic review of the literature concerning technical analysis in equity markets was conducted using MDPI, Semantic Scholar, ScienceDirect, ResearchGate, SSRN, JSTOR with no restrictions placed on country or publication date. Search terms included the following: “technical analysis” and “equity markets” and “trading strategy”. The largest portion of relevant articles were found by scanning the references of found articles (backward search) and locating newer articles that included the original cited paper (forward search).

The main inclusion criteria were the article was written in the English language, the study focused on technical analysis in the equity markets and were excluded if they did not focus specifically on the equity markets. Information concerning technical analysis model design, market efficiency, and results were extracted from the articles. The conclusions drawn by the investigators were also noted and tallied whether the paper was in support or against technical analysis in a table accompanied by a discussion on the review.

1.2 Theories of the Financial Markets

There are two primary and popular theories about the nature of financial markets. The most influential is the efficient market hypothesis (EMH) developed by Eugene Fama in his dissertation for his PHD in 1970. The EMH states that asset prices reflect all available information and therefore it is impossible to beat the market, which is exactly what technical analysts attempt to achieve. In addition, it also states that the use of fundamental analysis to discover undervalued stocks is impossible. Fama categorized efficient markets into three different forms. Weak Form assumes that prices might not reflect new information that is not yet available to the public, however, it still assumes that past prices do not influence future prices. Semi-Strong Form assumes that all new public information is instantly priced into the market. Strong Form assumes that all information, both public and private, is incorporated into an assets price. In effect, this hypothesis, which is taught in all financial education institutions and is held in remarkably high regard, states that technical analysis is useless. It is however, not without its critics, which was well covered by Burton J Maikel of Princeton University in his work from 2003 '*The Efficient Market Hypothesis and Its Critics'.* Many of the critics derive their arguments from the evidence of investors beating the market, valuing stocks differently and irrational behavior of participants. Fama never intended that his theory would work one hundred percent of the time, and there is evidence that markets can be less efficient than others if, for example, there is corruption or political instability.

The second and related theory is called the Random Walk Theory of Financial Markets. Widely popular and championed by the above-mentioned Maikel in his influential book *'A Random Walk Down Wall Street'*. The theory states that the markets effectively exist in a completely random fashion. Each bar acts completely randomly and independently of the previous bar and therefore no forecast can be made from historical price data. It implies that the market chart is completely indistinguishable from a chart of random coin tosses. Many of the literature and studies conducted by academics are attempts to either support or disapprove these theories.

1.3 Research on Candlestick Patterns

Candlestick charting developed originally by rice farmers in Japan in the 1700s. It was brough to the western zeitgeist first by Steve Nison 1991.

The reader of this paper is expected to already be versed in techniques of technical analysis, however it is appropriate to offer a brief explanation of candlestick charts.

Candlestick bars have a "high", "low", "close" and "open". The high and low represent the highest and lowest price, respectively, the security reached on the specific trading range. The open, is the price the security opened at, and the close, is the final price for the security on that trading range. If the close and open are equal for a particular day, then the ‘body’ of the candlestick collapses into a single horizontal line.

Figure 1: An example of a candlestick

1.3.1 US Markets

1998 *Caginalt & Laurent* published the first paper on candlestick charting. The authors tested their model on the S&P500 from 1992-1996. The model was tested on daily candlebars. The paper presented results that showed *compelling evidence* that investors are impacted by price movements and use them to predict the behavior of other investors as well as concluding that one could attain triple their initial investment over a one-year period.

2006 *Marshall, Young, and Rose* was one of the first significant papers to follow *Caginalt & Laurent* and were not able to produce equivalent results. The authors applied fourteen candlestick trading strategies to thirty-five stocks in the Dow Jones Industrial Average (DJIA) from 1992 – 2001 and concluded that the tested candlestick trading strategies were not profitable on the tested period and advised investors not to develop trading strategies solely on these candlestick patterns.

2007 *Horton* This paper examines Japanese Candlestick methods of technical analysis for 349 stocks. The paper tested the same bull and bear signals of *Caginalt & Laurent* finding little value in the use of candlesticks and providing more support for the weak form of the Efficient Markets Hypothesis, concluding the paper with a recommendation by the author not to use candlestick charting strategies.

2012 *Duvinage et al.* tested candlestick charting methods on an intraday trading range, specifically the 5-minute time interval on the Dow Jones Industrial Average. The authors tested 83 candlestick signals and once trading costs were accounted for, none were profitable and could not beat the ‘buy and hold’ strategy. The authors concluded that their study supported the weak form efficiency of the US equity markets.

2015 *Hutton* examined the predictive power of two Japanese Candlestick patterns for a 49-stock sample of small capitalization stocks drawn from the S&P 600 for the period 1 June 2005 to 15 May 2015. The results of the study deliver no statistically significant evidence that candlestick charting can be used to forecast future price data. As such, this paper supports Fama’s efficient market hypothesis.

1.3.2 Asian Markets

2007 *Goo, Chen & Chang* tested candlestick patterns in the Taiwan market from 1997 – 2006. The paper tested a total of 26 candlestick patterns. The paper produced a result and conclusion that candlestick patterns can help investors earn significant positive mean rates of return. The implication from the study is also that the tested Taiwanese markets are not efficient.

2008 *Marshall, Young & Cahan* found that candlestick charting methods are not profitable in the Japanese equity market over the 1975–2004 period.

2011 *Shiu & Lu* investigated the profitability of candlestick 2-day patterns. The data set included daily prices and volumes for sixty-nine securities listed at the Taiwan Stock Exchange between 1998 and 2007. The results of the paper suggest that harami candlestick signals can generate excess returns and predict future stock prices.

2012 *Lu & Shiu* tested the efficacy of candlestick patterns on the stock of the Taiwan 50 Index. The period tested was from 2002 to 2009. The authors find that certain bullish candlestick patterns consistently outperform others. Moreover, they notice that buying signals are generally more effective than selling signals.

2012 *Lu et al.* tested candlestick patterns in the Taiwanese market. The model was a two-day candlestick pattern that consisted of buying on the bullish or bearish signal and selling when the inverse signal was identified. The period tested was from 2002 to 2008. The authors found that three bullish reversal patterns were profitable in the Taiwan stock market.

2014 *Lu & Shiu* tested candlestick patterns on the Taiwan 50 Index from 2002 to 2009. A four-digit numbers approach is employed to categorize two-day candlestick patterns. The authors found that the Taiwanese stock market is not efficient. They also documented that two candlestick bullish patterns consistently outperform others.

2016 *Chen, Bao & Zhou* studied the predictive power of four popular pairs of two-day bullish and bearish Japanese candlestick patterns in Chinese stock market. Statistical results showed that the predictive power differs from pattern to pattern, three of the eight patterns provide both short-term and relatively long-term prediction, another one pair only provide significant forecasting power within a very short-term period, while the rest of the three patterns present contradictory results for different market value groups. The authors found that long term predictions were less accurate than short term and that the strategy performed better on medium market capitalization stocks than large market capitalization stocks.

2017 *Zhu et al.* This paper examined the effectiveness of five different candlestick reversal patterns in predicting short-term stock movements. Using the two Chinese exchanges' data from 1999 to 2008, the authors statistical analysis suggests that bearish harami, and cross signals perform well in predicting head reversals for stocks of low liquidity, while bullish harami, engulfing, and piercing patterns were profitable when applied to highly liquid, small companies' stocks.

2017 *Tharavaniji et al.* investigated candlestick patterns with holding periods of 1, 3, 5, and 10 days. Two exit strategies were studied. One is the Marshall–Young–Rose (MYR) exit strategy and the other is the Caginalp–Laurent (CL) exit strategy, both included in this literature review. Stocks examined were from the SET50 index (the 50 largest capitalization stocks in the Stock Exchange of Thailand [SET]) for a 10-year period from July 3, 2006, to June 30, 2016. Once a statistical analysis was conducted, the authors concluded there was little use for either the bullish or bearish patterns. In addition, the article found that filtering by Stochastics, Relative Strength Index or Money Flow Index generally does not increase profitability nor prediction accuracy of candlestick patterns.

2018 *Anh, Bui et al.* this paper conducted empirical research to examine the predictability and profitability of the candlestick reversal patterns analysis on the Vietnamese stock market over the period from Jan 2, 2013, to May 15, 2018. The results showed that the tested reversal candlesticks do not demonstrate the ability to predict the market trend and generated profitability is low on the stock market in Vietnam.

2022 *Deng, Su & Wei* investigated the profitability of ten well-known Japanese candlestick charting patterns using daily-based data on the component stocks of the Chinese SSE50 index, which involved a sample period from January 2000 to December 2018. The results of the study indicate that bullish candlestick patterns produce a positive return. The Long White and Bullish Gap were the best performers. In addition, empirical results showed that none of the bearish candlestick patterns the authors examined offered predictive power. However, without considering trend and overbought/oversold conditions, the authors found that the bearish pattern Gravestone Doji over a 10-day holding period has superior profitability if it is applied as a contrary trading signal.

1.3.3 Other Markets

2013 *Prado et al.* tested 16 candlestick patterns on the Brazilian market. The authors considered the data series of ten stocks between 2005 and 2009, totaling approximately 40% of Ibovespa (São Paulo Stock Exchange Index) turnover. The paper aimed to test the same method and candlestick patterns as presented by Greg Morris is his 2006 book. The results were not positive for the candlestick patterns however they found some predictive ability for particular candlestick patterns, leading the authors to concluded that investors must adapt the candlestick patterns for the market they will be operating in. Ultimately concluding that the tested candlestick pattens do not have predictive ability in the Brazilian market.

2016 *Jönsson* examined the predictive power and the profitability of technical analysis indicators based on candlesticks patterns. The intent was to evaluate the short-term profitability of the indicators for potential day traders or other short-term investors. The author examined twenty-nine stocks included in the Swedish NASDAQ OMXS30 index. The period evaluated was from October 2007 to December 2015. The predictive power and profitability were shown to be poor for both individual stocks and all stocks combined. The study found little value in candlestick patterns as buy/short indicators over short holding periods. The results lend additional support to the theory that the Swedish stock market is weakly efficient and that the random walk model is in effect.

Table 1. Candlestick Literature Review

Author	Year	Used Candlestick Pattern	Market	Conclusion	Comments
Caginalt & Laurent	1998	Three White Soldiers, Three Black Crows, Three Inside Up/ Down, Three Outside Up/Down, Morning Star, Evening Star	US - S&P500	Strong Support	
Marshall, Young, and Rose	2006	28 in total	US - DJIA	Against	
Horton	2007	Followed Caginalt & Laurent	US	Against	
Goo, Chen & Chang	2007	26 in total	Taiwan	Support	Bullish Signals Most Profitable
Marshall, Young & Cahan	2008	28 in total (same as 2006)	Japan	Against	
Shiu & Lu	2011	Piercing, Bullish/Bearish Engulfing, Bullish/Bearish Harami, Dark-Cloud Clover	Taiwan	Support	Harami pattern performed best
Duvinage et al	2012	83 in total	US - DJIA	Against	Few rules beat null hypothesis after costs
Lu & Shiu	2012	24 in total	Taiwan	Support	Nisson 1991 found to be unprofitable
Lu et al.	2012		Taiwan	Support	
Prado et al	2013	16 in total	Brazil	Against	Agrees with Horton
Lu & Shiu	2014		Taiwan	Mixed	
Hutton	2015	Three Outside Up, Three Outside Down	US - S&P600	Against	Small Cap Stocks

Table 1. Candlestick Literature Review

Author	Year	Used Candlestick Pattern	Market	Conclusion	Comments
Chen, Bao & Zhou	2016		China	Mixed	
Jönsson	2016	Hammer, Hanging Man, Bullish/Bearish Engulfing, Piercing Lines, Dark Cloud Clover, Bullish/Bearish Harami	Sweden	Against	
Zhu et al.	2017		China	Support	
Tharavaniji et al	2017	14 in total	Thailand	Against	
Anh, Bui et al.	2018	10 in total	Vietnam	Against	
Deng, Su & Wei	2022	10 in total	China	Support	Bullish Gap and Long White can create value
18 Studies - 7 Support - 11 Against					

1.4 Research on Chart Patterns

2000 *Lo, Mamaysky & Wang* used a pattern recognition algorithm to detect ten chart patterns in the data of the NYSE and NASDAQ over the period of 1962 to 1996. The algorithm was based on smoothing techniques including nonparametric kernel regression to identify nonlinear patterns from the noisy data of the stock history. The authors support some forecasting ability of the chart patterns identified including the head and shoulders, however the authors concluded that it was not enough to be able to gain excess profits over the buy and hold strategy. Yet they noted that it can add to the investment decision making process.

2002 *Leigh, Paz & Purvis* evaluated a bull flag in the US market on the NYSE index history. The authors definition of a bull flag comes from Downes & Goodman 1998 in which the pattern resembles a "flag shaped like a parallelogram with masts on either side showing a consolidation within a trend." The period evaluated was 1980 to 1999 which can largely be considered a bull period for most of the duration. Transaction costs were not considered. The authors concluded that the results failed to confirm the null hypothesis of the buy and hold and that the results support the efficacy of chart patterns in forecasting the future price trend.

2002 *Leigh, Modani, Purvis & Roberts* evaluated two variations of the bull flag pattern and test it on the NYSE index on the bull period of 1980-1999. During the data mining period of the test, the authors found a possible relationship between trading volume and the subsequent price volume and decided to include it in their further testing. The results of the study found in favour of chart patterns in that they can succeed in generating excess returns over the buy and hold.

2003 *Dawson & Steeley* replicated and extended the work of *Lo, Mamaysky & Wang* by testing chart patterns including the head and shoulders pattern in the UK market. The authors tested chart patterns on the FTSE100 and the FTSE250 over the period of 1986 to 2001. The authors concluded that the results they presented occurred with different frequencies than the US market and that UK stock returns are less influenced by chart patterns than the US markets.

2012 *Zaprinis & Tsinaslanidis* developed a model that identified rounding bottoms, otherwise known as saucers and chart resistance levels. The authors performed the test on seven US tech stocks. The results demonstrated that resistance levels were more effective at indicating future stock price than the saucer chart pattern. Further, the authors noted that the performance of the trading rules deteriorated over time, as has been seen in several studies in this review. Indicating that US tech stocks are getting more efficient over time.

2015 *Cervello Royo et al.* tested the flag chart pattern on the Dow Jones Industrial Average over 3 non overlapping sub periods. The total period ran from 2000 to 2013 in which there were bull, bear, and sideways market stages. The three sub periods were 2000-2004, 2004-2007, and 2007-2013. This paper also included a stop loss and a take profit, and tested the pattern on an intraday period using a 15-minute time frame. The test returned positive results for the flag chart pattern and confirmed previous papers testing similar rules.

2017 *Arevalo, Garcia, Guijarro & Peris* also tested the flag pattern, and added a few new details. They used a dynamic window that allowed the stop loss and take profit to be updated on a quarterly basis. They added an EMA indicator to filter trades as the flag pattern is a trend-following pattern. They tested the model on both 15 minute and 1-day timeframes to consider intraday and medium term (swing) trading. The model was tested on the Dow Jones Industrial Average. The results generated from the test returned greater profits than previous studies and the buy and hold strategy, both in profitability and risk while also considering transaction costs.

2021 *Tsinaslanidis & Guijarro* designed a model that analyzed historical price data and identified any chart pattern which was profitable in the past, not just those already known such as head and shoulders. The model was tested on 560 stocks on the NYSE over the period 2006 to 2015. 92.5% of the experiments were profitable even after transactions costs.

Table 2. Chart Patterns Literature Review

Author	Year	Used Candlestick Pattern	Market	Conclusion	Comments
Lo, Mamysaky & Wang	2000	10 Chart Patterns	US - NYSE & NASDAQ	Against	1962 - 1996
Leigh, Paz & Purvis	2002	Bull Flag	US - NYSE	Support	1980 - 1999
Leigh, Modani, Purvis & Roberts	2002	Bull Flag variations	US - NYSE	Support	1980 - 1999
Dawson & Steeley	2003	Followed Lo et al.	UK - FTSE	Against	Bullish Signals Most Profitable. 1986 - 2001
Zaprinis & Tsinaslanidis	2012	Rounding Bottoms, Resistance Levels	US	Mixed	Less effective over time
Cervello Royo et al.	2015	Flag Pattern	US - DJIA	Support	2000 - 2013. 3 Sub Period of different market conditions.
Arevalo, Garcia, Guijarro & Peris	2017	Flag Pattern	US - DJIA	Support	
Tsinaslanidis & Guijarro	2021	"Generic" Patterns	US - NYSE	Support	2006 - 2015

8 Studies - 5 Support - 1 Mixed - 2 Against

1.5 Research on Technical Indicators

Technical Indicators are mathematical patterns derived from historical price data of the pertaining stock. As with candlestick charts, technical indicators are represented graphically for ease of understanding. When it comes to moving averages, there are two that are most often applied.

Simple Moving Average (SMA) shows the average value of a stock over a selected period. The indication is formed by having two moving averages, one with a longer date, e.g., 150 days and one with a shorter date e.g., 20 days. A buy signal is created when the 20-day moving average rises above 150 days and vice versa. The formula is offered below.

$$\text{SMA} = \frac{A_1 + A_2 + A_3 \ldots A_n}{n}$$

The Exponential Moving Average (EMA) is similar except that it weighs more recent prices heavier. By doing so it reacts quicker to recent price movements.

$$EMA_{Today} = \left(Value_{Today} * \left(\frac{Smoothing}{1 + Days}\right)\right) + EMA_{Yesterday} * \left(1 - \left(\frac{Smoothing}{1 + Days}\right)\right)$$

The Relative Strength Index (RSI) is a momentum indicator which signals when a stock is oversold, which suggests a price pullback, and when it is undersold, which suggests a price rise. It was developed by J. Welles Wilder Jr. in his book from 1978 '*New Concepts in Technical Trading Systems*'. The RSI indicator uses a two-part calculation. The first part seen below, uses a standard of fourteen periods.

$$RSIt_t = 100\ (1 - \frac{\mathrm{Dt}}{\mathrm{Dt + Ut}})$$

where Dt, or average downward change, and Ut, or average upward change, are computed using exponential moving averages of closing prices Ct

$$Dt = \frac{1}{p} \cdot \max(0; Ct{-}1 - Ct) + (1 - \frac{1}{p}) \cdot Dt{-}1$$

$$Ut = \frac{1}{p} \cdot \max(0; Ct - Ct{-}1) + (1 - \frac{1}{p}) \cdot Ut{-}1$$

The RSI is represented on a graph from 0 to 100. Under thirty is considered undersold and over seventy is considered oversold. RSI formulas and definitions taken from *Marek & Sediva* 2017.

The Moving Average Convergence Divergence (MACD) is one of the most popular momentum indicators. Created by Gerard Appel in the late 1960s it is still widely used today. It consists of MACD line, which is the difference between a fast EMA line and a slow EMA line, the signal line, which is the EMA line of MACD and a Histogram, which is the difference between MACD line and Signal Line.

Let the fast EMA be 12 and the slow EMA be 26. The calculation for the EMA of 12 periods is:

$$EMA_{12} = \frac{2}{(12+1)} * closing\ price_{12} + \left(1 - \frac{2}{(12+1)}\right) * EMA_{12-1}$$

The calculation for the EMA of 26 periods is:

$$EMA_{26} = \frac{2}{(26+1)} * closing\ price_{26} + \left(1 - \frac{2}{(26+1)}\right) * EMA_{26-1}$$

By using these EMAs the MACD line can be found by using the following calculation

$$MACD = EMA_{12} - EMA_{26}$$

The signal line is calculated using the following calculation

$$Signal = EMA_9$$

Lastly, the histogram is used to represent the difference between the MACD line and the Signal line.

$$Hist = MACD - Signal$$

The MACD is similar to the RSI as it indicated when prices are overbought or oversold. However, whereas the RSI has specific levels that it considers overbought/oversold, the MACD applies a relative value for investors to determine the level. MACD formulas and definitions taken from *Chio* 2022.

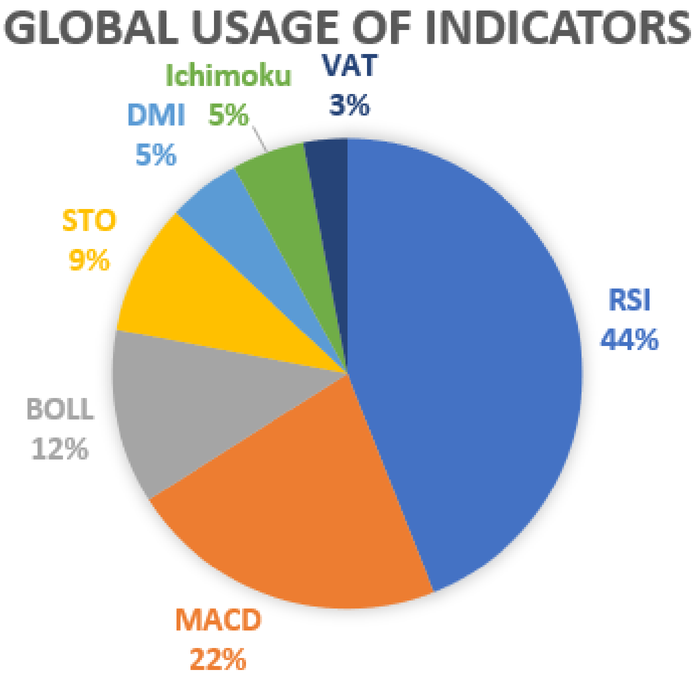

Figure 2: Global Usage of Indicators. New Frontiers in Technical Analysis 1st Edition by Paul Ciana

1.5.1 Developed Markets

1992 *Brock et al.'s* study has had a significant impact on the field of financial analysis, as it demonstrates that even basic trading strategies can produce returns that are both statistically and economically significant. Using daily data from the Dow Jones Industrial Average (DJIA) spanning over a hundred years, the authors found that trading rules based on moving averages and range breaks consistently outperformed a cash benchmark. These results could not be explained by random walk or low-order autoregressive moving average models with time-varying volatilities, suggesting that the observed profits were not simply due to chance or a risk premium. This research suggests that simple trading rules may be a viable approach for generating returns in the financial markets.

