Dung, Khuc

The Profitability of Technical Trading System in Vietnamese Stock Market

Thesis

Kajaani University of Applied Sciences

School of Business

International Business

Autumn 2013

KAJAANIN AMMATTIKORKEAKOULU
UNIVERSITY OF APPLIED SCIENCES

THESIS

ABSTRACT

School	Degree Programme
Business	International Business

Author(s)
Dung, Khuc

Title
The Profitability of Technical Trading System in Vietnamese Stock Market

Optional Professional Studies	Supervisor(s)
	Esa Kyyhkynen
	Commissioned by

Date	Total Number of Pages and Appendices
27/11/13	78

Previous studies have reported mixed conclusion about the efficiency of Vietnam's Stock Market being at weak form level. As an attempt to verify prior conclusions, this research simulates simple technical trading systems on daily data of the Vietnam Index for the period from 2003-2012. Five trading techniques have been employed in this study: Simple Moving Averages, N-day Momentum, Exponential Smoothing, N-day Break out and Linear Regression. Four out of five trading systems generate positive excess return. The initial student t-test showed that these excess returns are statistically significant. However, it was also found out that there are extreme positive daily returns generated from the trading systems. When the bootstrapping technique is employed with trimmed means, the trading systems fail to produce significant results.

Language of Thesis English

Keywords Technical analysis, efficient market hypothesis, simulation, Vietnam

Deposited at	☒ Electronic library Theseus

PREFACE

This thesis is original, unpublished, independent work by the author, D. Khuc.

CONTENTS

LIST OF ABBREVIATIONS

VN-Index:	Vietnam Index
SMA:	simple moving averages
CI:	confidence interval
df:	degree of freedom

1 INTRODUCTION

Efficient Market Hypothesis has been a classic topic for empirical research. The weak-form of Efficient Market Hypothesis is the most scrutinized among the academics. This might due to the fact that the theory attempts to reject one of the most popular practice in the stock market – technical trading. It implies that one can gain profit on historical information such as historical prices, volumes and open interest.

In the recent decades, Efficient Market Hypothesis has been heavily tested on different stock markets. Two types of study can be found in most popular markets: the first one tests the randomness of stock price movement; and the second one tests the profitability of different trading techniques. These studies have been very useful for both academics and practitioners.

Vietnam's Stock Market has been operating for only thirteen years. There have been a few empirical studies testing the weak form of efficient market hypothesis in Vietnam. The results are mixed. Some studies concluded that Vietnam's stock market is in weak-form efficiency. Meanwhile, there were others claiming the contrary. However, the previous studies only examined the randomness of stock price movements. Thus, it is essential to answer a question: Can one gain significant profit using technical trading rules on Vietnam stock market?

This thesis will examine the ability to earn risk adjusted returns on the main index of Vietnam's stock market. The most basic technical trading techniques are simulated in this thesis. As far as the author knows, a research on this topic has not been executed yet on the targeted stock market.

2 STOCK AND STOCK MARKET

This chapter introduces basic general definitions in stock market. First, stock market will be defined. Subsequently, market indices and their fundamentals will be explained in details.

2.1 What is a Stock Market

A stock market (also referred to as equity market), as the name implies, is a market in which equities are bought and sold. Equities represent ownership rights in companies (CFA Institute, 2011, 163). This means that parts of ownership are being traded on the stock market. The stock market allows external investors to participate in the financial result of the businesses whose share they hold, and any remaining assets in the event of liquidation, after all claims are paid (CFA Institute, 2011, 164). Typically, investors would expect to profit from their investment. This can be achieved either by receiving dividends that businesses pay out or by selling stocks at a higher price (CFA Institute, 2011, 185). The profit gained from selling appreciated stocks is called capital gain. On the other hand, stock price may depreciate, thus generate negative capital gain (or loss). It is important to note that, the profitability assessment in this thesis is solely based on capital gain. The fact that dividends can be added to profit is completely ignored because the simulation trades on high frequency.

There are typically two types of stock market: over-the-counter markets or formal stock exchanges. Over-the-counter trades are settled individually between two market participants. This characteristic allows the two parties to customize the agreements (including stock prices and other conditions) based on their needs. However, the process is usually much slower than that of formal stock exchange, hence makes high frequency trading impossible in this market.

This thesis only concerns trading in a formal stock exchanges. Exchanges are intermediaries where traders can meet to arrange their trades (CFA Institute, 2011, 30). Traditionally, brokers and dealers met on an exchange floor to negotiate and carry trades (CFA Institute, 2011, 30). Nowadays, most stock exchanges act like a broker itself which arranges trades based on order electronically submitted to them (CFA Institute, 2011). They then utilize electronic order matching systems to arrange trades among their clients (CFA Institute, 2011, 31).

With regard to a stock, investors may typically take two positions: *long* and *short*. Investors have long positions when they own a stock (CFA Institute, 2011, 41). A long position benefits from stock price appreciation. On the contrary, investors have shorts position when they sell stocks that they do not own (CFA Institute, 2011, 41). Short-sellers benefit from depreciation of particular stock prices. Stock markets in many countries forbid the practice of short-selling. Vietnamese stock market is among them, thus short-selling will not be considered in this thesis.

To initialize trades, buyers and sellers issue orders to buy or sell a specific stock (CFA Institute, 2011, 47). These buy and sell orders (so called *bids* and *offers*) make the market. More specifically, the highest bids and lowest offers will be quoted on the stock exchanges (CFA Institute, 2011, 47).

Trading stocks on the stock exchange has many advantages which makes high frequency trading viable. Some of these advantages are: rapid execution times, information transparency, comparability and prices are set by investors. These characteristics enable various types of analysis to profit in this market. Typically, as prices are set by the investors, trends and patterns may develop. This opens a window for technical trading systems to profit by predicting future price movement.

2.2 Market Indices

This thesis majorly utilizes Vietnam-Index (VN-Index), thus the author finds it necessary to revise the definition and construction of a market index.

2.2.1 Fundamentals of Market Indices

By definition, a security market index represents a specific security market, market segment, or asset class (CFA Institute, 2011, 85). Hence, a stock index typically represents performance of a stock market, or of stocks in a particular market segment. Data used to calculate the value of an index are market prices of constituent securities (CFA Institute, 2011, 85). There are usually two versions of stock index: *price return index* (also referred to as *price index*), and *total return index*.

Price index only reflects the prices of its constituent stocks, and is calculated by following formula (CFA Institute, 2011, 85):

$$V_{PRI} = \frac{\sum_{i=1}^{N} n_i P_i}{D} \tag{1}$$

where:

V_{PRI}: value of the price return index

n_i: number of units of constituent stocks i held in the index portfolio

N: number of constituent securities in the index

P_i: unit price of constituent stock i

D: value of the divisor

The divisor is number chosen at inception so that the price index has a pleasant value. The divisor can be adjusted by the index maintainer so that index value does not reflect changes unrelated to stock prices.

The number of units measures the weight of a specific stock in the index. There are four popular index weighting method: price weighting, equal weighting, market-capitalization weighting, and fundamental weighting CFA Institute (2011, 90).

In price weighting, the weight in calculated using following formula (CFA Institute, 2011, 90):

$$w_i^P = \frac{P_i}{\sum_{i=1}^{N} P_i} \tag{2}$$

where

- w_i^p: weight of stock i in price weighting index
- P_i: price of stock i
- N: total number of stock in the price weighting index

This is the simplest index weighting method, used in Dow Jones Industrial Average. Price weighting benefits from simplicity, while arbitrary weights of securities is the main disadvantage.

Equal weighting is another simple index weighting method. Each constituent stock in an equal weighting index is weighted equally, using following formula (CFA Institute, 2011, 92):

$$w_i^E = \frac{1}{N} \tag{3}$$

where

- w_i^E: weight of security i in an equal weighting index
- N: number of securities in the index

The primary advantage of equal price weighting is also simplicity. However, it has many disadvantages causing frequent maintenance.

Market-capitalization weighting is a weighting method based on listed company's value. The weight on each constituent stock is calculated using the following formula (CFA Institute, 2011, 93):

$$w_i^M = \frac{Q_i P_i}{\sum_{j=1}^{N} Q_j P_j} \tag{4}$$

where

- w_i^M: weight of stock i in the market-capitalization weighted index.
- Q_i: number of outstanding shares of stock i
- P_i: price of stock i
- N: number of stocks in the index

The main advantage of market-capitalization weighting is that constituent stocks' contribution to the value of the index is proportionate to their value. On the other hand, market-capitalization weighted index can be distorted by some particular stocks' overweight (or overvalue).

Fundamental weighting tries to address the disadvantages of market-capitalization weighting by using measures that are independent to the stock prices. These measures includes book value, cash flow, revenues, earnings, dividends, and number of employees (CFA Institute, 2011). The formula used to calculate the weight of a particular stock in a fundamental weighted index is as follow (CFA Institute, 2011, 98):

$$w_i^F = \frac{F_i}{\sum_{j=1}^{N} F_j} \tag{5}$$

where

- w_i^F: the weight of stock i in the fundamental weighted index
- N: number of stocks in the index

Fundamentally weighted index, however, has the so-called "contrarian" effect. The portfolio weights will shift away from stocks that increases in relative value.

2.2.2 The Uses of Market Indices

Some of major uses of indices are (CFA Institute, 2011, 101):

- gauges of market sentiment;
- proxies for measuring and modelling returns, systematic risk, and risk-adjusted performance;
- proxies for asset classes in asset allocation models; benchmarks for actively managed portfolios;
- model portfolios for such investment products as index funds and exchange-traded funds.

Since indices can be very much different in various characteristics (mentioned in the last sub-section), investors must be familiar with the construction of the indices in order to select the appropriate ones.

3 VIETNAMESE STOCK MARKET

This chapter gives a quick introduction to Vietnam's Stock Market and its main index – Vietnam Index.

3.1 Development

Vietnamese stock market was established by State Securities Commission of Vietnam (SSC) on 28/11/1998 in Decree No. 75/CP. However, it was not until two years later, on 28/07/2000 that the stock market was officially launched. From inception, there were only two individual stocks (REE and SAM) listed with a total market capitalization of VND 444 billion (approx. USD 30.64 million at the time). After five years of operations, at the end of 2005, the number of listed companies had grown quickly to 32 with total market capitalization of USD 461.33 million (current exchange rate). As of 31/12/2012, there were over 400 listed companies with total market capitalization of USD 32.93 billion (World Bank's Data).

3.2 Vietnam Index

SSC introduced Vietnam Index (VN-Index) to track the performance of Vietnamese Stock Market. The index has its inception point on 28/7/2000, when Vietnamese Stock Market officially went into practice. Constituent members of VN-Index include are all stocks listed on Ho Chi Minh Stock Exchange. Paasche's method to calculate the index value:

$$\text{VN-Index} = \frac{100 \cdot \sum_{i=1}^{N} P_{1i}Q1i}{\sum_{i=1}^{N} P_{0i}Q_{0i}} \tag{6}$$

where:

P_{i1}: current spot price of stock i

Q_{i1}: current number of issued stock i

P_{i0}: base spot price of stock i

Q_{i0}: base number of outstanding stock i

It can be easily recognized that VN-Index employs market-capitalization weighting method, with initial divisor $D = 0.01$ (refer to (1)). In the events that require reconstitution (e.g. new issuance), the divisor will be readjusted as follows:

$$D_1 = \frac{D_0 V_1}{(V_1 + AV)} \tag{7}$$

where:

D_1: new divisor

D_0: old divisor

V_1: total market capitalization of listed stocks - $V_1 = \sum_{i=1}^{N} P_{i1} Q_{i1}$

AV: changes in market capitalization

By adjusting the divisor, the value of the index remain constant regardless corporate actions. This adjustment preserves the accuracy of VN-Index as an indicator of stock market performance.

4 THEORETICAL BACKGROUND

There are two theoretical concepts that are concerned in this thesis: firstly, the well-known Efficient Market Hypothesis; and secondly, the existence of trends and patterns in stock price movement, which technical analysts seek to find.

4.1 Efficient Market Hypothesis

The development of efficient market hypothesis could be traced back to the introduction of the theory of random walks by Bachelier (1900). Osborne (1959) came up with a more precise formulation. Nevertheless, both Bachelier's and Osborne's models are based on two fundamental assumptions:

- information is independently generated and
- evaluation of information is independent.

By having these two assumptions, Bachelier and Osborne believes that market price would change in a random manner.

Based on that finding, Fama (1970) has defined efficient market, where there are large number of investors who rationally forecast future values of stocks, and where all information are free and publicly available. The essential property of an efficient market is instantaneous correction. Fama (1970) claims that all change in prices in this market will be independent and immediate. As Fama's (1970) definition emphasizes the role of information in price settings, his definition is often referred to as the informational efficiency of financial markets Kian (2009).

Other than Fama's, various definitions has been suggested by (Rubinstein, 1975), (Jensen, 1978), and (Black, 1986). Besides, recent studies such as Milionis' (2007) proposed more modern approaches to market efficiency. Hence, there has not been consensus on the definition of market efficiency. As a result, methods to empirically test efficiency of a market varies according to adopted definition. Lo (2008) concludes that none of thousands published articles have yet agreed on whether financial markets are efficient. This research will adopt Fama's definition of market efficiency.

In this efficient market, the price of a security reflects its investment value, where investment value includes future cash flows expected by reasonable investors (Sharpe, 1990). Thus, the only factor that can influence the stock in this market is new unexpected information. Yet, as soon as new information is published, price correction takes place immediately.

Nevertheless, Fama (1970) argues that violations of the assumptions to some extent do not necessarily reject the efficiency of a market by dividing market efficiency into three forms: weak, semi-strong and strong. This thesis primarily relates to the weak-form market efficiency, where Fama (1970) claims that it is impossible to beat the market using historical information. This directly rejects the profitability of technical trading systems.

4.1.1 The Three Forms of Market Efficiency

To relieve some assumptions of Efficient Market Hypothesis, Fama (1970) introduces three forms of market efficiency: weak form, semi-strong form, and strong form. Stronger forms of efficiency incorporate all requirements of weaker forms (Fama, 1970). The three forms are essentially distinguished by the availability of information and the influence of the information on stock prices.

Weak-form market efficiency definition is simple: stock prices reflect their historical performance and other related trading data (Fama, 1970). Historical trading data includes information, such as past prices and volume. This kind of data is generally publicly available and is updated with minimal time lag in most markets.

Consequently, this definition effectively means that, in a weak form efficient market, future prices of stocks cannot be predicted by analyzing historical data. Any forms of technical analysis will not be able to product excess returns in the long run, because there are no trends in the movement of asset prices. Nevertheless, weak-form efficiency does not necessarily reject the profitability of fundamental analysis which utilizes other information sources.

Weak-form efficiency has a huge body of literature. Studies of this topic can be divided into three significant lines of groups. The first one tests the predictability of past price movements. This strand of studies employs a wide array of statistical test to detect evidence of random walk in time series of historical prices. Past studies about market efficiency of Vietnamese Stock Market fall under this subcategory. The second line of studies is based on Fama's (1991) reclassification of weak-form Efficient Market Hypothesis as tests for return predictability. This group focuses on using financial ratios and various measures of interest rates. Many recent studies have discussed this topic such as Ang & Bekaert (2007); Campbell & Thompson (2008); Welch & Goyal (2008). Finally, the last group of studies examines the profitability of trading strategies based on historical data. Examples of this strand of studies utilize technical trading systems are Park & Irwin (2007), momentum strategies Chou & Wei (2007). This research falls into the third subcategory, which examines the profitability of technical trading rules.

Fama (1970) defines semi-strong form efficiency as a class of Efficient Market Hypothesis in which all "obviously publicly available" information is reflected in stock price. This definition implies that neither technical analysis nor fundamental analysis can consistently produce excess returns. Fundamental analysis, as the name implies, takes fundamental data of a business into consideration. This data includes product line, owned patents, expected earnings, management and accounting practices (Bodie et al., 2005, 357). The semi-strong class of efficiency implies that only insider (not publicly available) information can produce consistent abnormal returns. Fama (1991) states that testing for semi-strong form of efficiency is similar to event studies. Fundamental data is generally updated much less frequently comparing to technical data. Most official information, such as financial statements is published on a quarterly or yearly basis. Given that this data is kept confidential until the publishing date, in a semi-strong efficient market, stock price will adjust exactly at the time of publishing. According to Fama's definition, there should be virtually no time lag between the time of publishing and price corrections.

Strong Form of Market Efficiency According to Fama’s (1970) definition, stock prices in a strong-form efficient market can reflect all the information relevant to a business, including insider information. U.S. Security and Exchange Commission (2013) defines corporate insiders as officers, directors, and employees who buy and sell stock in their own companies. With this interest group included, this definition implies no excess return can be yielded in this kind of market, thus capital is efficiently allocated. This is the most debatable form of market efficiency. In most markets, the use of material non-public information for personal benefit is strictly prohibited. The prohibition essentially makes the strong form of efficiency invalid as corporate insiders cannot freely act on confidential information. Consequently, stock prices in reality cannot adjust in such precise and immediate manner. Fama (1970) himself did not expect this extreme efficiency to be "literally true".

4.1.2 Evidence of Efficient Market Hypothesis

Fama (1970) states in his research that there are no important evidence against the Efficient Market Hypothesis in weak and semi-strong form. On the other hand, the strong form of the model is generally refuted.

Evidence of weak-form market efficiency Early empirical work on market efficiency of similar level as Fama’s weak form were generally based on "fair game" and Bachelier’s (1900) random walk model. "Fair game" models implies the rejection of trading system profitability Fama (1970). The random walk hypothesis states that stock price movement is random and thus unpredictable Bachelier (1900). The first rigorous evidence of weak-form market efficiency was probably of Kendall (1953). After extensive statistical analysis of serial correlations, he concluded that the weekly spot price movement for cotton in New York market, and wheat in Chicago market does not follow any trends. Roberts (1959) implicated the conclusion for stock market research and financial analysis. However, Kendall and Roberts’ works were solely based on observation. Economic rationale had not been provided to back the conclusion. Other tests based on serial covariances are of Moore (1962), Alexander (1961), and Godfrey et al. (1964). There appeared no substantial linear dependence between price changes or returns. Alexander (1961) provided the important evidence of weak-form efficiency by examining a variety of trading systems, referred to as filter tests. He extensively studied daily data on price indices from 1897 to 1959. In the end, Alexander (1964) concluded in his final paper on the subject that technical trading techniques are not superior to simple buy-and-hold. Fama & Blume (1966) further support the existence of weak-form efficient market hypothesis by comparing the profitability of different filters to buy-and-hold for individual stocks of Dow-Jones Industrial Average. Interestingly, Fama (1970) admitted that there were some minor evidences against the weak form of market efficiency. There were evidences of linear dependence in aforementioned studies. The findings of Alexander (1964) and Fama & Blume (1966) showed that high frequency trading systems would on average outperform buy-and-hold. However, Fama (1970) argues that these findings in both methods of testing, serial correlations and filter tests, cannot prove that technical trading systems can be profitable when take even the minimum transaction costs into account.

4.2 Technical Trading Analysis

Technical analysis are one of the oldest technique to predict price movements in many financial markets (Pauwels, et al., 2011). These methods are widely used by practitioners to detect buy and sell signals. Thus, they have been the subjects of many academic research.

By definition, technical is "the systematic evaluation of price, volume, breadth, and open interest, for the purpose of price forecasting." (Kaufman, 2013, 1). It may utilize any quantitative analysis as well as different forms of pattern recognition to precisely decide price movement over specific time period. Fundamentally, technical analysis base on following principles (Murphy, 1999): history repeats itself and price move in trends. However, Kaufman (2013, 1) claims that technical analysis has evolved into a more complex type of study that encompasses intra market analysis, complex indicators, mean reversions, and the evaluation of test result.

Despite the prominent existence of efficient market hypothesis (Fama, 1965), technical trading has been evolving rapidly due to various reasons. Lo (2004) introduces Adaptive Market Hypothesis and argues the efficiency of market to be a dynamic process. This implies that profitable technical trading opportunities may appear from time to time.

The studies of technical analysis mostly deal with the predictability of price movement. Historically, empirical tests concerning technical analysis utilized statistical tests, such as the auto-correlation tests and the runs test (Park & Irwin, 2004). Others tested the profitability of simple trading strategies (Park & Irwin, 2004). Trading strategies examined in these studies were based on price channel breakout, moving averages, and more specifically Alexander's filter systems.

Donchian (1960) introduced a foundation trading system for range breakout studies. His idea is that a trend continues when the price cross the threshold of a support or a resistance level. Donchian (1960) reports that his trading strategy generated positive profit. However, Donchian did not take commissions into account, thus made the validity of the test questionable.

Alexander's (1961) filter test, as mentioned earlier, also failed to conclude the profitability of technical trading systems when he examined the Dow Jones Industrial Average and Standard and Poor Industrials during two period 1897-1929 and 1929-1959 respectively. In his findings, excess returns generated by trading system are essentially wiped out by commissions. Fama & Blume (1966) re-examined Alexander's trading systems and once again concludes that they are unprofitable.

