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1 Introduction

Stock market anomalies and their existence in global financial markets have long been a highly debated topic among both finance professionals and researchers. In accordance with mainstream finance theory and Fama's (1970) efficient market hypothesis (EMH), stock prices may temporarily deviate from fair values, but under the assumption of a perfectly efficient market, such deviations will be exploited and priced out by profit-seeking investors in the long run. Consequently, the EMH suggests that stock prices move in a random-walk pattern where prices today are independent of the prices yesterday, and hence historical data cannot be used to predict future stock prices (Malkiel, 2003).

A number of studies have found evidence of 'seasonal anomalies' or 'calendar effects' in global stock markets (Cross, 1973; French, 1980; Wang, Li & Erickson, 1997). Such anomalies exhibit a cyclical pattern that result in certain days of the week or specific months of the year offering higher or lower returns than others (Agrawal & Tandon, 1994). Researchers have found both intertemporal and geographical differences in the existence of seasonal anomalies, suggesting country-specific patterns of returns. For example, in Sweden there is an expression that goes "buy to the herring and sell to the crayfish" while in the US market the old saying is to "sell in May and go away". Whereas the first expression suggests that June to August is the best period to own stocks, the latter suggests that the period between November and April offers the highest returns. By challenging the core assumptions of market efficiency, seasonal anomalies in stock market prices are a direct violation of the weak form of the EMH (Wong, Ho & Dollery, 2007), and consequently, stock prices may be predictable at certain periods during the year. This naturally raises the question if the predictability of stock prices can be used to develop successful investment strategies that allow clever investors to outperform the market by timing sales and purchases to coincide with the ups and downs in the market.

While a number of studies have examined the existence of seasonal anomalies in the US and other major stock markets, little research has been conducted on the fast-growing markets of Southeast Asia. With an increasing interest in financial markets, and the growing importance of countries such as Singapore, Thailand and Malaysia to the global economy, interest in these markets should be greater than ever. Singapore, as one of the leading financial centres in the Asia-Pacific region, and recently predicted to overtake Hong Kong as Asia's number one financial centre by 2016 (Wealth Briefing Asia, 2011), is a particularly interesting market.

The purpose of this thesis is to study the possible existence of day-of-the-week effects and month-of-the-year effects in the Singapore Straits Times Index (STI) over the period January 1st 1993 to December 31st 2011. The findings are analysed with the intention of developing investment strategies and to investigate if behavioural finance can help to explain the existence seasonal anomalies.

To meet the purpose, several research questions are posed:

(1) Are day-of-the-week effects and month-of-the-year effects present in the Singapore stock market over the period between January 1st 1993 and December 31st 2011?
(2) Following the evidence of seasonal anomalies, can investment strategies be developed to capitalize on such effects and earn returns in excess of the market?
(3) Can behavioural finance help to explain the existence of seasonal anomalies?

This study is based on daily closing prices retrieved from Yahoo! Finance, which are used to compute average daily and monthly returns. Statistical hypothesis tests and significance analysis are further used to confirm the potential existence of seasonal anomalies. The identified anomalies are used to develop two investment strategies, a day-of-the-week strategy and a month-of-the-year strategy, which are designed to capitalize on both positive and negative effects by taking different exposures to the market during good and bad times.

The results of this study suggest evidence of several seasonal anomalies in the Singapore stock market. A negative Monday effect exists over the full sample period and in the 2000 to 2005 sub-period, where a positive Friday effect is also present. Contrary to most studies of western markets, evidence is found of a negative January effect, with other negative effects occurring in May, August and September. Positive effects are observed in April, July, November and December, with April returns being the highest.

Despite a lower level of risk, both the abovementioned investment strategies are proven to outperform the market, with the day-of-the-week strategy earning a return of 220.6% in excess of the market, and the month-of-the-year strategy earning an excess return of 752.37%.

The remainder of this thesis is divided into four main sections. First, a theoretical background, including a number of definitions and explanations as well as the major findings of previous studies is presented. Second, the methodology is outlined along with an introduction to statistical hypothesis testing and significance analysis. In the third section, the results of the statistical investigation are presented and analysed, and lastly, the fourth and final section presents the conclusions and their implications for the purpose of this study.

2 Theoretical background

This section presents the theoretical foundations of the study. The Singapore Exchange and the Straits Times Index are introduced together with an introduction to seasonal anomalies, including day-of-the-week effects and month-of-the-year effects. This is followed by a presentation of mainstream finance theory and behavioural finance, and to conclude the section, the link between behavioural finance and seasonal anomalies is discussed and the findings of previous studies are reviewed.