1995 *Grinblatt et al.* explored the behaviors and investment strategies of mutual fund managers to assess the extent to which technical analysis was being employed by these professionals. The study found that 77% of the mutual funds surveyed could be classified as "momentum investors," meaning they purchased stocks based on their past performance. On average, these funds outperformed those that did not use momentum investing strategies. This research indicates that technical analysis may be a common approach among mutual fund managers and may contribute to their investment success.

1999 *Sullivan et al.* wanted to test whether the best trading rules in 1986 would continue to perform well over the next decade. The authors found that, from over eight thousand technical rules, the 5-day moving average was the most successful trading rule. However, when applied over the following decade they found that the 5-day moving average underperformed the cash benchmark.

2000 *Baron* is a follow up to *Brock at al.* and discovered that the trading rules followed in *Brock et al.* were overly complex and similar results were found with simpler trading rules and also that the trading rules did not make the same profits over the last 10 years that they had in the last ninety. Further, *Brock et al.'s* most successful trading rule, the 150-day moving average, performed very poorly in the most recent decade.

2001 *Jegadeesh & Titman* in a follow up to their 1993 article, which developed momentum strategies that were quite profitable, the authors review their previous research and offer their reasoning as to why their trading rules were successful. This was in part due to certain criticism levied against the original research. The authors found that their strategy which buys stocks with high returns over the previous 3 – 12 months earned profits of about 1% per month in the following 12 months. This was found in the original work and was successfully duplicated whilst expanding the time period from 1990-1998 and still yielded a profitable strategy.

2002 *Ready* investigated the moving average rules studies by *Brock et al.* and determined that the success of *Brock et al.* study was a result of data snooping and not due to the effectiveness of technical analysis. The author's data consisted of daily returns on the S&P 500 index for non-overlapping 5-year sub-periods between 1970 and 1995. The author found that apart from the earliest sub-period (1970 – 1974), the trading rules generally underperformed the buy-and-hold strategy

2002 *Kwon & Kish* also extended the work of *Brock et al.* by including trading volume moving averages and the broader indices of the S&P500 and NASDAQ. The authors believe that technical trading rules are more profitable than the buy and hold strategy and support *Brock et al.'s* results. However, when the trading rules are applied to the past decade, results show a weakening of profits over time, which may imply that the market is becoming more efficient.

2005 *Fong & Wong* investigated moving average trading rules in internet stocks. The authors simulated real time technical trading with a recursive trading strategy and applied it to eight hundred moving average rules. The authors found no evidence of significant trading profits and concluded that internet stocks behave as random walks.

2006 *Masteika and Simutis* (of Vilnius University and Kaunas University of Technology, respectively) developed a new technical pattern that they call the “precursor of reverse” pattern. After a long price decline of about 5 to 6 days with a strong trading volume, the stock price and trading volume stabilise, and the price prepares for a rebound. The strategy then calls for a buy and hold for between 2 to 5 days. The authors then developed a ranking technique. To do this they would apply their new pattern to a substantial number of companies and then using a mathematical equation they estimated the quality of each trading pattern and ranked them. They then choose between 1 to 15 stocks for the study and applied a buy action. The results of this strategy are very promising with a total return at the end of the trading period of 742% compared to the total return for the S&P 500 Index of 112%. The best results were obtained when the strategy when the strategy was limited to using only five stocks.

2007 *Park & Irwin* delivered a seminal work that reviewed the expansive research on the profitability of technical analysis. The authors categorize the empirical studies into two groups, “early” and “modern”. Early studies indicated that technical trading strategies were profitable in foreign exchange markets and futures markets, but not in stock markets before the 1980s. Modern studies indicated that technical trading strategies consistently generated economic profits in a variety of speculative markets at least until the early 1990s. Among a total of ninety-two modern studies, twenty-four studies found positive results regarding technical trading strategies in the stock market, while twelve studies obtained negative results, and five were mixed.

2007 *Lento & Gradojevic* tested multiple trading rules both in isolation and in conjunction with each other. The authors found that the moving average crossover rules and the trade break out range rules generated excess returns in the S&P500 and the NASDAQ. The authors also found that when using a combined signal approach, by only entering a position when seven out of twelve of the applied signals indicate a long position, all but one combination generated returns more than the buy and hold strategy, even after accounting for transactions costs. The authors highlight that indicators deployed in combination perform better than indicators in isolation.

2010 *Menkhoff* produced a paper that analysed the use of technical analysis by fund managers. Not dissimilar to *Park & Irwin, Menkhoff's* work has become highly influential and very often cited. The author analysed survey evidence from 692 fund managers in five countries and found that at a forecasting horizon of weeks, technical analysis is the most important form of analysis and that the survey participants are largely trend followers. 87% of fund managers consider technical analysis to be of at least some importance.

2010 *Kabasinskas & Macys* tested various configurations of Bollinger bands to determine the optimal settings for the Baltic Stock Market. Bollinger bands are an extremely popular indicator which shows a simple moving average and then two trendlines plotted two standard deviations away from it. The study concluded that for short term investors the best configurations are to set the moving average to 10 days and set the outer bands to 1.8 standard deviations away from the moving average.

2014 *Taylor* tested moving average and trading range break, once again following *Brock et al.* and tested them on the Dow Jones Industrial Average (DIJA) over the period 1928-2012. The main conclusions of the author were that risk-adjusted profits were confined to the period from around the mid-1960s to the mid-1980s peaking during the early 1970s and coincided with periods of high mark illiquidity and high macroeconomic uncertainty, and that profits are only available to investors who can conduct short sales in stocks.

2016 *Širůček & Šíma* tested multiple indicators on the S&P 500 on the New York Stock Exchange. The selected indicators were the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands (BB), and a Simple Moving Average (SMA). The dates back tested were from November 2014 to October 2015. Of the eight tested settings, four indicators and two settings each, only three settings produced a profitable result. These were Optimized Bollinger Bands with a total profit of 15.16%, Recommended Relative Strength Index with a profit of 1.94% and Optimized Moving Average Convergence Divergence with a profit of 4.74%.

2016 *Nazario et al.* performed a literature review of technical analysis in the stock market. The authors reviewed a total of eighty-five papers, forty-four of which included moving averages, ten included relative strength index and nine included stochastics. Seventy-nine of the papers supported technical analysis while only six did not support it. Four papers were deemed not applicable.

2017 *Martinsson & Liljenquist* tested different RSI and stop loss configurations on a trading algorithm based on candlestick patterns. The total number of configurations was six and they were tested on the Swedish OMXS30 and FTSE100. Bollinger Bands were also included to provide entry and exit points. The paper concluded that different RSI and stop loss configurations have substantial impact on the performance of a trading algorithm which instructs investors to test their configurations carefully before implementing their strategy

1.5.2 Emerging Markets

1995 *Bessembinder & Chan* investigated the profitability of technical analysis in the Asian stock market and has been a highly influential paper since its publication. The authors found that the rules were quite successful in the emerging markets of Malaysia, Thailand and Taiwan but were less effective in the more developed markets of Hong Kong and Japan.

2004 *Chang et al.* tested the predictive power of technical analysis in emerging markets. The results found that emerging equity stocks do not follow a random walk pattern. The authors tested the Variable Moving Average and the Trading Range Break rules and found that there is some evidence of forecasting power however after taking transaction costs into account, they do not beat a buy and hold strategy, with only a few rules (out of 1559) generating excess returns. The authors noted that the Variable Moving Average suggested in *Brock et al.* does not seem to have forecasting power on the recent period tested. Suggesting that due to the popularity of *Brock et al.* and the mass of traders not using their suggested rules, any potential abnormal gains have been eroded.

2008 *Fifield, Power & Knipe* studied moving average rules in fifteen emerging market markets and three developed markets over the period 1989-2003. Their results showed that moving average rules were more profitable when tested using emerging stock market indices and that this profitability persisted for longer moving averages, suggesting that trends were larger and more persistent in emerging markets.

2012 *Shynkevich* tested many trading rules on a set of technology industry stocks and a small cap sector portfolio over the period of 1995-2010. The author found that the rules had superior predictability in the first half of the period, however, they were not able to outperform the buy and hold strategy in the second half of the period. The finding that the short-term return predictability becomes much weaker in the more recent period suggests that the underlying segments of the equity market have become more efficient over time.

2013 *Zuzik, Weiss & Antosov* tested the Relative Strength Indicator (RSI) on 21 steel companies over a period of 1 year. The RSI is usually used with parameters of 70 and 30. If the RSI shows the stock to be above 70 it implies that the stock is overbought, and a bearish movement will occur. Inversely if it shows the stock to be below 30 it signals that a bullish movement will occur. In this paper the authors used parameters of 80 and 20. 332 events were analyzed and of those, if action was taken based on the RSI signal, 216 would have been profitable. The paper concluded that the RSI is well applicable in steel companies over the tested period.

2013 *Yu et al.* tested moving average and trading range break in Souteast Asian markets over the period from January 1991 to December 2008. Their results show that the trading rules have stronger predictive ability in the emerging markets of Malaysia, Thailand, Indonesia and the Philipines than in the more developed market of Singapore. They also noted that short term variants of the trading rules had better predictive ability over longer term variants and that trading costs can eliminate trading profits implying weak form efficiency.

2014 *Lubnau & Todorova* examined the forecasting power of a moving average and a trading range break for ten Asian stock indices from January 1990 to September 2010. The authors found that the moving average rules had predictive ability whereas the results were inconclusive for the trading range break. The authors found that the moving average rules consistently generated positive excess returns with greater returns being seen in less developed markets and that short term variants of the rules outperform long term variants.

2017 *Masry* tested technical analysis in the emerging market in the Egyptian stock exchange. The paper used a Simple Moving Average Strategy made up of different time parameters. Overall, the paper presented that 67% of the rules tested achieved abnormal returns and were more profitable than a buy and hold strategy. The paper concluded with the suggestions that this strategy is especially effective in times where the markets are inefficient and that short term and daily moving averages produce the highest returns.

2018 *Souza et al.* tested technical analysis in BRICS counties to test their effectiveness. The paper used an automated trading system with a buy signal being triggered when the short-term moving average rose above the long-term moving average and a sell signal is triggered when the short-term moving average dropped below the long-term moving average, commonly known as a moving average cross strategy. The study concluded that only a few moving average combinations were able to outperform a simple buy and hold strategy.

2020 *Khand, Anand & Qureshi* investigated variable and fixed length moving averages and trading range break rules in the Pakistan Stock Market over the period of January 1997 to December 2013. The authors found that the variable moving averages rule had significant predictive power and generated profits superior to the buy and hold strategy.

2020 *Teresiene & Aleksynaite* investigated whether technical analysis is the same in different markets or whether it operates differently. The selected markets were the US, Europe, and Asia. Some of the selected indicators tested were the Moving Average Convergence Divergence (MACD), Simple Moving Average (SMA) and Relative Strength Index (RSI). The authors found that with equally directed stock price movements in each market, the conclusions of the technical analysis indicators were the same.

Table 3. Technical Indicators Literature Review

Author	Year	Used Technical Indicators	Market	Conclusion	Comments
Brock et al.	1992	Moving Average, Trading Range Break	US - DJIA	Strong Support	Influential Study
Grinblatt et al.	1995	Mutual Fund Managers Survey	US	Support	
Bessembinder & chan	1995		Asia	Mixed	Support TA in inefficent markets of Malaysia, Thailand and Taiwan. Against TA in Hong Kong and Japan
Sullivan et al	1999	8000 rules tested	US - DJIA	Mixed	5 day moving average most successful, but underperformed cash benchmark
LeBaron	2000	Followed Brock et al	US - DJIA	Against	Brock et al. not successful in 10 years tested
JEGADEESH et al	2001	Momentum Strategies	US	Support	
Ready	2002	Followed Brock et al	US - S&P500	Against	Concluded Brock et al. was a result of Data Snooping and was void.
Kwon & Kish	2002	Extended Brock et al. - trading volume moving average	US - S&P500 & NASDAQ	Mixed	Weakening of profits over time, suggesting market becoming more efficient.
Fong and Wong	2003	800 Moving Averages	US - Internet Stocks	Against	Internet Stocks behave as random walk

Table 3. Technical Indicators Literature Review

Author	Year	Used Technical Indicators	Market	Conclusion	Comments
Chang et al	2004	Variable Moving Average, Trading Range Break. 1559 rules tested	Emerging Markets	Against	Some evidence of forecasting power but does not beat the null hypothesis
Masteika S., Simutis R.	2006	Novel Precursor of Reverse	US - S&P500	Support	
Park & Irwin	2007	Large Literature Review		Support	Influential Work. 58 studies support TA out of 92.
Lento	2007	Moving Average Cross, Filter Rules, Bollinger Bands, Trand Range Break	US	Support	Moving Average Cross and Trading Range Break Out performed best. Combind Signals enhances performance
Fifield , Power & Knipe	2008	Moving Averages	15 Emerging Markets, 3 Developed Markets	Support	Rules performed better in emerging markets
Kabasinskas, Audrius & Macys, Ugnius	2010	Bollinger Bands	Baltic Stock Market	Support	
Menkhoff	2010	Survey of Fund Managers			87% of fund managers consider TA to be of at least some importance
Shynkevich	2012	Multiple Rules Tested	Small Cap	Against	Not able to outperform null hypothesis in recent period. Suggesting increasing efficiency
Yu et al.	2013	Moving Average and Trading Range Break	Southeast Asia	Mixed to Support	Support in Malaysia, Thailand, Indonesia and Philipines. Against in Singapore.

Table 3. Technical Indicators Literature Review

Author	Year	Used Technical Indicators	Market	Conclusion	Comments
Zuzik, Jozef & Weiss, Roland & (Antošová), Maria.	2014	Relative Stregth Index		Support	
Taylor	2014	Followed Brock et al	US - DJIA	Against	Weakening of profits over time. Profits confined to short sellers.
Lubnau & Todorova	2014	Moving Average and Trading Range Break	Asia	Suport for MA	MA Rules were successful in less developed markets
Širůček, M., & Šíma, K.	2016	Relative Stregth Index, Moving Average Convergence Divergence, Bollinger Bands, Simple Moving Average	US - S&P500	Mixed	Support for Bollinger Bands and Moving Average Convergence Divergence
Nazário	2016	Literature Review		Support	79 papers support TA out of 85.
Masry	2017	Simple Moving Average	Egypt	Support	67% of rules were more profitable than null hypothesis. Especcially effective when market is inefficent
Martinssson, F., & Liljeqv	2017	Relative Stregth Index nad Bolling Bands with different Stop Loss configurations	Sweden and FTSE100	Support	Stop Loss is substantially impactful on performance
Souza, Matheus & Ramos	2018	Moving Average Cross	Emerging Markets	Mixed	Only a few rules could beat the null hypothesis
Teresiene	2020	Relative performance of TA indicators in different markets	US, Europe, Asia		
Khand et al	2020	Moving Average and Trading Range Break	Pakistan	Support	Variable Moving Average has significant predice power and generated profits superior to null hypothesis

28 studies - 14 Support - 6 Mixed - 6 Against

1.6 Research on Machine Learning

Machine learning techniques use the computational power of computers to intelligently learn from input data to output accurate predictions. Artificial neural networks have been exceedingly popular in forecasting stock prices and this popularity is not without its justification. Neural networks operate in a way that mimics the biological brain. Neural networks each contain multiple nodes that connect to each other including input nodes, hidden nodes, and output nodes.

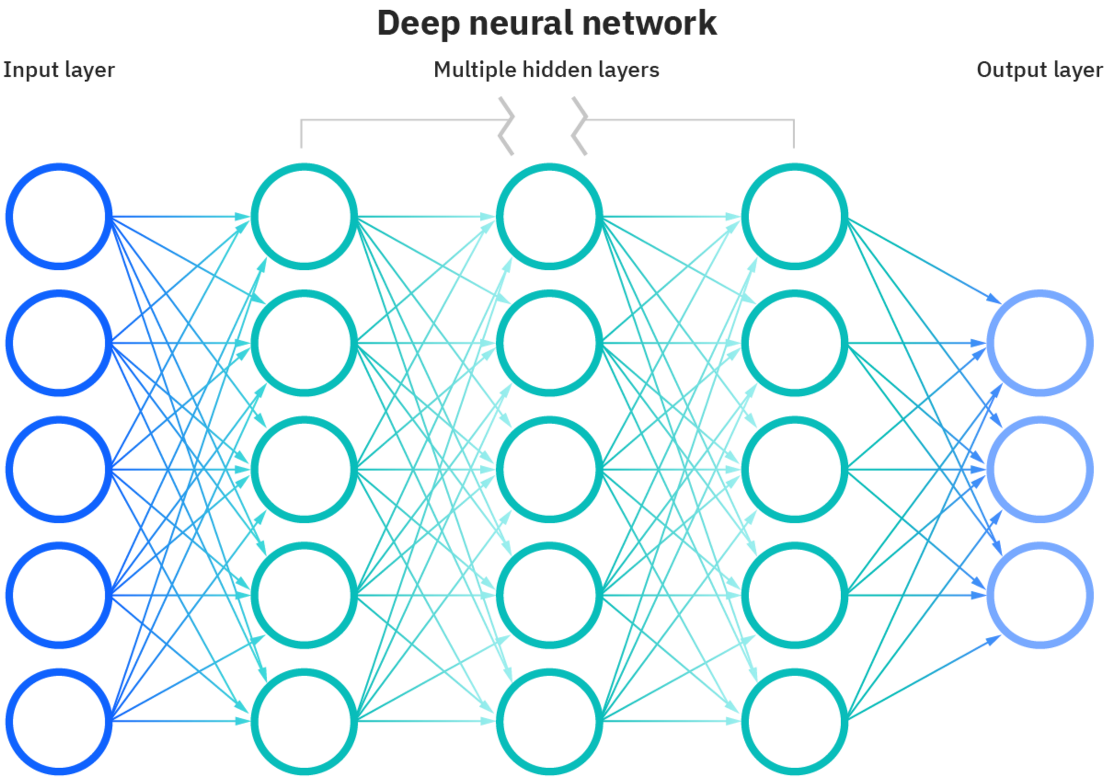

Figure 3. Diagram of Deep Neural Network Source: IBM

Each node can be thought of as a singular linear regression model. Each node has an input, weights, a threshold, and an output. The computer scientist can modify the settings of the nodes to pivot the outcome. The formula for a node is stated below

$$\sum_{i=1}^{m} w_i x_i + bias = w_1 x_1 + w_2 x_2 + w_3 x_3 + bias$$

With the output formula show below

$$output = f(x) = \begin{cases} 1\ if\ \sum w_1 x_1 + b \geq 0 \\ 0\ if \sum w_1 x_1 + b < 0 \end{cases}$$

Neural networks have the ability to perform immense calculations very quickly once trained. For example, one could have the neural network take the open, high, low and close of a stock as one input node each and have it determine whether the stock price will go up or done the next day. A deep neural network is simply a normal neural network that instead of having a standard set of three hidden layers, will have a higher number of hidden layers.In the following literature review, there will be a lot of mention about a particular type of neural network called Long Short-Term Memory (LSTM). LSTM is a recurrent neural network which has feedback connections. The difference that recurrent neural networks have is that they have an internal state that can keep information about past inputs for an amount of time. It also past already acted data to be looped back in at a later stage of the calculation to be applied with a new contextual state. They are hugely successful at image and speech recognition and have been garnering staunch support at forecasting stock prices. Information extracted from Bengio et al. 1994.

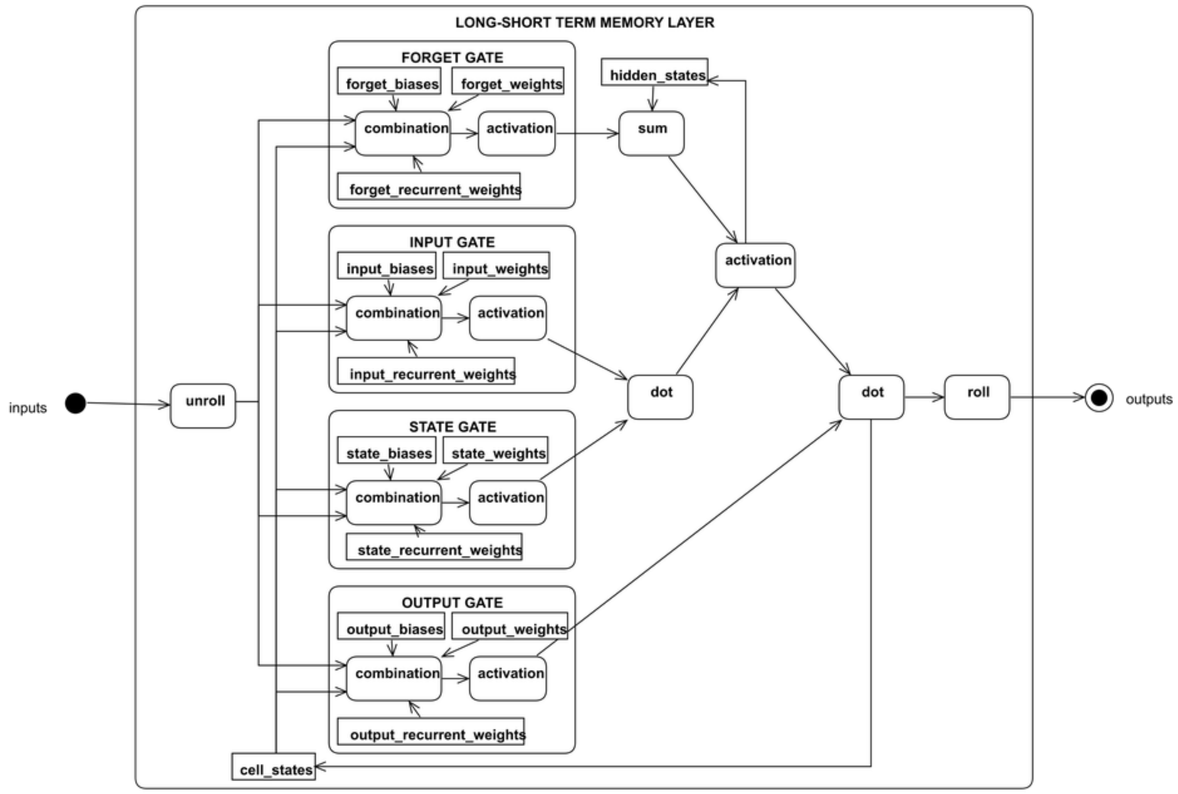

Figure 4. Long Short-Term Memory

1998 *Allen & Karjalainen* used genetic algorithms to find technical trading rules. Genetic algorithms constitute a class of search, adaptation, and optimization techniques based on the principles of natural evolution. Their research was set over the period of 1928-1995 and was for the S&P500. Authors found that after transactions costs the rules do not earn consistent excess returns over a simple buy and hold strategy.