The trading techniques of moving average crossovers was pioneered by James (1968). He used two moving averages, one short-term and one long-term, to generate signals. The two moving averages were drawn using monthly data of the stocks traded on New York's Stock Exchange during 1926-1960. The system generates a buy signal when short-term average crosses above the long-term average, while generates sell signal by a short-term average crossing below a long-term average. Nevertheless, James (1968) concluded that the system produced no abnormal returns.

Early failures in proving profitability of trading systems had resulted in the dominance of Efficient Market Hypothesis in financial market. It was not until the late 1980s that technical analysis regained its popularity. The improvement in electronic computing speed empowers trading systems to perform much more complex algorithms.

Lukac et al. (1988) published the first modern empirical study. They applied 12 different trading strategies on various exchanges between 1975 and 1984. The trading systems did take parameter optimization, risk factors and sub-sampling into account. They reported significant risk-adjusted return using Jensen's α test.

Brock et al. (1992) tested a variety of moving averages and trend breakout trading systems. The selected data sample is the time series of closing price of the Down Jones Industrial Average during 1897-1986. Using standard t-test, Brock et al. (1992) concluded that all trading strategies produced significant excess returns. They were also aware of the data snooping problem, which means patterns in a data set might exist by chance. They attempted to address this problem by testing different sub-samples. Furthermore, they utilize bootstrapping techniques to ensure the consistency of excess return. Based on the test results, Brock et al. (1992) reckoned that technical trading strategies could outperform buy-and-hold. However, Brock et al. (1992) did not include transaction costs in their tests.

Another modern approach to find profitable trading rules was to utilize genetic programming. Genetic programming enables trading systems to learn and optimize as time progressed. Using genetic programming technique Koza (1992), Allen & Karjalainen (1999) looked for optimal technical trading rules that can be applied to daily Standard and Poor's 500 data set of 1929-1995. Their findings was disappointing as discovered rules failed to outperform buy-and-hold strategy. Nevertheless, Allen & Karjalainen (1999) speculated that the rules might be more useful on risk-adjusted basis.

Chang & Osler (1999) examined the profitability of charting techniques, specifically head-and-shoulders pattern. They evaluated these patterns for daily exchange rates over 1973 to 1994. Head-and-shoulders pattern is described comprising of three peaks with the highest in the middle. Chang & Osler (1999) cited that "a large group" of technical analysts considered such patterns precede trend reversals. However, their research had shown that, despite being profitable for the two out of six currencies, head-and-shoulders trading was dominated by simpler trading rules that were readily available. Thus, Chang & Osler (1999) concluded that technical analysts' reliance on the head-and-shoulders pattern appeared to represent a source of predictable exchange-rate forecasts errors.

One problem of tremendous empirical studies on technical analysis is that on set of data might be used many times to infer patterns. This increases the probability that any satisfactory results obtained are by chance. The problem, widely referred to as *data snooping*, is a dangerous practice. White (2000) introduced reality check, a procedure for "testing the null hypothesis that best model encountered in a specification search has no predictive superiority over a given benchmark model." He claimed that this procedure permitted data snooping to be undertaken with certain degree of confidence. White's procedure has been used extensively in later studies regarding technical trading rules, e.g. in studies of Pauwels et al. (2011), Tian et al. (2002).

With regards to Asian stock market, Bessembinder & Chan (1995) examined the profitability of technical trading strategies on Asian stock markets (Hong Kong, Japan, Korea, Thailand, Malaysia, and Taiwan). The data sample is daily returns on stock indices during the period 1975-1989. Thailand and Malaysia, the two Southeast Asian countries in their research, post strong results.

5 METHODOLOGY

This section explains data selection, applied technical trading systems, and statistical tests that are used in this thesis. In addition, mechanism of the simulator is described in details.

5.1 Data Selection

Daily performance of Vietnam Stock market (VN-Index) for the 2003-2012 are used as the full sample period. The data is obtained from VNDirect (n.d.) by extracting the following columns in the database: open price, close price, day-high, day-low. In total, there are 2493 observations during this 10 years period.

All trading systems will use only this one data set. This effectively means that trading strategies that require data over longer time horizon will initiate position later.

5.2 Technical Trading Systems

Five basic trading systems will be used in this research, including: Simple Moving Average, N-day Momentum, Exponential Smoothing, N-day Breakout, and Linear Regression Slope.

5.2.1 Simple Moving Average

Simple moving average, as the name suggests, is the most basic of moving average indicators. Simple moving average can be computed by taking the arithmetic mean of closing price during a time period:

$$SMA_t = \frac{p_t + p_{t-1} + p_{t-2} + \cdots + p_{t-(n-2)} + p_{t-(n-1)}}{t} \tag{8}$$

In which:

SMA_t: Simple moving average at time t

p_t: Closing price at time t

The trading simulator will take position as follow:

- Buy when: $SMA_t > SMA_{t-1}$
- Sell when: $SMA_t < SMA_{t-1}$

5.2.2 N-day Momentum

Momentum is a simple analysis indicator calculated by taking the difference a stock price's between two points in time.

$$momentum = close_t - close_{t-n} \tag{9}$$

N-day momentum trading system suggests taking position based on stock price momentum compared to n days before. A buy signal is given when the momentum is positive; and a sell signal is given when the momentum is negative. In other words, the simulator will:

- Buy when: $close_t > close_{t-N}$
- Sell when: $close_t < close_{t-N}$

N-day momentum is very much related to N-day simple moving average. The difference between SMA_t and SMA_{t-1} can be calculated from momentum value (refer to (8) and (9)):

$$SMA_t - SMA_{t-1} = \frac{momentum}{N} \tag{10}$$

Consequently, given the conditions used in this thesis, the two trading rules will return similar result.

5.2.3 Exponential Smoothing

Exponential smoothing is a widely used technique that can be applied to time series data to make forecasts. It is commonly applied to financial market data. In this research, the simplest form of exponential smoothing is utilized. The price at time t is exponentially smoothed:

$$E_t = E_{t-1} + a(p_t - E_{t-1}) \tag{11}$$

In which:

E_t: Exponential smoothing values of stock price at time t.
p_t: Stock price at time t.
a: The smoothing constant, $0 \leq a \leq 1$.

The smoothing process started by letting $E_1 = p_1$. Getting the results from smoothing process, trading simulator will get the signals as follows:

- Buy when: $E_t > E_{t-1}$
- Sell when: $E_t < E_{t-1}$

5.2.4 N-day Breakout

N-day break out is another simple trading system, yet being one of the most popular technique (Kaufman, 2013, 222). According to this system, the simulator will work as follows:

Buy when closing price at time t is above the high of the previous N days.
Sell when closing price at time t is below the low of the previous N days.

Choosing N will fundamentally set the nature of the technique. The longer calculation period, N, the greater risk is caused. In this research, the author will use calculation period from 10 days to 100 days, in increment of 5-days.

5.2.5 Linear Regression Slope

Linear regression is a method to find a straight-line fit to historical stock price. In order to find best straight line fit, equation for straight line is used:

$$y = \alpha + \beta x \tag{12}$$

where

- y: the price, a variable dependent of x
- x: sequential days
- α: y-intercept, is an adjustment in the price level to align x and y
- β: the slope, indicates relative change in y for every unit change in x

In order to solve for α and β, a technique called the method of least squares is used. The rationale behind this method is to choose the line that has smallest total deviation from the time series of prices. The mathematical expression to calculate the total errors is:

$$S = \sum_{i=t-N+1}^{t} (y_i - \hat{y}_i)^2 \tag{13}$$

where

- S: sum of squares error at each price point on the straight line
- y_i: stock price on day i
- $\hat{y}_i$: estimated value of price on the straight line

From the above equation, the value of α and β can be expressed as:

$$\beta = \frac{N\sum xy - \sum x \sum y}{N\sum x^2 - (\sum x)^2} \tag{14}$$

$$\alpha = \frac{1}{N}(\sum y - b\sum x) \tag{15}$$

where

- x: time sequence

- y: time series of prices
- N: number of data points
- $\sum$: sum over N points

In this research, the value of linear regression slope will be taken for buy and sell signals. The data series in consideration are stock price and business days. The simulator will take position as follows:

- Buy when $Slope(close, t, N) > 0$
- Sell when $Slope(close, t, N) < 0$

The slope function takes three parameters: closing price ($close$), current day (t), calculation period (N). The function will return α value (refer to (12) and (14)) Calculation period from 10 days to 200 days, in increment of 10 days, will be utilized.

5.3 Simulator Mechanism

There are two possible positions in Vietnamese Stock market: long and neutral (short selling is forbidden in Vietnam). Accordingly, the simulator assigns value to position at time t (Pos_t) as follows:

- $Pos_t = 1$ if buy signal is received.
- $Pos_t = 0$ if sell signal is received.

In which:

$Pos_t = 1$ means holding long position at time t

$Pos_t = 0$ means holding no position at time t

Consequently, return of trading systems are computed as follows:

- $r_t^k = r_t \cdot Pos_t$
- $r_t^k = (1 + r_t \cdot Pos_t) \cdot (1 - c) - 1$ if position changed at time $(t + 1)$

In which:

r_t^k is the return of trade system k at time t

r_t is the return of the index at time t

c is transaction cost in case the simulator takes a new position

This thesis will use the following set of commissions:

$$c = \{0.00\%, 0.25\%, 0.50\%, 0.75\%, 1.00\%\}$$

5.4 Profitability of the Trading Systems

To assess the profitability of the trade systems, the arithmetic mean of returns from each trade system will be compared with the mean of the index's return. Continuous return is used to measure profit. It is calculated using following formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{16}$$

The significance of difference between the two means is first determined using well-known dependent t-test. We chose dependent test as different trading systems are tested upon same sets of data. The t value is determined by following equation (Field et al., 2012, 386):

$$t = \frac{\overline{D} - \mu_D}{s_D/\sqrt{N}} \tag{17}$$

In which:

- $\overline{D}$: mean difference between samples
- μ_D: expected difference between population means
- $s_D/\sqrt{N}$: standard error of the difference

If the null hypothesis is true, then we expect that there is no difference between the population means ($\mu_D = 0$). From t we can calculate the *effect size* r (Field et al., 2012, 384):

$$r = \sqrt{\frac{t^2}{t^2 + df}} \tag{18}$$

where

- r: Effect size
- df: Degree of Freedom: $df = N - 1$

Effect size r is an objective and standardized measure of the magnitude of observed effect. Cohen (1988, 1992) suggested that:

- $r = 0.10$ (small effect): The effect explains 1% of the total variance
- $r = 0.30$ (medium effect): The effect explains 9% of the total variance
- $r = 0.50$ (large effect): The effect explains 25% of the total variance

Additionally, as two means are involved in this comparison, another hypothesis testing method will be used. Wilcox (2005, 198) describes Bootstrap-t method for marginal trimmed means - a robust procedures for comparing two means from independent data series. The method is summarized in the following steps (Wilcox, 2005, 198):

1. Compute the sample trimmed means, $\overline{X}_{t1}$ and $\overline{X}_{t2}$, and estimate of the squared standard errors, d_1 and d_2, given by following formula:

$$d_j = \frac{(n_j - 1)s_{\omega j}^2}{h_j(h_j - 1)}$$

2. Generate a bootstrap sample by randomly sampling with replacement n_j observations from observations from $X_{1j}, \cdots, X_{nj}$, yielding $X_{1j}^*, \cdots, X_{nj}^*$.

3. Using the bootstrap samples just obtained, compute the sample trimmed means plus the estimate of the squared standard error, and label the results $\overline{X}_{tj}^*$ and d_j^*, respectively, for the j group. Set $C_{ij}^* = X_{ij}^* - \overline{X}_{tj}$.

4. Compute:

$$T_y^* = \frac{C_{t1}^* - C_{t2}^*}{\sqrt{d_1^* + d_2^* - 2d_{12}}}$$

5. Repeat steps 2 through 4 B times, yielding $T_{y1}^*, \cdots, T_{yB}^*$. $B = 599$ when $\alpha = 0.05$

6. Order the results ascendingly. The $T_{yb}^*, b = 1, \cdots, B$ values provide an estimate of the distribution of:

$$\frac{(\overline{X}_{t1} - \overline{X}_{t2}) - (\mu_{t1} - \mu_{t2})}{\sqrt{d_1 + d_2}}$$

7. Let $\ell = \alpha B/2$, rounding to the nearest integer, and let $u = (1 - \alpha/2)B$, rounding to nearest integer. The equal-tailed $1 - \alpha$ confidence interval for μ_t is:

$$(\overline{X}_{t1} - \overline{X}_{t2} + T^*_{y(u)}\sqrt{d_1 + d_2 - 2d_{12}}), (\overline{X}_{t1} - \overline{X}_{t2} - T^*_{y(\ell+1)}\sqrt{d_1 + d_2 - 2d_{12}})$$

The output of the test is the test statistics value and confidence interval. The difference is significant if the confidence interval does not cross zero.

Bootstrap-t has advantages over simple student t-test as extreme values are trimmed and it benefits from bootstrapping procedure (e.g. the data snooping effect is reduced). Hence, this statistical test gives more control over the stability of the results (Wilcox, 2005, 161).

6 EMPIRICAL RESULTS

This chapter reports results generated from the trading simulator. First, average daily returns of each trading system are reported in comparison to buy-and-hold strategy. Second, the significance of the excess returns are explained using two statistical test: student t-test and Wilcox's bootstrap-t test for trimmed means.

6.1 Average daily returns

In general, the simulator has shown positive excess returns in all trading system. However, the amount of excess returns varies. Details of the results are described in following sub-sections.

6.1.1 SMA and N-day momentum

The average returns generated from SMA and N-day momentum is remarkably higher than that of simple buy-and-hold strategy. All trading systems, across all cost cases, reports positive average daily returns. In contrary, simple buy-and-hold strategy generate negative average returns over the period. The highest average returns are achieved when using the least datum points: $N = \{10, 20, 30, 40, 50\}$. There seems to be a trend that, the more datum points are taken into consideration, the lower generated returns are (see table 1).

Table 1 Average returns of SMA and N-day momentum trading system ($\times 10^{-4}$). Source: Author's calculation from the dataset.

	c=0.000	c=0.005	c=0.010	c=0.015	c=0.020	Buy-and-hold
SMA10	22.00	19.17	16.34	13.50	10.67	-3.26
SMA20	14.98	13.30	11.63	9.95	8.28	-3.26
SMA30	12.79	11.44	10.09	8.74	7.39	-3.26
SMA40	11.72	10.41	9.09	7.78	6.47	-3.26
SMA50	10.68	9.55	8.42	7.29	6.16	-3.26
SMA60	9.46	8.47	7.48	6.49	5.50	-3.26
SMA70	8.45	7.62	6.79	5.96	5.12	-3.26
SMA80	7.42	6.61	5.80	4.99	4.18	-3.26
SMA90	5.85	5.20	4.55	3.90	3.25	-3.26
SMA100	7.80	7.11	6.42	5.73	5.04	-3.26
SMA110	7.73	7.04	6.35	5.66	4.97	-3.26
SMA120	6.98	6.33	5.68	5.03	4.38	-3.26
SMA130	6.36	5.81	5.26	4.71	4.16	-3.26
SMA140	4.50	4.01	3.52	3.03	2.54	-3.26
SMA150	6.14	5.50	4.87	4.24	3.61	-3.26
SMA160	5.76	5.33	4.90	4.47	4.04	-3.26
SMA170	6.00	5.61	5.22	4.83	4.44	-3.26
SMA180	4.20	3.71	3.22	2.73	2.24	-3.26
SMA190	4.93	4.50	4.07	3.63	3.20	-3.26
SMA200	5.59	5.02	4.45	3.88	3.31	-3.26

It is also noteworthy that strategies higher trading frequency generally performs better using SMA and N-day momentum trading system. Even when commission costs are taken into account, higher trading frequency strategies still outperforms lower frequency ones, though the gap of profit is thinner (See figure 1).

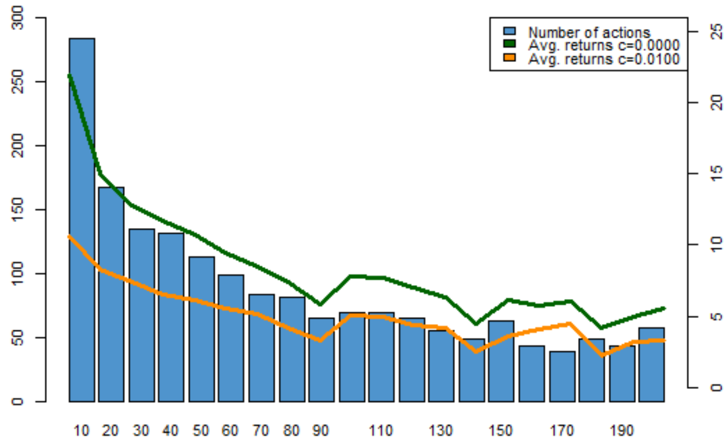

Figure 1 Actions taken based on emitted signals in SMA and N trading system. Source: Author's calculation from the dataset.

6.1.2 Exponential Smoothing

It is a consistent trend that the higher average return is achieved when smoothing constant a moving towards 1.00. The average return is tremendously high at $a = 1.00$. It is also can be observed that average returns decreases at a faster rate as a approaches 0.05. Overall, exponential smoothing technique generates positive return on all listed smoothing constant, and across all cost cases, comparing to buy-and-hold strategy (see table 2).

Table 2 Average returns of Exponential Smoothing trading system ($\times\ 10^{-4}$). Source: Author's calculation from the dataset.

	c=0.000	c=0.005	c=0.010	c=0.015	c=0.020	Buy-and-hold
a=0.05	19.01	17.43	15.86	14.29	12.72	-3.26
a=0.10	27.38	24.84	22.30	19.77	17.23	3.26
a=0.15	32.79	29.49	26.19	22.90	19.60	-3.26
a=0.20	35.76	32.28	28.80	25.32	21.83	-3.26
a=0.25	39.43	35.24	31.05	26.87	22.68	-3.26
a=0.30	41.22	36.56	31.89	27.22	22.55	-3.26
a=0.35	43.45	38.32	33.18	28.05	22.92	-3.26
a=0.40	46.35	40.55	34.75	28.95	23.15	-3.26
a=0.45	48.11	41.95	35.78	29.62	23.46	-3.26
a=0.50	49.62	43.18	36.73	30.28	23.84	-3.26
a=0.55	51.02	44.25	37.48	30.71	23.94	-3.26
a=0.60	52.33	45.07	37.82	30.56	23.31	-3.26
a=0.65	53.13	45.60	38.06	30.52	22.98	-3.26
a=0.70	53.84	46.07	38.31	30.55	22.79	-3.26
a=0.75	54.34	46.21	38.09	29.96	21.84	-3.26
a=0.80	55.13	46.58	38.03	29.48	20.93	-3.26
a=0.85	55.48	46.57	37.65	28.74	19.82	-3.26
a=0.90	55.72	46.46	37.20	27.94	18.69	-3.26
a=0.95	55.89	46.23	36.57	26.91	17.25	-3.26
a=1.00	55.94	45.87	35.81	25.74	15.67	-3.26

Exponential smoothing trading system makes remarkably large amount of trading actions. The most aggressive case ($a = 1.00$) make 999 actions based on trade signals, out of 2493 observations. It is important to notice that the profitability of the trading system significantly decreases as trade aggression is lowered (lower a). Exponential smoothing also generates the highest average daily return across all cost cases out of five trading systems.

Nevertheless, as commission cost is raised, aggressive strategies greatly suffered (see figure 2). The most aggressive strategy finds its average daily return lowered to just above 10×10^{-4}. It can be observed that, at $c = 0.0100$, most profitable strategies centered around $a = 0.50$.

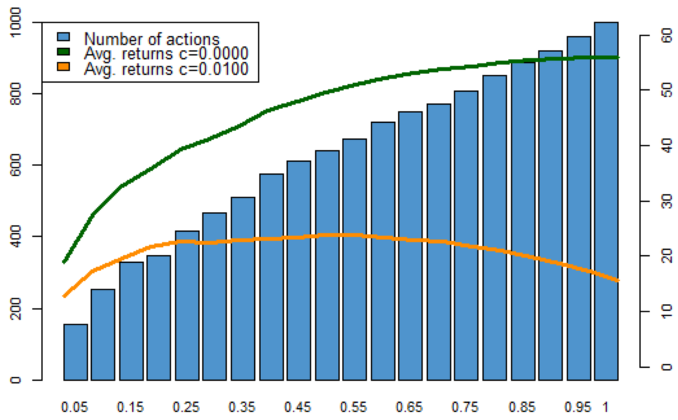

Figure 2 Actions taken based on signals emitted from Exponential Smoothing trading system. Source: Author's calculation from the dataset.