2.1 The Singapore Exchange

The Singapore Exchange (SGX) was constructed on December 1st 1999 as a result of the merger between the Stock Exchange of Singapore (SES) and the Singapore International Monetary Exchange (SIMEX). The SGX is Asia-Pacific's first demutualized and integrated securities and derivatives exchange, and on November 23rd 2000, it became the first publicly held stock exchange in Asia-Pacific, listing its shares on its own exchange. In doing so, the SGX stock also became part of certain benchmark indices such as the Straits Times Index (Securities Investors Association Singapore, 2012). As illustrated in figure 2.1, the SGX is a growing exchange. In January 2012, it listed 772 securities with a total market capitalization of S$830.3 billion (Monetary Authority of Singapore, 2012), and with 40% of the total market capitalization attributable to foreign companies, the SGX is highly international (Singapore Exchange Ltd, 2012).

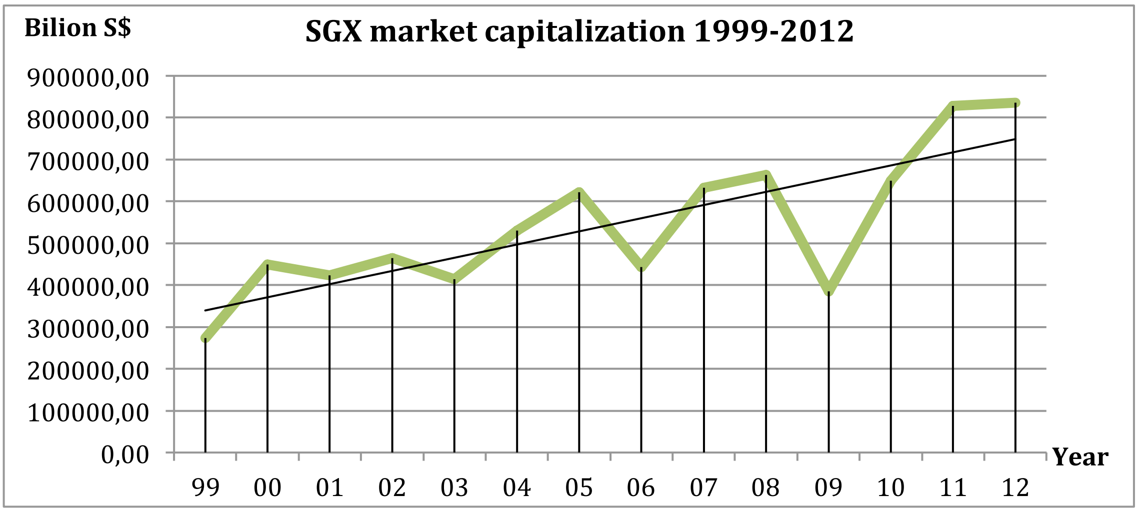

Figure 2.1. *SGX market capitalization 1999-2012.* (Monetary Authority of Singapore, 2012)

2.2 The Straits Times Index

The Straits Times Index (STI) comprises the top 30 stocks listed on the SGX as ranked by market capitalization[1]. It is widely regarded as the benchmark index of the Singapore stock market, and its primary objective is to reflect the daily trading activity on the Singapore exchange (FTSE, 2012).

The index started as part of SES in 1966, but since then, both the methodology and the composition have been altered several times. In 1998, a major re-classification of companies and the removal of the 'industrials' category resulted in the STI replacing the Straits Times Industrial Index (STII), and in January 2008, a new partnership between Singapore Press Holdings (SPH), SGX and FTSE Group (FTSE) resulted in another reconstruction of the STI. The number of constituent stocks was reduced from 50 to 30, the index was re-calculated using FTSE's methodology, and companies were classified according to the Industry Classification Benchmark (ICB)[2] (Straits Times, 2012, a).

2.3 Price development of the Straits Times Index 1993-2011

Figure 2.2 shows the price development of the STI between 1993 and 2011, a period over which the index has exhibited a positive development of 73.6%.