2007 *Moreno & Almedia* performed a literature review on the predictability of emerging and developed stock markets as well as tested the predictive capabilities of Artificial Neural Networks (ANN). Of the studies reviewed by the authors, most suggested some degree of profitability. However, these studies did not consider transaction costs which negatively alter the quality/dependability of their findings. The authors concluded that once trading costs are included neither the emerging nor developed stock returns are predictable, and ANN do not provide superior performance over linear models.

2012 *Shen, Jiang & Zhang* used the machine learning algorithm Support Vector Machine (SVM) to exploit the temporal correlation among global stock markets to predict the next day stock trend. In essence they tested the correlation between closing stock prices of markets that stop trading right before or at the beginning of the US market open. Their numerical results indicated a prediction accuracy with a mean of 75% when applied to the NASDAQ, S&P500 and Dow Jones.

2013 *Vui, Soon, On, Alfred & Anthony* produced a paper that provides a review of the applications of Artificial Neural Networks (ANN) in the stock market. Of the many studies reviewed by the authors, the mean prediction accuracy result was 75% which showed promise for further research into ANNs.

2016 *Dash & Dash* developed a novel decision support system using a Computational Efficient Functional Link Artificial Neural Network (CEFLANN) along with traditional technical analysis rules, including Simple Moving Average (SMA) and Moving Average Convergence and Divergence (MACD). The authors concluded that the CEFLANN model produced a superior profit percentage compared to other known machine learning techniques such as Support Vector Machines.

2017 *Yong et al.* utilized a feed-forward deep neural network (DNN) to forecast index price of the Singapore stock market using the FTSE Straits Index. The author's model had a total of forty input nodes of DNN which were the past 10 days of the opening, closing, minimum and maximum prices and consisted of three hidden layers with ten neurons per layer. The authors trading system showed promising results with a profit factor of 18.67, 70.83% profitable trades and a Sharpe ratio of 5.34.

2018 *Paluch & Jackowska-Strumillo* developed and tested three hybrid models for stock prediction. They combined elements of Technical Analysis, Fractal Analysis and Artificial Neural Networks (ANN) and tested them on the Warsaw Stock Exchange. The first model was a combination of Technical Analysis with the ANN, the second combined technical and fractal analysis with an ANN and the third combines fractal analysis with an ANN. The results produced presented that the second model, technical and fractal with an ANN and the third model, fractal analysis with an ANN provided the highest accuracy with the third model producing the best accuracy. The worst results were produced by a purely ANN based approach which were significantly inferior to the hybrid models. The paper concluded suggesting that a hybrid ANN based model with fractal analysis may offer a particularly useful tool for investors.

2018 *Gurav & Sidnal* recognized the apparent weakness in back propagation with Artificial Neural Networks (ANN) and Deep Neural Networks (DNN). To handle the large density of nonlinear data, the authors presented a modified back propagation neural network (MBNN). The authors presented conclusions that indicated an average Root Mean Squared Error (RMSE) performance improvement of 34.68%, 26.93% and 35.48% by their MBNN model over existing models for the S&P500, NASDAQ and NYSE, indicating the additive nature of their proposed MBNN.

2018 *Abe & Nakayama* investigated the machine learning method known as Deep Learning (DL). Deep Learning achieves high performance in image recognition and speech recognition. They compared their DL model in various configurations against the popular Support Vector Machine (SVM) and Random Forest (RF). Their DL model outperformed SVM and RF and the highest accuracy in each variation of the test was their DL model.

2019 *Selvamuthu, Kumar & Mishra* compared the performance of three Neural Network learning algorithms. Levenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization by predicting over tick-by-tick dataset and 15-minute dataset. The results showed that using tick by tick data for the stock market gives much better results than prediction using 15-minute dataset. All three algorithms provide an accuracy of 99.9% using tick data. The results obtained on the 15-minute dataset is significantly poor in comparison to the tick-by-tick data.

2019 *Akiyoshi* evaluated Artificial Neural Network (ANN) and Support Vector Machines (SVM) on three metrics, directional accuracy, closeness, and profit generated by trading simulation and specifically designed the model to forecast the future stock price rather than just the direction. The author implanted the models on the S&P500 Index and had multiple time periods. 1 day, 3-day, 5-day, 10 day and 20-day. The directional accuracy yielded from the test was less than results of previous studies which was 90%. The most accurate directional accuracy result was from the SVM for the 20-day period at an accuracy of 71.46%. In conclusion, the author noted that the trading simulation showed that ANN and SVM did not predict profits accurately and may not be suitable for live trading.

2019 *Site, Birant & Isik* observed the predictive abilities of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to forecast the stock price of Google and Amazon on a monthly and weekly basis. LSTM outperformed GRU by predicted the close prices of both stocks more accurately.

2019 *Shah, Isah & Zulkernine* produced a review of all the current research achievements in stock analysis and prediction. They created a taxonomy of prediction methods and made four categories: statistical, pattern recognition, machine learning, and sentiment analysis. The paper reviewed the current literature for each category and then discussed the effectiveness of each method. For statistical methods, the paper put forward Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing Model (ESM) and Neural Network Models as popular analysis methods. The paper stated that these methods were effective at forecasting stock direction. Pattern recognition techniques were found to show promise but cannot on their own deliver consistently accurate stock predictions. The paper suggested using pattern recognition techniques in combination with other prediction techniques.

Machine Learning is split into supervised learning and unsupervised learning. The paper held that specifically supervised learning has shown great promise for stock prediction. The best performing algorithms listed were Random Forest, logistic regression, and neural networks. The paper stated while reviewing the studies in unsupervised machine learning that this type was equally strong for stock prediction.

Sentiment Analysis is the method of using machines to analyze news reports and social media posts to gauge a sentiment and produce a stock prediction based on it. The paper noted the difficulties of creating an effective algorithm due to the complexity and nuance of language, especially in social media. However, several studies were presented which had prediction models which had accuracy results of 86.7% and 81.81% and 71.82%. If the model can be coded effectively it can produce profitable results, however, it is not technical analysis so is not relevant to the scope of this thesis.

The last method discussed was the use of Hybrid models which by combining some of the techniques above produced greater accuracy predictions than the sum of its parts. In the conclusion of the paper, it noted the difficulties and dangers that come with algorithmic trading such as Knight Capital's $460 million USD loss due to a glitch but also recognized that algorithmic trading makes up most of the trading in the equities markets. It finalized by stating that a hybrid approach that combines statistical and machine learning techniques will be more useful than algorithmic trading for stock prediction.

2019 *Fazeli* developed a deep learning model using technical indicators and past data of Apple, Microsoft, Google, and Intel stocks in a Long Short-Term Memory (LSTM) network. The authors results suggested that it is not possible to predict the exact price of a stock in the future and gain profit but deep learning can be used to predict the trend of stock markets to generate buy and sell signals.

2020 *Zhang, Li & Chen* proposed a novel two stage ensemble machine learning model named SVR-ENANFIS which combined features of Support Vector Regression (SVR) and Ensemble Adaptive Neuro Fuzzy Inference System (ENANFIS). In the first stage, the future values of technical indicators are forecasted by SVR. The second stage consists of ENANFIS forecasting the future price based on the predictions of the SVR in the first stage. Finally, the proposed model SVR-ENANFIS is evaluated on four securities randomly selected from the Shanghai and Shenzhen Stock Exchanges with data collected from 2012 to 2017, and the predictions are completed 1–10, 15 and 30 days in advance. The result of the experimental study shows that the papers developed model of SVR-ENANFIS has superior forecasting power than a single stage model and several two stage models.

2020 *Li & Bastos* conducted a systematic review of studies that centered on deep learning and technical analysis to forecast future stock prices. A total of thirty-four studies were included in the review. 73.5% of the studies applied Long Short-Term Memory (LSTM) with the authors suggesting that the widespread usage of LSTM is due to its memory storage capacity and the ability to solve the vanishing gradient problem that comes with stock price forecasting.

2020 *Chen, Zhang & Lou* proposed a novel hybrid deep learning model integrating attention mechanism, multi-layer perception and a bidirectional Long Short-Term Memory Neural Network. Their knowledge base for the model included historical price of stocks, technical indicators if stocks closing prices, natural resources prices and historical data of the Google index. The model was tested on the S&P500, Dow Jones, NASDAQ, and Russel 2000. When compared to other of different models including standard SVM and LSTM, the author's model performed best and demonstrated good forecasting ability.

2021 *Rodríguez-Cándido, Espin-Andrade, Solares & Pedrycz* formulated a novel approach to predicting financial asset prices by combining compensatory fuzzy logic (CFL) with technical analysis. The paper used standard and popular technical indicators such as Bollinger Bands (BB) and MACD, along with the CFL. The paper tested the developed model to crypto assets as well as stocks. The results of the paper were that the model generated positive returns in more than 93% of the operations performed.

2021 *Singh & Khushi* selected five technical indicators and twenty-three fundamental indicators along with machine learning models and tested it from 1999 – 2019 on the S&P500 dataset. The results were very promising with an accuracy rating of 85% when predicting the possibility of a stock's price going up by 1% on 10th day and a recall of 100% for sell signals, which the authors suggested would be a great model for a shorting strategy.

1.7 Literature Review Summary

In this literature review, studies focusing on technical analysis were divided into four categories, analysed, summarised, and presented for consideration. A total of eighteen studies were included for candlestick charting. Several market locations were present including the US, Taiwan, Japan, Brazil, China, Thailand, Vietnam, and Sweden. The earliest study was 1998 and the most recent study included was published in 2022. The most common candlesticks studied were bullish/bearish harami, bullish/bearish engulfing, and three outside up/down. Of the eighteen studies included, seven supported technical analysis while eleven studies were included that presented conclusions opposing its efficacy. Of the seven supporting studies, five returned profitability in Taiwan with the authors concluding that the results suggested the inefficiency of the Taiwanese equity market. Candlestick charting methods are not a promising candidate for further research in this paper as overall the results do not indicate a potential for profitability however, the clear increase in performance as efficiency decrease is noted.

Similar to candlestick patterns, chart patterns are graphical indicators, this can result in an issue with identification, with different viewers having different opinions as to when a chart pattern occurs. Due to their nature of being visual indicators, the concept of chart patterns is easily understood and therefore are extremely popular among new and novice traders. However as academic literature requires a more scientific and systematic method for examination, the visual nature of chart patterns can pose challenges. In the collection of studies for this review, the author had difficulty in finding studies which focused on equity markets, only tested chart patterns in isolation and were of a quality standard deemed appropriate for this thesis. Of the eight studies analysed, seven were tested in the US market and one was tested in the UK market. Five studies supported the efficacy of chart, one was mixed, demonstrating a reducing in efficacy as efficiency increased over time and two studies presented opposing conclusions on the efficacy of chart patterns. The earliest study included was included was from 2000 and the latest weas from 2021. The most common pattern tested was the flag pattern. While the consensus is in support of chart patterns, the limited number of studies found that met the criteria of selection, prohibits chart patterns from being the most optimal technical analysis method to study in this paper.

There was a total of twenty-eight studies found for technical indicators that met the search criteria set by the author. These studies were set both in developed and emerging markets to get an insight into the effect that the inefficiency of a market has on the profitability of technical analysis. Technical indicators experienced a period of popularity in the 1990s with both academics and professional investors find positive returns with their methods. However, several studies since then have retested those trading rules and found a weakening of profit in more recent time. Park & Irwin is a very influential and cited work that found twenty-four positive studies for technical indicators with only twelve against. The studies suggest that developed markets demonstrated an exploitable level of inefficiency in the 1990s but has since become efficiency as the trading rules are no longer as effective. Emerging markets, however, offer a more optimistic view of technical indicators. Of the X studies included, Y presented positive results with many studies testing the same indicators in both developed (Hong Kong, Japan) markets and emerging markets and only finding profitability with emerging markets. Moving averages were the most popular and presented the most promising results with authors noting that indicators in combination performed better than indicators in isolation.

Machine learning technique are the most studied methods in recent times. Machine learning could be further sub divided many times in a future work as the author does not feel it is necessary for the purposes of this paper. The vast majority of machine learning focused studies presented positive returns and supported the use of these algorithms for predicting future stock prices. The major stand out was Long Short-Term Memory. Machine learning was not selected to be studied further in this paper as the author feels the computer scientists can offer a better study.

Based on this literature review technical analysis can be profitable once the correct method is used and the correct market is chosen for it to be deployed to.

Table 4. Machine Learning Literature Review

Author	Year	Machine Learning Technique	Market	Conclusion	Comments
Allen & Karjalainen	1998	Genetic Algorithim	US - S&P500	Against	Deso not beat null hypothesis after transaction costs
Moreno & Almedia	2007	Artificial Neural Netowrks	49 MSCI Indices	Against	
Shen et al.	2012	Support Vector Machine	US	Support	
Vui et al.	2013	Literature Review of Artificial Neural Network Studies		Support	Mean prediction accuracy of 75%
Dash & Dash	2016	Novel CEFLANN	US - S&P500 and India - BSE SENSEX	Support	Superior to other ML techniques
Yong et al.	2017	Feed Forward Deep Neural Network	UK - FTSE	Support	Profit Factor of 18.67 and 70.83% profitable
Paluch & Jackowska-Strumillo	2018	Combined Technique	Warsaw	Support	Combined Model of ANN and fractal analysis performed best
Gurav & Sidnal	2018	Modified Back Propagation Neural Network	US - S&P500 & NASDAQ	Support	Improved results over other techniques
Murkute & Sarode	2018		US		
Dhule et al.	2018				
Abe & Nakayamaa	2018	Deep Learning Neural Network	Japan	Support	Performed better than other techniques

Table 4. Machine Learning Literature Review

Author	Year	Machine Learning Technique	Market	Conclusion	Comments
Shah, Isah and Zulkernine	2019	Large Literature Review		Support	
Lam, Dong and Yu	2019				
Akiyoshi	2019	Artificial Neural Netoworks and Support Vector Machines	US - S&P500	Against	
Site et al	2019	Long Short-Term Memory and Gated Recurrent Unit	GOOG and AMZN	Support	LSTM performed best
Fazeli	2019	Long Short-Term Memory	GOOG, APPL,MSFT,INTL	Support	Cannot predict exact price but can predict trend
Selvamuth et al.	2019	Neural Networks	India	Support	
Li and Bastos	2020	Systematic Review of Literature		Support	LSTM performed best
Zhang et al.	2020	Novel Technique - SVR-ENANFIS	US	Support	
Chen et al	2020	Novel Technique with LSTM	US	Suport	
Rao et al	2020	Survey of Machine Learning Prediction			
Rodríguez-Cándido, Espin-Andrade, Solares & Pedrycz	2021	Fuzzy Logic with Technical Analysis - Bollinger Bands and MACD		Support	Postive results in more than 93% of tests

Table 4. Machine Learning Literature Review

Author	Year	Machine Learning Technique	Market	Conclusion	Comments
Singh and Khushi	2021	Technical analysis and Machine Learning	US - S&P500	Support	
Houssein et al	2021	Review of Literature			
Rao et al	2022	Multistage Wavelet Regression			

25 studies - 22 Support - 3 Against

2. METHODOLOGY FOR EVALUATING THE EFFECT THAT EFFICIENCY LEVEL HAS ON THE PROFITABILITY OF TECHNICAL ANALYSIS

2.1 Introduction

The aim of this paper is to investigate the profitability of technical analysis in equity markets. To accomplish this goal qualitative research was conducted in the literature review and in this section quantitative research will be conducted on a technical analysis-based trading strategy. In the following subsection the insight from the literature will be presented and the model in which the quantitative research will be conducted will be identified, selected indicators presented and explained. Then the entry and exit conditions for the model will be presented. The backtesting system which is necessary to test the model and hypothesis will then be explained and reasons given for its selection. In the latter half of this section, the financial environment that the hypothesis will be tested in will be explained including the geographic market selection, the market capitalization level selection, and the market period selection. Finally, the performance measures and selected statistical tests will be identified.

This methodology was constructed using the concept of the research onion developed by Saunders et al. (2007) which has become very influential among researchers since its publication. This paragraph will present the relevant consideration that this research will take according to the research onion. As with many quantitative studies a positivistic philosophy was taken by this paper in order to discover the objective reality as to the profitability of technical analysis in equity markets. The research conducted in this paper will be of a deductive nature as technical analysis has been researched extensively yet a consensus has not been reached. This paper aims to add new research to the literature. The empirical research of this paper will be of a quantitative nature. The strategy taken in this research is of an experimental nature. The null hypothesis will be represented by a buy and hold strategy which is in effect the 'control' as no settings will be manipulated. The trading strategy will be acting as the representative of hypothesis one. As the paper is testing the time series data of equity instruments it is longitudinal research. In addition, as the data is sampled in a linear fashion it is a non-probability sample, however a t test sample of means will be conducted to test for statistical significance. The specific methods and techniques for model development, data collection and analysis are presented in the following subsections.

2.2 Model Development

To achieve the stated goal of understanding the determinants of the profitability of technical analysis, the literature review must be analysed and the method with the most potential to provide insight must be determined and then tested. Candlestick patterns were shown in the literature review to perform sub optimally in any market and therefore do not necessitate any further research, or at least do not indicate large potential for insight. Technical indicators were a much more mixed affair, with the US market being rather unprofitable due to the efficiency versus the Taiwanese market which showed more promise. Machine learning techniques have the most successful studies however the author does not have the technical ability or skills in computer programming to be able to develop and execute a machine learning model of interest. Hence the developed models will be formed of technical indicators.

Once the category of technical indicators was selected, the specific indicators had to be investigated and identified. Technical Indicators can largely be grouped into three categories: Trend, Momentum and Volume. The review of the literature presented many studies that tested technical indicators in isolation to low success, and there is evidence that indicators perform better in combination with other indicators. For these two reasons the developed model will consist of indicators of either all or two of the three categories.

The models will have total cash available of one thousand USD and will enter 100% of its equity per trade. This will have a noticeable effect on the drawdown statistics as the drawdown measures per total equity. If, for example, the total cash was set to ten thousand USD and it would enter 10% per trade and only allow one trade at a time, a drawdown that would have been 60% will now appear as 6%. Hence it is important to know the total equity before considering the drawdown percentage. The model will be tested on an intraday chart of 5 minutes per bar. This is to consider the model as a day trading model.

2.2.1 Moving Average Indicator

For the model, the extremely popular and successful Moving Average was chosen. More specifically the model will be using the moving average following from *Brock et al. (1992)* and using a moving average cross as a buy signal. While one may argue that due to the large number of studies conducted on moving averages already there may be a futility in testing it once again, the testing in this paper adds several nuances by including it in a combination of indicators and by testing it in two markets, one efficient and one inefficient, and in two market capitalization levels. *Brock et al.'s* 150 long simple moving average and a 21 short simple moving average will be used as a buy/sell signal.

Algorithm 1 Simple Moving Average Cross for Buy Signal

```
Create Moving Average for Buy Signal
    define variable 'shortlen' and set it equal to inputs (definitive value of 5, title, and minimum possible value)
    define variable 'longlen' and set it equal to inputs (definitive value of 21, title, and minimum possible value)
    define variable 'short' and set it equal to pine_sma(close, shortlen)
    sum equals 0.0
    for i - 0 to shortlen - 1
        sum += close(i) / shortlen
    sum
    define variable 'long' and set it equal to pine_sma(close, longlen)
    sum equals 0.0
    for i - 0 to longlen - 1
        sum += close(i) / longlen
    sum
    plot the short sma on the chart with the color #FF6D00
    plot the long sma on the chart with the color #43A047
    plot when the short sma crosses the long sma on the chart as a cross symbol with the color #2962FF

End Create
```

2.2.2 On Balance Volume Indicator

This will be used in combination with a Volume Indicator, specifically, On Balance Volume (OBV). OBV is used as a strengthening signal to support or deny the moving average's buy/sell signals. A volume indicator supports the moving average by confirming that a price action buy signal is supported by a sufficiently strong level of orders. A moving average buy signal, as it is solely based on the price and its change, is vulnerable to erroneous buy/sell signals as it is possible that the prices rise/fall with a small number of orders. This does not indicate that market sentiment is strong one way or the other. By including the OBV indicator, it confirms that the price rise is backed strongly by the market, demonstrated by the order volume. OBV provides a running total of an assets volume and indicates whether this volume is flowing in or out of the given security. It instructs the analyst as to the flow of institutional money in or out of the stock.