Once again, without transaction cost, the average daily returns tend to be higher as more transactions are made. In addition, it can be recognized that the line of average daily return in figure 6 is steeper on the left side. It signals that the effect of high trade frequency may dilute as more transactions are generated.

6.1.3 N-Day Breakout

N-Day breakout also posts positive results in the student t-test. The trading system also beats buy-and-hold strategy in the period 2003-2013, reporting positive daily average returns on all N and across all cost cases. The five highest returns are achieved when $N = \{10, 20, 30, 40, 50\}$. As N increases, average daily returns seem to drop (See table 3).

Table 3 Average returns of N-day Breakout trading system ($\times 10^{-4}$). Source: Author's calculation from the dataset.

	c=0.000	c=0.005	c=0.010	c=0.015	c=0.020	Buy and hold
N=10	14.32	13.10	11.87	10.65	9.42	-3.26
N=20	9.08	8.39	7.70	7.02	6.33	-3.26
N=30	7.77	7.33	6.88	6.43	5.98	-3.26
N=40	5.69	5.30	4.91	4.52	4.13	-3.26
N=50	4.77	4.44	4.12	3.79	3.46	-3.26
N=60	4.01	3.74	3.47	3.21	2.94	-3.26
N=70	4.12	3.91	3.70	3.49	3.28	3.26
N=80	2.48	2.27	2.06	1.85	1.65	-3.26
N=90	2.77	2.58	2.39	2.20	2.01	-3.26
N=100	1.59	1.41	1.22	1.03	0.84	3.26
N=110	1.60	1.43	1.26	1.10	0.93	-3.26
N=120	1.13	0.99	0.84	0.69	0.54	-3.26
N=130	0.85	0.72	0.59	0.46	0.33	-3.26
N=140	0.49	0.36	0.23	0.10	0.03	3.26
N=150	1.69	1.58	1.47	1.36	1.25	-3.26
N=160	1.36	1.25	1.14	1.03	0.92	-3.26
N=170	2.04	1.97	1.90	1.83	1.77	-3.26
N=180	1.84	1.77	1.70	1.63	1.57	-3.26
N=190	1.32	1.25	1.18	1.11	1.04	-3.26
N=200	1.25	1.18	1.11	1.04	0.97	-3.26

This pattern is also observed in the trading results of SMA/N-day momentum system. In addition, the trade results aimlessly oscillate in the interval $(0.50, 2.00)$. Also, the average returns seem to correlate with number of transactions. Strategies which made lower amount of transaction report significantly less average daily return.

Taking transaction costs into consideration, rationally, strategies with higher trade frequency suffer the most from cost. Nevertheless, the first five strategies still lead in term of daily average returns reported.

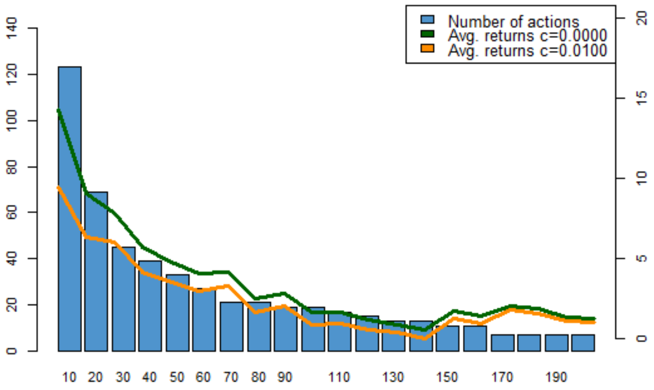

Figure 3 Transactions made in N-day Breakout trading systems. Source: Author's calculation from the dataset.

It can be observed in figure 3 that trading strategies which create more transaction tend to generate higher average daily return. This observation is consistent with findings of previous trading systems.

6.1.4 Linear Regression Slope

Linear regression beats buy-and-hold strategy on all N. However, here one may recognize some negative results. In addition, the results are generally worse than previous trading systems. The system posts mostly very slim average profits (around 0). Highest average returns centers around $N = 110$, unlike previous systems whose highest figures lies in either the first part or last part of the table. Furthermore, it is difficult to find correlation between number of transactions and average generated returns. In fact, table 4 shows that the most aggressive strategy in this trading system even reports negative average return. In short, hardly any pattern can be recognized from the daily average return of this system.

Table 4 Average returns of Linear regression trading system ($\times 10^{-4}$) . Source: Author's calculation from the dataset.

	c=0.000	c=0.005	c=0.010	c=0.015	c=0.020	Buy-and-hold
N=10	-1.38	-3.46	-5.53	-7.61	-9.68	-3.26
N=20	0.28	-0.71	-1.70	-2.70	-3.69	-3.26
N=30	-2.84	-3.53	-4.22	-4.91	-5.60	-3.26
N=40	-2.47	-3.00	-3.53	-4.07	-4.60	-3.26
N=50	-1.19	-1.62	-2.05	-2.48	-2.91	-3.26
N=60	-0.90	-1.25	-1.60	-1.95	-2.30	-3.26
N=70	-2.30	-2.61	-2.92	-3.23	-3.54	-3.26
N=80	0.39	0.13	-0.13	-0.39	-0.65	-3.26
N=90	0.85	0.59	0.33	0.07	-0.19	-3.26
N=100	1.78	1.56	1.34	1.12	0.90	-3.26
N=110	2.66	2.48	2.29	2.11	1.93	-3.26
N=120	2.48	2.30	2.12	1.94	1.76	-3.26
N=130	1.29	1.13	0.97	0.81	0.65	-3.26
N=140	0.89	0.71	0.53	0.35	0.17	-3.26
N=150	0.41	0.25	0.08	0.08	0.24	3.26
N=160	0.20	0.03	-0.13	-0.29	-0.45	-3.26
N=170	0.05	-0.09	-0.23	-0.37	-0.52	-3.26
N=180	0.35	0.21	0.07	0.07	0.21	3.26
N=190	0.15	0.05	-0.05	-0.15	-0.25	-3.26
N=200	0.09	-0.01	-0.11	-0.21	-0.31	-3.26

When cost is taken into account, aggressive strategies reports remarkable losses. Some strategies are completely beaten by buy-and-hold. For example, at $N = 10$ and $c = 0.010$, linear regression trading system triples ($-9.68 \cdot 10^{-4}$) the loss as compared to buy-and-hold ($-3.26 \cdot 10^{-4}$).

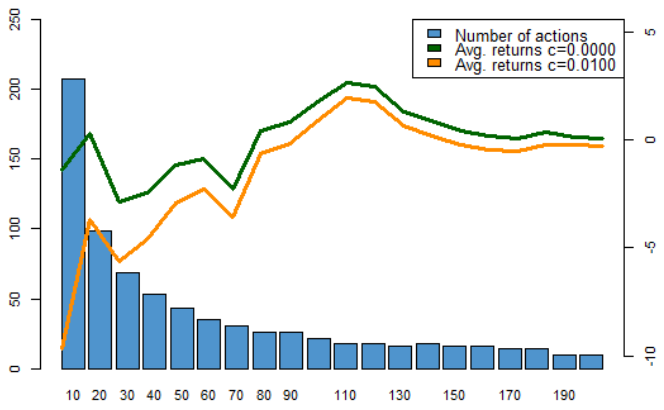

Figure 4 Transaction made in Linear Regression trading systems. Source: Author's calculation from the dataset.

Figure 4 has shown that the relation between number of transactions and average daily returns cannot be observed in the case of linear regression trading system. Moreover, trading strategies with higher frequency tend to perform worse, and heavily suffer from transaction cost.

6.2 Student t-test

Student t-test is the first statistical test utilized in this thesis. This test shows the significance of trading results (presented in previous parts) in comparison to buy-and-hold strategy. Following sub-sections will illustrate the test results.

6.2.1 SMA/N-day Momentum

Testing the trading results again using bootstrap-t method for marginal trimmed means, the significance of excess return generated by the two technical trading systems is remarkably reduced.

Table 5 Student t test result for SMA/N-day momentum trading system. Source: Author's calculation from the dataset.

	c=0.0000		c=0.0025		c=0.0050		c=0.0075		c=0.0100	
	t	p	t	p	t	p	t	p	t	p
N−10	10.7567	0.0000	9.4566	0.0000	8.1471	0.0000	6.8460	0.0000	5.5695	0.0000
N 20	7.9501	0.0000	7.1729	0.0000	6.3878	0.0000	5.6018	0.0000	4.8218	0.0000
N=30	6.9613	0.0000	6.3381	0.0000	5.7090	0.0000	5.0788	0.0000	4.4519	0.0000
N=40	6.5804	0.0000	5.9760	0.0000	5.3647	0.0000	4.7509	0.0000	4.1393	0.0000
N=50	6.1517	0.0000	5.6356	0.0000	5.1122	0.0000	4.5847	0.0000	4.0566	0.0001
N=60	5.7084	0.0000	5.2520	0.0000	4.7888	0.0000	4.3215	0.0000	3.8528	0.0001
N−70	5.1982	0.0000	4.8174	0.0000	4.4316	0.0000	4.0426	0.0001	3.6524	0.0003
N 80	4.7262	0.0000	4.3554	0.0000	3.9806	0.0001	3.6035	0.0003	3.2260	0.0013
N=90	4.0567	0.0001	3.7578	0.0002	3.4561	0.0006	3.1528	0.0016	2.8489	0.0044
N=100	4.9482	0.0000	4.6325	0.0000	4.3120	0.0000	3.9881	0.0001	3.6622	0.0003
N=110	4.8285	0.0000	4.5145	0.0000	4.1966	0.0000	3.8762	0.0001	3.5545	0.0004
N=120	4.5473	0.0000	4.2545	0.0000	3.9575	0.0001	3.6573	0.0003	3.3551	0.0008
N−130	4.2588	0.0000	4.0070	0.0001	3.7523	0.0002	3.4956	0.0005	3.2377	0.0012
N 140	3.3786	0.0007	3.1623	0.0016	2.9438	0.0033	2.7237	0.0065	2.5026	0.0124
N–150	3.9955	0.0001	3.7222	0.0002	3.4459	0.0006	3.1674	0.0016	2.8877	0.0039
N=160	3.7720	0.0002	3.5861	0.0003	3.3983	0.0007	3.2092	0.0013	3.0192	0.0026
N=170	3.8563	0.0001	3.6941	0.0002	3.5296	0.0004	3.3630	0.0008	3.1948	0.0014
N=180	3.0350	0.0024	2.8274	0.0047	2.6189	0.0089	2.4101	0.0160	2.2014	0.0278
N=190	3.3574	0.0008	3.1755	0.0015	2.9921	0.0028	2.8077	0.0050	2.6225	0.0088
N 200	3.6164	0.0003	3.3771	0.0007	3.1357	0.0017	2.8930	0.0038	2.6498	0.0081

Examining table 5, it is obvious that all strategies generate statistically significant excess return with comparing to buy-and-hold strategy. An example is the case of $a = 1.00$ and $c = 0.0000$, the strategy significantly outperforms ($CI = (55.27 \cdot 10^{-4}, 63.13 \cdot 10^{-4})$) buy-and-hold, $t(2492) = 29.55$, $p < 0.05$. It can be seen that the t-value is tremendously high in this case.

Using the same strategy at cost case $c = 0.0100$, t-value is remarkably lower. Nevertheless, the excess return generated by this strategy is significant ($CI = (14.45 \cdot 10^{-4}, 23.42 \cdot 10^{-4})$) against buy-and-hold strategy, $t(2492) = 8.29$, $p < 0.05$. The lowest t-value is reported by strategy $a = 0.05$ at cost case $c = 0.0100$. Again, the average daily return of this strategy is significantly higher ($CI = (14.46 \cdot 10^{-4}, 23.42 \cdot 10^{-4})$) than reported by buy-and-hold strategy, $t(2492) = 6.79$, $p < 0.05$.

6.2.2 Exponential Smoothing

As shown in table 6, exponential smoothing sees statistically significant excess return across all cost cases. In addition, table 6 shows that the t-statistic is extremely high, and the p-value is very low in all cases. Using smoothing constant $a = 1.00$, for example, the trading system performs significantly better ($CI = (55.27 \cdot 10^{-4}, 63.13 \cdot 10^{-4})$) than buy-and-hold, $t(2492) = 29.56$, $p < 0.05$. The same strategy observes drastic decreases in t-statistic as transaction cost is raise. However, at the highest cost case $c = 0.0100$, the system still significantly outperforms ($CI = (14.45 \cdot 10^{-4}, 23.31 \cdot 10^{-4})$) the market , $t(2492) = 8.29$, $p < -0.05$.

Table 6 Student t-test results for Exponential Smoothing trading system. Source: Author's calculation from the dataset.

	c=0.0000		c=0.0025		c=0.0050		c=0.0075		c=0.0100	
	t	p	t	p	t	p	t	p	t	p
a=0.05	9.8196	0.0000	9.0774	0.0000	8.3200	0.0000	7.5546	0.0000	6.7880	0.0000
a=0.10	13.5345	0.0000	12.3274	0.0000	11.0896	0.0000	9.8390	0.0000	8.5927	0.0000
a=0.15	15.9338	0.0000	14.3167	0.0000	12.6684	0.0000	11.0184	0.0000	9.3929	0.0000
a=0.20	17.3152	0.0000	15.5659	0.0000	13.7862	0.0000	12.0095	0.0000	10.2648	0.0000
a=0.25	19.2768	0.0000	17.1223	0.0000	14.9356	0.0000	12.7645	0.0000	10.6498	0.0000
a=0.30	20.3251	0.0000	17.8942	0.0000	15.4310	0.0000	12.9947	0.0000	10.6340	0.0000
a=0.35	21.5299	0.0000	18.8210	0.0000	16.0822	0.0000	13.3844	0.0000	10.7843	0.0000
a−0.40	23.4161	0.0000	20.3037	0.0000	17.1492	0.0000	14.0459	0.0000	11.0676	0.0000
a=0.45	24.5207	0.0000	21.1856	0.0000	17.8003	0.0000	14.4716	0.0000	11.2834	0.0000
a=0.50	25.4586	0.0000	21.9610	0.0000	18.3996	0.0000	14.8933	0.0000	11.5355	0.0000
a=0.55	26.3210	0.0000	22.6501	0.0000	18.9003	0.0000	15.2036	0.0000	11.6644	0.0000
a−0.60	27.1763	0.0000	23.2265	0.0000	19.1933	0.0000	15.2261	0.0000	11.4413	0.0000
a=0.65	27.6819	0.0000	23.5704	0.0000	19.3728	0.0000	15.2485	0.0000	11.3213	0.0000
a=0.70	28.1480	0.0000	23.9230	0.0000	19.5998	0.0000	15.3476	0.0000	11.2985	0.0000
a=0.75	28.4578	0.0000	24.0253	0.0000	19.5027	0.0000	15.0699	0.0000	10.8647	0.0000
a=0.80	29.0120	0.0000	24.3808	0.0000	19.6379	0.0000	14.9804	0.0000	10.5614	0.0000
a=0.85	29.2403	0.0000	24.4157	0.0000	19.4829	0.0000	14.6502	0.0000	10.0773	0.0000
a=0.90	29.4025	0.0000	24.4198	0.0000	19.3220	0.0000	14.3287	0.0000	9.6081	0.0000
a=0.95	29.5216	0.0000	24.3453	0.0000	19.0527	0.0000	13.8750	0.0000	8.9889	0.0000
a=1.00	29.5529	0.0000	24.1744	0.0000	18.6871	0.0000	13.3322	0.0000	8.2923	0.0000

The most conservative strategy produces the lowest t-value across all cost cases. Nevertheless, without transaction cost, it manages to produce significantly higher average daily return ($CI = (17.82 \cdot 10^{-4}, 26.72 \cdot 10^{-4})$), than the buy-and-hold strategy, $t(2492) = 9.81$, $p < 0.05$. Despite being much less affected by risen commission, the strategy keeps producing lowest t-value. Yet, at the highest cost $c = 0.0100$, this strategy still performs significantly better ($CI = (11.37 \cdot 10^{-4}, 20.60 \cdot 10^{-4})$), than the market, $t(2492) = 6.79$, $p < 0.05$.

6.2.3 N-day Breakout

From the test results shown in table 7, it seems that N-day Breakout performs slightly worse than previously mentioned systems. This trading system does not report statistically significant excess returns in all cases. For example, at cost case $c = 0.0000$, the strategy utilizing $N = 140$ reports higher average daily return ($CI = (-0.71 \cdot 10^{-4}, 8.21 \cdot 10^{-4})$), than that generated by buy-and-hold strategy. This difference is not significant: $t(2492) = 1.64$, $p < 0.05$. However, it did represent a medium sized effect $r = 0.34$.

Table 7 Student t-test results for N-day Breakout trading system. Source: Author's calculation from the dataset.

	c=0.0000		c=0.0025		c=0.0050		c=0.0075		c=0.0100	
	t	p	t	p	t	p	t	p	t	p
N=10	7.4524	0.0000	6.8788	0.0000	6.3018	0.0000	5.7251	0.0000	5.1522	0.0000
N=20	5.1711	0.0000	4.8647	0.0000	4.5554	0.0000	4.2442	0.0000	3.9324	0.0001
N=30	4.8071	0.0000	4.6006	0.0000	4.3916	0.0000	4.1805	0.0000	3.9681	0.0001
N=40	3.8661	0.0001	3.6923	0.0002	3.5166	0.0004	3.3394	0.0009	3.1610	0.0016
N=50	3.4296	0.0006	3.2857	0.0010	3.1403	0.0017	2.9936	0.0028	2.8459	0.0045
N=60	3.0814	0.0021	2.9648	0.0031	2.8470	0.0044	2.7283	0.0064	2.6088	0.0091
N=70	3.3829	0.0007	3.2847	0.0010	3.1852	0.0015	3.0846	0.0021	2.9831	0.0029
N=80	2.6360	0.0084	2.5387	0.0112	2.4404	0.0147	2.3413	0.0193	2.2415	0.0251
N=90	2.7957	0.0052	2.7059	0.0069	2.6152	0.0090	2.5236	0.0117	2.4314	0.0151
N=100	2.2351	0.0255	2.1469	0.0319	2.0579	0.0397	1.9684	0.0491	1.8784	0.0604
N=110	2.2972	0.0217	2.2150	0.0268	2.1323	0.0331	2.0491	0.0406	1.9654	0.0495
N=120	2.0219	0.0433	1.9517	0.0511	1.8811	0.0601	1.8101	0.0704	1.7387	0.0822
N=130	1.8540	0.0639	1.7939	0.0729	1.7335	0.0831	1.6728	0.0945	1.6119	0.1071
N=140	1.6472	0.0996	1.5884	0.1123	1.5293	0.1263	1.4700	0.1417	1.4107	0.1585
N=150	2.0833	0.0373	2.0356	0.0419	1.9876	0.0470	1.9393	0.0526	1.8908	0.0588
N=160	1.9340	0.0532	1.8865	0.0593	1.8387	0.0661	1.7906	0.0735	1.7424	0.0816
N=170	2.1655	0.0304	2.1367	0.0327	2.1077	0.0352	2.0784	0.0378	2.0489	0.0406
N=180	2.0817	0.0375	2.0528	0.0402	2.0237	0.0431	1.9943	0.0462	1.9648	0.0496
N=190	1.8590	0.0631	1.8303	0.0673	1.8013	0.0718	1.7722	0.0765	1.7429	0.0815
N=200	1.8275	0.0677	1.7984	0.0722	1.7692	0.0770	1.7399	0.0820	1.7104	0.0873

Out of 20 trading strategies in this system, there are 5 strategies which do not report significant excess average daily return without taking into account transaction cost. As transaction cost is raised, fewer strategies can perform significantly better than buy-and-hold. At the cost of $c = 0.0100$, only 12 strategies report average daily returns that are significantly higher than buy-and-hold strategy ($p < 0.05$).

Nevertheless, aggressive strategies in this system still post statistically significant better results than buy-and-hold's across all cost cases. For instance, using $N = 10$ strategy at cost case $c = 0.0000$, a significant ($CI = (12.96 \cdot 10^{-4}, 22.21 \cdot 10^{-4})$) daily excess return is reported, $t(2492) = 7.45$, $p < 0.05$. The same strategy also posts significantly higher average daily return ($CI = (7.86 \cdot 10^{-4}, 17.51 \cdot 10^{-4})$), than simple buy-and-hold strategy, $t = 5.15$, $p < 0.05$.

6.2.4 Linear Regression Slope

In general, table 8 shows that Linear Regression Slope trading system performs dramatically worse than the rest in this thesis. At the lowest cost case $c = 0.0000$, only 5 strategies reports statistically significant excess returns. The best strategy at all cost cases in this system is $N = 110$. At $c = 0.0000$, it performs significantly better ($CI = (1.72 \cdot 10^{-4}, 10.11 \cdot 10^{-4})$), than buy and hold strategy, $t = 2.77$, $p < -0.05$. At the highest cost case $c = 0.0100$, this strategy still generate significantly higher ($CI = (0.98 \cdot 10^{-4}, 9.41 \cdot 10^{-4})$) average daily return, $t = 2.41$, $p < 0.05$.