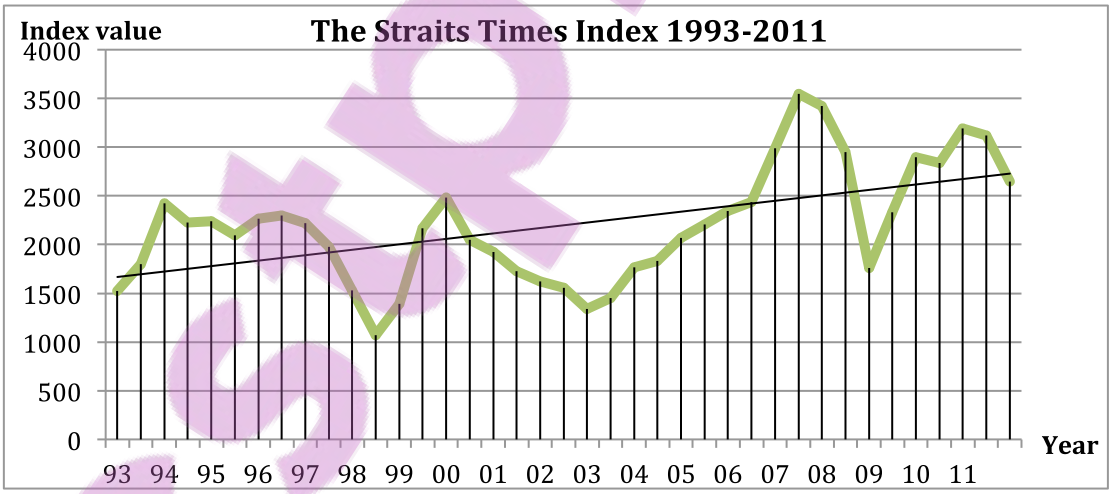

Figure 2.2. *The Straits Times Index 1993-2011.* (Yahoo! Finance, 2012 a)

[1] A full list of STI constituents along with their respective industry classifications and index weights is available in appendix 1.

[2] An international industry classification system developed by Dow Jones and FTSE that classifies companies into 10 industries within which there are 19 supersectors, 41 sectors and 141 subsectors (ICB, 2012).

While the overall development has been positive, it has been a rough journey to the current levels with significant positive and negative trends over the years. As illustrated in figure 2.2, three significant falls can be identified over the period 1993 to 2011. Between 1997 and 1998, the index fell sharply by 37.2% as a result of the Asian financial crisis. The second downturn was of more extended character, stretching from 1999 to 2002 when the STI plunged by 45.9%. This fall may have been triggered by the IT-bubble and worsened by the negative price development that followed after the events on September 11th 2001. The most recent decline occurred in connection to the global financial crisis in 2008, when the index fell by 48.5%. Interestingly, this fall is the largest during the sample period, exceeding the decline around the Asian financial crisis, and a possible explanation may be Singapore's high dependence on foreign investors and the increasing global economic integration. Each crisis has however been followed by an even greater recovery, and the Asian financial crisis was followed by 19 months of strong growth in 1998 and 1999 where the index rose by 132.4%. The decline between 1999 and 2002 was followed by a positive 5-year period 2002-2007 where the STI accumulated wealth of 155%. Just as these crises were followed by significant upturns, so was the financial crisis in 2008, when the STI rose by 81% over the two-year period 2009-2010.

2.4 Seasonal anomalies

An anomaly is something that deviates from theoretical expectations, and in the financial markets, anomalies refer to stock price irregularities that result in short-term and long-term inefficiencies. Such anomalies can be either temporary or cyclical, and if cyclical anomalies exist, investors can earn abnormal returns by exploiting the predictable patterns in stock price movements (Mehdian & Perry, 2002).

Fama & French (1996) defines seasonal anomalies as repetitive patterns in stock market returns, and in this thesis, seasonal anomalies are referred to as repetitive cyclical market trends that are associated with abnormally positive or negative returns. These anomalies can be categorized according to calendar frequency, for example daily, weekly, monthly or yearly patterns, and consequently, seasonal anomalies in stock returns are commonly referred to as calendar anomalies. While a lot of research has been carried out on seasonal market anomalies, the reasons for their existence are highly debated.