Algorithm 2 On Balance Volume

```
Create On Balance Volume C
    define variable 'cumVol' and set it equal to 0
    set cumVol += undefined(volume of the current bar)
    if the last bar of the volume is the last and cumVol is equals to 0
        print an error message stating 'No Volume Provided by Data Vendor.'
    define variable 'srcobv' and set it equal to the close price of the current bar
    define variable 'obv' and set it equal to the cumulative sum of the difference between the current bar and srcobv and then
        multiply the sum by the volumeof the current bar
    define variable 'smoothingLength' and set it equal to inputs (definitive value of 99, min value of 1 and max value of 100)
    define variable 'smoothingLength1' and set it equal to inputs (definitive value of 5, min value of 1 and max value of 100)
    define variable 'smoothingLine' and set it equal to pine_sma(obv, smoothingLength)
    sum equals 0.0
    for i - 0 to smoothingLength - 1
        sum += obv(i) / smoothingLength
    sum
    define variable 'smoothingLine1' and set it equal to pine_sma(obv, smoothingLength1)
    sum equals 0.0
    for i - 0 to smoothingLength1 - 1
        sum += obv(i) / smoothingLength1
    sum
    plot smoothingLine on the chart with the color #F37F20
End Create
```

2.2.3 Position Entry Conditions

As for the settings, this paper will test both an aggressive version of the model and a defensive version. The aggressive version is designed to enter positions quickly and be difficult to exit. The purpose of this is to take advantage of bull markets while hopefully cutting off the drawdown a standard buy and hold strategy has. Its aims to accomplish this with the moving average setting of a moving average cross set to a long simple moving average of 9 with a short simple moving average of 5. Once the short SMA crosses above the long SMA, it generates a buy signal. This is the ‘easy entry’. For the difficult exit, the OBV must descend below its own simple moving average and the price moving average must cross under with settings long SMA of 150 and a short SMA of 9.

The defensive version of the model is the opposite of the aggressive version. For a buy signal the moving average settings are set to a long SMA of 150 and a short SMA of 9 ensuring that if the short crosses over the long it indicates a significant bullish sentiment for the stock. For a sell signal, the moving average is set to a long SMA of 21 and a short SMA of 5 allowing for a quick exit. The OBV buy signal must have its OBV greater than its SMA which is set to 99 and for the sell signal it must cross under its SMA of 5.

Once the results from both the defensive model and aggressive model are generated, an 'optimal' model will be created and evaluated on the full period. The optimal model will consist of the aggressive model settings for the bull period and then will apply the defensive model settings for the bear period.

Algorithm 3 Conditions Needed for Position Entry & Exit

```
Create Position Entry Conditions
    if short crosses over long, and obv is greater than smoothingLine
        Enter position
End Create
Create Position Exit Conditions
    if short1 crosses under long1, and obv crosses under smoothingLine
        Exit position
End Create
```

The model will be tested in a five-minute time period. This will allow adequate comparison of models developed for intraday or short-term trading. The strategy cash amount is one thousand united states dollars, and it will enter the entirety of this amount when it enters a position.

2.3 Backtesting System

2.3.1 Platform Selection

Once the model has been developed it must be tested, the most time efficient way to do this is through backtesting. The strategy is applied to the historical data of the stock, and it returns how the strategy would have performed if it were used on that stock data. There are many different platforms, software, and ways to backtest. Many traders prefer to create their own backtesting program if they have the skills. Python is the dominant programming language in finance and the majority of backtesting is done with it. Other options include backtesting software which allows the users to select the model parameters including indicators on settings on a dial like input, however this limits the customizability of the model for the investor. A strong option between the two is the highly popular platform TradingView and their in-house developed programming language PineScript. PineScript was developed specifically for the applications of trading, backtesting and model development. It is significantly easier to learn than Python while still offering the ability to code and precisely tune a model. For these reasons TradingView and Pinescript were selected for model development and backtesting.

2.3.2 Geographic Market Selection

To improve the accuracy and quality of the test results, the model will be tested in two markets and two market capitalization levels. This will allow for evaluation of the efficiency of both the markets and the market capitalization levels. It also will test whether technical analysis’s performance improves as the inefficiency of the market increases as academics believe. The markets tested will be the US market which represents the efficient market as shown from the results of the literature review. The Taiwanese market will be used for the inefficient market as this was the conclusion of many of the studies in the literature review.

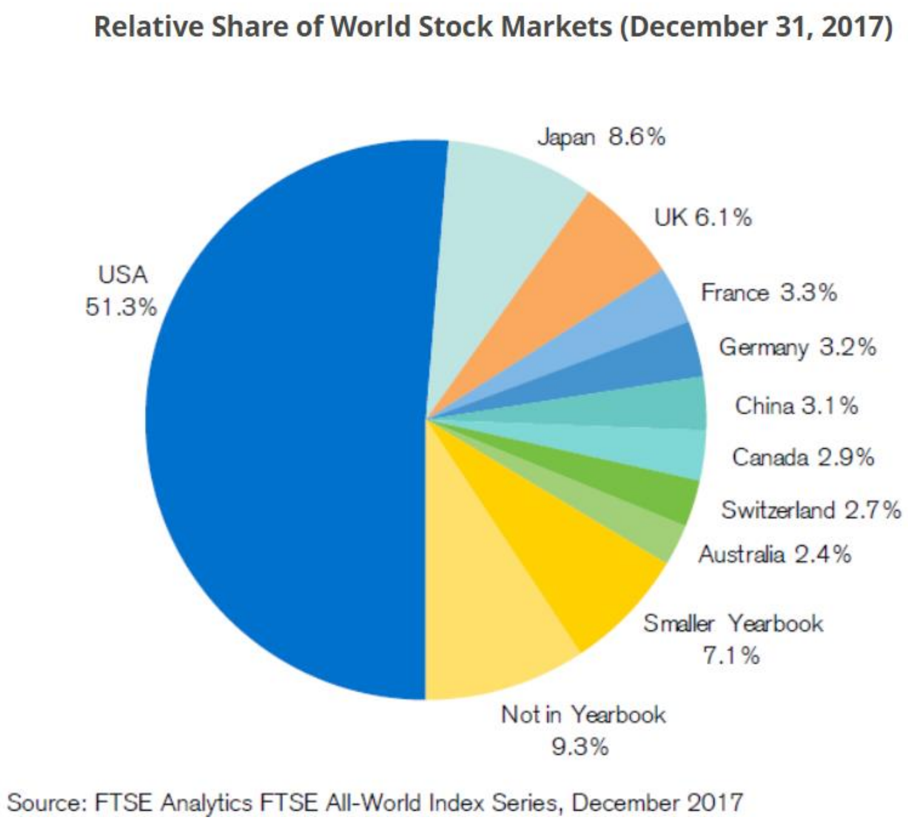

Figure 5. Relative Share of World Stock Markets

2.3.3 Market Capitalization Criteria

As for market capitalization, the model will be tested on companies with a large market capitalization as defined as greater than 10 billion USD. Studies have shown that large market capitalization stocks are more efficient. The small market cap will be defined as between 300 million USD and 2 billion USD. In addition, all stocks must have an average volume of more than two million. Ten stocks were chosen for each category at random using TradingView stock screener. Stocks were only removed if they did not exist as a public company for the entirety of the testing period as otherwise the results would not be a 1:1 comparison.

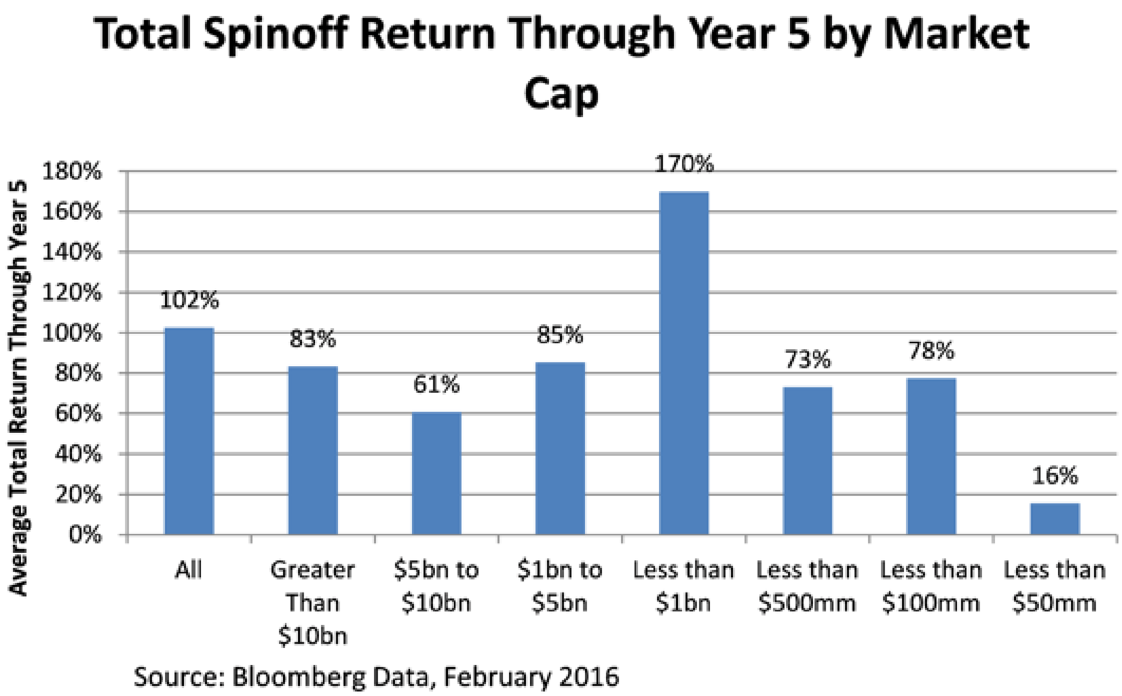

Figure 6. Total Spinoff Through Year 5 by Market Cap

2.3.4 Market Period Selection

The models will be tested on a bull period and a bear period. This will allow the performance of technical analysis to be evaluated under different market conditions. The aggressive model which allows profits to run, the author would estimate outperforms the defensive model in the bull market. Conversely, as the defensive model is designed to cut losses quickly and only enter with strong momentum, the author assumes it outperforms the aggressive model in the bear market. The question is, if the defensive strategy can cut enough of the losses to perform better than the aggressive overall. The Bull market used is run from the date April 01, 2020, to December 01, 2021, the post covid crash bull run. The Bear market used is the current bear market of 2022, being run for 12 months from the test date, December 02, 2021 – November 22, 2022. The model will be tested on both and then on the total date to see which model would have performed better overall. The five-minute time period will be used to represent intraday trading.

2.3.5 Performance Measures

The Trading View backtesting report produces a total of twenty-seven metrics for model evaluation. The model will use six of the most relevant of these twenty-seven metrics. Net profit percentage, number of trades, percentage profitable, profit factor, drawdown and buy and hold percentage. These will then be extracted from the backtest results and transferred into Microsoft Excel for analysis and presentation. To test for statistical significance, a t-Test Two Sample of Means will be conducted with a significance level of 5% following *Brock et al.* (1992)

Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %

2.4 Summary

To summarise, the model will be a combination of a moving average cross and the on-balance volume indicator. Two model variants will be examined, an aggressive variant and a defensive variant. The model will be tested in two geographic markets, one efficient, the US and one reportedly inefficient, Taiwan. To further examine the effects that the efficiency of a market has on the profitability of technical analysis, the model will also be tested on stock of two market capitalization levels, large and small. Finally, it will be tested using TradingView and its PineScript programming language. The performance of the model will be determined by a range of measures including its net profit vs the buy and hold strategy (null hypothesis). The validity of the results data will be verified using a two-sample t test of means.

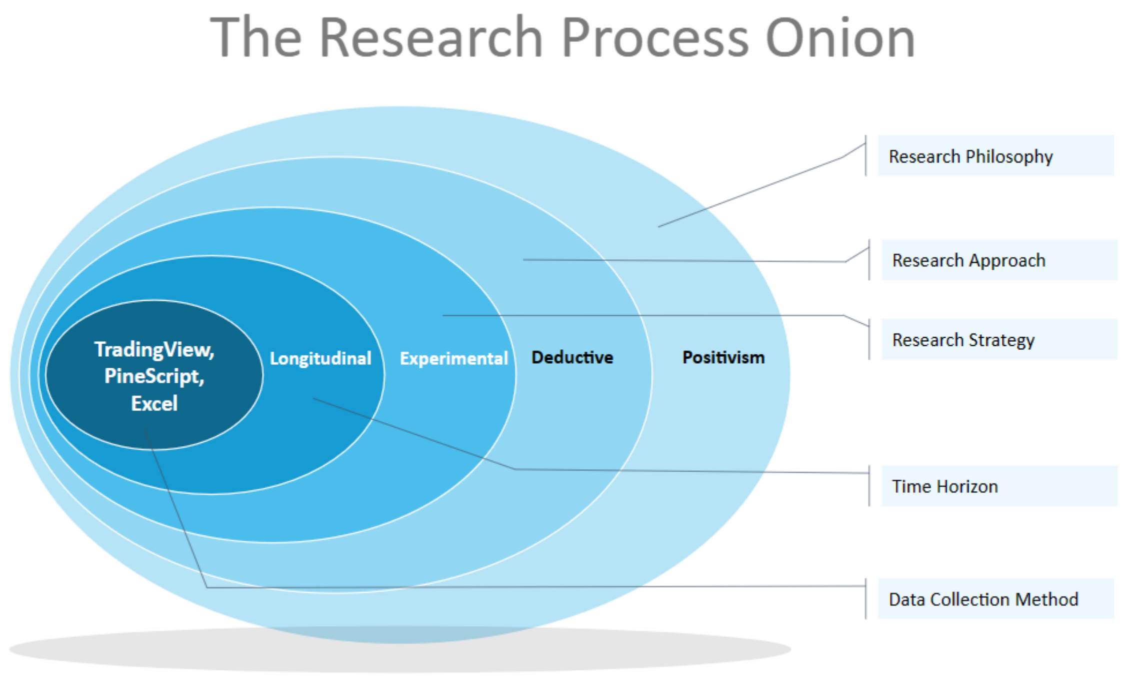
The Research Process Onion
TradingView, PineScript, Excel
Longitudinal
Experimental
Deductive
Positivism
Research Philosophy
Research Approach
Research Strategy
Time Horizon
Data Collection Method

Figure 7.

3. EMPIRICAL RESEARCH CONDUCTED TO INVESTIGATE THE PROFITABILITY OF TECHNICAL ANALYSIS

3.1 Introduction

The aim of the following quantitative research is to investigate the profitability of technical analysis in equity markets. In this section the results of both variants of the model will be presented in each scenario along with the result of a buy and hold strategy which is representative of the null hypothesis. The aggressive model is presented first, results in each scenario are shown in tables, starting with the US Large Cap market, and finishing with the Taiwanese Small Cap market for both periods. A brief summary follows each model's results. Lastly there will be an overall summary of the results presented.

3.2 Results of Aggressive Model

3.2.1 Bull Market

The Bull market of 2020-2021 was a period of high speculation and asset appreciation. Virtually all assets appreciated significantly. The speculation and market euphoria were at such a height that even a new asset class was created, the Non-Fungible Token commonly known as an NFT. These were assets with zero fundamental value and could be recreated and copied easily. The aggressive model is designed to allow the trades to run with profits like a buy and hold strategy. As mentioned in the methodology section, the entry is very easy, meaning, if the market shows even a little bull sentiment, the strategy will enter a position and only if there is a strong bearish sentiment will it exit. The exit is there to hopefully cut off some of the drawdown that a buy and hold strategy faces. The results for the US Large Cap market are as follows:

3.2.1.1 US Large Cap

Table 5. Results of the Aggresive Model in the US Large Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
UBER	47.12	45.04	55.17	1.227	58	32.81
EPD	48.9	54.24	48.65	1.486	37	30.82
TGT	124.14	145.97	64.71	2.726	51	15.8
SBUX	42.24	57.61	57.58	1.85	33	16.61
CRM	114.98	81.31	60	1.9	50	27.33
BMY	3.97	0.86	53.49	1.074	43	16.82
TSLA	846.34	1031.4	64.81	2.555	54	35.85
AMZN	80.89	76.38	51.22	1.908	41	17.93
GOOG	139.63	146.23	49.02	3.872	51	10.5
AAPL	111.43	166.14	56.25	2.478	48	18.58
Mean	**155.96**	**180.52**	**56.09**	**2.11**	**46.60**	**22.31**

The model was profitable with a mean net profit of 155.96% yet the buy and hold had 180.52%. Overall, this would not have been unexpected as the US Large Cap market would be one of the most efficient in the world. If trading costs are considered, which can range from one dollar per roundtrip to one dollar per order, the buy and hold beats the strategy by 80%. There are no significant stand outs results worth analysis. The model simply failed the capture the gains that the buy and hold was able to. This result would fail to reject the null hypothesis and would support the EMH and random walk theory. The model achieved a profitability of sixty percent or above in only three out of the ten stocks and beat the buy and hold in four out of the ten stocks but only by an insignificant amount. For BMY the model was able to beat the buy and hold buy 30% yet if transactions costs are considered, it would not beat it.

3.2.1.2 US Small Cap

Table 6. Results of the Aggressive Model for the US Small Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
LAUR	18.58	-4.41	55	1.119	40	45.91
CVNA	473	411.01	66.67	2.049	48	26.71
TELL	341.05	229.48	48.78	1.602	41	53.71
IMGN	42.36	101.57	46	1.161	50	45.87
VERU	141.99	123.06	33.33	1.288	42	64.99
SI	2118.03	2158.13	0.6275	2.837	51	54.68
FSLY	175.51	103.66	61.82	1.222	55	69.21
PRVB	-30.65	-12.75	53.85	0.895	39	72.44
SIX	145.64	204.54	47.5	1.525	40	43.12
APPS	1383.82	1114.51	62.5	1.736	40	37.03
Mean	**480.93**	**442.88**	**47.61**	**1.54**	**44.60**	**51.37**

For the US Small Cap in a bull period the model outperformed the buy and hold strategy. This may be due to the reduced efficiency of the US Small Cap market, further analysis and discussion will be in the discussion section. One may notice that the profitability percentage and profit factor is lower than the US Large Cap, yet the return is significantly higher. The tickers *SI* and *APPS* had outstanding returns for the period which is what causes the mean to skew so high. By removing these two stocks from the mean formula the results return a mean net profit percentage for the model of 163.43% and buy and hold for the model of 144.52%. The aggressive model still beats the buy and hold by 18.91% however, once transaction costs are considered, the model fails to beat the buy and hold. In addition, once a t- test is performed, the model results return a one tail p value of 0.13 and a two-tail p value of 0.26. With the Critical t stat for both tails being higher than the t stat. Both these render the result statistically insignificant and state that these results fail to reject the null hypothesis.

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	480.933	442.88
Variance	500371.3788	470893.9144
Observations	10	10
Pearson Correlation	0.990241424	
Hypothesized Mean Difference	0	
df	9	
t Stat	1.208109843	
P(T<=t) one-tail	0.12889529	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.257790581	
t Critical two-tail	2.262157163	

Figure 8. US Small Cap t-Test

3.2.1.3 Taiwanese Large Cap

Table 7. Results of the Aggresive Model for the Taiwanese Large Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
HON	36.6	46.9	44	1.747	25	13.23
MED	150.2	203.7	64.71	4.461	17	13.92
CHU	1	4.5	35.63	1.043	87	6.49
FOR	23.52	17.04	55	1.71	20	16.48
DELT	107.55	108.4	64.29	3.208	14	22.92
FUB	162.04	116.87	70.59	30.196	17	5.61
NAN	49.27	49.86	47.37	3.185	19	12.47
UNIT	385.88	359.28	85.71	30.456	14	20.74
FORM	28.51	35.23	44.44	1.846	27	11.95
CATH	57.65	69.02	52	4.476	25	9.42
Mean	**100.22**	**101.08**	**56.37**	**8.23**	**26.50**	**13.32**

Similar to US Large Cap market, the model does not beat the buy and hold however it performed better relative to buy and hold compared to the US Large Cap. For the US Large Cap, the model was 86% of the buy and hold return, for the Taiwanese Large Cap it is 99% of the buy and hold. Has the model performed better relative to the buy and hold due to the Taiwanese Large Cap market being less efficient? Analysis to follow in the discussion section. The profit factor is skewed by *FUB* and *UNIT* who both had a profit factor of thirty. Compared to the two previous results, the mean number of trades was significant lower, which would result in lower transaction costs.

3.2.1.4 Taiwanese Small Cap

Table 8. Results of the Aggresive Model for the Taiwanese Small Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
TECC	31.97	27.27	47.62	2.075	21	10.74
COM	28.56	31	58.33	1.269	24	39.67
KINS	437.55	480	61.9	5.467	21	28.19
LOT	87.9	80.8	48	1.732	25	41.01
HTC	202.8	166.26	54.17	4.549	24	21.76
WIST	36.14	41.61	55.56	1.778	18	29.17
TSE	484.53	639.63	57.14	3.828	14	30.52
GLOR	35.54	40.87	42.86	1.654	21	22.44
PHAR	38.35	33.35	28.57	1.4	14	38.22
TAIW	165.19	149.12	66.67	5.02	15	39.67
Mean	**154.85**	**168.99**	**52.08**	**2.88**	**19.70**	**30.14**

It is visible that the model did not beat the buy and hold. However, the ticker *TSE* performed very well, and the buy and hold captured this. The model failed to capture as much profit and lost out on 155% of returns. By removing this ticker, the mean net profit for the model would be 118% and the mean buy and hold return would be 116%. This would necessitate another test of randomly selected stocks to see another representation of the model's performance and thereby the market efficiency.