Table 8 Student t-test results for Linear Regression trading system. Source: Author's calculation from the dataset.

	c=0.0000		c=0.0025		c=0.0050		c=0.0075		c=0.0100	
	t	p	t	p	t	p	t	p	t	p
N=10	0.8097	0.4182	-0.0840	0.9331	-0.9719	0.3312	-1.8450	0.0651	-2.6951	0.0071
N=20	1.5019	0.1332	1.0792	0.2806	0.6568	0.5114	0.2368	0.8129	-0.1788	0.8581
N=30	0.1775	0.8591	-0.1125	0.9104	-0.4017	0.6879	-0.6891	0.4908	-0.9737	0.3303
N=40	0.3444	0.7306	0.1137	0.9095	-0.1167	0.9071	-0.3461	0.7293	-0.5739	0.5661
N=50	0.9234	0.3559	0.7315	0.4645	0.5395	0.5896	0.3478	0.7280	0.1571	0.8752
N=60	1.0700	0.2847	0.9107	0.3625	0.7511	0.4527	0.5915	0.5542	0.4322	0.6656
N=70	0.4562	0.6483	0.3091	0.7573	0.1620	0.8713	0.0151	0.9879	-0.1311	0.8957
N=80	1.7507	0.0801	1.6259	0.1041	1.5003	0.1337	1.3740	0.1696	1.2473	0.2124
N=90	1.9842	0.0473	1.8596	0.0631	1.7338	0.0831	1.6072	0.1081	1.4799	0.1390
N=100	2.3957	0.0167	2.2898	0.0221	2.1829	0.0291	2.0752	0.0381	1.9669	0.0493
N=110	2.7673	0.0057	2.6803	0.0074	2.5925	0.0096	2.5039	0.0123	2.4147	0.0158
N=120	2.6482	0.0081	2.5668	0.0103	2.4844	0.0130	2.4011	0.0164	2.3169	0.0206
N=130	2.0349	0.0420	1.9626	0.0498	1.8897	0.0589	1.8164	0.0694	1.7426	0.0815
N=140	1.8524	0.0641	1.7718	0.0766	1.6906	0.0910	1.6088	0.1078	1.5267	0.1270
N=150	1.6514	0.0988	1.5782	0.1146	1.5046	0.1325	1.4307	0.1526	1.3564	0.1751
N=160	1.5678	0.1171	1.4937	0.1354	1.4193	0.1559	1.3446	0.1789	1.2697	0.2043
N=170	1.5007	0.1336	1.4372	0.1508	1.3734	0.1697	1.3092	0.1906	1.2447	0.2134
N=180	1.6610	0.0968	1.5965	0.1105	1.5315	0.1258	1.4662	0.1427	1.4005	0.1615
N=190	1.5770	0.1149	1.5305	0.1260	1.4837	0.1380	1.4366	0.1510	1.3893	0.1649
N=200	1.5614	0.1186	1.5150	0.1299	1.4683	0.1421	1.4213	0.1554	1.3739	0.1696

On the other hand, some strategies are not even significantly effective at the lowest cost case. $N = 10$, for example, failed to generate significant ($CI = (-2.67 \cdot 10^{-4}, 6.43 \cdot 10^{-4})$) excess return, $t = 0.81$, $p > 0.05$. The effect size is below medium, $r = 0.016$. The worst outcome from this trading system is of the strategy $N = 10$ at $c = 0.100$. In this case, the system generate significantly worse result ($CI = (-11.09 \cdot 10^{-4}, -1.75 \cdot 1.74)$). This is the only case throughout the test that is significantly beaten by the market.

6.3 Testing Significance Using Marginal Bootstrap-t

Testing significance of mean differences using marginal bootstrap-t is considered more robust. This section will report the bootstrap-t test results and compare them with the earlier test.

6.3.1 SMA/N-day Momentum

Table 9 shows that, using bootstrap-t method for marginal trimmed means, the statistical significance of the excess return generated by SMA/N-day momentum is drastically lowered. Through the first cost case to the fourth cost case, there are only three strategies reporting significant excess returns ($CI(0.00, 11.98 \cdot 10^{-4})$). At the highest cost cases $c = 0.0100$, only two out of twenty strategies performs significantly better ($CI = (0.59 \cdot 10^{-4}, 10.41 \cdot 10^{-4})$). The rest strategies perform slightly better (greater upper bounds of confidence interval) than the market. However, the difference is not significant, as the confidence intervals cross 0 and p-values are greater than 0.05.

Table 9 Results of Bootstrap-t method for trimmed means, SMA/N-day Momentum. Source: Author’s calculation from the dataset.

	c=0.0000			c=0.0025			c=0.0050			c=0.0075			c=0.0100		
	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p
N=10	2.95	11.98	0.00	2.26	11.20	0.00	1.88	10.80	0.00	1.52	10.56	0.00	1.30	10.41	0.01
N=20	1.95	10.90	0.00	1.12	9.90	0.02	0.89	9.62	0.02	0.73	9.47	0.02	0.59	9.33	0.03
N=30	1.17	10.13	0.02	0.43	9.25	0.04	0.20	9.13	0.04	0.05	8.99	0.05	-0.09	8.89	0.06
N=40	0.50	9.44	0.03	-0.40	8.44	0.08	-0.61	8.27	0.10	-0.79	8.16	0.10	-0.95	8.06	0.12
N=50	-0.05	8.96	0.05	-0.84	8.15	0.12	-1.09	8.02	0.14	-1.24	7.88	0.15	-1.28	7.75	0.16
N=60	-0.42	8.61	0.08	-1.03	7.87	0.15	-1.02	7.65	0.16	-1.18	7.53	0.17	-1.34	7.43	0.19
N=70	-0.85	8.53	0.11	-1.21	7.95	0.15	-1.30	7.87	0.16	-1.42	7.78	0.18	-1.51	7.66	0.19
N=80	-1.24	8.09	0.16	-1.74	7.63	0.20	-1.85	7.55	0.22	-1.93	7.46	0.23	-2.00	7.34	0.25
N=90	-1.58	7.78	0.20	-1.97	7.26	0.25	-2.07	7.19	0.27	-2.12	7.06	0.28	-2.17	6.99	0.30
N=100	-0.75	8.36	0.12	-1.00	7.94	0.14	-1.06	7.90	0.14	-1.16	7.90	0.15	-1.19	7.84	0.16
N=110	-0.97	8.22	0.13	-1.15	7.80	0.15	-1.18	7.74	0.15	-1.24	7.68	0.16	-1.29	7.65	0.16
N=120	-1.50	7.92	0.19	-1.70	7.56	0.21	-1.76	7.51	0.22	-1.77	7.45	0.22	-1.78	7.44	0.22
N=130	-1.81	7.78	0.22	-1.96	7.60	0.23	-1.96	7.60	0.23	-2.00	7.59	0.23	-2.03	7.51	0.24
N=140	-2.11	7.42	0.27	-2.22	7.28	0.29	-2.24	7.29	0.30	-2.30	7.26	0.30	-2.30	7.22	0.30
N=150	-2.10	7.62	0.25	-2.24	7.44	0.28	-2.32	7.37	0.29	-2.32	7.33	0.29	-2.38	7.33	0.29
N=160	-2.34	7.46	0.29	-2.38	7.43	0.30	-2.40	7.43	0.30	-2.41	7.41	0.31	-2.42	7.42	0.31
N=170	-2.45	7.42	0.31	-2.48	7.38	0.31	-2.48	7.37	0.32	-2.48	7.37	0.32	-2.48	7.36	0.32
N=180	-2.78	7.23	0.37	-2.78	7.09	0.38	-2.79	7.08	0.38	-2.82	7.07	0.38	-2.85	7.03	0.39
N=190	-2.67	7.28	0.35	-2.70	7.18	0.36	-2.70	7.15	0.36	-2.70	7.16	0.36	-2.73	7.16	0.36
N=200	-2.81	7.26	0.36	-2.79	7.12	0.37	-2.82	7.10	0.38	-2.82	7.08	0.38	-2.85	7.09	0.39

For example, at cost case $c = 0.0000$, the strategy utilizing $N = 60$ failed to significantly outperforms ($CI = (-0.42 \cdot 10^{-4}, 8.61 \cdot 10^{-4})$) the market, $p > 0.05$. In addition, it can be observed that the higher N is used, the wider the confidence interval expands into negative domain. Nevertheless, the two most aggressive strategies still manage to maintain significant excess return across all cost cases. Using $N = 10$ strategy at the lowest cost case, for illustration, the trading system significantly outperforms ($CI = (2.95 \cdot 10^{-4}, 11.98 \cdot 10^{-4})$)

buy-and-hold, $p < 0.05$. At $c = 0.0100$, the strategy still produce significantly higher average daily return ($CI = (1.30 \cdot 10^{-4}, 10.41 \cdot 10^{-4})$), than that of market, $p < 0.05$.

6.3.2 Exponential Smoothing

Table 10 shows that, without transaction cost, exponential smooth still reports significant excess return ($CI = (2.18 \cdot 10^{-4}, 11.06 \cdot 10^{-4})$) in all strategies, $p < 0.05$. To illustrate, the most aggressive strategy $a = 1.00$, at cost case $c = 0.0000$, performs significantly better ($CI = 18.97 \cdot 10^{-4}, 25.06 \cdot 10^{-4}$)) than buy-and-hold strategy, $p < 0.05$. However, risen transaction cost dramatically affects the trading system.

Table 10 Results of Bootstrap-t method for trimmed means, Exponential Smoothing. Source: Author's calculation from the dataset.

	c=0.0000			c=0.0025			c=0.0050			c=0.0075			c=0.0100		
	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p
a=0.05	2.175	11.055	0.003	1.832	10.758	0.003	1.706	10.546	0.003	1.550	10.440	0.007	1.545	10.214	0.010
a=0.10	4.741	12.929	0.000	4.117	12.537	0.000	3.743	12.114	0.000	3.393	11.832	0.000	3.118	11.572	0.000
a=0.15	6.211	14.271	0.000	5.370	13.587	0.000	4.786	13.068	0.000	4.373	12.712	0.000	4.023	12.459	0.000
a=0.20	7.095	14.888	0.000	6.223	14.068	0.000	5.481	13.570	0.000	5.012	13.198	0.000	4.620	12.897	0.000
a=0.25	8.482	16.183	0.000	7.319	15.158	0.000	6.434	14.375	0.000	5.654	13.815	0.000	5.001	13.329	0.000
a=0.30	9.457	17.095	0.000	8.012	15.829	0.000	6.860	14.758	0.000	5.821	13.985	0.000	4.958	13.303	0.000
a=0.35	10.410	17.970	0.000	8.762	16.369	0.000	7.220	15.079	0.000	5.788	14.121	0.000	4.579	13.243	0.000
a=0.40	12.086	19.294	0.000	9.955	17.410	0.000	7.956	15.847	0.000	6.153	14.271	0.000	4.330	12.941	0.000
a=0.45	13.189	20.199	0.000	10.722	17.930	0.000	8.382	16.003	0.000	6.125	14.210	0.000	3.903	12.508	0.000
a=0.50	14.238	20.960	0.000	11.437	18.613	0.000	8.915	16.373	0.000	6.399	14.304	0.000	3.908	12.327	0.000
a=0.55	15.190	21.756	0.000	12.191	19.113	0.000	9.458	16.586	0.000	6.532	14.363	0.000	3.652	12.117	0.000
a=0.60	15.990	22.368	0.000	12.605	19.314	0.000	9.385	16.434	0.000	5.821	13.871	0.000	2.330	11.103	0.003
a=0.65	16.464	22.937	0.000	12.947	19.587	0.000	9.477	16.441	0.000	5.735	13.462	0.000	1.716	10.572	0.007
a=0.70	17.156	23.363	0.000	13.312	19.972	0.000	9.716	16.569	0.000	5.686	13.430	0.000	1.520	10.214	0.010
a=0.75	17.481	23.722	0.000	13.384	19.951	0.000	9.257	16.340	0.000	4.953	12.665	0.000	0.256	9.070	0.037
a=0.80	18.258	24.309	0.000	13.824	20.323	0.000	9.361	16.338	0.000	4.503	12.332	0.000	-0.696	8.203	0.100
a=0.85	18.543	24.571	0.000	13.818	20.237	0.000	8.946	15.885	0.000	3.633	11.378	0.000	-2.027	6.729	0.317
a=0.90	18.809	24.825	0.000	13.696	20.146	0.000	8.320	15.335	0.000	2.498	10.337	0.000	-3.606	5.102	0.723
a=0.95	18.958	24.992	0.000	13.522	19.860	0.000	7.413	14.798	0.000	1.157	9.201	0.008	-5.534	3.406	0.643
a=1.00	18.974	25.059	0.000	13.071	19.527	0.000	6.588	13.883	0.000	-0.217	7.860	0.060	-7.371	1.508	0.214

The trading system starts failing to produce significant excess return at cost case $c = 0.0074$, where the strategy $a = 1.00$ does not significantly outperforms ($CI = (0.22 \cdot 10^{-4}, 7.86 \cdot 10^{-4})$) the market, $p > 0.05$. At the highest cost case $c = 0.0100$, there are only 15 strategies which manage to produce significant (

$CI = (0.26 \cdot 10^{-4}, 9.07 \cdot 10^{-4})$) excess return, $p < 0.05$. It is noteworthy that two strategies are slightly outperformed by the market (greater lower bounds of confidence). The strategy $a = 1.00$, despite producing most significant return at $c = 0.0000$, produces the worst result at $c = 0.0100$.

Meanwhile, significant excess return is consistently generated by conservative strategies in this system. The strategy $a = 0.05$, for example, significantly outperforms ($CI = (1.55 \cdot 10^{-4}, 11.055 \cdot 10^{-4})$) the market across all cost cases, $p < 0.05$

6.3.3 N-day Breakout

N-day Breakout trading system also show less significance in excess return generated using the Bootstrap-t method for marginal trimmed means (see table 11). Across all cost cases, only one strategy manages to generate statistically significant excess daily return. On average, strategy using $N = 10$ outperforms ($CI = (0.46 \cdot 10^{-4}, 9.68 \cdot 10^{-4})$) the buy-and-hold strategy, $p < 0.05$. This strategy also reports significant excess return ($CI = (0.41^1 0^{-4}, 9.5 \cdot 10^{-4})$) at the highest cost case $c = 0.0100$, $p < 0.05$.

Table 11 Results of Bootstrap-t method for marginal trimmed means, N-day breakout. Source: Author's calculation from the dataset.

	c=0.0000			c=0.0025			c=0.0050			c=0.0075			c=0.0100		
	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p
N−10	0.560	9.683	0.028	0.458	9.541	0.033	0.417	9.509	0.037	0.416	9.502	0.037	0.416	9.502	0.037
N−20	-0.476	8.782	0.087	-0.693	8.548	0.100	-0.735	8.539	0.100	-0.756	8.521	0.102	-0.779	8.499	0.103
N−30	-0.235	8.853	0.063	-0.506	8.481	0.085	-0.511	8.440	0.085	-0.506	8.416	0.085	-0.506	8.416	0.085
N=40	-1.557	7.764	0.202	-1.707	7.465	0.229	-1.731	7.418	0.230	-1.731	7.409	0.230	-1.731	7.409	0.230
N−50	-1.806	7.382	0.244	-1.966	7.212	0.271	-2.029	7.205	0.276	-2.046	7.181	0.277	-2.046	7.161	0.279
N=60	-2.407	7.270	0.312	-2.490	7.180	0.324	-2.542	7.184	0.329	-2.560	7.163	0.331	-2.569	7.160	0.332
N−70	-1.380	7.449	0.189	-1.597	7.281	0.209	-1.663	7.267	0.214	-1.677	7.208	0.217	-1.689	7.189	0.222
N=80	-2.168	7.043	0.284	-2.298	6.815	0.322	-2.338	6.787	0.329	-2.346	6.719	0.341	-2.347	6.689	0.344
N=90	-1.878	7.136	0.235	-2.067	6.966	0.265	-2.033	6.874	0.269	-2.067	6.856	0.272	-2.087	6.842	0.272
N=100	-2.422	7.079	0.305	-2.503	6.883	0.332	-2.519	6.865	0.344	-2.537	6.844	0.347	-2.547	6.827	0.349
N=110	-1.984	6.907	0.264	-2.175	6.773	0.290	-2.187	6.723	0.290	-2.231	6.714	0.295	-2.233	6.682	0.299
N−120	-2.349	7.028	0.310	-2.415	6.883	0.327	-2.418	6.886	0.327	-2.449	6.888	0.327	-2.458	6.870	0.329
N=130	-2.433	7.093	0.317	-2.456	6.938	0.324	-2.456	6.938	0.322	-2.486	6.931	0.336	-2.503	6.888	0.344
N−140	-2.604	7.046	0.351	-2.655	6.976	0.361	-2.655	6.976	0.359	-2.658	6.976	0.359	-2.660	6.944	0.357
N−150	-2.780	7.181	0.364	-2.817	7.183	0.364	-2.817	7.183	0.364	-2.817	7.183	0.364	-2.817	7.160	0.367
N=160	-2.815	7.135	0.372	-2.850	7.135	0.372	-2.850	7.135	0.372	-2.850	7.135	0.372	-2.857	7.121	0.377
N−170	-3.032	7.108	0.407	-3.032	7.108	0.407	-3.032	7.108	0.407	-3.032	7.108	0.407	-3.037	7.112	0.407
N=180	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409
N−190	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409
N=200	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409	-3.037	7.112	0.409

Despite not reporting significant results, the other strategies performs slightly better (greater upper bounds of confidence) than the market. For instance, utilizing the strategy $N = 200$ at cost case $c = 0.0100$, the trading system generates marginally higher average daily return ($CI = (-3.03 \cdot 10^{-4}, 7.11 \cdot 10^{-4})$). However, the difference is not significance as $p > 0.05$.

6.3.4 Linear Regression Slope

In Bootstrap-t test for marginal trimmed means, linear regression trading system fails to report significant excess return across all strategy (See table 12). The results are generally worse than those reported by student t-test.

Table 12 Results of Bootstrap-t method for marginal trimmed means, Linear Regression Slope. Source: Author's calculation from the dataset.

	c=0.0000			c=0.0025			c=0.0050			c=0.0075			c=0.0100		
	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p	Lower	Upper	p
N=10	-2.124	6.978	0.299	-3.918	4.758	0.861	-5.021	3.287	0.705	-5.500	2.811	0.522	-5.814	2.471	0.442
N=20	-2.187	6.884	0.324	-3.122	6.007	0.526	-3.275	5.711	0.596	-3.443	5.561	0.646	-3.541	5.458	0.683
N=30	-2.871	6.491	0.434	-3.527	5.831	0.618	-3.636	5.585	0.671	-3.712	5.444	0.713	-3.743	5.390	0.736
N=40	-2.892	6.379	0.456	-3.403	5.827	0.586	-3.504	5.681	0.631	-3.553	5.654	0.643	-3.618	5.628	0.654
N=50	-2.881	6.311	0.447	-3.341	5.798	0.583	-3.410	5.626	0.626	-3.481	5.587	0.653	-3.508	5.538	0.663
N 60	-2.632	5.913	0.462	-3.110	5.586	0.588	-3.122	5.351	0.634	-3.157	5.341	0.636	-3.167	5.333	0.636
N 70	-2.906	5.644	0.539	-3.297	5.396	0.633	-3.469	5.263	0.696	-3.506	5.237	0.700	-3.510	5.200	0.710
N=80	-2.375	6.331	0.384	-2.607	6.124	0.434	-2.622	6.071	0.446	-2.679	6.002	0.459	-2.736	5.947	0.477
N=90	-2.351	6.474	0.372	-2.621	6.236	0.417	-2.682	6.228	0.421	-2.682	6.211	0.421	-2.707	6.181	0.429
N=100	-2.208	6.848	0.329	-2.330	6.583	0.357	-2.390	6.569	0.361	-2.419	6.545	0.361	-2.455	6.527	0.367
N=110	-2.150	7.041	0.309	-2.236	6.831	0.331	-2.276	6.766	0.344	-2.301	6.753	0.347	-2.323	6.752	0.349
N=120	-2.288	6.938	0.326	-2.360	6.764	0.346	-2.373	6.729	0.352	-2.366	6.699	0.354	-2.366	6.699	0.354
N−130	-2.565	6.830	0.362	-2.672	6.729	0.382	-2.672	6.715	0.384	-2.672	6.715	0.384	-2.672	6.715	0.384
N−140	-2.587	6.905	0.356	-2.679	6.774	0.381	-2.693	6.764	0.381	-2.714	6.754	0.386	-2.735	6.731	0.389
N=150	2.665	6.873	0.376	2.758	6.780	0.392	2.795	6.771	0.396	2.801	6.771	0.396	2.801	6.771	0.396
N=160	-2.586	6.923	0.362	-2.628	6.810	0.377	-2.652	6.792	0.381	-2.686	6.766	0.386	-2.695	6.762	0.387
N=170	-2.389	6.881	0.344	-2.484	6.814	0.356	-2.518	6.815	0.356	-2.543	6.811	0.359	-2.559	6.793	0.362
N=180	-2.343	6.751	0.339	-2.475	6.652	0.364	-2.502	6.653	0.371	-2.502	6.653	0.371	-2.502	6.653	0.371
N=190	-2.323	6.743	0.331	-2.380	6.655	0.349	-2.373	6.648	0.351	-2.373	6.648	0.351	-2.381	6.638	0.357
N=200	-2.057	6.746	0.305	-2.089	6.647	0.314	-2.069	6.627	0.316	-2.069	6.627	0.316	-2.069	6.627	0.316

For illustration, at cost case $c = 0.0000$, the most conservative strategy ($N = 200$) reports only a slightly better average daily return ($CI = (-2.06 \cdot 10^{-4}, 6.47 \cdot 10^{-4})$), compared to buy-and-hold strategy. However, the difference is not statistically significant, as $p < 0.05$. At cost case $c = 0.0100$, this strategy still perform marginally better ($CI = (-2.060 \cdot 10^{-4}, 6.63 \cdot 10^{-4})$) than the market.