2.4.1 Day-of-the-week effects

Day-of-the-week effects imply that returns in a particular market are not equally distributed during all trading days of the week. Rather, certain days may offer abnormally positive or negative returns compared to other days, violating the random-walk assumptions of the EMH. Numerous previous studies have identified day-of-the-week effects in global stock markets, with the most common findings being a positive Friday effect and a negative Monday effect. This has given rise to the notion of a weekend effect (Gibbons & Hess, 1981; Wang, Li & Erickson, 1997), which some researchers suggest is a consequence of the negative returns that occur during weekends. For example, Penman (1986) suggests that listed companies tend to release bad news over the weekend, which can explain the poor returns on Mondays when the markets re-open. Although the weekend effect is the most famous and heavily researched weekly anomaly, several other day-of-the-week effects have also been identified, including a negative Tuesday effect (Dubois & Louvet, 1994) and a positive Wednesday effect (Gibbons & Hess, 1981; Keim & Stambaugh, 1984).

2.4.2 Month-of-the-year effects

"October. This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August, and February" (Twain, 1894, p.167). Since Mark Twain's early observations, a large number of studies have found convincing evidence that certain months of the year yield significantly higher or lower returns than others. Two commonly identified month-of-the-year effects are negative September and October effects, but the January effect is possibly the most well known month-of-the-year effect, where January returns tend to be higher than returns of other months (Rozeff & Kinney, 1976; Mehdian & Perry, 2002). One compelling explanation to the January effect is tax-induced selling, which is commonly referred to as the tax-loss hypothesis. According to the hypothesis, investors in countries where December is the last month of the tax year tend to sell securities that have underperformed, realizing capital losses to reduce taxes paid on capital gains. As the new tax year starts in January, capital is reinvested which eventually drives stock prices upwards and causes a positive January effect (Poterba & Weisbenner, 2001).

2.5 Mainstream finance theory

Classical economic theory is based on the assumption of efficient markets in which investors cannot earn higher returns without assuming additional risk. During several decades, Fama's (1965) efficient market hypothesis (EMH) has dominated finance theory, and according to the hypothesis, the efficiency of financial markets ensures that stock prices instantaneously incorporate and reflect all relevant information. Consequently, it should not be possible for investors to earn abnormally high returns by purchasing undervalued stocks or selling stocks for inflated prices. In a random-walk market where prices cannot be predicted, investors do not have to worry about the timing of purchases and sales of stocks, and a simple buy-and-hold strategy should yield the same return as strategies based on more advanced procedures for timing purchases and sales. The only way for investors to earn higher returns is therefore to undertake additional risk (Fama, 1965).

With this theory, Fama (1965) effectively rejected the usefulness of both technical and fundamental valuation methods. Whereas technical methods assume dependence in successive price movements and use historical prices to forecast future stock prices, fundamental valuation methods use company fundamentals to determine the earnings potential of a security, which is then used to predict future stock prices. In efficient markets, technical analysis is therefore more or less useless since there is no dependence in successive price movements, and there is no way of predicting future prices based on historical data (Malkiel, 2003). Fundamental analysis is also of little use unless the investor possesses additional information that is not fully incorporated in the current market price. Consequently, a security chosen by a mediocre analyst should yield no higher return than a randomly selected security of equal risk (Fama, 1965).

The EMH does however not imply that stock prices always reflect fair values. In the long run, stock prices may reflect all available information, but prices can temporarily deviate from fair values as a result of for example uncertainty over the future prospects of the company. However, the EMH suggests that these fluctuations are completely randomized, and there is an equal chance of positive and negative development in stock prices. New information can also cause the intrinsic value of a security to change over time, and because of uncertainty over the new information, prices may initially over- or under-adjust. The lag in the complete adjustment of stock prices may seem like an arbitrage opportunity, but according to Fama (1965), the adjustment process itself is an independent random variable. When the market anticipates the triggering event before it occurs, the price adjustment tends to precede the actual event, while on other occasions, the price adjustment is a direct consequence of the occurrence of the event (Fama, 1965).

In the article *Efficient Capital Markets: A Review of Theory and Empirical Work*, Fama (1970) defines an efficient market as "a market in which prices always fully reflect available information". In the same publication, he suggests three different levels of market efficiency depending on how much information has been factored into stock prices:

> ***1. Weak-form market efficiency:*** *Stock prices reflect only historical information about the company. Stock prices therefore follow the random-walk pattern and technical analysis cannot be used as a tool to forecast future prices.*
>
> ***2. Semi-strong form market efficiency:*** *Stock prices reflect all historical information about the company, but also all sorts of relevant public information, for example announcements of annual earnings and stock splits.*
>
> ***3. Strong-form market efficiency:*** *Stock prices reflect all available information about the company. This includes both historical and public information, but also private or insider information. In such markets, there is no additional information that can be used to earn abnormal returns since all information is already reflected in the stock price (Fama, 1970).*

Mainstream finance theory is based on three main theoretical arguments. First, investors act rationally, so securities are valued rationally and always reflect fair values. Second, investors consider all available information before making investment decisions, and third, investors always pursue their self-interests and act to maximize the expected utility in any investment decision. Despite dominating finance theory for several decades, this traditional view and the EMH is being challenged by the more recent field of behavioural finance which suggests that investors are not as rational as suggested by mainstream finance theory (Shiller, 2003; Thaler, 2005).