3.2.1.5 Summary

In summary, relative to the buy and hold the aggressive model in the Bull market of 2020-2021 had the following results:

Table 9. Summary of the Results of the Aggresive Model in the Bull Period Relative to the Buy and Hold

US Large Cap	US Small Cap	Taiwanese Large Cap	Taiwanese Small Cap
86.40%	108.59%	99.15%	101.31%

From these results there is a trend of the model performing better as the efficiency of the market and stock decreases. By comparing cap to cap, the model performed better in the Taiwanese Large cap versus the US Large Cap. This result, based on the theory that the Taiwanese market is less efficient than the US and therefore is capable of being exploitable by technical analysis. To the point that the model performed may have performed better due to the potential for growth in the Taiwanese market versus the US market, if that were the case, only the overall profits would be larger in the Taiwanese market. The performance relative to the buy and hold would remain around the same. However, it returns a >12% increase in performance relative to the buy and hold.

3.2.2 Bear Market

The bear market used is the trailing twelve months from the testing date of late November 22nd, 2022. Rising inflation, the necessary interest rate hikes to combat it, and war in Ukraine are a few of the causes of the 2022 bear market. In this section the results of the aggressive model will be presented. The design of this model is fast entry and slow exit. It is not anticipated that it will perform well under bear market conditions.

3.2.2.1 US Large Cap

Table 10. Results of the Aggresive Model for the US Large Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
UBER	-29.6	-32.91	38.1	0.573	21	51
EPD	12.23	11.61	47.62	1.422	21	15.82
TGT	-31.19	-34.28	43.33	0.525	30	40.28
SBUX	-17.93	-10.72	42.11	0.556	19	39.13
CRM	-41.52	-46.01	40	0.325	25	46.31
BMY	41.91	46.55	62.5	4.066	24	7.22
TSLA	-34.73	-45	46.15	0.52	26	36.31
AMZN	-35.64	-43.7	45.16	0.543	31	42.81
GOOG	-23.67	-31.26	41.38	0.605	29	37.3
AAPL	-14.41	-9.6	47.63	0.709	21	26.98
Mean	**-17.46**	**-19.53**	**45.40**	**0.98**	**24.70**	**34.32**

As expected, the model was not profitable, as few models would be, however, it is somewhat surprising that the model was able to slightly beat the buy and hold by reducing the loss by 2.08%. There is no significant abnormal performance of any individual stock which would require further analysis. The aggressive models' settings allowed it to run when stocks performed well as the case for *EPD* and *BMY* while cutting the losses from several the other tickers, relative to the buy and hold.

3.2.2.2 US Small Cap

Table 11. Results of the Aggresive Model for the US Small Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
LAUR	-10.85	-5.22	40	0.781	25	25.81
CVNA	-92.11	-83.34	33.33	0.155	21	92.4
TELL	-5.25	-21.74	52.38	0.972	21	64.34
IMGN	-4.15	7	19.35	0.965	31	60.48
VERU	-32.66	-28.64	40	0.825	20	64.55
SI	-54.57	-70.34	45.83	0.583	24	62.79
FSLY	-70.08	-76.68	46.88	0.343	32	76.4
PRVB	8.53	7.59	46.15	1.067	26	60.29
SIX	-45.93	-45.57	54.55	0.486	22	61.27
APPS	-57.15	-69.62	34.38	0.542	32	75.6
Mean	**-36.42**	**-38.66**	**41.29**	**0.67**	**25.40**	**64.39**

Small Market Cap stocks intrinsically bring a higher volatility which allows for the opportunity to receive higher profits but will also have an inversely high probability of losses. The results of the model were still better than the buy and hold and were better in the US Small Cap market compared to the US Large Cap market relative to the buy and hold. There were no major outliers where the model performed either very well or very poorly.

3.2.2.3 Taiwanese Large Cap

Table 12. Results of the Aggresive Model for the Taiwanese Large Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
HON	-1.8	-4.05	32.56	0.942	43	12.06
MED	-32.4	-25.1	26.67	0.232	15	39
CHU	-8	-3.2	34.62	0.718	52	20.14
FOR	-18.19	-14.7	41.18	0.32	17	26.4
DELT	0	9.9	44.44	1	27	21.27
FUB	-21.36	-21.32	43.33	0.546	30	30.84
NAN	-17.16	-13.31	42.11	0.577	19	34.09
UNIT	-36.77	-29.25	23.08	0.333	13	43.36
FORM	-22.31	-15.12	35.48	0.46	31	29.12
CATH	-30.14	-31.04	35	0.398	20	39.29
Mean	**-18.81**	**-14.72**	**35.85**	**0.55**	**26.70**	**29.56**

The results of the individual stocks relative to the buy and hold were noticeably less uniform during this period than previously ones. Tickers *Med, FUB, NAN* had saved 50% of losses compared to the buy and hold, yet the model failed to capture the profits on *UNIT* and *FOR*.

Further investigation as to the specific causes of these results may yield informative for a second iteration of the aggressive model.

3.2.2.4 Taiwanese Small Cap

Table 13. Results of the Aggresive Model for the Taiwanese Small Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
TECC	-18.8	-9.92	40	0.311	20	21.33
COM	19.55	13.91	60	1.723	15	19.16
KINS	-38.2	-46.6	33.33	0.334	12	55.73
LOT	42.35	68.85	50	2.181	16	25.05
HTC	-34.55	-38.61	30.77	0.4	13	47.54
WIST	17.33	9.62	50	1.783	16	20.07
TSE	2.42	-13.13	38.46	1.052	13	23.09
GLOR	37.93	49.35	70	4.172	10	21.31
PHAR	83.25	126.65	53.85	2.098	13	25.91
TAIW	-3.52	-6.12	61.11	0.941	18	28.94
Mean	**10.78**	**15.40**	**48.75**	**1.50**	**14.60**	**28.81**

Surprisingly, the Taiwanese Small Cap market performed exceedingly well in the Bear market of 2022. The chart for the Taiwanese small cap index will be in the appendix labelled as Figure X. Both the buy and hold and the aggressive model returned a positive mean result. The model was not able to capture the profits that the buy and hold was, analysis as to the cause would provide insightful. Were there significant and fast price spikes that the model was not able to capitalise on? Additionally, the number of trades in these results were the lowest of the results so far.

3.2.2.5 Summary

Table 14. Summary of the Results of the Aggresive Model in the Bear Period Relative to the Buy and Hold

US Large Cap	US Small Cap	Taiwanese Large Cap	Taiwanese Small Cap
110.63%	105.78%	72.19%	69.97%

As expected, the aggressive model results in the bear market were quite mixed relative to a buy and hold strategy and it would be immensely preferable for a trader to stay out of the market rather than use an aggressive model in a confirmed bear market. Clearly visible in the table above, the performance relative to the buy and hold decreases from US Large to Taiwanese Small which is contrary to what one would expect if adhering to the efficient market hypothesis. There is a big drop off in performance from the US market to the Taiwanese market.

3.2.3 Results on combined Bull and Bear Periods

By taking the result of the Bull period and the Bear period together, it can be determined how the model performed in the full period. Whether the models' specific attributes would allow it to be superior to the buy and hold and another model can be analysed.

Table 15. Aggressive Model Results in the Full Period

	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
US Large Cap	69.25	80.49	45.60	1.55	35.65	28.31
US Small Cap	222.26	202.11	44.45	1.11	35.00	57.88
TW Large Cap	40.70	43.18	46.11	4.39	26.60	21.44
TW Small Cap	82.81	92.20	50.42	2.19	17.15	29.48

Over both the bull and bear period the model performed worse than the buy and hold strategy except in the US Small Cap market. Two curious data points can be seen in the table above. The most profitable result, both in total and relative to the buy and hold, is the US Small Cap, however, it has the lowest Profit Factor of all the models tested. This is likely due to the large losses of the model in the US Small Cap for the bear period. Secondly, the Taiwanese Large Cap has the highest profit factor by a large amount, owing to its performance in the bull market which was skewed by *FUB* and *UNIT*.

While the US Small Cap results were positive, beating the buy and hold, upon the completion of statistical analysis, as seen in the below tables, the results are not statistically significant and as they have a higher p value than the significance level of 5% and both critical tail results are greater than the t stat. Therefore, the model results do not reject the null hypothesis.

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	222.2555	202.112
Variance	307968.8812	284663.703
Observations	20	20
Pearson Correlation	0.992186156	
Hypothesized Mean Difference	0	
df	19	
t Stat	1.263223252	
P(T<=t) one-tail	0.110895451	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.221790902	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.992186156
R Square	0.984433368
Adjusted R Square	0.983568555
Standard Error	71.13630341
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5760322.017	5760322	1138.3195	1.00252E-17
Residual	18	91086.72594	5060.374		
Total	19	5851408.743			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	13.67551447	17.06569187	0.801345	0.4333833	-22.17817371	49.52920266	-22.1781737	49.52920266
B&H %	1.032001987	0.030587814	33.73899	1.003E-17	0.967739373	1.0962646	0.967739373	1.0962646

Figure 9. Statistical tests for Full Period for US Small Cap

3.3 Results of the Defensive Model

The defensive model is designed to only allow an entry when there is a significant bullish sentiment in the market and to allow very quick exits. While it is not anticipated to perform well in the bull market compared to the aggressive model, it is expected to be able to cut off significantly more losses in the bear market. The decision as to which option to use would depend on if the defensive model can cut off more losses in the bear market than the aggressive model gains in the bull market, which is unlikely.

3.3.1 Bull Market

3.3.1.1 US Large Cap

Table 16. Results of the Defensive Model for the US Large Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
UBER	44.27	45.28	50	1.271	76	29.36
EPD	-9.85	45.61	44.12	0.878	68	36.37
TGT	36.57	122.65	56.52	1.674	69	11.32
SBUX	24.01	64.98	54.79	1.414	73	15.2
CRM	-18.01	81.25	44.44	0.724	81	35.4
BMY	-0.61	8.54	47.14	0.99	70	-6.51
TSLA	405.07	995.16	60	2.622	80	27.38
AMZN	43.82	76.18	52.7	1.48	74	17.42
GOOG	73.2	129.79	60.53	2.447	76	8.59
AAPL	58.23	166.3	0.5422	1.616	83	20.39
Mean	**65.67**	**173.57**	**47.08**	**1.51**	**75.00**	**19.49**

The defensive model, as expected, performed significantly worse than the buy and hold strategy, leaving over 100% of mean net returns on the table. The mean number of trades of seventy-five is noteably greater than the aggessive model which in real trading would bring with it a large transcation amount cost, further reducing the net profit percentage. As mentioned, however this was not only expected but intrinsic to the strategy instilled in this model. It is expected to see a similar performace in the entirety of the bull market results.

3.3.1.2 US Small Cap

Table 17. Results ofthe Defensive Model for the US Small Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
LAUR	-41.58	0.41	44.26	0.632	61	45.93
CVNA	133.17	434.78	53.14	1.497	64	29.88
TELL	-58.49	97.24	44.44	0.62	45	70.64
IMGN	41.8	98.74	47.37	1.208	76	45.46
VERU	310.78	121.66	41.27	1.526	63	49.43
SI	17.84	2098.9	47.14	1.062	70	58.8
FSLY	239.86	95.47	58.23	1.504	79	45.23
PRVB	6.16	-11.97	40.63	1.027	64	50.68
SIX	26.06	204.88	50	1.175	68	25
APPS	168.16	1104.68	48	1.248	75	63.58
Mean	**84.38**	**424.48**	**42.78**	**1.15**	**66.50**	**48.46**

Not only did the strategy fail to capture the massive gains in *SI* and *APPS*, but it also posted large losses in *LAUR* and *TELL*, whereas the buy and hold was positive. However, it did perform better than the buy and hold strategy for the tickers *VERU* and *FSLY*.

3.3.1.3 Taiwanese Large Cap

Table 18. Results of the Defensive Model for the Taiwanese Large Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
HON	17.6	46.9	33.33	1.373	60	15.26
MED	88.2	132	66.04	3.167	53	14.34
CHU	-7.45	3.6	20.91	0.628	110	10.65
FOR	28.13	16.8	40.68	1.095	59	8.1
DELT	2.2	108	37.04	1.028	54	34.72
FUB	58.72	115.94	50	3.454	48	11.98
NAN	40.28	41.14	46.94	2.056	49	8.89
UNIT	110.84	346.15	48.94	1.7	47	36.18
FORM	-6.16	24.84	32.73	0.867	55	16.94
CATH	25.66	68.74	59.56	1.803	47	7.62
Mean	**35.80**	**90.41**	**43.62**	**1.72**	**58.20**	**16.47**

The model did perform better relative to the buy and hold in the Taiwanese Large Cap than the US Large cap potentially hinting to the weaker efficiency of the Taiwanese market however, most likely it is caused by the significantly larger gain in the US market.

3.3.1.4 Taiwanese Small Cap

Table 19. Results of the Defensive Model for the Taiwanese Small Cap Market in the Bull Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
TECC	7.5	18.43	50	1.255	52	10.23
COM	36.87	19.46	63.16	1.454	38	21.55
KINS	242.65	455.4	58.49	2.357	53	23.55
LOT	-13.75	49.4	30.95	0.834	42	35.16
HTC	40.2	156.75	42.86	1.7	49	15.81
WIST	20.91	23.52	55.56	1.43	36	23.41
TSE	197.84	603.68	50	1.548	42	46.02
GLOR	-3.36	39.27	36.36	0.952	44	21.84
PHAR	59.15	18	40.63	1.766	32	24.19
TAIW	225.63	147.84	57.58	3.481	33	23.05
Mean	**81.36**	**153.18**	**48.56**	**1.68**	**42.10**	**24.48**

The model performed as expected. The only significant stand out was in the model's performance on stock *TAIW* with a net profit of 225.63 % vs the B&Hs net profit of 147.84% and the aggressive model's 165.19%. The difference is mainly due to a well performed position entry when the stock jumped 165% and an exit immediately thereafter before it corrected down 45% which the B&H and aggressive model did not avoid.

3.3.1.5 Summary

Table 20. Summary of the Results of the Defensive Model in the Bull Period Relative to the Buy and Hold

US Large Cap	US Small Cap	Taiwanese Large Cap	Taiwanese Small Cap
37.83%	19.88%	39.60%	53.12%

As expected, the model performed very poorly. However, it did perform better in the Taiwanese market versus the US market and in the Small Cap versus the Large Cap. Possibly due to the weakened efficiency of those markets relative to its counterparty. There is once again a correlation in the results between the US Small Cap and the Taiwanese Large Cap, suggesting a similarity in efficiency levels of these markets.

3.3.2 Bear Market

A bear market is where the defensive strategy is designed to perform well, potentially even exceeding the buy and hold strategy.

3.3.2.1 US Large Cap

Table 21. Results of the Defensive Model for the US Large Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
UBER	12.76	-26.93	58.14	1.138	43	23.5
EPD	-0.69	11.57	62.79	0.984	43	14.53
TGT	4.01	-36.21	42.86	1.074	42	17.25
SBUX	3.95	-11.55	48.65	1.09	37	22.96
CRM	-23.47	-43.17	41.86	0.673	43	39.05
BMY	18.61	43.49	55.56	1.837	36	15.22
TSLA	-19.96	-41.46	42.22	0.807	45	37.23
AMZN	-24.9	-43.51	40	0.586	45	34.72
GOOG	-37.25	-29.92	28.26	0.393	46	43.17
AAPL	15.2	-8.27	53.19	1.305	47	15.44
Mean	**-5.17**	**-18.60**	**42.09**	**0.99**	**42.70**	**23.98**

For the first set of results the model, as the first iteration in a model’s development performed well. It achieved the design goals for which it was implemented. Namely, its goal was to cut off the losses that the buy and hold strategy would not. The defensive model would have reduced the loss of the investor by 13.34% before transaction costs.

3.3.2.2 US Small Cap

Table 22. Results of the Defensive Model for the US Small Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
LAUR	17.38	0.96	54.55	1.469	33	15.12
CVNA	-64.9	-83.32	45.71	0.662	35	76.78
TELL	40.49	-16.22	58.33	1.151	36	71.35
IMGN	112.47	7	47.92	1.632	48	22.05
VERU	-14.32	-17.94	32.5	0.965	40	68.02
SI	-59.74	-85.87	16.67	0.61	30	70.22
FSLY	-67.2	-77.04	36.17	0.398	47	72.31
PRVB	12.47	7.73	43.75	1.116	32	53.23
SIX	4.38	-41.99	48.65	1.048	37	43.26
APPS	-49.29	-69.72	35.9	0.619	39	71.81
Mean	**-6.83**	**-37.64**	**42.02**	**0.97**	**37.70**	**56.42**

By using the defensive model, the investor would have reduced his losses by 30.82%. Not an insignificant amount. *TELL* and *IMGN,* not only did the model reduced the downside, but it was also able to capture the upswings. Both these instances will be analysed further in the next section to gain a deeper understanding of what makes technical analysis profitable.

3.3.2.3 Taiwanese Large Cap

Table 23. Results of the Defensive Model for the Taiwanese Large Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
HON	-5.8	-4.95	32.69	0.752	52	7.65
MED	-29.7	-26.7	30	0.306	20	33.4
CHU	-5.6	-3.6	28.33	0.666	60	12.78
FOR	-19.51	-14.1	29.63	0.374	27	22.16
DELT	0.4	9.15	46.43	1.014	28	10.79
FUB	-7.72	-21.98	37.5	0.597	32	14.11
NAN	10.6	-12.65	50	2.134	22	6.12
UNIT	-4.67	-27.9	42.11	0.865	38	20.29
FORM	0.93	-15.57	32.61	1.065	46	8.03
CATH	-9.9	-31.2	48.15	0.708	27	22.28
Mean	**-7.10**	**-14.95**	**37.75**	**0.85**	**35.20**	**15.76**

The model performed similarly in both Large Cap markets. There was no significant result that stands out and necessitates in depth analysis. The percentage of profitable trades is the second lowest of the results so far only beating the aggressive model also in the bear period for the Taiwanese Large Cap. The best performance from the model in this scenario was for the ticker *NAN* which beat the buy and hold by >20% with a profit factor of 2.134 and a percentage of profitable trades of 50%.

3.3.2.4 Taiwanese Small Cap

Table 24. Results of the Defensive Model for the Taiwanese Small Cap Market in the Bear Period

Ticker	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
TECC	-7.05	-7.26	34.38	0.733	32	14.69
COM	-9.42	14.03	45	0.775	20	22.97
KINS	-47.55	-48.4	34.38	0.325	32	54.56
LOT	71.4	60	46.67	1.857	30	22.16
HTC	-13.32	-33.44	45.83	0.727	24	41.04
WIST	24.3	8.84	41.67	2.083	24	13.96
TSE	0.33	-14.56	59.26	1.005	27	33.53
GLOR	74.58	49.59	46.43	2.821	28	11.16
PHAR	130.1	116.8	64	3.35	25	17.57
TAIW	4.44	-1.2	52.38	1.08	21	25.59
Mean	**22.78**	**14.44**	**47.00**	**1.48**	**26.30**	**25.72**

The ten randomly chosen stocks of the Taiwanese Small Cap market surprisingly posted a positive return both in the buy and hold, and by the defensive model. Driven primarily by *LOT, GLOR,* and *PHAR.* As the trades were conducted with a cash amount of one thousand dollars, the mean results achieve a cash return of 227 USD for the model strategy and 144 USD for the buy and hold strategy. By considering the transaction costs of one dollar per trade, the model strategy still beats the buy and hold by 55 USD which is 5.5%. After a t-Test is conducted the results return a one-tail p value of 0.04 and a two-tail p value of 0.08 which indicates that the result is not statistically significant and does not reject the null hypothesis.

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	22.781	14.44
Variance	2842.620343	2402.021489
Observations	10	10
Pearson Correlation	0.967751951	
Hypothesized Mean Difference	0	
df	9	
t Stat	1.928475966	
P(T<=t) one-tail	0.042941034	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.085882067	
t Critical two-tail	2.262157163	

Figure 10. Taiwanese Small Cap t-Test Two Sample of Means

3.3.2.5 Summary

Table 25. Summary of Results of the Defensive Model in the Bear Market Relative to the Buy and Hold

US Large Cap	US Small Cap	Taiwanese Large Cap	Taiwanese Small Cap
172%	181%	152%	158%

For the bear market, the model performed better in the US market versus the Taiwanese. In both markets it performed better in the Small Cap versus the Large Cap.

3.3.3 Results on combined Bull and Bear Periods

Table 26. Defensive Model Results for the Full Period

	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
US Large Cap	30.25	77.49	44.58	1.25	58.85	21.74
US Small Cap	38.78	193.42	42.40	1.06	52.10	52.44
TW Large Cap	14.35	37.73	40.68	1.28	46.70	16.11
TW Small Cap	52.07	83.81	47.78	1.58	34.20	25.10

The defensive model performed very poorly. It was not able to reduce the downside more than the aggressive model was able to capture the upside.

3.4 Optimal Model

As seen above the models performed as expected and designed, the aggressive model performed well in the bull market and the defensive model performed well in the bear market. By combining the models and using the aggressive in the bull period and the defensive in the bear period, it can be seen if it is possible that they beat the buy and hold.

Table 27. Optimal Model Results for the Full Period

	Net Profit %	B&H %	% Profitable	Profit Factor	Trades	Drawdown %
US Large Cap	75.40	80.96	46.30	1.55	44.65	23.14
US Small Cap	237.05	202.62	44.81	1.26	41.15	53.89
TW Large Cap	46.56	43.07	47.06	4.54	30.85	14.54
TW Small Cap	88.82	91.72	49.54	2.18	23.00	27.93

The optimal model was able to beat the buy and hold strategy in two areas, the US Small Cap and the Taiwanese Large Cap. When analysed with a t-test for means, the US Small Cap Optimal model results were significant with a one tail p value of .02 and a two tail p value of .04. The Taiwanese Large Cap Optimal model results were not significant with a one tail p value of 0.22 and a two tail p value of 0.45.