The most aggressive strategy in this trading system ($N = 10$) also does not significantly outperform ($CI = (-2.124 \cdot 10^{-4}, 6.078 \cdot 10^{-4})$) the market, $p > 0.05$. Moreover, at the highest cost case $c = 0.0100$, this strategy is slightly outperformed ($CI = (-5.91 \cdot 10^{-4}, 2.47 \cdot 10^{-4})$) by buy-and-hold strategy, $p = 0.442$.

Overall, using this testing method, it can be concluded that Linear Regression Slope trading system does not generate significant excess return over the period.

6.4 Discussion

Four out of five trading systems reports significant excess return in Vietnam's stock market during the period 2003-2013. The four include: SMA/N-day momentum, Exponential Smoothing, N-day Breakout. Among them, Exponential Smoothing trading system generates the most transactions as well as highest average daily return. The student t-test has shown that the four systems have the ability to yield positive returns in the market except in extreme cost cases.

Within the successful trading systems, it can be observed that more aggressive strategy usually leads to higher return. On the other hand, high frequency trading can be heavily punished by transaction cost, in the case of Exponential Smoothing trading system, for example, the most aggressive strategies are rapidly outperformed by moderate conservative strategies as the cost rises. However, commissioning fee in Vietnam's Stock market is typically 0.35% (as compared to 1.00% in the extreme cost case). Thus, more aggressive strategies can be utilized.

The trading system using linear regression technique is the only one which does not report consistent excess return. Only a few moderately conservative strategies in this system can generate significant excess return at lower cost cases. In addition, there seems to be no relation between performances of different strategies in this system.

Nevertheless, the aforementioned results include all out-liners in the data. Furthermore, it is affected by the assumption of student t-test that statistic of stock data is normally distributed. Wilcox's bootstrap-t test for marginal trimmed means is applied to address these problems.

Trading systems generally perform worse in Wilcox's test using 20% trimmed means. For example, SMA/N-day Momentum trading system reports significant excess return in the five most aggressive strategies. N-day Breakout trading method reports significantly higher average daily return in only one strategy. Meanwhile, exponential smoothing trading results stay strong, except in extreme cost cases.

The reason that creates such difference in the two tests might be the upper out-liners in the returns. The trading systems seem to greatly rely on these extreme returns to post positive result.

However, the performance in the latter test should not nullify positive results of the trading systems, as it might be the fact that these systems are able to predict extreme increases in stock price.

6.5 Limitations

There are several limitations in this thesis. First, the sample size is still relative small. Second, tested trade systems might be too simple. And finally, only historical daily data are taken into account.

Given that Vietnam's stock market is relatively new, only ten year period data has been included in the research. Data of longer time period would be preferred to prove the consistency of trading systems. Also, one may argue taking the full sample from the inception of the stock market. However, the author believes that early trading activities can be irregular, thus will add noises to the result.

In addition, the trade systems that are tested in this thesis are the simplest ones. They are all readily available on the market for investors to use. More complex system might potentially generate higher excess returns.

Last but not least, it can be oversimplified to only use end-day data. It might not be possible to purchase the particular share at the close price of previous day. Moreover, using intra-day data to generate trading signals make high frequency trading available. As this research has shown the correlation between number of transactions and excess return, intra-day trading can potentially produce even higher excess returns.

7 CONCLUSION

Fama's weak-form of efficient market hypothesis has been prominent in a few decades. However, it has been facing many challenges due to the growing popularity of technical trading systems since the late 1980s. This thesis attempts to verify mixed conclusions regarding the efficiency of the Vietnam's Stock Market during the period 2003-2013.

The author sees significant excess return generated by four out of five trading systems based on student t-test. The simulation also shows that higher frequency trading tends to produce higher average return in the long-term. This agrees with Fama (1970) finding in his research. However, it is on the contrary to his claim that technical trading cannot generate excess return if commission fees are taken into account. In the extreme cost cases, strategies with moderate number of transactions outperform.

Testing the results again using trimmed means and bootstrapping method at a significance level of 5%, the significance of the excess returns are drastically reduced. Only one out of five produce significantly positive result using this test. The result of latter test does not necessarily nullify the positive excess return. Instead, this suggests that there are extreme positive returns generated. It is undetermined whether the trading systems can predict such extreme movement.

Overall, the thesis raises doubts about the efficiency of Vietnamese stock market. It rejects the claim that technical analysis cannot generate excess return in security market. The tests show signs that technical analysis can predict trends of stock price movement. However, it is undecided if extreme positive return are generated by technical analysis.

Further research should consider intra-day data to while testing the weak form of efficiency of VN-Index. Extreme returns in the stock market should be carefully scrutinized. Last but not least, trading system with higher degree of complexity should be tested on Vietnam's stock market.

8 SOURCES

Alexander, S. S. 1961, 'Price movements in speculative markets: Trends or random walks', *Industrial Management Review* **2**, 7–26.

Alexander, S. S. 1964, Price movements in speculative markets: Trends or random walks. no. 2, *in* P. Cootner, ed., 'The Random Character of Stock Market Prices', M.I.T, Cambridge.

Allen, F., Karjalainen, R. 1999 , 'Using genetic algorithms to find technical trading rules', *Journal of Financial Economics* **51***,* 171-245 .

Ang, A., Bekaert, G. 2007, 'Stock return predictability: is it there? ', *Review of Financial Studies* **20**(3), 651–707.

Bachelier, L. 1900, Theorie de la Speculation, PhD thesis, University of Paris.

Bessembinder, H., Chan, K. 1995 , 'The profitability of technical trading rules in the asian stock markets', *Pacific-Basin Finance Journal* pp. 257–184.

Black, F. 1986, 'Noise', *Journal of Finance* **11**(2), 529–543.

Bodie, Z., M, J. A. Kane, A. 2005, *Investment*, Irwin / McGraw Hill.

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.

Campbell, J. Y., Thompson, S. B. 2008, 'Pedicting excess stock returns out of sample: can anything beat the historical average? ', *Review of Financial Studies* **21**(4).

CFA Institute 2011, *CFA Program Curriculum: Equity and Fixed Income*, Pearson.

Chang, P. H. K. Osler, C. L. 1999, 'Methodical madness: Technical analysis and the irrationality of exchange-rate forecasts', *Economic Journal* **109**, 636–662.

Chou, P. H. Wei, K. C. J. 2007, 'Sources of contrarian profits in the japanese stock market', *Journal of Empirical Finance* **14**(3), 261–286.

Donchian, R. D. 1960, 'Commdities: High finance in copper', *Financial Analysts Journal* **16**(6), 133–142.

Fama, E. F. 1965, 'The behavior of stock market prices', *The Journal of Business* **38**, 34–105.

Fama, E. F. 1970, 'Efficient capital market: A review of theory and empirical work', *Journal of Finance* **25**, 383–417.

Fama, E. F. 1991, 'Efficient capital market: 2', *Journal of Finance* **46**(5), 1575–1617.

Fama, E. F. Blume, M. 1966, 'Filter rules and stock market trading profits', *Journal of Business* **39**, 226–241.

Field, A., Miles, J. Field, Z. 2012, *Discovering Statistics Using R*, Sage, Thousand Oaks, CA.

Godfrey, M. D., Granger, C. W. J. Morgenstern, O. 1964, 'The random walk hypothesis of stock market behavior', *Kyklos* **17**, 1–30.

James, F. E. 1968, 'Monthly moving averages: An effective investment tool? ', *Journal of Financial and Quantitative Anaysis* **3**, 315–326.

Jensen, M. C. 1978, 'Some anomalous evidence regarding market efficiency', *Journal of Financial Economics* **6**(2-3), 95–101.

Kaufman, J. P. 2013, *Trading system and methods*, 5th edn, John Wiley and Sons, Inc., Hoboken.

Kendall, M. G. 1953, 'The analysis of economic time-series, part I: Prices', *Journal of the Royal Statistical Society* **42**, 167–247.

Kian, P. L. 2009, An Empirical Analysis of the Weak-form Efficiency of Stock Markets, PhD thesis, Monash University.

Koza, J. 1992, *Genetic programming: On the programming of computers by means of natural selection*, MIT Press, Cambridge, MA.

Lo, A. 2004, 'The adaptive markets hypothesis: Market efficiency form.', *Journal of Portfolio Management* **30**, 15–29.

Lo, A. W. 2008, *Efficient market hypothesis*, 2nd edn, Palgrave Macmillan, New York.

Lukac, L. P., Brorsen, B. V. Irwin, S. H. 1988, 'A test of futures market disequilibrium using twelve different technical trading systems', *Applied Economics* **20**, 623–639.

Milionis, A. E. 2007, 'Efficient capital markets: a statistical definition and comments', *Statistics and Probability Letters* **77**(6), 607–113.

Moore, A. 1962, A Statistical Analysis of Common Stock Prices, PhD thesis, Graduate School of Business, University of Chicago.

Muphy, J. 1999, *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods*, New York Institute of Finance, New York.

Osborne, M. F. M. 1959, 'Brownian motion in the stock market', *Operation Research* **VII**(2), 145–173.

Park, C. H. Irwin, S. H. 2007, 'What do we know about the profitability of technical analysis? ', *Journal of Economic Surveys* **21**(4), 786–826.

Park, C. Irwin, S. 2004, The profitability of technical analysis: A review, Technical report, AgMAS Project.

Pauwels, S., Inghelbrecht, K., Heyman, D. Marius, P. 2011, 'Technical trading rules in emerging stock', *World Academy of Science* pp. 2241–2264.

Roberts, H. V. 1959, 'Stock market 'patterns' and financial analysis: Methodological suggestions', *Journal of Finance* **14**, 1–10.

Rubinstein, M. 1975, 'Securities market efficiency in an arrow-debreu economy', *American Economic Review* **65**(5), 812–824.

Sharpe, W. F. 1990, *Investment*, 4th edn, Prentice Hall.

Tian, G. G., Wan, G. H. Guo, M. 2002, 'Market efficiency and the returns to simple technical trading rules: new evidence from u.s. equity market and chinese equity markets', *Asia-Pacific Financial Markets* **9**(3-4), 241–258.

Truong, D. L. 2006, 'Equitisation and stock-market development', Master Thesis, Rijksuniversiteit Groningen, Can Tho

U.S. Security and Exchange Commission 2013, 'Insider trading'. http://www.sec.gov/answers/insider.htm (*accessed 08.11.2013).*

Vo, V. X. Le, T. D. B. 2013, 'Empirical investigation of efficient market hypothesis in vietnam stock market', Master Thesis, University of Economics, Ho Chi Minh

VNDirect, n.d., 'VN-Index indicator', available at: https://www.vndirect.com.vn/portal/lich-su-gia/vnindex.shtml (*accessed 08.11.2013).*

Welch, I. Goyal, A. 2008, 'A comprehensive look at the empirical performance of equity premium prediction', *Review of Financial Studies* **21**(4), 1455–1509.

White, H. 2000, 'A reality check for data snooping', *Econometrica* **68**, 1097–1126.

Wilcox, R. R. 2005, *Introduction to robust estimation and hypothesis testing*, 2nd edn, Elsevier, Burlington, MA.

LIST OF APPENDICES

SIMULATOR SOURCE CODE (R)

```
require("TTR")
require("WRS")
require("xtable")

# Method list:
# 1. Simple Moving Averages
# 2. N-day momentum
# 3. Exponential Smoothing
# 4. N-day Breakout
# 5. Linear Regression Slope
# 6. Swing

# Import stock data
data <- read.csv("D:/Dropbox/Thesis/historical_price.csv", header = TRUE)
time <- as.POSIXct(data$DATE, format = "%d/%m/%Y") # Convert time to POSIXct

# Calculate hold return
r.hold <- 0
for (i in 2:nrow(data)) {
  r.tmp <- round(10000*log(data$CLOSE[i]/data$CLOSE[i-1], base = exp(1)),digits=2)
  r.hold <- c(r.hold, r.tmp)
  rm(r.tmp)
}

# Different n's
n = seq(10,200,10)

# Store SMA vectors in a list
# Each vector store SMA value of a specific order
method <- list() # Store lists of positions of different methods
SMA <- list()
POS.SMA <- list()
for (i in 1:length(n)) {
  SMA[[i]] <- SMA(data$CLOSE, n = n[i])
}

# Create positions from SMA vectors
for (i in 1:length(n)){
  POS_tmp <- 0
  for (j in 2:length(SMA[[i]])){
    if(is.na(SMA[[i]][j] > SMA[[i]][j-1]) == T){
      POS_tmp <- c(POS_tmp, 0)
    } else{
     if(SMA[[i]][j] > SMA[[i]][j-1]){
       POS_tmp <- c(POS_tmp, 1)
     }
     else{
       POS_tmp <- c(POS_tmp, 0)
     }
    }
```

```
  }
  POS.SMA[[i]] <- POS_tmp
  rm(POS_tmp, i, j)
}
method[[1]]<-POS.SMA

# Transaction costs
cost <- c(0.0000, 0.0025, 0.0050, 0.0075, 0.0100)

# N-DAY MOMENTUM
# Assign position according to momentum
POS.momentum <- list() # Store list of position using N-day momentum
for (i in n){
  POS.tmp <- NULL
  for (j in 1:length(data$CLOSE)) {
    if (i>=j) {
      POS.tmp <- c(POS.tmp, 0)
    }
    else {
      if ((data$CLOSE[j] - data$CLOSE[j-i]) >0) {
        POS.tmp <- c(POS.tmp, 1)
      }
      else {
        POS.tmp <- c(POS.tmp, 0)
      }
    }
  }
  POS.momentum[[i/10]] <- POS.tmp
}
method[[2]] <- POS.momentum

# EXPONENTIAL SMOOTHING
# Assign positions according to momentum
a <- seq(0.05, 1, 0.05) # Smoothing constant
POS.esmooth <- list() # Store list of position using smoothing momentum
for (i in a) {
  POS.tmp <- NULL
  smooth <- NULL
  for (j in 1:length(data$CLOSE)) {
    if (j == 1) {
      POS.tmp <- c(POS.tmp, 0)
      smooth <- c(smooth, data$CLOSE[j])
    }
    else {
      increase <- round(i*(data$CLOSE[j]-smooth[j-1]), digits = 2)
      smooth[j] <- smooth[j-1] + increase
      if (smooth[j]>smooth[j-1]) {
        POS.tmp <- c(POS.tmp, 1)
      }
      else {
        POS.tmp <- c(POS.tmp, 0)
```

```
      }
    }
  }
  POS.esmooth[[i*20]] <- POS.tmp
  rm(POS.tmp)
}
method[[3]] <- POS.esmooth

# N-DAY BREAKOUT
POS.nbreak <- list() # Store list of position using smoothing momentum
for (i in n) {
  POS.tmp <- NULL
  for (j in 1:length(data$CLOSE)) {
    if (i>=j) {
      POS.tmp <- c(POS.tmp, 0)
    }
    else {
      n.high <- max(data$HIGH[(j-i):(j-1)])
      n.low <- min(data$LOW[(j-i):(j-1)])
      if (data$CLOSE[j] > n.high) {
        POS.tmp <- c(POS.tmp, 1)
      }
      else {
        if (data$CLOSE[j] < n.low) {
          POS.tmp <- c(POS.tmp, 0)
        }
        else{
          POS.tmp <- c(POS.tmp, POS.tmp[j-1])
        }
      }
    }
  }
  POS.nbreak[[i/10]] <- POS.tmp
}
method[[4]] <- POS.nbreak

# lINEAR REGRESSION SLOPE
# Convert close price to xts
CLOSE.xts <- as.xts(data$CLOSE, order.by = time, unique = TRUE, frequency = 1)
# Store slope vectors
SLOPE <- list()
for (i in 1:length(n)) {
  slope.tmp <- rollSFM(CLOSE.xts, .index(CLOSE.xts), n[i])
  SLOPE[[i]] <- slope.tmp$beta
}

# Create position based on beta
POS.SLOPE <- list() # Store list of position using linear regression slope
for (i in n) {
  count <- i/10
  POS.tmp <- NULL
```

```
  for (j in 1:length(data$CLOSE)) {
    if (i > j) {
      POS.tmp <- c(POS.tmp, 0)
    }
    else {
      if (SLOPE[[count]][j]==0){
        POS.tmp <- c(POS.tmp, POS.tmp[j-1])
      }
      else{
        if(SLOPE[[count]][j]>0){
          POS.tmp <- c(POS.tmp, 1)
        }
        else{
          POS.tmp <- c(POS.tmp, 0)
        }
      }
    }
  }
  POS.SLOPE[[count]] <- POS.tmp
}
method[[5]] <- POS.SLOPE

# Calculate return function
# This returns lists of return of 5 cost cases
# Input method_number as argument (See method list)
calc_return <- function(method_number) {
  x <- method[[method_number]]
  cc.x <- list() # Create a list to store lists of returns for different cost
  for (i in 1:length(cost)) {
    r.x <- list()
    for (k in 1:length(n)) {
      r_temp <- 0
      for (j in 2:length(x[[k]])) {
        if(x[[k]][j] == 1) {
          r.calc <- round(log(data$CLOSE[j]/data$CLOSE[j-1], base = exp(1)), 6)
        }
        else{
          r.calc <- 0
        }
        if(is.na(x[[k]][j] != x[[k]][j+1])) {
          r_temp <- c(r_temp, r.calc)
        }
        else{
          if(x[[k]][j] != x[[k]][j+1]) {
#           r.calc <- round((1+r.calc)*(1-cost[i])-1, digit =6)
            r.calc <- round((1+r.calc)-abs((1+r.calc)*cost[i])-1, digit =6)
            r_temp <- c(r_temp, r.calc*10000)
          }
          else{
            r_temp <- c(r_temp, r.calc*10000)
          }
```

```
      }
    }
    r.x[[k]] <- r_temp
  }
  cc.x[[i]] <- r.x
 }
 return(cc.x)
}

# Calculate arithmetic mean of return function
calc_mean <- function(method_number) {
 mean.tmp <- list() # Prepare a list to store lists of means
 r.list <- calc_return(method_number) # Fetch a list of return from a specific method
 for (i in 1:length(cost)) {
  tmp.list <- list() # Prepare a list to store means
  for (k in 1:length(n)) {
   tmp.list[[k]] <- round(mean(unlist(r.list[[i]][k])), digits = 2)
  }
  mean.tmp[[i]] <- tmp.list
 }
 return(mean.tmp)
}

# Get number of actions taken
calc_posno <- function(method_number) {
 posno_vect <- NULL
 x <- method[[method_number]]
 for (i in 1:length(n)) {
  posno_tmp<-0
  for (j in 2:length(x[[i]])) {
   if (x[[i]][j]!=x[[i]][j-1]) {
    posno_tmp <- posno_tmp+1
   }
  }
  posno_vect <- c(posno_vect,posno_tmp)
 }
 return(posno_vect)
}
# TEST STATISTICS STARTS HERE
# Get return
student.t.test <- list()
ydbt.t.test <- list()
t.calc <- function(method_number) {
 stu_return <- list()
 ydbt_return <- list()
 for (i in 1:length(cost)) {
  stu_tmp <- list() # Create list to store student t-test
  r.list <- calc_return(method_number)
  for (k in 1:length(n)) {
   stu_tmp[[k]] <- t.test(unlist(r.list[[i]][k]), r.hold, paired = T)
  }
```

```
    stu_return[[i]] <- stu_tmp
  }
  return(stu_return)
}

t.data <- function(method_number) {
  x <- t.calc(method_number)
  cc <- list()
  for (i in 1:length(cost)) {
    t.tmp <- NULL
    p.tmp <- NULL
    for (j in 1:length(n)) {
      t.tmp <- c(t.tmp, unlist(x[[i]][j], recursive = F)$statistic)
      p.tmp <- c(p.tmp, unlist(x[[i]][j], recursive = F)$p.value)
    }
    result <- data.frame(round(t.tmp,digits =4), round(p.tmp,digits=4))
    cc[[i]] <- result
  }
  return(cc)
}

ydbt_calc <- function(method_number) {
  ydbt_return <- list()
  for (i in 1:length(cost)) {
    print(paste(i,"of",length(cost),sep=""))
    ydbt_tmp <- list() # Create list to store yuen marginal bootstrap-t test
    r.list <- calc_return(method_number)
    for (k in 1:length(n)) {
      ydbt_tmp[[k]] <- ydbt(unlist(r.list[[i]][k]), r.hold, tr = .2, nboot = 599, alpha = .05)
    }
    ydbt_return[[i]] <- ydbt_tmp
  }
  return(ydbt_return)
}

ydbt.data <- function(method_number) {
  x <- ydbt_calc(method_number)
  cc <- list()
  for (i in 1:length(cost)) {
    print(paste("Getting data from method", i, "of", length(cost), sep= " "))
    cidown.tmp <- NULL
    ciup.tmp <- NULL
    p.tmp <- NULL
    for (j in 1:length(n)) {
      cidown.tmp <- c(cidown.tmp, unlist(x[[i]][j], recursive = F)$ci[1])
      ciup.tmp <- c(ciup.tmp, unlist(x[[i]][j], recursive = F)$ci[2])
      p.tmp <- c(p.tmp, unlist(x[[i]][j], recursive = F)$p.value)
    }
    result <- data.frame(round(cidown.tmp,digits =4), round(ciup.tmp, digits = 4),
round(p.tmp,digits=4))
    cc[[i]] <- result
```

```
  }
  return(cc)
}

a <- ydbt.data(1)


a<- unlist(all.t.test.LINEAR[[1]][1], recursive = F)
str(k)



# TEST STATISTICS ENDS HERE
# CALCULATE RESULTS

# MEAN RETURNS OF SMA AND N-DAY STARTS HERE
SMA.N.return <- calc_mean(1)
# Cost case 1
SMA.N.return.cc1 <- unlist(SMA.N.return[[1]])
# Cost case 2
SMA.N.return.cc2 <- unlist(SMA.N.return[[2]])
# Cost case 3
SMA.N.return.cc3 <- unlist(SMA.N.return[[3]])
# Cost case 4
SMA.N.return.cc4 <- unlist(SMA.N.return[[4]])
# Cost case 5
SMA.N.return.cc5 <- unlist(SMA.N.return[[5]])

SMA.N.mean.return <- da-
ta.frame(SMA.N.return.cc1,SMA.N.return.cc2,SMA.N.return.cc3,SMA.N.return.cc4,SMA.N
.return.cc5,rep(mean(r.hold),each = 20))
colnames(SMA.N.mean.return) <- c("Cost case 1","Cost case 2", "Cost case 3", "Cost case
4", "Cost case 5", "Buy-and-hold Average Return")
rownames(SMA.N.mean.return) <- c("SMA10", "SMA20", "SMA30", "SMA40", "SMA50",
"SMA60", "SMA70","SMA80", "SMA90","SMA100","SMA110",
"SMA120","SMA130","SMA140","SMA150","SMA160","SMA170","SMA180","SMA190","
SMA200")
xtable(SMA.N.mean.return, caption = "Average returns of SMA and N-day momentum
trading system ($\\times 10^{-4}$)")
# MEAN RETURNS OF SMA AND N-DAY ENDS HERE

# PLOT ACTIONS GENERATED BY SMA AND N-DAY
par(cex=0.7)
barplot(calc_posno(1),beside=FALSE,names=levels(interaction(n)), col = "steelblue3",
ylim=c(0,300))
par(new = T)
plot(SMA.N.return.cc1,type = "l", axes =F, xlab = "", ylab="", col = "darkgreen", lwd = 3,
ylim=c(0,25))
lines(SMA.N.return.cc5, col = "darkorange", lwd= 3)
axis(4)
```

```
legend("topright", "(x,y)", c("Number of actions", "Avg. returns c=0.0000", "Avg. returns
c=0.0100"), fill = c("steelblue3", "darkgreen", "darkorange"))
# COUNT ACTIONS GENERATED BY SMA AND N-DAY ENDS

# MEAN RETURNS EXPONENTIAL SMOOTHING STARTS HERE
esmooth.return <- calc_mean(3)
# Cost case 1
esmooth.return.cc1 <- unlist(esmooth.return[[1]])
# Cost case 2
esmooth.return.cc2 <- unlist(esmooth.return[[2]])
# Cost case 3
esmooth.return.cc3 <- unlist(esmooth.return[[3]])
# Cost case 4
esmooth.return.cc4 <- unlist(esmooth.return[[4]])
# Cost case 5
esmooth.return.cc5 <- unlist(esmooth.return[[5]])
# Create data frame
esmooth.mean.return <- da-
ta.frame(esmooth.return.cc1,esmooth.return.cc2,esmooth.return.cc3,
esmooth.return.cc4,esmooth.return.cc5, rep(mean(r.hold),each = 20))
colnames(esmooth.mean.return) <-
c("c=0.000","c=0.005","c=0.010","c=0.015","c=0.020","Buy-and-hold")
rownames(esmooth.mean.return) <- c("a=0.05", "a=0.10", "a=0.15","a=0.20",
"a=0.25","a=0.30","a=0.35","a=0.40","a=0.45",
"a=0.50","a=0.55","a=0.60","a=0.65","a=0.70","a=0.75","a=0.80","a=0.85","a=0.90","a=0.
95","a=1.00")
xtable(esmooth.mean.return, caption = "Average returns of Exponential Smoothing trading
system ($\\times10^{-4}$")
# MEAN RETURNS EXPONENTIAL SMOOTHING ENDS HERE

# PLOT ACTIONS GENERATED BY EXPONENTIAL SMOOTHING
par(cex=0.7)
barplot(calc_posno(3),beside=FALSE,names=levels(interaction(a)), col = "steelblue3",
ylim=c(0,1000))
par(cex=0.7, new=T)
plot(esmooth.return.cc1,type = "l", axes =F, xlab = "", ylab="", col = "darkgreen", lwd = 3,
ylim=c(0,60))
lines(esmooth.return.cc5, col = "darkorange", lwd= 3)
axis(4, cex=0.7)
legend("topleft", "(x,y)", c("Number of actions", "Avg. returns c=0.0000", "Avg. returns
c=0.0100"), fill = c("steelblue3", "darkgreen", "darkorange"),cex = 1.2)
?par
# PLOT ACTIONS GENERATED BY EXPONENTIAL SMOOTHING

#N-DAY BREAKOUT STARTS HERE
NBREAK.return <- calc_mean(4)
# Cost case 1
NBREAK.return.cc1 <- unlist(NBREAK.return[[1]])
# Cost case 2
NBREAK.return.cc2 <- unlist(NBREAK.return[[2]])
# Cost case 3
```

```
NBREAK.return.cc3 <- unlist(NBREAK.return[[3]])
# Cost case 4
NBREAK.return.cc4 <- unlist(NBREAK.return[[4]])
# Cost case 5
NBREAK.return.cc5 <- unlist(NBREAK.return[[5]])
#Create data frame
NBREAK.mean.return <- da-
ta.frame(NBREAK.return.cc1,NBREAK.return.cc2,NBREAK.return.cc3,NBREAK.return.
cc4,NBREAK.return.cc5,rep(mean(r.hold),each = 20))
colnames(NBREAK.mean.return) <-
c("c=0.000","c=0.005","c=0.010","c=0.015","c=0.020","Buy-and-hold")
rownames(NBREAK.mean.return) <- c("N=10", "N=20", "N=30", "N=40", "N=50",
"N=60", "N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
xtable(NBREAK.mean.return, caption = "Average returns of N-day Breakout trading sys-
tem ($\\times 10^{-4}$)")
#N-DAY BREAKOUT ENDS HERE

# PLOT ACTIONS GENERATED BY N-DAY BREAKOUT
par(cex=0.7)
barplot(calc_posno(4),beside=FALSE,names=levels(interaction(n)), col = "steelblue3",
ylim=c(0,150))
par(cex=0.7, new=T)
plot(NBREAK.return.cc1,type = "l", axes =F, xlab = "", ylab="", col = "darkgreen", lwd =
3, ylim=c(0,20))
lines(NBREAK.return.cc5, col = "darkorange", lwd= 3)
axis(4, cex=0.7)
legend("topright", "(x,y)", c("Number of actions", "Avg. returns c=0.0000", "Avg. returns
c=0.0100"), fill = c("steelblue3", "darkgreen", "darkorange"),cex = 1.2)
# PLOT ACTIONS GENERATED BY N-DAY BREAKOUT

#LINEAR REGRESSION START HERE
LINEAR.return <- calc_mean(5)
# Cost case 1
LINEAR.return.cc1 <- unlist(LINEAR.return[[1]])
# Cost case 2
LINEAR.return.cc2 <- unlist(LINEAR.return[[2]])
# Cost case 3
LINEAR.return.cc3 <- unlist(LINEAR.return[[3]])
# Cost case 4
LINEAR.return.cc4 <- unlist(LINEAR.return[[4]])
# Cost case 5
LINEAR.return.cc5 <- unlist(LINEAR.return[[5]])
#Create data frame
LINEAR.mean.return <- da-
ta.frame(LINEAR.return.cc1,LINEAR.return.cc2,LINEAR.return.cc3,LINEAR.return.cc4,
LINEAR.return.cc5,rep(mean(r.hold),each = 20))
colnames(LINEAR.mean.return) <-
c("c=0.000","c=0.005","c=0.010","c=0.015","c=0.020","Buy-and-hold")
```

```
rownames(LINEAR.mean.return) <- c("N=10", "N=20", "N=30", "N=40", "N=50",
"N=60", "N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
xtable(LINEAR.mean.return, caption = "Average returns of Linear regression trading sys-
tem ($\\times 10^{-4}$)")
#LINEAR REGREESSION ENDS HERE

# PLOT ACTIONS GENERATED BY LINEAR REGRESSION
par(cex=0.7)
barplot(calc_posno(5),beside=FALSE,names=levels(interaction(n)), col = "steelblue3",
ylim=c(0,250))
par(cex=0.7, new=T)
plot(LINEAR.return.cc1,type = "l", axes =F, xlab = "", ylab="", col = "darkgreen", lwd =
3, ylim=c(-10,5))
lines(LINEAR.return.cc5, col = "darkorange", lwd= 3)
axis(4, cex=0.7)
legend("topright", "(x,y)", c("Number of actions", "Avg. returns c=0.0000", "Avg. returns
c=0.0100"), fill = c("steelblue3", "darkgreen", "darkorange"),cex = 1.2)
# PLOT ACTIONS GENERATED BY LINEAR REGRESSION

# RETURN TEST STATISTICS SMA
all.t.test.SMA <- t.calc(1)
z <- t.data(1)
y <- data.frame(z[[1]],z[[2]],z[[3]],z[[4]],z[[5]])
rownames(y) <- c("N=10", "N=20", "N=30", "N=40", "N=50", "N=60",
"N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
x <- data.frame(t(y))
colnames(y) <- c("t", "p", "t", "p", "t", "p", "t", "p", "t", "p")
xtable(y, digits = 4)
# RETURN TEST STATISTICS SMA

# RETURN TEST STATISTICS ESMOOTH
all.t.test.ESMOOTH <- t.calc(3)
p.t.ESMOOTH <- t.data(3)
p.t.table.ESMOOTH <- da-
ta.frame(p.t.ESMOOTH[[1]],p.t.ESMOOTH[[2]],p.t.ESMOOTH[[3]],p.t.ESMOOTH[[4]],p.
t.ESMOOTH[[5]])
rownames(p.t.table.ESMOOTH) <- c("a=0.05", "a=0.10", "a=0.15","a=0.20",
"a=0.25","a=0.30","a=0.35","a=0.40","a=0.45",
"a=0.50","a=0.55","a=0.60","a=0.65","a=0.70","a=0.75","a=0.80","a=0.85","a=0.90","a=0.
95","a=1.00")
colnames(p.t.table.ESMOOTH) <- c("t", "p", "t", "p", "t", "p", "t", "p", "t", "p")
xtable(p.t.table.ESMOOTH, digits = 4)
# RETURN TEST STATISTICS ESMOOTH

# RETURN TEST STATISTICS N-DAY BREAKOUT
all.t.test.BREAKOUT <- t.calc(4)
p.t.BREAKOUT <- t.data(4)
```

```
p.t.table.BREAKOUT <- da-
ta.frame(p.t.BREAKOUT[[1]],p.t.BREAKOUT[[2]],p.t.BREAKOUT[[3]],p.t.BREAKOUT[
[4]],p.t.BREAKOUT[[5]])
rownames(p.t.table.BREAKOUT) <- c("N=10", "N=20", "N=30", "N=40", "N=50",
"N=60", "N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
colnames(p.t.table.BREAKOUT) <- c("t", "p", "t", "p", "t", "p", "t", "p", "t", "p")
xtable(p.t.table.BREAKOUT, digits = 4)
# RETURN TEST STATISTICS N-DAY BREAKOUT

# RETURN TEST STATISTICS LINEAR REGRESSION SLOPE
all.t.test.LINEAR <- t.calc(5)
p.t.LINEAR <- t.data(5)
p.t.table.LINEAR <- da-
ta.frame(p.t.LINEAR[[1]],p.t.LINEAR[[2]],p.t.LINEAR[[3]],p.t.LINEAR[[4]],p.t.LINEAR[[
5]])
rownames(p.t.table.LINEAR) <- c("N=10", "N=20", "N=30", "N=40", "N=50", "N=60",
"N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
colnames(p.t.table.LINEAR) <- c("t", "p", "t", "p", "t", "p", "t", "p", "t", "p")
xtable(p.t.table.LINEAR, digits = 4)
# RETURN TEST STATISTICS LINEAR REGRESSION SLOPE

# RETURN ROBUST TEST STATISTICS SMA/N-DAY
ci.p.SMA <- a
ci.p.table.SMA <- da-
ta.frame(ci.p.SMA[[1]],ci.p.SMA[[2]],ci.p.SMA[[3]],ci.p.SMA[[4]],ci.p.SMA[[5]])
rownames(ci.p.table.SMA) <- c("N=10", "N=20", "N=30", "N=40", "N=50", "N=60",
"N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
colnames(ci.p.table.SMA) <- c("Lower", "Upper", "p", "Lower", "Upper", "p", "Lower",
"Upper", "p", "Lower", "Upper", "p", "Lower", "Upper", "p")
xtable(ci.p.table.SMA, digits = 4)
# RETURN ROBUST TEST STATISTICS SMA/N-DAY

# RETURN ROBUST TEST STATISTICS EXPONENTIAL SMOOTHING
ci.p.ESMOOTH <- ydbt.data(3)
ci.p.table.ESMOOTH <- da-
ta.frame(ci.p.ESMOOTH[[1]],ci.p.ESMOOTH[[2]],ci.p.ESMOOTH[[3]],ci.p.ESMOOTH[[4
]],ci.p.ESMOOTH[[5]])
rownames(ci.p.table.ESMOOTH) <- c("a=0.05", "a=0.10", "a=0.15","a=0.20",
"a=0.25","a=0.30","a=0.35","a=0.40","a=0.45",
"a=0.50","a=0.55","a=0.60","a=0.65","a=0.70","a=0.75","a=0.80","a=0.85","a=0.90","a=0.
95","a=1.00")
colnames(ci.p.table.ESMOOTH) <- c("Lower", "Upper", "p", "Lower", "Upper", "p",
"Lower", "Upper", "p", "Lower", "Upper", "p", "Lower", "Upper", "p")
xtable(ci.p.table.ESMOOTH, digits = 3)
# RETURN ROBUST TEST STATISTICS EXPONENTIAL SMOOTHING

# RETURN ROBUST TEST STATISTICS NBREAKOUT
ci.p.NBREAKOUT <- ydbt.data(4)
```

```
ci.p.table.NBREAKOUT <- da-
ta.frame(ci.p.NBREAKOUT[[1]],ci.p.NBREAKOUT[[2]],ci.p.NBREAKOUT[[3]],ci.p.NBR
EAKOUT[[4]],ci.p.NBREAKOUT[[5]])
rownames(ci.p.table.NBREAKOUT) <- c("N=10", "N=20", "N=30", "N=40", "N=50",
"N=60", "N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
colnames(ci.p.table.NBREAKOUT) <- c("Lower", "Upper", "p", "Lower", "Upper", "p",
"Lower", "Upper", "p", "Lower", "Upper", "p", "Lower", "Upper", "p")
xtable(ci.p.table.NBREAKOUT, digits = 3)
# RETURN ROBUST TEST STATISTICS NBREAKOUT

# RETURN ROBUST TEST STATISTICS LINEAR
ci.p.LINEAR <- ydbt.data(5)
ci.p.table.LINEAR <- da-
ta.frame(ci.p.LINEAR[[1]],ci.p.LINEAR[[2]],ci.p.LINEAR[[3]],ci.p.LINEAR[[4]],ci.p.LINE
AR[[5]])
rownames(ci.p.table.LINEAR) <- c("N=10", "N=20", "N=30", "N=40", "N=50", "N=60",
"N=70","N=80", "N=90","N=100","N=110",
"N=120","N=130","N=140","N=150","N=160","N=170","N=180","N=190","N=200")
colnames(ci.p.table.LINEAR) <- c("Lower", "Upper", "p", "Lower", "Upper", "p", "Low-
er", "Upper", "p", "Lower", "Upper", "p", "Lower", "Upper", "p")
xtable(ci.p.table.LINEAR, digits = 3)
# RETURN ROBUST TEST STATISTICS LINEAR
```

APPENDIX 2: FULL TEST RESULT (SOURCE: AUTHOR'S CALCULATION FROM THE DATASET)

APPENDIX 2.1: STUDENT T-TEST

APPENDIX 2. FULL TEST RESULTS

	c=0.0000						c=0.0025						c=0.0050					
	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif
N=10	9.82	2492.00	0.00	17.82	26.72	22.27	9.08	2492.00	0.00	16.23	25.17	20.70	8.32	2492.00	0.00	14.62	23.63	19.13
N=20	13.53	2492.00	0.00	26.20	35.08	30.64	12.33	2492.00	0.00	23.63	32.58	28.10	11.09	2492.00	0.00	21.05	30.09	25.57
N=30	15.93	2492.00	0.00	31.62	40.49	36.05	14.32	2492.00	0.00	28.27	37.24	32.76	12.67	2492.00	0.00	24.90	34.02	29.46
N=40	17.32	2492.00	0.00	34.60	43.44	39.02	15.57	2492.00	0.00	31.06	40.02	35.54	13.79	2492.00	0.00	27.50	36.62	32.06
N=50	19.28	2492.00	0.00	38.35	47.03	42.69	17.12	2492.00	0.00	34.09	42.91	38.50	14.94	2492.00	0.00	29.81	38.82	34.32
N=60	20.33	2492.00	0.00	40.20	48.78	44.49	17.89	2492.00	0.00	35.46	44.18	39.82	15.43	2492.00	0.00	30.68	39.62	35.15
N=70	21.53	2492.00	0.00	42.46	50.97	46.72	18.82	2492.00	0.00	37.25	45.91	41.58	16.08	2492.00	0.00	32.00	40.89	36.45
N=80	23.42	2492.00	0.00	45.46	53.77	49.61	20.30	2492.00	0.00	39.58	48.05	43.81	17.15	2492.00	0.00	33.67	42.36	38.02
N=90	24.52	2492.00	0.00	47.26	55.48	51.37	21.19	2492.00	0.00	41.03	49.40	45.21	17.80	2492.00	0.00	34.75	43.35	39.05
N=100	25.46	2492.00	0.00	48.81	56.96	52.88	21.96	2492.00	0.00	42.29	50.59	46.44	18.40	2492.00	0.00	35.73	44.25	39.99
N=110	26.32	2492.00	0.00	50.24	58.33	54.28	22.65	2492.00	0.00	43.40	51.63	47.51	18.90	2492.00	0.00	36.52	44.97	40.74
N=120	27.18	2492.00	0.00	51.58	59.60	55.59	23.23	2492.00	0.00	44.26	52.42	48.34	19.19	2492.00	0.00	36.88	45.28	41.08
N=130	27.68	2492.00	0.00	52.40	60.39	56.40	23.57	2492.00	0.00	44.79	52.92	48.86	19.37	2492.00	0.00	37.14	45.50	41.32
N=140	28.15	2492.00	0.00	53.12	61.08	57.10	23.92	2492.00	0.00	45.29	53.38	49.34	19.60	2492.00	0.00	37.41	45.73	41.57
N=150	28.46	2492.00	0.00	53.63	61.57	57.60	24.03	2492.00	0.00	45.44	53.51	49.48	19.50	2492.00	0.00	37.19	45.51	41.35
N=160	29.01	2492.00	0.00	54.45	62.34	58.39	24.38	2492.00	0.00	45.83	53.85	49.84	19.64	2492.00	0.00	37.17	45.41	41.29
N=170	29.24	2492.00	0.00	54.80	62.68	58.74	24.42	2492.00	0.00	45.83	53.83	49.83	19.48	2492.00	0.00	36.80	45.03	40.91
N=180	29.40	2492.00	0.00	55.05	62.91	58.98	24.42	2492.00	0.00	45.73	53.71	49.72	19.32	2492.00	0.00	36.36	44.57	40.46
N=190	29.52	2492.00	0.00	55.23	63.08	59.16	24.35	2492.00	0.00	45.51	53.48	49.49	19.05	2492.00	0.00	35.73	43.93	39.83
N=200	29.55	2492.00	0.00	55.27	63.13	59.20	24.17	2492.00	0.00	45.15	53.12	49.14	18.69	2492.00	0.00	34.97	43.17	39.07