3.5 Summary of Results

As well as having different efficiencies, different markets and market capitalisation levels have different risk and return characteristics. The US Small Cap had the most volatility in its price. This is due to investors trading in this market to try to capture the potential high gains of these companies. The Taiwanese Small Cap market did not have the same volatility. The Taiwanese Large Cap was in fact more similar to the US Small Cap in this regard. This is due to investors taking into account the market that the company is in not only the Capitalisation levels. The risk that comes with a company in the Taiwanese Large Cap market is more similar to the US Small Cap. Also, a company in the US Small Cap market is in the perfect political and economic environment that it can grow relatively exponentially if its performance allows. Whereas in Taiwan, due to political, economic, and infrastructural restraints its growth may be hindered.

Table 28. Summary of All Results for the Full Period Relative to the Buy and Hold

	US Large Cap	US Small Cap	TW Large Cap	TW Small Cap
Aggressive	87.52%	109.97%	94.27%	89.82%
Defensive	41.12%	20.05%	38.04%	62.13%
Optimal	93.13%	116.99%	108.12%	96.84%

DISCUSSION AND ANALYSIS

Introduction

The aim of this paper is to investigate the profitability of technical analysis in equity markets. To achieve this goal, a systematic literature review was undertaken to gain a consensus on the current body of knowledge and a quantitative investigation into a technical analysis-based strategy was conducted. The conflicting hypotheses were the null hypothesis which stated that alpha can not be gained by using technical analysis on historical price data to forecast future price movement and the alternative hypothesis or h1, which stated that alpha can be gained by using technical analysis on historical price data to forecast future price movement. The following subsection will discuss and analyse the findings in the literature review and in the empirical research section. The literature review will be discussed first, followed by empirical research. The discussion and analysis will follow the structure of respective data sections. A summary will conclude the section.

Discussion of Literature Review

Candlestick Methods

Candlestick charting operates as the least complex and sophisticated method for forecasting future stock prices, however it is still marketed, particularly to the uneducated or unfamiliar, as a reliable way to predict future stock prices. In 2022, since the advent of retail, 'fee-less' trading apps and a massive surge of popularity for trading, investing, and the stock market since Bitcoin and the bull run of 2020, more individuals are putting their money into trading without educating themselves first. Candlestick charting is being marketed by online "gurus" and "educators" as a sure way to predict the market and make money. The empirical evidence, however, would dispute this claim.

While in 1998 *Caginalt & Laurent* presented convincing evidence of the effectiveness of candlestick charting, *Horton* in 2007, evaluated the same candlestick charting techniques and methods as *Caginalt & Laurent* and found zero value in trading using candlestick charting methods. The general finding that candlestick charting methods holds little to no value is corroborated by *Marshall, Young & Rose, Duvinage et al.* and *Hutton.* The conclusion that the results of these studies suggest is that candlestick charting methods are not profitable, at least in the US market.

Jonsson in 2016 presented an overall negative view of candlestick charting methods when trying to predict future stock prices in the Swedish stock exchange. Of the six studies of candlestick charting methods in developed markets, five did not support candlestick charting and with only one supporting. From the above studies there is a keen sense that candlestick charting methods are ineffective in efficient markets.

However, there is some evidence, that when candlestick charting methods are applied to inefficient markets, they may be of some use.

Deng, Su & Wei in 2022 evaluated ten well know candlestick patterns on the Chinese SSE 50 index. They found that over a 10-day holding period the 'Bullish Gap' reliably delivered profitability and ultimately concluded that candlestick patterns can create value for investors in this market. *Zhu et al* in 2017 also evaluated the Chinese markets and found that bearish harami, and cross signals perform well in predicting head reversals for stocks of low liquidity, while bullish harami, engulfing, and piercing patterns were profitable when applied to highly liquid, small companies' stocks. *Chen, Bao & Zhou* found that the predictive power of the patterns differs from pattern to pattern in the Chinese market although of the eight patterns evaluated, three provided both short term and medium-term prediction. The Chinese market therefore would be seen to be inefficient and eligible to be exploited by technical analysis, including candlestick charting patterns.

The Taiwanese market has been a popular target market for researchers with *Goo, Chen & Chang, Shiu & Lu, Lu & Shiu, Lu et al., Lu & Shiu 2014* all finding that candlestick charting methods are profitable pointing to the conclusion that the Taiwanese market is inefficient.

Candlestick patterns have been found to not have predictive ability in the Thai market (*Tharavaniji et al.)* or in Vietnam (*Anh, Bui et al.*) or Brazil (*Prado et al.*)

Technical Indicators

Many of the studies that evaluated technical indicators evaluated multiple indicators and found only certain ones effective. However, the studies did not investigate the exact causes for the success of certain candlesticks, they simply state whether they were or were not effective. The authors may have not been able to determine an exact cause but if they had, it would prove especially useful for future research in attempting to duplicate the results or expand the research to other markets. Of the twelve studies evaluated from developing markets, four were supportive totally, three were mixed or only supported certain indicators and four did not support candlestick charting methods.

Moving averages have been studied at length, largely beginning with the seminal case of *Brock et al.* (BLL) in 1992. They have received some support in developed markets (*Brock et al., Kwon & Kish, Lento*) however most studies have found them not to be profitable in developed markets (*Sullivan et al., LeBaron, Ready, Fong & Wong, Taylor, Sirucek & Sima).* Emerging markets offer a more positive outlook, with many studies finding profitability when using moving averages (*Fifield, Power & Knipe, Yu et al., Lubnau & Todorova, Masry, Khand et al.*) with only a few presented largely negative conclusions (*Chang et al., Souza et al.*

One of the most seminal and influential studies is *Brock et al* (BLL) which found convincing evidence for the profitability of moving average rules and trading range break rules. These rules, however, have been re-evaluated by many authors over the years to discover whether *Brock et al.* (BLL) was valid or a result of data snooping or another error that would shine doubt about the finding, and or can the results be duplicated in the more recent times. One of the strongest rules found by BLL was the 150-day moving average, *LeBaron* 2000 found that this 150-day moving average performed very poorly in the preceding decade and that BLL's trading rules did not make the same profits over the last 10 years prior to the study that they did in the preceding 90 years. *Ready* 2002 determined that BLL's success was a result of data snooping and not due to the effectiveness of technical analysis. The authors retested the trading rules and found them to underperform the buy and hold strategy. *Kwon & Kish* 2002 supports BLL's results but noted that the trading rules showed a weakening of profits over the preceding decade implying that the market is becoming more efficient.

Trading Break Range was often paired with or evaluated in the same studies as the moving average method and mostly generate positive returns but would perform less positively than the Moving Average (*Yu et al., Brock et al., Lubnau & Todorova).* Similar to moving averages TRB performed better in emerging markets than developed markets. (*Khand et al., Yu et al.*)

The Moving Average Convergence Divergence was tested in Sirucek and Sima, amongst other indicators, on daily bars over the course of 12 months (Nov 2014 – Oct 2015) on the S&P 500 Financials Index. The 'optimised settings', returned a net profit % of 4.74 with a total of six trades, the 'recommended settings' had a net profit % of -0.55 with a total of nine trades versus the buy and hold of -4.7%. Certainly, showing promise despite the limited scope of the test.

Machine Learning Methods

Of the methods of technical analysis, machine learning methods are both the most sophisticated with the highest barriers to entry but also ostensibly the most profitable. Out of the studies included in the literature review, only three out of twenty had negative outlooks on Machine Learning. (Allen & Karjalainen, Moreno & Almedia, Akiyoshi) Artificial Neural Networks (ANN) had several positive studies (Vui et al., Yong et al., Selvamuthu et al., Shah et al.) as well as Support Vector Machines (Shen et al.). However, the method which has both received increased attention in the last 5 years and has proven to present a very promising predictive ability is Long Short-Term Memory (Site et al., Fazeli, Li & Bastos, Chen et al., Mndawe et al.) Machine learning, and in particular LSTM, seems to be the most optimal way to forecast future stock prices and seems to be profitable.

Discussion of Empirical Results

Markets

The markets of the US and Taiwan were included as representatives of an efficient and inefficient market, respectively, with the assumption that technical analysis would be more effective in an inefficient market. The results are varied. Cap versus cap, the models performed better in the US markets with the aggressive US Small, defensive US Large and optimal US Small. The results were fifty-fifty. The clear standout was the US Small market, driven primarily by the aggressive model and its ability to capture profits, profits which the US Small market had the most of.

Two variants of the model were evaluated. The aggressive model was more successful than the defensive model. While the defensive model cut off more losses in the bear period, these savings were not greater than the profits that the aggressive model could capture in the bull period. The optimal variant performed best overall, which can be achieved with an indicator to confirm a major trend such as a fourteen-week moving average.

Two geographic markets were used to further evaluate the effect efficiency has on the profitability of technical analysis, the US market, and the Taiwanese market. The aggressive variant in the bull period performed better in the Taiwanese market. The mean net proft return in the US market was 308.82% for the variant and 301.87 for the buy and hold.

However, once the results of *SI* and *APPS* are removed which skewed the returns by 1383.82% and 2118.03% respectively, the readjusted mean returns are 157.02% for the variant and 161.42% for the buy and hold giving a performance for the variant relative to the buy and hold of 0.97%. In the Taiwanese market, the aggressive variant returned a mean net profit gain of 108.75% while the buy and hold return was 108.48% giving the performance relative to the buy and hold buy and hold of 1.00249. Only slightly beating the buy and hold, but when transaction costs are considered, the mean return does not beat the buy and hold and once a t-Test is conducted the results are not statistically significant. The variant did perform better in the Taiwanese market which may suggest an increase in profitability and effectiveness due to the weakened efficiency of the Taiwanese market. The defensive variant in the bull period returned 73.03% in the US market and the buy and hold returned 154.28% giving the variant's performance relative to the buy and hold of 0.47%. The Taiwanese market had a mean return of 58.58% for the variant and 121.79% giving a performance relative to the buy and hold of 0.48%. Both variants in the bull period had a better performance relative to the buy and hold in the Taiwanese market supporting the suggestion that technical analysis is more profitable in inefficient markets.

As for the bear period, the aggressive variant relative to the buy and hold performed worse in the Taiwanese market. For the US market, the variant had a mean net profit of -26.94% while the buy and hold returned -29.09%. In the Taiwanese market the variant returned a mean net profit of -4.02% and the buy and hold returned 0.34%. While the variant did perform better in the Taiwanese market in absolute terms, relative to the buy and hold it performed better in the US. The defensive variant relative to the buy and hold performed better in the Taiwanese market. The absolute return in the US market was -6% for the variant and -28.12% for the buy and hold. In the Taiwanese market the variant had a mean return of 7.84% and the buy and hold had a mean return of -0.26%.

Market Capitalization Levels

The thesis problem was evaluated on two market capitalisation levels, large cap and small cap, in both the US market and the Taiwanese market. The aggressive model in the full period performed best in the US Small Cap market being the only market in which it beat the buy and hold. The defensive model failed to beat the buy and hold in any market and performed worst in the US Small Cap market. The optimal model beat the buy and hold in the US Small Cap market and the Taiwanese Large Cap market. Throughout the results there is a correlation between the performance of each model between the markets of the US Small Cap and the Taiwanese Large Cap suggesting similar efficiency levels. Overall the results indicated that technical analysis can perform in weaker efficiencies once that efficiency level does not fall below a certain threshold.

Models Performances

The three models tested were aggressive model, the defensive model and the optimal model, which used the aggressive mode setting for the bear period and the defensive model settings for the bear period. Of the twelve results, only three beat the buy and hold. The optimal model performed best overall, beating the buy and hold in the US Small Cap market and TW Large Cap market. The defensive model performed worst overall which would make it very unwise for an investor to try to beat the market with this model's settings.

Analysis of Stand Out Performances

In this subsection, stand out performances are analysed for further insight which may allow for a more robust conclusion.

Figure 12 shows the performance of the buy and hold strategy as the blue line, and the defensive strategy as the red and green line with a gradient depending on whether it is positive or negative. It can be seen in Figure 8 that the strategy was not able follow the gains of the buy and hold and once a large drop in share price came it sunk significantly. The result of this large drop was a special dividend of USD 7.01 with a record date in June, pay date of 29th of October 2021 and ex-dividend date of the 1st of November as seen in Figure 7.

Trade Record of Defensive Strategy on LAUREATE EDUCATION, INC (LAUR)

Trade #	Type	Signal	Date/Time	Price	Profit
58	Exit Long	MA & OBV	01/11/2021 09:35	9.82 USD	-427.61 USD
	Entry Long	Crossover MA & OBV	28/10/2021 14:05	16.83 USD	-41.65%

Figure 11.

This causes the massive drop of the strategy of 41%. Herein lies a fundamental flaw with a strategy devised of solely historical price data. By limiting the input data to historical price data and ignoring fundamental information such as earning announcements and other corporate actions, all technical analysis strategies will continually increase exposure to volatility. If a strategy used fundamental data, it would have known about the upcoming dividend and exited prior to the pay date/ ex-date if its goal was to reduce volatility.

Chart of Defensive Strategy for LAUREATE EDUCATION, INC (LAUR)

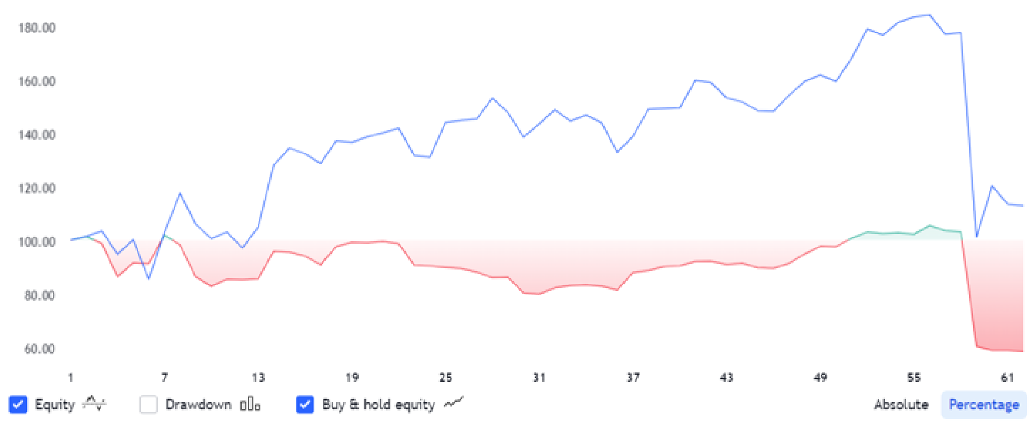

Figure 12.

For the aggressive model in the bull period, there were three standouts results that were 40-60% less than the buy and hold. These were the tickers in the US Small Cap market of *IMGN* and *SIX*, and the ticker in the Taiwanese Large Cap market of *MED.* The missed gains were largely caused in each scenario by the model producing false bear signals in periods of high volatility and or market uncertainty and or a sideways channel.

Sideways Channel in *MED*

Figure 13.

In the above sideways channel from August to October 2020, the model entered and exited five positions, resulting in missing several percentages of profits. Cumulatively these would then add up to the 40% missing of gains over the total period evaluated as this pattern occurred several times. This explains the missed gains.

The aggressive model in the bear was largely unremarkable, performing largely in line with the buy and hold strategy. There were no large savings or gains.

The defensive model in the bull period performed as poorly as expected.

Chart for Defensive Model on Salesforce in Bull Period

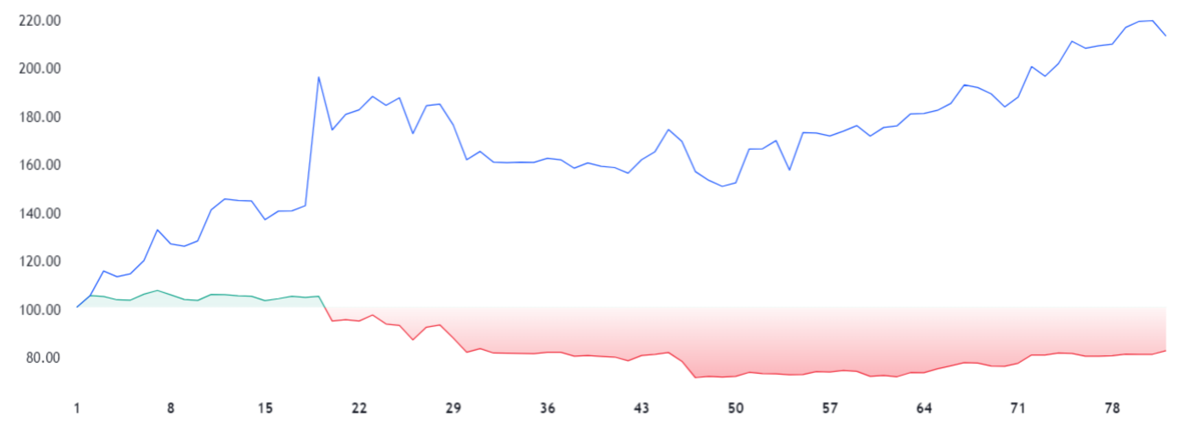

Figure 14.

To illustrate the failure of the strategy figure 10 is presented for analysis. The blue line is the buy and hold performance, the green/red line with a gradient is the model performance. There is a quite noticeable spike between order 15 and 22. This was caused by an earnings release on the 25th of August 2020 jumping the share price up 35%. The defensive model not only did not get in position before the jump, but it also sold on the slight price retracement after it, plunging it into negative equity in which it would never recover once again highlighting the drawbacks of a technical analysis-based model.

For comparison, the aggressive model got into position the day before the earnings release and exited seven days later for a gain of 29.1%. The earnings release exceeded analysts' expectations by 115% which jumped the share price.

Trade Record for the Aggressive Model on *CRM* for Bull Period					
Trade #	Type	Signal	Date/Time	Price	Profit
9	Exit Long	MA & OBV	31/08/2020 10:30	268.31 USD	29.83%
	Entry Long	Crossover MA & OBV	24/08/2020 14:55	207.38 USD	

Figure 15.

The market anticipates whether the earnings is going to be positive or negative and it will be priced in the share in the period leading up to the release. The aggressive model was able to read this increase and get into position which then allowed it to ride the profit when the earnings exceeded expectations. Yet while this is a good indicator for the model, it still only barely beats the buy and hold.

Chart for the Aggressive Model for *CRM* in the Bull Period

Figure 16.

The overall worst performer for the full period was the defensive strategy in the US Small Cap market. The settings of the defensive model and the US Small Cap market could not be worse matches for each other. Small Cap stocks often have low share prices which further increases the volatility of the share price beyond the volatility that comes with being a small cap stock. As a quick example the results for the ticker *TELL* will be presented. The defensive model returned a net profit of -58.49% while the buy and hold return was 97.24%. Quite an abysmal performance for the model especially given it was a bull market. The price for *TELL* ranged between USD 1.13 and USD 3.07 for the bull period. During this period *TELL* had multiple quick price surges followed by immediate corrections. Two surges were over 200% followed by a correction of 44% and 27%, two more surged around 100% and had immediate correction of 50% effectively wiping out the gains of the quick surge. They were multiple more around 67%, 72%. In total there was about ten price surges and corrections. Due to the defensive model's quick exit, by the time it has registered the following corrective pullback the price has already dropped >25%. The model had nine trades with a greater than 10% loss including one with 29.52% and one with 33.2%. As an example of the volatility of a large cap stock, MSFT's highest spike during the period was 13%.

Bull Period Chart for *TELL*

Figure 17.

The momentum model is effectively a reactionary strategy, it will only enter or exit a trade when the movement has already happened. This design, as can be seen, opens the model to volatility, both positive and negative. As a defensive strategy it should try to remove itself from volatile conditions. Bollinger Bands, for example of an oscillator, would be able to inform the model that the price has exceeded the standard deviation of the last *n* periods, thereby confirming its volatility and suggesting the volatility cautious model to exit. It would be interesting to see if could allow the model to stay positive in the bear market period.

As mentioned however, the volatility has a potential upside and in two cases the defensive model took advantage of this, *VERU* and *FSLY*, achieving a 189% and 144% gain over the buy and hold and in fact significantly beat the aggressive model. By analysing the data and chart for *VERU* we can see how it performed so well. The two large centre spikes were an increase of >150% immediately after an earnings report both of which the model was in position for. The price after the first spike maintained this level for 2 months in which time the defensive model had exited and re-entered in preparation for the second spike. Not that it expected a spike, but it recognised the increase in momentum. The second spike while it did have a correction, was a more gradual correction than Figure 13, as viewable in the above chart. This allowed the model to gain a return of 120%. In addition, the price entered a relative flat period in a sideways channel without much volatility which allowed the model to enter and exit comfortable whereas the aggressive model acted as a buy and hold and followed the price down. *FSLY* is similar in which it made a large spike of 500% and then gradually over a year and a half corrected back to a gain of 120%. The defensive model was able to keep most of the profits it achieved during the spike due to this gradual nature of the decline. Chart will be in the appendix.

Bull Period Chart for *VERU*

Figure 18.

Limitations

The thesis has some limitations that should be acknowledged. One limitation of this research is the use of TradingView for data collection. TradingView is a popular platform, but the data may not be as precise as data from a primary source, which can introduce errors into the analysis and limit external validity of the research. By only using data from one source, it can limit the results, as it may not hold true on other platforms. Another limitation is the lack of experience in statistics and coding that the author had before conducting the study. This lack of expertise may have affected the quality and precision of the data analysis and development of the model, which may have led to errors in the interpretation of the data. Furthermore, not having a deeper knowledge of statistical methods could have limited the capacity to conduct more robust and sophisticated analysis.