Table 1: Full result of student t-test: SMA/N-day momentum

	c=0.0075						c=0.0100					
	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif
N=10	7.555	2492.000	0.000	12.998	22.111	17.554	6.788	2492.000	0.000	11.365	20.599	15.982
N=20	9.839	2492.000	0.000	18.441	27.621	23.031	8.593	2492.000	0.000	15.818	25.172	20.495
N=30	11.018	2492.000	0.000	21.503	30.814	26.159	9.393	2492.000	0.000	18.088	27.633	22.860
N=40	12.009	2492.000	0.000	23.912	33.245	28.578	10.265	2492.000	0.000	20.302	29.890	25.096
N=50	12.764	2492.000	0.000	25.502	34.759	30.130	10.650	2492.000	0.000	21.166	30.720	25.943
N=60	12.995	2492.000	0.000	25.881	35.080	30.481	10.634	2492.000	0.000	21.052	30.571	25.812
N=70	13.384	2492.000	0.000	26.725	35.900	31.313	10.784	2492.000	0.000	21.418	30.938	26.178
N=80	14.046	2492.000	0.000	27.718	36.714	32.216	11.068	2492.000	0.000	21.737	31.098	26.417
N=90	14.472	2492.000	0.000	28.429	37.341	32.885	11.283	2492.000	0.000	22.078	31.366	26.723
N=100	14.893	2492.000	0.000	29.129	37.962	33.546	11.536	2492.000	0.000	22.493	31.706	27.099
N=110	15.204	2492.000	0.000	29.590	38.353	33.972	11.664	2492.000	0.000	22.628	31.774	27.201
N=120	15.226	2492.000	0.000	29.470	38.183	33.827	11.441	2492.000	0.000	22.018	31.126	26.572
N=130	15.248	2492.000	0.000	29.436	38.124	33.780	11.321	2492.000	0.000	21.695	30.785	26.241
N=140	15.348	2492.000	0.000	29.492	38.132	33.812	11.299	2492.000	0.000	21.529	30.571	26.050
N=150	15.070	2492.000	0.000	28.901	37.547	33.224	10.865	2492.000	0.000	20.569	29.628	25.098
N=160	14.980	2492.000	0.000	28.454	37.025	32.740	10.561	2492.000	0.000	19.698	28.680	24.189
N=170	14.650	2492.000	0.000	27.716	36.282	31.999	10.077	2492.000	0.000	18.592	27.576	23.084
N=180	14.329	2492.000	0.000	26.936	35.478	31.207	9.608	2492.000	0.000	17.470	26.429	21.950
N=190	13.875	2492.000	0.000	25.906	34.434	30.170	8.989	2492.000	0.000	16.035	24.983	20.509
N=200	13.332	2492.000	0.000	24.738	33.270	29.004	8.292	2492.000	0.000	14.460	23.416	18.938

Table 2: Full result of student t-test: SMA/N-day momentum (continue)

	c=0.0000						c=0.0025						c=0.0050					
	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif
N=10	9.820	2492.000	0.000	17.823	26.717	22.270	9.077	2492.000	0.000	16.227	25.169	20.698	8.320	2492.000	0.000	14.618	23.634	19.126
N=20	13.534	2492.000	0.000	26.202	35.080	30.641	12.327	2492.000	0.000	23.634	32.575	28.104	11.090	2492.000	0.000	21.047	30.089	25.568
N=30	15.934	2492.000	0.000	31.617	40.492	36.054	14.317	2492.000	0.000	28.270	37.242	32.756	12.668	2492.000	0.000	24.898	34.017	29.457
N=40	17.315	2492.000	0.000	34.605	43.444	39.024	15.566	2492.000	0.000	31.065	40.020	35.542	13.786	2492.000	0.000	27.500	36.620	32.060
N=50	19.277	2492.000	0.000	38.349	47.034	42.691	17.122	2492.000	0.000	34.094	42.914	38.504	14.936	2492.000	0.000	29.812	38.823	34.317
N=60	20.325	2492.000	0.000	40.196	48.780	44.488	17.894	2492.000	0.000	35.455	44.182	39.819	15.431	2492.000	0.000	30.683	39.617	35.150
N=70	21.530	2492.000	0.000	42.461	50.971	46.716	18.821	2492.000	0.000	37.249	45.914	41.581	16.082	2492.000	0.000	32.003	40.891	36.447
N=80	23.416	2492.000	0.000	45.459	53.768	49.613	20.304	2492.000	0.000	39.583	48.046	43.814	17.149	2492.000	0.000	33.668	42.362	38.015
N=90	24.521	2492.000	0.000	47.265	55.481	51.373	21.186	2492.000	0.000	41.026	49.395	45.210	17.800	2492.000	0.000	34.746	43.349	39.048
N=100	25.459	2492.000	0.000	48.812	56.958	52.885	21.961	2492.000	0.000	42.292	50.585	46.438	18.400	2492.000	0.000	35.730	44.254	39.992
N=110	26.321	2492.000	0.000	50.239	58.327	54.283	22.650	2492.000	0.000	43.399	51.626	47.513	18.900	2492.000	0.000	36.515	44.969	40.742
N=120	27.176	2492.000	0.000	51.581	59.604	55.592	23.227	2492.000	0.000	44.256	52.418	48.337	19.193	2492.000	0.000	36.885	45.279	41.082
N=130	27.682	2492.000	0.000	52.403	60.393	56.398	23.570	2492.000	0.000	44.794	52.923	48.858	19.373	2492.000	0.000	37.137	45.501	41.319
N=140	28.148	2492.000	0.000	53.121	61.076	57.099	23.923	2492.000	0.000	45.292	53.380	49.336	19.600	2492.000	0.000	37.415	45.733	41.574
N=150	28.458	2492.000	0.000	53.632	61.570	57.601	24.025	2492.000	0.000	45.437	53.514	49.475	19.503	2492.000	0.000	37.192	45.507	41.350
N=160	29.012	2492.000	0.000	54.446	62.339	58.393	24.381	2492.000	0.000	45.833	53.850	49.842	19.638	2492.000	0.000	37.168	45.414	41.291
N=170	29.240	2492.000	0.000	54.803	62.682	58.743	24.416	2492.000	0.000	45.826	53.830	49.828	19.483	2492.000	0.000	36.796	45.031	40.913
N=180	29.402	2492.000	0.000	55.045	62.912	58.979	24.420	2492.000	0.000	45.729	53.714	49.722	19.322	2492.000	0.000	36.358	44.571	40.464
N=190	29.522	2492.000	0.000	55.226	63.084	59.155	24.345	2492.000	0.000	45.507	53.480	49.494	19.053	2492.000	0.000	35.732	43.931	39.832
N=200	29.553	2492.000	0.000	55.273	63.130	59.202	24.174	2492.000	0.000	45.150	53.121	49.136	18.687	2492.000	0.000	34.970	43.169	39.070

Table 3: Full result of student t-test: Exponential Smoothing

	c=0.0075						c=0.0100					
N=10	7.555	2492.000	0.000	12.998	22.111	17.554	6.788	2492.000	0.000	11.365	20.599	15.982
N=20	9.839	2492.000	0.000	18.441	27.621	23.031	8.593	2492.000	0.000	15.818	25.172	20.495
N=30	11.018	2492.000	0.000	21.503	30.814	26.159	9.393	2492.000	0.000	18.088	27.633	22.860
N=40	12.009	2492.000	0.000	23.912	33.245	28.578	10.265	2492.000	0.000	20.302	29.890	25.096
N=50	12.764	2492.000	0.000	25.502	34.759	30.130	10.650	2492.000	0.000	21.166	30.720	25.943
N=60	12.995	2492.000	0.000	25.881	35.080	30.481	10.634	2492.000	0.000	21.052	30.571	25.812
N=70	13.384	2492.000	0.000	26.725	35.900	31.313	10.784	2492.000	0.000	21.418	30.938	26.178
N=80	14.046	2492.000	0.000	27.718	36.714	32.216	11.068	2492.000	0.000	21.737	31.098	26.417
N=90	14.472	2492.000	0.000	28.429	37.341	32.885	11.283	2492.000	0.000	22.078	31.366	26.723
N=100	14.893	2492.000	0.000	29.129	37.962	33.546	11.536	2492.000	0.000	22.493	31.706	27.099
N=110	15.204	2492.000	0.000	29.590	38.353	33.972	11.664	2492.000	0.000	22.628	31.774	27.201
N=120	15.226	2492.000	0.000	29.470	38.183	33.827	11.441	2492.000	0.000	22.018	31.126	26.572
N=130	15.248	2492.000	0.000	29.436	38.124	33.780	11.321	2492.000	0.000	21.695	30.785	26.241
N=140	15.348	2492.000	0.000	29.492	38.132	33.812	11.299	2492.000	0.000	21.529	30.571	26.050
N=150	15.070	2492.000	0.000	28.901	37.547	33.224	10.865	2492.000	0.000	20.569	29.628	25.098
N=160	14.980	2492.000	0.000	28.454	37.025	32.740	10.561	2492.000	0.000	19.698	28.680	24.189
N=170	14.650	2492.000	0.000	27.716	36.282	31.999	10.077	2492.000	0.000	18.592	27.576	23.084
N=180	14.329	2492.000	0.000	26.936	35.478	31.207	9.608	2492.000	0.000	17.470	26.429	21.950
N=190	13.875	2492.000	0.000	25.906	34.434	30.170	8.989	2492.000	0.000	16.035	24.983	20.509
N=200	13.332	2492.000	0.000	24.738	33.270	29.004	8.292	2492.000	0.000	14.460	23.416	18.938

Table 4: Full result of student t-test: Exponential Smoothing (continue)

	c=0.0000						c=0.0025						c=0.0050					
	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif
N=10	9.820	2492.000	0.000	17.823	26.717	22.270	9.077	2492.000	0.000	16.227	25.169	20.698	8.320	2492.000	0.000	14.618	23.634	19.126
N=20	13.534	2492.000	0.000	26.202	35.080	30.641	12.327	2492.000	0.000	23.634	32.575	28.104	11.090	2492.000	0.000	21.047	30.089	25.568
N=30	15.934	2492.000	0.000	31.617	40.492	36.054	14.317	2492.000	0.000	28.270	37.242	32.756	12.668	2492.000	0.000	24.898	34.017	29.457
N=40	17.315	2492.000	0.000	34.605	43.444	39.024	15.566	2492.000	0.000	31.065	40.020	35.542	13.786	2492.000	0.000	27.500	36.620	32.060
N=50	19.277	2492.000	0.000	38.349	47.034	42.691	17.122	2492.000	0.000	34.094	42.914	38.504	14.936	2492.000	0.000	29.812	38.823	34.317
N=60	20.325	2492.000	0.000	40.196	48.780	44.488	17.894	2492.000	0.000	35.455	44.182	39.819	15.431	2492.000	0.000	30.683	39.617	35.150
N=70	21.530	2492.000	0.000	42.461	50.971	46.716	18.821	2492.000	0.000	37.249	45.914	41.581	16.082	2492.000	0.000	32.003	40.891	36.447
N=80	23.416	2492.000	0.000	45.459	53.768	49.613	20.304	2492.000	0.000	39.583	48.046	43.814	17.149	2492.000	0.000	33.668	42.362	38.015
N=90	24.521	2492.000	0.000	47.265	55.481	51.373	21.186	2492.000	0.000	41.026	49.395	45.210	17.800	2492.000	0.000	34.746	43.349	39.048
N=100	25.459	2492.000	0.000	48.812	56.958	52.885	21.961	2492.000	0.000	42.292	50.585	46.438	18.400	2492.000	0.000	35.730	44.254	39.992
N=110	26.321	2492.000	0.000	50.239	58.327	54.283	22.650	2492.000	0.000	43.399	51.626	47.513	18.900	2492.000	0.000	36.515	44.969	40.742
N=120	27.176	2492.000	0.000	51.581	59.604	55.592	23.227	2492.000	0.000	44.256	52.418	48.337	19.193	2492.000	0.000	36.885	45.279	41.082
N=130	27.682	2492.000	0.000	52.403	60.393	56.398	23.570	2492.000	0.000	44.794	52.923	48.858	19.373	2492.000	0.000	37.137	45.501	41.319
N=140	28.148	2492.000	0.000	53.121	61.076	57.099	23.923	2492.000	0.000	45.292	53.380	49.336	19.600	2492.000	0.000	37.415	45.733	41.574
N=150	28.458	2492.000	0.000	53.632	61.570	57.601	24.025	2492.000	0.000	45.437	53.514	49.475	19.503	2492.000	0.000	37.192	45.507	41.350
N=160	29.012	2492.000	0.000	54.446	62.339	58.393	24.381	2492.000	0.000	45.833	53.850	49.842	19.638	2492.000	0.000	37.168	45.414	41.291
N=170	29.240	2492.000	0.000	54.803	62.682	58.743	24.416	2492.000	0.000	45.826	53.830	49.828	19.483	2492.000	0.000	36.796	45.031	40.913
N=180	29.402	2492.000	0.000	55.045	62.912	58.979	24.420	2492.000	0.000	45.729	53.714	49.722	19.322	2492.000	0.000	36.358	44.571	40.464
N=190	29.522	2492.000	0.000	55.226	63.084	59.155	24.345	2492.000	0.000	45.507	53.480	49.494	19.053	2492.000	0.000	35.732	43.931	39.832
N=200	29.553	2492.000	0.000	55.273	63.130	59.202	24.174	2492.000	0.000	45.150	53.121	49.136	18.687	2492.000	0.000	34.970	43.169	39.070

Table 5: Full result of student t-test: N-day Breakout

	c=0.0075						c=0.0100					
N=10	7.555	2492.000	0.000	12.998	22.111	17.554	6.788	2492.000	0.000	11.365	20.599	15.982
N=20	9.839	2492.000	0.000	18.441	27.621	23.031	8.593	2492.000	0.000	15.818	25.172	20.495
N=30	11.018	2492.000	0.000	21.503	30.814	26.159	9.393	2492.000	0.000	18.088	27.633	22.860
N=40	12.009	2492.000	0.000	23.912	33.245	28.578	10.265	2492.000	0.000	20.302	29.890	25.096
N=50	12.764	2492.000	0.000	25.502	34.759	30.130	10.650	2492.000	0.000	21.166	30.720	25.943
N=60	12.995	2492.000	0.000	25.881	35.080	30.481	10.634	2492.000	0.000	21.052	30.571	25.812
N=70	13.384	2492.000	0.000	26.725	35.900	31.313	10.784	2492.000	0.000	21.418	30.938	26.178
N=80	14.046	2492.000	0.000	27.718	36.714	32.216	11.068	2492.000	0.000	21.737	31.098	26.417
N=90	14.472	2492.000	0.000	28.429	37.341	32.885	11.283	2492.000	0.000	22.078	31.366	26.723
N=100	14.893	2492.000	0.000	29.129	37.962	33.546	11.536	2492.000	0.000	22.493	31.706	27.099
N=110	15.204	2492.000	0.000	29.590	38.353	33.972	11.664	2492.000	0.000	22.628	31.774	27.201
N=120	15.226	2492.000	0.000	29.470	38.183	33.827	11.441	2492.000	0.000	22.018	31.126	26.572
N=130	15.248	2492.000	0.000	29.436	38.124	33.780	11.321	2492.000	0.000	21.695	30.785	26.241
N=140	15.348	2492.000	0.000	29.492	38.132	33.812	11.299	2492.000	0.000	21.529	30.571	26.050
N=150	15.070	2492.000	0.000	28.901	37.547	33.224	10.865	2492.000	0.000	20.569	29.628	25.098
N=160	14.980	2492.000	0.000	28.454	37.025	32.740	10.561	2492.000	0.000	19.698	28.680	24.189
N=170	14.650	2492.000	0.000	27.716	36.282	31.999	10.077	2492.000	0.000	18.592	27.576	23.084
N=180	14.329	2492.000	0.000	26.936	35.478	31.207	9.608	2492.000	0.000	17.470	26.429	21.950
N=190	13.875	2492.000	0.000	25.906	34.434	30.170	8.989	2492.000	0.000	16.035	24.983	20.509
N=200	13.332	2492.000	0.000	24.738	33.270	29.004	8.292	2492.000	0.000	14.460	23.416	18.938

Table 6: Full result of student t-test: N-day Breakout (continue)

	c=0.0000						c=0.0025						c=0.0050					
	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif	t	df	Lower	Upper	p	dif
N=10	0.810	2492.000	0.418	-2.672	6.431	1.879	-0.084	2492.000	0.933	-4.752	4.362	-0.195	-0.972	2492.000	0.331	-6.849	2.309	-2.270
N=20	1.502	2492.000	0.133	-1.084	8.180	3.548	1.079	2492.000	0.281	-2.086	7.193	2.554	0.657	2492.000	0.511	-3.096	6.214	1.559
N=30	0.177	2492.000	0.859	-4.246	5.092	0.423	-0.112	2492.000	0.910	-4.940	4.404	-0.268	-0.402	2492.000	0.688	-5.639	3.721	-0.959
N=40	0.344	2492.000	0.731	-3.730	5.319	0.794	0.114	2492.000	0.909	-4.264	4.788	0.262	-0.117	2492.000	0.907	-4.802	4.263	-0.270
N=50	0.923	2492.000	0.356	-2.335	6.490	2.078	0.732	2492.000	0.465	-2.769	6.064	1.647	0.539	2492.000	0.590	-3.207	5.641	1.217
N=60	1.070	2492.000	0.285	-1.964	6.682	2.359	0.911	2492.000	0.362	-2.317	6.335	2.009	0.751	2492.000	0.453	-2.672	5.990	1.659
N=70	0.456	2492.000	0.648	-3.193	5.129	0.968	0.309	2492.000	0.757	-3.506	4.819	0.656	0.162	2492.000	0.871	-3.822	4.511	0.344
N=80	1.751	2492.000	0.080	-0.439	7.751	3.656	1.626	2492.000	0.104	-0.700	7.492	3.396	1.500	2492.000	0.134	-0.963	7.234	3.136
N=90	1.984	2492.000	0.047	0.048	8.181	4.115	1.860	2492.000	0.063	-0.210	7.920	3.855	1.734	2492.000	0.083	-0.471	7.662	3.596
N=100	2.396	2492.000	0.017	0.915	9.170	5.042	2.290	2492.000	0.022	0.693	8.952	4.822	2.183	2492.000	0.029	0.468	8.736	4.602
N=110	2.767	2492.000	0.006	1.725	10.113	5.919	2.680	2492.000	0.007	1.540	9.936	5.738	2.592	2492.000	0.010	1.354	9.761	5.558
N=120	2.648	2492.000	0.008	1.489	9.987	5.738	2.567	2492.000	0.010	1.312	9.805	5.558	2.484	2492.000	0.013	1.133	9.624	5.379
N=130	2.035	2492.000	0.042	0.166	8.950	4.558	1.963	2492.000	0.050	0.004	8.791	4.398	1.890	2492.000	0.059	-0.160	8.634	4.237
N=140	1.852	2492.000	0.064	-0.243	8.548	4.152	1.772	2492.000	0.077	-0.424	8.368	3.972	1.691	2492.000	0.091	-0.606	8.190	3.792
N=150	1.651	2492.000	0.099	-0.688	8.027	3.670	1.578	2492.000	0.115	-0.851	7.868	3.509	1.505	2492.000	0.133	-1.015	7.710	3.347
N=160	1.568	2492.000	0.117	-0.867	7.785	3.459	1.494	2492.000	0.135	-1.032	7.628	3.298	1.419	2492.000	0.156	-1.197	7.472	3.138
N=170	1.501	2492.000	0.134	-1.015	7.634	3.310	1.437	2492.000	0.151	-1.155	7.493	3.169	1.373	2492.000	0.170	-1.296	7.353	3.029
N=180	1.661	2492.000	0.097	-0.653	7.888	3.617	1.597	2492.000	0.110	-0.794	7.748	3.477	1.532	2492.000	0.126	-0.935	7.609	3.337
N=190	1.577	2492.000	0.115	-0.831	7.661	3.415	1.530	2492.000	0.126	-0.932	7.561	3.314	1.484	2492.000	0.138	-1.034	7.462	3.214
N=200	1.561	2492.000	0.119	-0.858	7.560	3.351	1.515	2492.000	0.130	-0.957	7.458	3.251	1.468	2492.000	0.142	-1.057	7.356	3.150