Suggestions for Further Research

Further research in this topic would benefit from addressing the above mentioned limitations such as the selection of the TradingView platform. To further investigate the profitability of technical analysis future research could expand the testing parameters to include more markets, both efficient and inefficient. Additionally, it would be beneficial to test the models on an expanded time frame, while this thesis focused on the period from 2020 – 2022, future research could expand the timeframe to check for enhanced or reduced model performance. Overall, there is much ground to cover and many areas to explore with regards to the profitability of technical analysis.

Summary

The results of this thesis revealed that the technical analysis based strategy performed best with the optimal variant settings in the US Small Cap market. The results suggest that technical analysis can be profitable in certain market conditions and market capitalisation levels but more research is need to investigate the relationship between market efficiency, market capitalisation levels and the profitability of technical analysis.

CONCLUSION

The purpose of this thesis was to investigate the profitability of technical analysis in equity markets. This can be broken down two ways. First, is technical analysis profitable? Second, if it is, what causes the profitability\What conditions are necessary for technical analysis to be profitable. To do this a systematic review was conducted. In doing so, a consensus on the profitability of technical analysis was gathered and the most promising\profitable trading rules were identified. These patterns were then evaluated in a variety of conditions and the results were analysed for insight.

The literature review evaluated the four main methods of technical analysis. Candlestick charting, being the oldest and most primitive, performed worst, with seven studies supporting and eleven opposing its efficacy. Notably, there was a statistical abnormality with several studies supporting candlestick charting in Taiwan. Chart patterns performed well, and the majority of studies reached positive conclusions as to its effectiveness. Technical indicators performed more favourably with fourteen studies supporting, six mixed and six against. One of the main conclusions drawn from the review of technical indicators studies is that technical indicators performed well\better in inefficient markets with several of the mixed result papers having evaluated the same indicator in multiple markets and only finding support for technical indicators in inefficient markets. Machine learning techniques performed best with twenty-three studies supporting and three against. Long Short-Term Memory was the significant standout. An implication can be drawn from these strong results, historical price data does hold the potential to forecast future price movement and can be acquired once the correct method is used. Not unlike a mountain which contains within in a hoard of diamonds. The profitability depends on the tools used to extract the resources, one requires explosives, not a toothbrush. Machine learning techniques were not pursued further in this paper due to the lack of skill of the author in computer science and programming to provide a worthy analysis.

A key takeaway from the literature review was that the profitability of technical analysis depends heavily on the efficiency of the market to which it is deployed. This pertains both to the country and to the market capitalisation level. It was decided to develop and test a strategy on one efficient market, the US, and one inefficient market, Taiwan. In addition, the strategy would be evaluated on ten large capitalisation stocks and ten small capitalisation stocks of each market. Momentum indicators, and models consisting of a combination of indicators stood out as the best performing strategies in the literature review so a combination strategy of a moving average cross with a volume indictor was developed. To garner a deeper insight from the results, a defensive variant and an aggressive variant of the strategy was formulated and was evaluated over three periods, one bull period, one bear period and full period combining both bull and bear periods. An optimal version of the strategy which deployed the aggressive variant in the bull period and the defensive variant in the bear period was also evaluated. The aggressive variant in the full period performed decently but only beat the buy and hold in the US small cap market and after statistical tests were performed, failed to be statistically significant. The defensive variant failed to beat the buy and hold in any market and performed quite poorly. The optimal model performed best overall and beat the buy and hold in the US small cap and the Taiwanese large cap markets by 17% and 8% (relative to buy and hold) respectively. However, once t-test statistical analysis was complete, only the US Small Cap Optimal model was statistically significant, before transaction costs are considered. Once transaction costs are considered of one dollar per trade, it still performed relative to the buy and hold better by 15%.

In conclusion, this thesis has successfully investigated the profitability of technical analysis in equity markets. A systematic literature review was conducted, and it was determined that technical analysis has the potential to generate alpha in equity markets and that market efficiency, as well as the method of technical analysis chosen, play a significant role in determining the effectiveness of technical analysis. An empirical investigation was conducted where a technical analysis-based strategy was developed, focusing on a moving average cross and a volume indicator and tested on the US and Taiwanese markets across different market capitalisation levels and time periods, consisting of a bull period and a bear period. The results showed that the strategy was most profitable in the US Small Cap market using the optimal variant of the developed strategy and was statistically significant. The findings of this thesis contribute to the current understanding of the profitability of technical analysis in equity markets and provide valuable insight for trades and investors who choose to include technical analysis in their investment decision making process. Future research may further explore the effect of market efficiency on the profitability of technical analysis by testing strategies in different geographic markets, market capitalisation levels and historic time periods.

LIST OF REFERENCES

Abe, M., & Nakayama, H. (2018). *Deep Learning for Forecasting Stock Returns in the Cross-Section*. Pacific-Asia Conference on Knowledge Discovery and Data Mining.

Akiyoshi, D. (2019). *Evaluating machine learning algorithms for stock market prediction*.

Allen, F., & Karjalainen, R. (1999). *Using genetic algorithms to find technical trading rules.* Journal of Financial Economics, 51, 245-271.

Anh, Bui & Thanh, Le & Tran, Quy Ban & Duong Xuan, Hoa & Son, Ngo. (2018). *An Analyze on Effectiveness of Candlestick Reversal Patterns for Vietnamese Stock Market*

Arévalo, R., García, J., Guijarro, F., & Peris, A. (2017). *A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting*. Expert Syst. Appl., 81, 177-192.

Y. Bengio, P. Simard and P. Frasconi. (1994). *Learning long-term dependencies with gradient descent is difficult*, in IEEE Transactions on Neural Networks, vol. 5, no. 2, pp. 157-166, March 1994, doi: 10.1109/72.279181.

Bessembinder, Hendrik & Chan, Kalok. (1995). *The profitability of technical trading rules in the Asian stock markets.* Pacific-Basin Finance Journal, Elsevier, vol. 3(2-3), pages 257-284, July.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). *Simple Technical Trading Rules and the Stochastic Properties of Stock Returns*. The Journal of Finance, 47(5), 1731–1764. https://doi.org/10.2307/2328994

Caginalp, Gunduz & Laurent, Henry. (1998). *The Predictive Power of Price Patterns*. Applied Mathematical Finance, Vol. 5, pp. 181-206, Available at SSRN: https://ssrn.com/abstract=932984

Cervelló-Royo, Roberto, Francisco Guijarro, and Karolina Michniuk. *Stock Market Trading Rule Based on Pattern Recognition and Technical Analysis: Forecasting the DJIA Index with Intraday Data*. Expert systems with applications 42.14 (2015): 5963–5975. Web.

Chang, E.J., Lima, E.J., & Tabak, B.M. (2004*). Testing for predictability in emerging equity markets*. Emerging Markets Review, 5, 295-316.

Chen, Shi & Bao, Si & Zhou, Yu. (2016). *The predictive power of Japanese candlestick charting in Chinese stock market*. Physica A: Statistical Mechanics and its Applications. 457. 10.1016/j.physa.2016.03.081.

Chen, Q., Zhang, W., & Lou, Y. (2020). *Forecasting Stock Prices Using a Hybrid Deep Learning Model Integrating Attention Mechanism, Multi-Layer Perceptron, and Bidirectional Long-Short Term Memory Neural Network*. IEEE Access, 8, 117365-117376.

Chio, Pat. (2022). *A comparative study of the MACD-base trading strategies: evidence from the US stock market*. 10.48550/arXiv.2206.12282.

Ciana, Paul. (2011) *New Frontiers in Technical Analysis.* 1st Edition. Wiley

Dash, R., & Dash, P.K. (2016). *A hybrid stock trading framework integrating technical analysis with machine learning techniques*. The Journal of Finance and Data Science, 2, 42-57.

Dawson, Edward & Steeley, James. (2003). *On the Existence of Visual Technical Patterns in the UK Stock Market*. Journal of Business Finance & Accounting. 30. 263-293. 10.1111/1468-5957.00492.

Deng, Su & Wei. (2022) *Can Japanese Candlestick Patterns be Profitable on the Component Stocks of the SSE50 Index?*

Dhule, P., Athare, H., Biradar, R., Dhulgande, H., & Rathod, A.G. (2018). *Stock Price Prediction Using Deep Learning*.

Duvinage, Matthieu & Mazza, Paolo & Petitjean, Mikael. (2013). *The Intraday Performance of Market Timing Strategies and Trading Systems Based on Japanese Candlesticks*. Quantitative Finance. 13. 1059-1070. 10.1080/14697688.2013.768774.

Fama, E. F. (1970). *Efficient Capital Markets: A Review of Theory and Empirical Work*. The Journal of Finance, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fazeli, A. (2019). *Using Deep Learning for Predicting Stock Trends*.

Fifield, Power & Knipe (2008) *The performance of moving average rules in emerging stock markets*, Applied Financial Economics, 18:19, 1515-1532, DOI: 10.1080/09603100701720302

Fong, Wai & Yong, Lawrence. (2005). *Chasing trends: Recursive moving average trading rules and internet stocks*. Journal of Empirical Finance. 12. 43-76. 10.1016/j.jempfin.2003.07.002.

Goo, Y.-J & Chen, Dar-Hsin & Chang, Y.-W. (2007). *The application of Japanese candlestick trading strategies in Taiwan*. Investment Management and Financial Innovations. 4. 49-79.

Grinblatt, Mark & Titman, Sheridan & Wermers, Russ. (1995). *Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior*. American Economic Review. 85. 1088-1105.

Gurav, Uma & Sidnal, Nandini. (2018). *Adaptive Stock Forecasting Model using Modified Backpropagation Neural Network* (MBNN). 380-385. 10.1109/CTEMS.2018.8769290.

Harvey, Campbell R., (2017). *The Scientific Outlook in Financial Economics*, Presidential Address.

Horton, M.J. (2009). *Stars, crows, and doji: The use of candlesticks in stock selection*. The Quarterly Review of Economics and Finance, 49, 283-294.

Houssein, E.H., Dirar, M., Hussain, K., & Mohamed, W.M. (2021). *Artificial Neural Networks for Stock Market Prediction: A Comprehensive Review*. Metaheuristics in Machine Learning: Theory and Applications.

Hutton S. (2015) *An Analysis of Candlestick Charting: The Predictive Power of the Three-Outside-Up and Three-Outside-Down Candlestick Patterns in the Context of Small Capitalization Stocks in the USA.*

Jegadeesh, Narasimhan and Titman, Sheridan. (1999). *Profitability of Momentum Strategies: An Evaluation of Alternative Explanations* NBER Working Paper No. w7159, Available at SSRN: https://ssrn.com/abstract=227349

Jönsson, Max. (2016). *The Predictive Power of Candlestick Patterns - An Empirical Test of Technical Indicators on the Swedish Stock Market Using GARCH-M and Bootstrapping.*

Kabasinskas, Audrius & Macys, Ugnius. (2010). *Calibration of Bollinger Bands Parameters for Trading Strategy Development in the Baltic Stock Market*. Engineering Economics. 21. 244-254.

Khand, Anand, & Qureshi. (2020) *The Predictability and Profitability of Simple Moving Averages and Trading Range Breakout Rules in the Pakistan Stock Market*. Review of Pacific Basin Financial Markets and Policies

Kwon, Ki-Yeol & Kish, Richard. (2002). *A comparative study of technical trading strategies and return predictability: An extension of Brock, Lakonishok, and LeBaron (1992) using NYSE and NASDAQ indices*. The Quarterly Review of Economics and Finance. 42.

Lam, Dong, & Yu. (2019). *Value Premium and Technical Analysis: Evidence from the China Stock Market. Economies*, 7(3), 92. MDPI AG. Retrieved from http://dx.doi.org/10.3390/economies7030092

Lebaron, Blake. (2000). *The Stability of Moving Average Technical Trading Rules on the Dow Jones Index*. Derivatives Use, Trading and Regulation. 5.

Leigh, W., Paz, N.M., & Purvis, R.L. (2002). *Market timing: a test of a charting heuristic*. Economics Letters, 77, 55-63.

Leigh, W., Modani, N., Purvis, R.L., & Roberts, T.L. (2002). *Stock market trading rule discovery using technical charting heuristics*. Expert Syst. Appl., 23, 155-159.

Lento, Camillo & Gradojevic, Nikola. (2007). *The Profitability Of Technical Trading Rules: A Combined Signal Approach*. Journal of Applied Business Research. 23. 10.19030/jabr.v23i1.1405.

Li, A.W., & Bastos, G.S. (2020). *Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review*. IEEE Access, 8, 185232-185242.

Lo, Andrew W., Harry Mamaysky & Jiang Wang. (2000). *Foundations Of Technical Analysis: Computational Algorithms, Statistical Inference, And Empirical Implementation,* Journal of Finance, 2000, v55(4,Aug), 1705-1765.

Lu, Tsung-Hsun & Shiu, Yung-Ming. (2011). *Pinpoint and synergistic trading strategies of candlesticks.* International Journal of Economics and Finance. 3. 10.5539/ijef.v3n1p234.

Lu, Tsung-Hsun & Yung-Ming Shiu (2012) *Tests for Two-Day Candlestick Patterns in the Emerging Equity Market of Taiwan*. Emerging Markets Finance and Trade, 48:sup1, 41-57, DOI: 10.2753/REE1540-496X4801S104

Lu, Tsung-Hsun. (2014). *The profitability of candlestick charting in the Taiwan stock market*. Pacific-Basin Finance Journal. 26. 65–78. 10.1016/j.pacfin.2013.10.006.

Lubnau, T., & Todorova, N. (2014*). Technical Trading Revisited: Evidence from the Asian Stock Markets*. Corporate Ownership and Control, 11, 511-532.

Malkiel, B. (1996) *A Random Walk down the Wall Street*. 6th Edition, W. W Norton, New York.

Marek, Patrice & Sediva, Blanka. (2017). *Optimization and Testing of RSI*.

Marshall, Ben & Young, Martin & Rose, Lawrence. (2006). *Candlestick technical trading strategies: Can they create value for investors?* Journal of Banking & Finance. 30. 2303-2323. 10.1016/j.jbankfin.2005.08.001.

Marshall, Ben & Young, Martin & Cahan, Rochester. (2008). *Are candlestick technical trading strategies profitable in the Japanese equity market?* Review of Quantitative Finance and Accounting. 31. 191-207. 10.1007/s11156-007-0068-1.

Martinssson, F., & Liljeqvist, I. (2017). *Short-Term Stock Market Prediction Based on Candlestick Pattern Analysis (Dissertation)*. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-209820

Masry, Mohamed. (2017). *The Impact of Technical Analysis on Stock Returns in an Emerging Capital Markets (ECM's) Country: Theoretical and Empirical Study*. International Journal of Economics and Finance. 9. 91. 10.5539/ijef.v9n3p91.

Masteika, S., & Simutis, R. (2006). *Stock Trading System Based on Formalized Technical Analysis and Ranking Technique*. International Conference on Computational Science.

Menkhoff, L. (2010). *The use of technical analysis by fund managers: International evidence.* Journal of Banking and Finance, 34, 2573-2586.

Moreno, David & Olmeda, Ignacio. (2007). *Is the predictability of emerging and developed stock markets really exploitable?* European Journal of Operational Research. 182. 436-454. 10.1016/j.ejor.2006.07.032.

Morris, Gregory. (2006). *Candlestick Charting Explained: Timeless Techniques for Trading Stocks and Futures.* 3rd Edition. McGraw Hill

Murkute, A., & Sarode, T.K. (2015). *Forecasting Market Price of Stock using Artificial Neural Network*. International Journal of Computer Applications, 124, 11-15.

Nazário, Rodolfo & Lima e Silva, Jéssica & Sobreiro, Vinicius & Kimura, Herbert. (2017). *A Literature Review Of Technical Analysis On Stock Markets*. The Quarterly Review of Economics and Finance. 66. 10.1016/j.qref.2017.01.014.

Nison (1991). *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East*

Paluch, M., & Jackowska-Strumiłło, L. (2018). *Hybrid Models Combining Technical and Fractal Analysis with ANN for Short-Term Prediction of Close Values on the Warsaw Stock Exchange*. Applied Sciences, 8(12), 2473. MDPI AG. Retrieved from http://dx.doi.org/10.3390/app8122473

Park, C., & Irwin, S.H. (2004). *The Profitability of Technical Analysis: A Review*. FEN: Behavioral Finance (Topic).

Prado, Hércules & Ferneda, Edilson & Morais, Luis & Luiz, Alfredo & Matsura, Eduardo. (2013*). On the Effectiveness of Candlestick Chart Analysis for the Brazilian Stock Market*. Procedia Computer Science. 22. 10.1016/j.procs.2013.09.200.

Rao, P.S., Srinivas, K., & Mohan, A. (2020). *A Survey on Stock Market Prediction Using Machine Learning Techniques*.

Rao, P., Parthasaradhi Varma, G., & Durga Prasad, C. (2022). *Financial time series forecasting using optimized multistage wavelet regression approach*. International Journal of Information Technology, 14, 2231 - 2240.

Ready, M. J. (2002). *Profits from Technical Trading Rules*. Financial Management, 31(3), 43–61. https://doi.org/10.2307/3666314

Rodríguez-Cándido, N. P., Espin-Andrade, R. A., Solares, E., & Pedrycz, W. (2021). *A Compensatory Fuzzy Logic Model in Technical Trading*. Axioms, 10(1), 36. MDPI AG. Retrieved from http://dx.doi.org/10.3390/axioms10010036

Sable, R.Y., Goel, S., & Chatterjee, P. (2019). *Empirical Study on Stock Market Prediction Using Machine Learning*. 2019 International Conference on Advances in Computing, Communication and Control (ICAC3), 1-5.

Saunders, M., Lewis, P., & Thornhill, A. (2007). *Research Methods for Business Students.* Upper Saddle River, NJ: Pearson Education.

Selvamuthu, Dharmaraja & Kumar, Vineet & Mishra, Abhishek. (2019). *Indian stock market prediction using artificial neural networks on tick data*. Financial Innovation. 5. 10.1186/s40854-019-0131-7.

Shah, D., Isah, H., & Zulkernine, F. (2019). *Stock Market Analysis: A Review and Taxonomy of Prediction Techniques*. International Journal of Financial Studies, 7(2), 26. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ijfs7020026

Shen, S., Jiang, H., & Zhang, T. (2012). *Stock Market Forecasting Using Machine Learning Algorithms*.

Shynkevich, Andrei. (2012). *Performance of technical analysis in growth and small cap segments of the US equity market*. Journal of Banking & Finance. 36. 193–208. 10.1016/j.jbankfin.2011.07.001.

Singh, J., & Khushi, M. (2021). *Feature Learning for Stock Price Prediction Shows a Significant Role of Analyst Rating*. Applied System Innovation, 4(1), 17. MDPI AG. Retrieved from http://dx.doi.org/10.3390/asi4010017

Širůček, Martin & Šíma, Karel. (2016). *Optimized Indicators of Technical Analysis on the New York Stock Exchange*. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis. 64. 2123-2131. 10.11118/actaun201664062123.

Site, Birant & Işık. (2019) *Stock Market Forecasting Using Machine Learning Models*. Innovations in Intelligent Systems and Applications Conference (ASYU), 2019, pp. 1-6, doi: 10.1109/ASYU48272.2019.8946372.

Souza, Matheus & Ramos, Danilo & Pena, Marina & Sobreiro, Vinicius & Kimura, Herbert. (2018). *Examination of the profitability of technical analysis based on moving average strategies in BRICS*. Financial Innovation. 4. 10.1186/s40854-018-0087-z.

Sullivan, Ryan M. and Timmermann, Allan and White, Halbert L., *Data-Snooping, Technical Trading Rule Performance, and the Bootstrap*. Available at SSRN: https://ssrn.com/abstract=160330

Taylor, Nicholas. (2013). *The Rise and Fall of Technical Trading Rule Success* Journal of Banking and Finance, 2014, Available at SSRN: https://ssrn.com/abstract=2202466 or http://dx.doi.org/10.2139/ssrn.2202466

Teresienė, D., & Aleksynaite, M. (2020). *The Use of Technical Analysis in the US, European and Asian Stock Markets*. Technium Social Sciences Journal.

Tharavanij, Piyapas & Siraprapasiri, Vasan & Rajchamaha, Kittichai. (2017). *Profitability of Candlestick Charting Patterns in the Stock Exchange of Thailand*. SAGE Open. 7. 215824401773679. 10.1177/2158244017736799.

Tsinaslanidis, Prodromos & Guijarro, Francisco. (2021). *What makes trading strategies based on chart pattern recognition profitable?* Expert Systems. 38. 10.1111/exsy.12596.

Vui, C.S., Gan, K.S., On, C.K., Alfred, R., & Anthony, P. (2013). *A review of stock market prediction with Artificial neural network (ANN)*. 2013 IEEE International Conference on Control System, Computing and Engineering, 477-482.

J. Welles Wilder Jr. (1978) '*New Concepts in Technical Trading Systems'*.

Yong, B.X., Rahim, M.R., & Abdullah, A.S. (2017). *A Stock Market Trading System Using Deep Neural Network*. AsiaSim 2017.

Yu, Hao & Nartea, Gilbert & Gan, Christopher & Yao, Lee. (2012). *Predictive ability and profitability of simple trading rules: Recent evidence from Southeast Asian stock markets*. International Review of Economics & Finance. 25. 356-371. 10.1016/j.iref.2012.07.016.

Zapranis, Achilleas & Tsinaslanidis, Prodromos. (2012). *A novel, rule-based technical pattern identification mechanism: Identifying and evaluating saucers and resistant levels in the US stock market.* Expert Systems with Applications. 39. 6301-6308. 10.1016/j.eswa.2011.11.079.

Zhang, J., Li, L., & Chen, W. (2020). *Predicting Stock Price Using Two-Stage Machine Learning Techniques.* Computational Economics, 1-25.

Zhong, X., & Enke, D. (2019). *Predicting the daily return direction of the stock market using hybrid machine learning algorithms*. Financial Innovation, 5, 1-20.

Zhu, M., Atri, S., & Yegen, E. (2016). *Are candlestick trading strategies effective in certain stocks with distinct features*. Pacific-basin Finance Journal, 37, 116-127.

Zuzik, Jozef & Weiss, Roland & (Antošová), Maria. (2014). *Use of technical analysis indicators at trading shares of steel companies*. Metalurgija -Sisak then Zagreb-. 53. 286-288.

AN INVESTIGATION INTO THE PROFITABILITY OF TECHNICAL ANALYSIS IN EQUITY MARKETS

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Master Thesis

Finance and Banking Master Programme

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SUMMARY

102 pages, 28 tables, 18 figures, 93 references

The main purpose of this master thesis is to determine if technical analysis is profitable in equity markets and if so, investigate the reasons for its profitability.

The Master thesis consists of three main parts, the analysis of previous research and literature, the development of a model to evaluate the profitability of technical analysis and its results, a conclusion and recommendations for further research.

The literature analysis reviews the research conducted on the four main types of technical analysis, candlestick charting, chart patterns, technical indicators, and machine learning techniques. A consensus is found for each technique and most profitable technical indicators are extracted for examination in this paper. The research is further categorised by the market in which it was evaluated in to investigate the effects that different markets have on the profitability of technical analysis.

Following the literature analysis, a model was developed from the information extracted from the reviewed studies. The model consisted of a moving average cross with a volume indicator in combination. Two variants of this model were used, one defensive and one aggressive. The model was deployed in two markets, one efficient, the US and one inefficient, Taiwan, two market capitalisation levels in each market, large and small, and during three periods, the bull period of 2020 to late 2021, the bear period of 2022 and a full period from early 2020 to late 2022. In total forty stocks were used to evaluate the two model variants. The results were extracted and matched against the buy and hold for the same period. Transaction costs were not included in the model but were considered upon analysis of the results. The results of the model were extracted manually and entered into excel for analysis and presentation.

The performed research revealed that i) the defensive model cannot cut off more losses in the bear market than the profits gained by the aggressive model in the bull market, ii) the US small cap market had the highest profits for the model compared to the buy and hold, iii) the Taiwanese large cap and the US small cap were closest in performance indicating a similar efficiency level. iv) a trend was witnessed that as efficiency decreased the performance of technical analysis increased.

The conclusion summarises the main concepts of the literature analysis as well as the results of the performed research. The author believes the results of the study could give useful guidance to investors and traders in determining if technical analysis is effective, which strategies are most beneficial, and which markets provide the most opportunity.

TECHNINĖS ANALIZĖS PELNINGUMO AKCIJŲ RINKOSE TYRIMAS

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SANTRAUKA

102 puslapių, 28 lentelės, 18 paveikslų, 93 nuorodų.

Pagrindinis šio magistro darbo tikslas - nustatyti, ar techninė analizė yra pelninga akcijų rinkose, ir ištirti jos pelningumo priežastis.

Magistro darbą sudaro trys pagrindinės dalys: ankstesnių tyrimų ir literatūros analizė, techninės analizės pelningumo tyrimo modelio sukūrimas ir jo rezultatai, išvados ir rekomendacijos tolesniems tyrimams.

Literatūros analizėje apžvelgiami atlikti keturių pagrindinių techninės analizės rūšių, žvakidžių grafikų, grafikų modelių, techninių indikatorių ir mašininio mokymosi metodų tyrimai. Nustatytas kiekvieno metodo sutarimas ir išskirti pelningiausi techniniai rodikliai, kurie nagrinėjami šiame straipsnyje. Tyrimai toliau skirstomi pagal rinką, kurioje jie buvo išbandyti, siekiant ištirti, kokį poveikį skirtingos rinkos daro techninės analizės pelningumui.

Atlikus literatūros analizę, remiantis iš apžvelgtų tyrimų gauta informacija buvo sukurtas modelis. Modelį sudarė slankiojo vidurkio kryžminis ir apimties rodiklio derinys. Buvo naudojami du šio modelio variantai: gynybinis ir agresyvus. Modelis buvo taikomas dviejose rinkose, vienoje efektyvioje - JAV ir vienoje neefektyvioje - Taivano, kiekvienoje rinkoje buvo nustatyti du rinkos kapitalizacijos lygiai - didelė ir maža, ir trimis laikotarpiais: bulių laikotarpiu nuo 2021 m. iki 2021 m. pabaigos, meškų laikotarpiu 2022 m. ir visu laikotarpiu nuo 2020 m. pradžios iki 2022 m. pabaigos. Dviem modelio variantams patikrinti iš viso naudota 40 akcijų. Rezultatai buvo išskirti ir sugretinti su to paties laikotarpio pirkimo ir laikymo rezultatais. Sandorių sąnaudos nebuvo įtrauktos, nes autorius mano, kad jos yra pašalinės techninės analizės pelningumui, kuris yra tiriamas. Modelio rezultatai buvo išgauti rankiniu būdu ir įvesti į "Excel" programą analizei ir pateikimui.

Atliktas tyrimas atskleidė, kad i) gynybinis modelis meškų rinkoje negali sumažinti didesnių nuostolių nei agresyvaus modelio gautas pelnas bulių rinkoje, ii) JAV mažos kapitalizacijos rinkoje buvo gautas didžiausias modelio pelnas, palyginti su "pirk ir laikyk", iii) pastebėta tendencija, kad mažėjant efektyvumui techninės analizės efektyvumas didėjo, iv) Taivano didelės kapitalizacijos ir JAV mažos kapitalizacijos rinkos efektyvumas buvo artimiausias, o tai rodo panašų efektyvumo lygį.

Išvadose apibendrinamos pagrindinės literatūros analizės koncepcijos ir atlikto tyrimo rezultatai. Autorius mano, kad tyrimo rezultatai galėtų būti naudingos gairės investuotojams ir prekiautojams nustatant, ar techninė analizė yra veiksminga, kokios strategijos yra naudingiausios ir kokios rinkos teikia daugiausia galimybių.

APPENDIX A

ADDITONAL TABLES AND FIGURES

A1. Aggressive US Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	69.2545	80.493
Variance	36995.33521	54580.4032
Observations	20	20
Pearson Correlation	0.997275738	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.138429544	
P(T<=t) one-tail	0.134546393	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.269092787	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.997275738
R Square	0.994558897
Adjusted R Square	0.994256613
Standard Error	14.57664277
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	699086.7556	699086.76	3290.1527	7.77184E-22
Residual	18	3824.61326	212.47851		
Total	19	702911.3689			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	3.165606477	3.457086233	0.9156863	0.3719366	-4.097462184	10.4286751	-4.097462184	10.4286751
B&H %	0.82105144	0.014314044	57.359853	7.772E-22	0.79097875	0.85112413	0.79097875	0.85112413

Descriptive Statistics

Net Profit%		*B&H %*	
Mean	69.2545	Mean	80.493
Standard Error	43.00891489	Standard Error	52.240025
Median	27.07	Median	28.325
Mode	#N/A	Mode	#N/A
Standard Deviation	192.3417147	Standard Deviation	233.62449
Sample Variance	36995.33521	Sample Variance	54580.403
Kurtosis	15.75171346	Kurtosis	16.324683
Skewness	3.794790586	Skewness	3.8904728
Range	887.86	Range	1077.41
Minimum	-41.52	Minimum	-46.01
Maximum	846.34	Maximum	1031.4
Sum	1385.09	Sum	1609.86
Count	20	Count	20

A2. Aggressive TW Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit%	*B&H %*
Mean	40.7045	43.1805
Variance	9977.087258	9123.42725
Observations	20	20
Pearson Correlation	0.98406774	
Hypothesized Mean Difference	0	
df	19	
t Stat	-0.616026997	
P(T<=t) one-tail	0.272593416	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.545186832	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.984068
R Square	0.968389
Adjusted R Square	0.966633
Standard Error	18.24565
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	183572.4	183572.4	551.4277373	5.92992E-15
Residual	18	5992.268	332.9038		
Total	19	189564.7			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-3.731559566	4.497333641	-0.82973	0.417561815	-13.1801069	5.716987803	-13.18010694	5.7169878
B&H %	1.029077004	0.043823148	23.4825	5.92992E-15	0.937007987	1.121146021	0.937007987	1.12114602

Net Profit %		*B&H %*	
Mean	40.7045	Mean	43.1805
Standard Error	22.33504786	Standard Error	21.35816852
Median	0.5	Median	7.2
Standard Deviation	99.88537059	Standard Deviation	95.51663335
Sample Variance	9977.087258	Sample Variance	9123.427247
Kurtosis	7.153628561	Kurtosis	5.867824221
Skewness	2.470574033	Skewness	2.291659553
Range	422.65	Range	390.32
Minimum	-36.77	Minimum	-31.04
Maximum	385.88	Maximum	359.28
Sum	814.09	Sum	863.61
Count	20	Count	20

A3. Aggressive TW Small Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	82.8145	92.1955
Variance	20260.21474	29453.96362
Observations	20	20
Pearson Correlation	0.986229871	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.072458269	
P(T<=t) one-tail	0.14847387	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.296947739	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.98623
R Square	0.972649
Adjusted R Square	0.97113
Standard Error	24.18501
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	374415.6	374415.6	640.1198603	1.60841E-15
Residual	18	10528.47	584.9149		
Total	19	384944.1			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	7.402922528	6.174938815	1.19886573	0.246125719	-5.570142526	20.37598758	-5.570142526	20.37598758
B&H %	0.81795291	0.0323294	25.30059012	1.60841E-15	0.75003136	0.88587446	0.75003136	0.88587446

Net Profit %		*B&H %*	
Mean	82.8145	Mean	92.1955
Standard Error	31.8278296	Standard Error	38.37574991
Median	35.84	Median	37.11
Standard Deviation	142.3383811	Standard Deviation	171.621571
Sample Variance	20260.21474	Sample Variance	29453.96362
Kurtosis	3.994641061	Kurtosis	5.920614931
Skewness	2.126700287	Skewness	2.461952858
Range	522.73	Range	686.23
Minimum	-38.2	Minimum	-46.6
Maximum	484.53	Maximum	639.63
Sum	1656.29	Sum	1843.91
Count	20	Count	20

A4. Defensive US Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	30.248	77.489
Variance	8656.665059	50592.72914
Observations	20	20
Pearson Correlation	0.978477113	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.561950757	
P(T<=t) one-tail	0.06740105	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.1348021	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.978477113
R Square	0.95741746
Adjusted R Square	0.955051763
Standard Error	19.72566424
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	157472.8032	157472.8032	404.7084625	8.70658E-14
Residual	18	7003.832931	389.1018295		
Total	19	164476.6361			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1.115316553	4.678207493	-0.238406816	0.814258592	-10.94386578	8.713232678	-10.94386578	8.713232678
B&H %	0.404745403	0.020119203	20.11736719	8.70658E-14	0.362476525	0.447014281	0.362476525	0.447014281

Net Profit %		*B&H %*	
Mean	30.248	Mean	77.489
Standard Error	20.80464498	Standard Error	50.29549142
Median	8.385	Median	27.53
Standard Deviation	93.04120087	Standard Deviation	224.9282755
Sample Variance	8656.665059	Sample Variance	50592.72914
Kurtosis	15.54549271	Kurtosis	16.51150856
Skewness	3.75570012	Skewness	3.918982022
Range	442.32	Range	1038.67
Minimum	-37.25	Minimum	-43.51
Maximum	405.07	Maximum	995.16
Sum	604.96	Sum	1549.78
Count	20	Count	20

A5. Defensive US Small Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	38.775	193.419
Variance	10930.97769	272596.0211
Observations	20	20
Pearson Correlation	0.20727432	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.353981318	
P(T<=t) one-tail	0.09581464	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.191629281	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.20727432
R Square	0.042962644
Adjusted R Square	-0.010206098
Standard Error	105.0834921
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	8922.850315	8922.850315	0.808043263	0.380567396
Residual	18	198765.7258	11042.54032		
Total	19	207688.5761			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	30.74687029	25.13739584	1.223152569	0.237044729	-22.06483865	83.558579	-22.06483865	83.5585792
B&H %	0.041506417	0.046174047	0.898912267	0.380567396	-0.055501656	0.1385145	-0.055501656	0.13851449

Net Profit %		*B&H %*	
Mean	38.775	Mean	193.419
Standard Error	23.37838498	Standard Error	116.7467389
Median	14.925	Median	3.98
Standard Deviation	104.5513161	Standard Deviation	522.1072889
Sample Variance	10930.97769	Sample Variance	272596.0211
Kurtosis	1.319668522	Kurtosis	9.985779215
Skewness	1.331242315	Skewness	3.097160778
Range	377.98	Range	2184.77
Minimum	-67.2	Minimum	-85.87
Maximum	310.78	Maximum	2098.9
Sum	775.5	Sum	3868.38
Count	20	Count	20

A6. Defensive TW Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit%	*B&H %*
Mean	14.3525	37.7305
Variance	1289.141588	7740.94311
Observations	20	20
Pearson Correlation	0.872112863	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.76215657	
P(T<=t) one-tail	0.047062025	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.09412405	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.872112863
R Square	0.760580846
Adjusted R Square	0.747279782
Standard Error	18.04971312
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	18629.43	18629.43	57.18195467	5.41405E-07
Residual	18	5864.259	325.7921		
Total	19	24493.69			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.924274548	4.409421877	0.20961354	0.836323469	-8.33957706	10.1881262	-8.33957706	10.18812615
B&H %	0.355898423	0.047064838	7.56187508	5.41405E-07	0.257018868	0.45477798	0.257018868	0.454777978

Net Profit %		*B&H %*	
Mean	14.3525	Mean	37.7305
Standard Error	8.028516638	Standard Error	19.6735141
Median	0.665	Median	6.375
Standard Deviation	35.90461792	Standard Deviation	87.9826296
Sample Variance	1289.141588	Sample Variance	7740.94311
Kurtosis	1.998929673	Kurtosis	7.66193609
Skewness	1.530706425	Skewness	2.51578623
Range	140.54	Range	377.35
Minimum	-29.7	Minimum	-31.2
Maximum	110.84	Maximum	346.15
Sum	287.05	Sum	754.61
Count	20	Count	20

A7. Defensive TW Small Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit%	*B&H %*
Mean	52.0725	83.8075
Variance	6980.999588	26687.0189
Observations	20	20
Pearson Correlation	0.809613289	
Hypothesized Mean Difference	0	
df	19	
t Stat	-1.319614626	
P(T<=t) one-tail	0.101322288	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.202644577	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.80961329
R Square	0.65547368
Adjusted R Square	0.63633333
Standard Error	50.3860784
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	86941.37	86941.37	34.24564525	1.52824E-05
Residual	18	45697.62	2538.757		
Total	19	132639			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	17.36931874	12.73203342	1.364222	0.189313388	-9.379690891	44.11832836	-9.37969089	44.11832836
B&H %	0.414082048	0.070759332	5.851978	1.52824E-05	0.265422208	0.562741889	0.265422208	0.562741889

Net Profit %		*B&H %*	
Mean	14.3525	Mean	37.7305
Standard Error	8.028516638	Standard Error	19.67351406
Median	0.665	Median	6.375
Standard Deviation	35.90461792	Standard Deviation	87.98262959
Sample Variance	1289.141588	Sample Variance	7740.94311
Kurtosis	1.998929673	Kurtosis	7.661936092
Skewness	1.530706425	Skewness	2.515786231
Range	140.54	Range	377.35
Minimum	-29.7	Minimum	-31.2
Maximum	110.84	Maximum	346.15
Sum	287.05	Sum	754.61
Count	20	Count	20

A8. Optimal US Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	75.395	80.961
Variance	35780.60186	54439.738
Observations	20	20
Pearson Correlation	0.995518557	
Hypothesized Mean Difference	0	
df	19	
t Stat	-0.51389879	
P(T<=t) one-tail	0.306623896	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.613247791	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.995518557
R Square	0.991057197
Adjusted R Square	0.990560375
Standard Error	18.37812495
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	673751.84	673751.8	1994.791744	6.81229E-20
Residual	18	6079.5986	337.7555		
Total	19	679831.44			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	10.05320974	4.362123607	2.30466	0.033312402	0.888728108	19.2176914	0.888728108	19.21769136
B&H %	0.807077362	0.018070343	44.66309	6.81229E-20	0.769112981	0.84504174	0.769112981	0.845041742

Net Profit %		*B&H %*	
Mean	75.395	Mean	80.961
Standard Error	42.2969277	Standard Error	52.17266452
Median	16.905	Median	27.53
Standard Deviation	189.1576112	Standard Deviation	233.3232489
Sample Variance	35780.60186	Sample Variance	54439.73846
Kurtosis	16.42876575	Kurtosis	16.38684909
Skewness	3.906971684	Skewness	3.901151162
Range	883.59	Range	1074.91
Minimum	-37.25	Minimum	-43.51
Maximum	846.34	Maximum	1031.4
Sum	1507.9	Sum	1619.22
Count	20	Count	20

A9. Optimal US Small Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	237.0535	202.6195
Variance	301164.0869	284523.6118
Observations	20	20
Pearson Correlation	0.991558786	
Hypothesized Mean Difference	0	
df	19	
t Stat	2.139963332	
P(T<=t) one-tail	0.022774219	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.045548438	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.991558786
R Square	0.983188826
Adjusted R Square	0.982254872
Standard Error	73.10400338
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5625922.136	5625922	1052.716417	2.00433E-17
Residual	18	96195.51558	5344.195		
Total	19	5722117.652			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	30.35270791	17.54410018	1.730081	0.10072462	-6.50607883	67.211495	-6.5060788	67.21149465
B&H %	1.020142642	0.031441641	32.44559	2.00433E-17	0.954086206	1.0861991	0.9540862	1.086199079

Net Profit %		*B&H %*	
Mean	237.0535	Mean	202.6195
Standard Error	122.7118753	Standard Error	119.27355
Median	29.535	Median	3.98
Standard Deviation	548.7841898	Standard Deviation	533.40755
Sample Variance	301164.0869	Sample Variance	284523.61
Kurtosis	7.853851868	Kurtosis	10.166241
Skewness	2.821211397	Skewness	3.1116858
Range	2185.23	Range	2244
Minimum	-67.2	Minimum	-85.87
Maximum	2118.03	Maximum	2158.13
Sum	4741.07	Sum	4052.39
Count	20	Count	20

A10. Optimal TW Large Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	46.5625	43.065
Variance	9263.3794	9134.9757
Observations	20	20
Pearson Correlation	0.97762375	
Hypothesized Mean Difference	0	
df	19	
t Stat	0.77047513	
P(T<=t) one-tail	0.22524651	
t Critical one-tail	1.72913281	
P(T<=t) two-tail	0.45049302	
t Critical two-tail	2.09302405	

Regression Statistics	
Multiple R	0.9776237
R Square	0.9557482
Adjusted R Square	0.9532898
Standard Error	20.801314
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	168215.7	168215.7	388.763054	1.23164E-13
Residual	18	7788.504	432.6947		
Total	19	176004.2			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	4.166271679	5.124277408	0.813046	0.426815766	-6.59943567	14.931979	-6.599435669	14.93197903
B&H %	0.984470645	0.049929852	19.71708	1.23164E-13	0.879571918	1.08936937	0.879571918	1.089369371

Net Profit %		*B&H %*	
Mean	46.5625	Mean	43.065
Standard Error	21.52136078	Standard Error	21.37168184
Median	5.8	Median	6.825
Standard Deviation	96.24645136	Standard Deviation	95.57706675
Sample Variance	9263.379399	Sample Variance	9134.975689
Kurtosis	7.970756967	Kurtosis	5.858754925
Skewness	2.630464701	Skewness	2.290223013
Range	415.58	Range	390.48
Minimum	-29.7	Minimum	-31.2
Maximum	385.88	Maximum	359.28
Sum	931.25	Sum	861.3
Count	20	Count	20

A11. Optimal TW Small Cap Full Period Statistical Tests

t-Test: Paired Two Sample for Means

	Net Profit %	*B&H %*
Mean	88.817	91.7155
Variance	20065.42687	29348.50705
Observations	20	20
Pearson Correlation	0.985785169	
Hypothesized Mean Difference	0	
df	19	
t Stat	-0.327173507	
P(T<=t) one-tail	0.373556899	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.747113798	
t Critical two-tail	2.093024054	

Regression Statistics	
Multiple R	0.985785
R Square	0.971772
Adjusted R Square	0.970204
Standard Error	24.45129
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	370481.5	370481.5	619.6737449	2.13762E-15
Residual	18	10761.58	597.8655		
Total	19	381243.1			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	14.05925156	6.237955211	2.253824	0.036910518	0.953793973	27.16470915	0.953793973	27.16470915
B&H %	0.815104845	0.032744015	24.89325	2.13762E-15	0.746312223	0.883897468	0.746312223	0.883897468

Net Profit %		*B&H %*	
Mean	88.817	Mean	91.7155
Standard Error	31.67445885	Standard Error	38.3069883
Median	35.84	Median	37.11
Standard Deviation	141.6524863	Standard Deviation	171.3140597
Sample Variance	20065.42687	Sample Variance	29348.50705
Kurtosis	3.69572968	Kurtosis	6.019388908
Skewness	2.027478357	Skewness	2.487584992
Range	532.08	Range	688.03
Minimum	-47.55	Minimum	-48.4
Maximum	484.53	Maximum	639.63
Sum	1776.34	Sum	1834.31
Count	20	Count	20

A.12

Table X. Bull Period Chart for FSLY