Table 7: Full result of student t-test: Linear Regression

	c=0.0075						c=0.0100					
N=10	-1.845	2492.000	0.065	-8.961	0.273	-4.344	-2.695	2492.000	0.007	-11.088	-1.748	-6.418
N=20	0.237	2492.000	0.813	-4.114	5.244	0.565	-0.179	2492.000	0.858	-5.139	4.280	-0.429
N=30	-0.689	2492.000	0.491	-6.344	3.044	-1.650	-0.974	2492.000	0.330	-7.054	2.373	-2.340
N=40	-0.346	2492.000	0.729	-5.345	3.741	-0.802	-0.574	2492.000	0.566	-5.892	3.224	-1.334
N=50	0.348	2492.000	0.728	-3.649	5.222	0.787	0.157	2492.000	0.875	-4.094	4.807	0.356
N=60	0.592	2492.000	0.554	-3.031	5.649	1.309	0.432	2492.000	0.666	-3.393	5.311	0.959
N=70	0.015	2492.000	0.988	-4.141	4.205	0.032	-0.131	2492.000	0.896	-4.463	3.903	-0.280
N=80	1.374	2492.000	0.170	-1.228	6.980	2.876	1.247	2492.000	0.212	-1.496	6.728	2.616
N=90	1.607	2492.000	0.108	-0.734	7.406	3.336	1.480	2492.000	0.139	-1.000	7.152	3.076
N=100	2.075	2492.000	0.038	0.241	8.522	4.382	1.967	2492.000	0.049	0.013	8.310	4.162
N=110	2.504	2492.000	0.012	1.166	9.588	5.377	2.415	2492.000	0.016	0.976	9.416	5.196
N=120	2.401	2492.000	0.016	0.953	9.445	5.199	2.317	2492.000	0.021	0.771	9.267	5.019
N=130	1.816	2492.000	0.069	-0.325	8.479	4.077	1.743	2492.000	0.082	-0.491	8.324	3.917
N=140	1.609	2492.000	0.108	-0.790	8.013	3.611	1.527	2492.000	0.127	-0.976	7.837	3.431
N=150	1.431	2492.000	0.153	-1.181	7.553	3.186	1.356	2492.000	0.175	-1.348	7.398	3.025
N=160	1.345	2492.000	0.179	-1.365	7.318	2.977	1.270	2492.000	0.204	-1.533	7.165	2.816
N=170	1.309	2492.000	0.191	-1.438	7.214	2.888	1.245	2492.000	0.213	-1.581	7.077	2.748
N=180	1.466	2492.000	0.143	-1.079	7.471	3.196	1.401	2492.000	0.162	-1.223	7.334	3.056
N=190	1.437	2492.000	0.151	-1.136	7.363	3.114	1.389	2492.000	0.165	-1.240	7.266	3.013
N=200	1.421	2492.000	0.155	-1.158	7.256	3.049	1.374	2492.000	0.170	-1.260	7.157	2.949

Table 8: Full result of student t-test: Linear Regression (Continue)

APPENDIX 2.2: BOOTSTRAP-T METHOD FOR MARGINAL TRIMMED MEANS

	c=0.0000				c=0.0025				c=0.0050				c=0.0075				c=0.0100			
	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif
N=10	2.948	11.979	0.000	7.464	2.264	11.199	0.000	6.731	1.876	10.798	0.002	6.337	1.517	10.562	0.005	6.039	1.300	10.406	0.008	5.853
N=20	1.949	10.897	0.003	6.423	1.119	9.899	0.018	5.509	0.886	9.617	0.022	5.252	0.731	9.469	0.023	5.100	0.585	9.332	0.027	4.959
N=30	1.174	10.132	0.017	5.653	0.427	9.252	0.035	4.840	0.196	9.132	0.040	4.664	0.052	8.985	0.050	4.519	-0.092	8.894	0.057	4.401
N=40	0.498	9.435	0.032	4.966	-0.399	8.442	0.077	4.022	-0.610	8.274	0.097	3.832	-0.790	8.160	0.100	3.685	-0.949	8.062	0.117	3.557
N=50	-0.051	8.961	0.052	4.455	-0.839	8.150	0.118	3.656	-1.095	8.016	0.137	3.461	-1.239	7.882	0.147	3.322	-1.279	7.755	0.159	3.238
N=60	-0.418	8.609	0.078	4.095	-1.031	7.870	0.145	3.419	-1.021	7.654	0.164	3.316	-1.183	7.526	0.174	3.171	-1.342	7.426	0.185	3.042
N=70	-0.847	8.528	0.114	3.840	-1.205	7.948	0.152	3.371	-1.296	7.875	0.164	3.289	-1.423	7.779	0.184	3.178	-1.507	7.658	0.189	3.075
N=80	-1.245	8.091	0.162	3.423	-1.739	7.629	0.204	2.945	-1.849	7.545	0.215	2.848	-1.926	7.460	0.229	2.767	-1.999	7.339	0.245	2.670
N=90	-1.582	7.775	0.197	3.097	-1.973	7.264	0.245	2.646	-2.074	7.188	0.267	2.557	-2.123	7.060	0.284	2.469	-2.175	6.988	0.295	2.407
N=100	-0.750	8.355	0.115	3.803	-1.000	7.944	0.139	3.472	-1.065	7.896	0.144	3.416	-1.159	7.899	0.149	3.370	-1.185	7.838	0.155	3.326
N=110	-0.973	8.221	0.132	3.624	-1.154	7.804	0.149	3.325	-1.185	7.739	0.152	3.277	-1.238	7.679	0.155	3.221	-1.287	7.647	0.162	3.180
N=120	-1.496	7.921	0.189	3.213	-1.704	7.562	0.212	2.929	-1.764	7.515	0.217	2.875	-1.766	7.448	0.219	2.841	-1.777	7.439	0.220	2.831
N=130	-1.807	7.776	0.215	2.984	-1.958	7.602	0.227	2.822	-1.964	7.602	0.227	2.819	-2.001	7.585	0.229	2.792	-2.027	7.512	0.235	2.742
N=140	-2.113	7.418	0.271	2.653	-2.223	7.282	0.292	2.529	-2.242	7.289	0.299	2.523	-2.296	7.265	0.300	2.485	-2.298	7.222	0.300	2.462
N=150	-2.103	7.619	0.252	2.758	-2.239	7.435	0.276	2.598	-2.319	7.369	0.287	2.525	-2.324	7.332	0.287	2.504	-2.383	7.331	0.292	2.474
N=160	-2.337	7.456	0.294	2.559	-2.382	7.428	0.295	2.523	-2.400	7.428	0.299	2.514	-2.412	7.410	0.307	2.499	-2.418	7.417	0.307	2.499
N=170	-2.453	7.420	0.307	2.484	-2.482	7.380	0.314	2.449	-2.482	7.373	0.316	2.446	-2.482	7.373	0.316	2.446	-2.484	7.359	0.316	2.437
N=180	-2.777	7.231	0.366	2.227	-2.777	7.086	0.377	2.155	-2.790	7.081	0.377	2.146	-2.822	7.067	0.379	2.122	-2.854	7.033	0.387	2.090
N=190	-2.670	7.280	0.349	2.305	-2.696	7.180	0.361	2.242	-2.697	7.153	0.357	2.228	-2.702	7.159	0.356	2.228	-2.728	7.159	0.357	2.215
N=200	-2.805	7.257	0.364	2.226	-2.794	7.122	0.371	2.163	-2.822	7.099	0.377	2.139	-2.821	7.077	0.379	2.128	-2.847	7.089	0.386	2.121

Table 9: Full test result for dependent bootstrap-t test: SMA/N-day momentum

	c=0.0000				c=0.0025				c=0.0050				c=0.0075				c=0.0100			
	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif
N=10	2.175	11.055	0.003	6.615	1.832	10.758	0.003	6.295	1.706	10.546	0.003	6.126	1.550	10.440	0.007	5.995	1.545	10.214	0.010	5.880
N=20	4.741	12.929	0.000	8.835	4.117	12.537	0.000	8.327	3.743	12.114	0.000	7.929	3.393	11.832	0.000	7.612	3.118	11.572	0.000	7.345
N=30	6.211	14.271	0.000	10.241	5.370	13.587	0.000	9.479	4.786	13.068	0.000	8.927	4.373	12.712	0.000	8.542	4.023	12.459	0.000	8.241
N=40	7.095	14.888	0.000	10.991	6.223	14.068	0.000	10.146	5.481	13.570	0.000	9.526	5.012	13.198	0.000	9.105	4.620	12.897	0.000	8.759
N=50	8.482	16.183	0.000	12.332	7.319	15.158	0.000	11.239	6.434	14.375	0.000	10.404	5.654	13.815	0.000	9.735	5.001	13.329	0.000	9.165
N=60	9.457	17.095	0.000	13.276	8.012	15.829	0.000	11.920	6.860	14.758	0.000	10.809	5.821	13.985	0.000	9.903	4.958	13.303	0.000	9.130
N=70	10.410	17.970	0.000	14.190	8.762	16.369	0.000	12.565	7.220	15.079	0.000	11.149	5.788	14.121	0.000	9.955	4.579	13.243	0.000	8.911
N=80	12.086	19.294	0.000	15.690	9.955	17.410	0.000	13.682	7.956	15.847	0.000	11.902	6.153	14.271	0.000	10.212	4.330	12.941	0.000	8.635
N=90	13.189	20.199	0.000	16.694	10.722	17.930	0.000	14.326	8.382	16.003	0.000	12.192	6.125	14.210	0.000	10.167	3.903	12.508	0.000	8.206
N=100	14.238	20.960	0.000	17.599	11.437	18.613	0.000	15.025	8.915	16.373	0.000	12.644	6.399	14.304	0.000	10.352	3.908	12.327	0.000	8.117
N=110	15.190	21.756	0.000	18.473	12.191	19.113	0.000	15.652	9.458	16.586	0.000	13.022	6.532	14.363	0.000	10.447	3.652	12.117	0.000	7.885
N=120	15.990	22.368	0.000	19.179	12.605	19.314	0.000	15.959	9.385	16.434	0.000	12.910	5.821	13.871	0.000	9.846	2.330	11.103	0.003	6.716
N=130	16.464	22.937	0.000	19.700	12.947	19.587	0.000	16.267	9.477	16.441	0.000	12.959	5.735	13.462	0.000	9.598	1.716	10.572	0.007	6.144
N=140	17.156	23.363	0.000	20.260	13.312	19.972	0.000	16.642	9.716	16.569	0.000	13.142	5.686	13.430	0.000	9.558	1.520	10.214	0.010	5.867
N=150	17.481	23.722	0.000	20.602	13.384	19.951	0.000	16.668	9.257	16.340	0.000	12.798	4.953	12.665	0.000	8.809	0.256	9.070	0.037	4.663
N=160	18.258	24.309	0.000	21.284	13.824	20.323	0.000	17.074	9.361	16.338	0.000	12.850	4.503	12.332	0.000	8.418	-0.696	8.203	0.100	3.754
N=170	18.543	24.571	0.000	21.557	13.818	20.237	0.000	17.027	8.946	15.885	0.000	12.416	3.633	11.378	0.000	7.506	-2.027	6.729	0.317	2.351
N=180	18.809	24.825	0.000	21.817	13.696	20.146	0.000	16.921	8.320	15.335	0.000	11.828	2.498	10.337	0.000	6.418	-3.606	5.102	0.723	0.748
N=190	18.958	24.992	0.000	21.975	13.522	19.860	0.000	16.691	7.413	14.798	0.000	11.105	1.157	9.201	0.008	5.179	-5.534	3.406	0.643	-1.064
N=200	18.974	25.059	0.000	22.017	13.071	19.527	0.000	16.299	6.588	13.883	0.000	10.235	-0.217	7.860	0.060	3.822	-7.371	1.508	0.214	-2.932

Table 10: Full test result for dependent bootstrap-t test: Esponential Smoothing

	c=0.0000				c=0.0025				c=0.0050				c=0.0075				c=0.0100			
	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif
N=10	0.560	9.683	0.028	5.122	0.458	9.541	0.033	5.000	0.417	9.509	0.037	4.963	0.416	9.502	0.037	4.959	0.416	9.502	0.037	4.959
N=20	-0.476	8.782	0.087	4.152	-0.693	8.548	0.100	3.927	-0.735	8.539	0.100	3.902	-0.756	8.521	0.102	3.882	-0.779	8.499	0.103	3.860
N=30	-0.235	8.853	0.063	4.309	-0.506	8.481	0.085	3.988	-0.511	8.440	0.085	3.964	-0.506	8.416	0.085	3.955	-0.506	8.416	0.085	3.955
N=40	-1.557	7.764	0.202	3.104	-1.707	7.465	0.229	2.879	-1.731	7.418	0.230	2.844	-1.731	7.409	0.230	2.839	-1.731	7.409	0.230	2.839
N=50	-1.806	7.382	0.244	2.788	-1.966	7.212	0.271	2.623	-2.029	7.205	0.276	2.588	-2.046	7.181	0.277	2.568	-2.046	7.161	0.279	2.558
N=60	-2.407	7.270	0.312	2.432	-2.490	7.180	0.324	2.345	-2.542	7.184	0.329	2.321	-2.560	7.163	0.331	2.301	-2.569	7.160	0.332	2.295
N=70	-1.380	7.449	0.189	3.034	-1.597	7.281	0.209	2.842	-1.663	7.267	0.214	2.802	-1.677	7.208	0.217	2.765	-1.689	7.189	0.222	2.750
N=80	-2.168	7.043	0.284	2.437	-2.298	6.815	0.322	2.259	-2.338	6.787	0.329	2.224	-2.346	6.719	0.341	2.187	-2.347	6.689	0.344	2.171
N=90	-1.878	7.136	0.235	2.629	-2.067	6.966	0.265	2.449	-2.033	6.874	0.269	2.420	-2.067	6.856	0.272	2.394	-2.087	6.842	0.272	2.377
N=100	-2.422	7.079	0.305	2.329	-2.503	6.883	0.332	2.190	-2.519	6.865	0.344	2.173	-2.537	6.844	0.347	2.153	-2.547	6.827	0.349	2.140
N=110	-1.984	6.907	0.264	2.462	-2.175	6.773	0.290	2.299	-2.187	6.723	0.290	2.268	-2.231	6.714	0.295	2.241	-2.233	6.682	0.299	2.224
N=120	-2.349	7.028	0.310	2.339	-2.415	6.883	0.327	2.234	-2.418	6.886	0.327	2.234	-2.449	6.888	0.327	2.220	-2.458	6.870	0.329	2.206
N=130	-2.433	7.093	0.317	2.330	-2.456	6.938	0.324	2.241	-2.456	6.938	0.322	2.241	-2.486	6.931	0.336	2.222	-2.503	6.888	0.344	2.193
N=140	-2.604	7.046	0.351	2.221	-2.655	6.976	0.361	2.161	-2.655	6.976	0.359	2.161	-2.658	6.976	0.359	2.159	-2.660	6.944	0.357	2.142
N=150	-2.780	7.181	0.364	2.201	-2.817	7.183	0.364	2.183	-2.817	7.183	0.364	2.183	-2.817	7.183	0.364	2.183	-2.817	7.160	0.367	2.171
N=160	-2.815	7.135	0.372	2.160	-2.850	7.135	0.372	2.143	-2.850	7.135	0.372	2.143	-2.850	7.135	0.372	2.143	-2.857	7.121	0.377	2.132
N=170	-3.032	7.108	0.407	2.038	-3.032	7.108	0.407	2.038	-3.032	7.108	0.407	2.038	-3.032	7.108	0.407	2.038	-3.037	7.112	0.407	2.038
N=180	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038
N=190	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038
N=200	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038	-3.037	7.112	0.409	2.038

Table 11: Full test result for dependent bootstrap-t test: N-day Breakout

	c=0.0000				c=0.0025				c=0.0050				c=0.0075				c=0.0100			
	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif	Lower	Upper	p	Est. Dif
N=10	-2.124	6.978	0.299	2.427	-3.918	4.758	0.861	0.420	-5.021	3.287	0.705	-0.867	-5.500	2.811	0.522	-1.344	-5.814	2.471	0.442	-1.671
N=20	-2.187	6.884	0.324	2.349	-3.122	6.007	0.526	1.443	-3.275	5.711	0.596	1.218	-3.443	5.561	0.646	1.059	-3.541	5.458	0.683	0.959
N=30	-2.871	6.491	0.434	1.810	-3.527	5.831	0.618	1.152	-3.636	5.585	0.671	0.974	-3.712	5.444	0.713	0.866	-3.743	5.390	0.736	0.824
N=40	-2.892	6.379	0.456	1.743	-3.403	5.827	0.586	1.212	-3.504	5.681	0.631	1.089	-3.553	5.654	0.643	1.050	-3.618	5.628	0.654	1.005
N=50	-2.881	6.311	0.447	1.715	-3.341	5.798	0.583	1.229	-3.410	5.626	0.626	1.108	-3.481	5.587	0.653	1.053	-3.508	5.538	0.663	1.015
N=60	-2.632	5.913	0.462	1.640	-3.110	5.586	0.588	1.238	-3.122	5.351	0.634	1.114	-3.157	5.341	0.636	1.092	-3.167	5.333	0.636	1.083
N=70	-2.906	5.644	0.539	1.369	-3.297	5.396	0.633	1.050	-3.469	5.263	0.696	0.897	-3.506	5.237	0.700	0.866	-3.510	5.200	0.710	0.845
N=80	-2.375	6.331	0.384	1.978	-2.607	6.124	0.434	1.759	-2.622	6.071	0.446	1.725	-2.679	6.002	0.459	1.661	-2.736	5.947	0.477	1.605
N=90	-2.351	6.474	0.372	2.061	-2.621	6.236	0.417	1.808	-2.682	6.228	0.421	1.773	-2.682	6.211	0.421	1.764	-2.707	6.181	0.429	1.737
N=100	-2.208	6.848	0.329	2.320	-2.330	6.583	0.357	2.126	-2.390	6.569	0.361	2.090	-2.419	6.545	0.361	2.063	-2.455	6.527	0.367	2.036
N=110	-2.150	7.041	0.309	2.446	-2.236	6.831	0.331	2.297	-2.276	6.766	0.344	2.245	-2.301	6.753	0.347	2.226	-2.323	6.752	0.349	2.214
N=120	-2.288	6.938	0.326	2.325	-2.360	6.764	0.346	2.202	-2.373	6.729	0.352	2.178	-2.366	6.699	0.354	2.167	-2.366	6.699	0.354	2.167
N=130	-2.565	6.830	0.362	2.133	-2.672	6.729	0.382	2.029	-2.672	6.715	0.384	2.022	-2.672	6.715	0.384	2.022	-2.672	6.715	0.384	2.022
N=140	-2.587	6.905	0.356	2.159	-2.679	6.774	0.381	2.048	-2.693	6.764	0.381	2.036	-2.714	6.754	0.386	2.020	-2.735	6.731	0.389	1.998
N=150	-2.665	6.873	0.376	2.104	-2.758	6.780	0.392	2.011	-2.795	6.771	0.396	1.988	-2.801	6.771	0.396	1.985	-2.801	6.771	0.396	1.985
N=160	-2.586	6.923	0.362	2.169	-2.628	6.810	0.377	2.091	-2.652	6.792	0.381	2.070	-2.686	6.766	0.386	2.040	-2.695	6.762	0.387	2.033
N=170	-2.389	6.881	0.344	2.246	-2.484	6.814	0.356	2.165	-2.518	6.815	0.356	2.149	-2.543	6.811	0.359	2.134	-2.559	6.793	0.362	2.117
N=180	-2.343	6.751	0.339	2.204	-2.475	6.652	0.364	2.088	-2.502	6.653	0.371	2.076	-2.502	6.653	0.371	2.076	-2.502	6.653	0.371	2.076
N=190	-2.323	6.743	0.331	2.210	-2.380	6.655	0.349	2.138	-2.373	6.648	0.351	2.138	-2.373	6.648	0.351	2.138	-2.381	6.638	0.357	2.129
N=200	-2.057	6.746	0.305	2.345	-2.089	6.647	0.314	2.279	-2.069	6.627	0.316	2.279	-2.069	6.627	0.316	2.279	-2.069	6.627	0.316	2.279

Table 12: Full test result for dependent bootstrap-t test: Linear Regression