2.6 Behavioural finance

Mainstream finance theory seeks to understand financial markets by assuming rationality, but it has been clear for a long time that individual investor behaviour cannot be fully understood in this traditional paradigm, and that a number of behavioural factors influence the decisions of investors (Thaler, 2005). In fact, psychological impacts and the irrationality of human behaviour have been noticed since the 1950s when Burrell (1951) released the article *Possibility of an Experimental Approach to Investment Studies*, which examines human behaviour patterns that may be of value in understanding how security markets operate. Although Burrell's findings received limited attention at that stage, much of the focus in academic discussions during the 1990s shifted away from traditional econometric analyses toward developing models of human psychology (Shiller, 2003), and accordingly, the field of behavioural finance bloomed.

Behavioural finance is an approach to financial markets that uses psychology to explain trading behaviour that cannot be fully explained by mainstream finance theory. It drops the assumptions of rational investors in efficient markets that act to maximize their expected utility, and instead it analyses irrationality and seeks to identify psychological factors that can explain why investors buy or sell stocks.

There are two solid building blocks of behavioural finance, limits to arbitrage and cognitive biases (Ritter, 2003). Limits to arbitrage refer to a situation of long-term and persistent mispricings in the stock market. While the theory of efficient markets suggests that security prices reflect fair value in the long run and that rational investors will quickly price away any deviations from fair values, behavioural finance proposes a different view. It suggests that asset prices can deviate from fundamental values as a result of investor irrationality, and that these deviations may result in arbitrage opportunities. However, such arbitrage opportunities are often very small and large amounts of capital are often needed to capitalize on such effects. Consequently, the mispricings are often too costly to arbitrage away, and hence there is a limit to arbitrage that results in long term, persistent mispricings in the market (Thaler, 2005).

Cognitive biases can also help explain deviations from the EMH. Shefrin (2009) presents risk seeking, over optimism, overconfidence and framing as both fundaments of behavioural finance and reasons behind many of the previous financial crises. He highlights the importance of understanding the irrational decision making of people, and suggests that many of the previous crashes, bubbles and panics in global stock markets can be explained by certain psychological pitfalls, including beliefs and preferences that cause investors to deviate from rationality (Shefrin, 2009). It may sound easy to follow the golden rule of buying low and selling high, but reality shows the complexity involved when psychology disturbs such easy trading plans. Instead, investors tend to do the reverse and suffer from the disposition effect, that is, selling winners too early and holding losers too long (Shefrin & Statman, 1984).

"What happens when the signs of the outcomes are reversed?" (Kahneman & Tversky, 1979, p.268). This question was the idea behind another important contribution to behavioural finance, the prospect theory, which was established by the well-known psychologists Daniel Kahneman and Amos Tversky (1979). Their study shows that people value gains and losses differently, and that the same people that are risk averse when having the possibility to earn money are risk seeking in the case of losing money. This was shown with an experiment where the participants were presented with two options, getting a specified amount of money with certainty, or having a 50-50 chance of getting more or nothing at all. The majority of the participants showed risk aversion in their behaviour by choosing the certain amount, even though the mathematical expectation of the uncertain option is higher. The same people were also presented with the options of losing a specified amount of money with certainty, or having a 50-50 chance of losing more or nothing. In this instance, the majority of the participants exhibited a risk seeking behaviour by choosing the risky option but having a 50% chance of losing nothing.

Behavioural finance offers an alternative paradigm to mainstream finance theory and the EMH (Daniel & Titman, 1999). Its usefulness and validity is however highly debated, and while some researchers consider it a contradiction to mainstream finance theory, others see it as a complement, and yet others fully neglect its usefulness.

2.7 Link between behavioural finance and seasonal anomalies

Psychology offers a promising explanation to calendar anomalies since they tend to occur at turning points in time (Jacobs & Levy, 1988), and accordingly, seasonal patterns in investor behaviour result in significant numbers of investors selling and buying securities at the same point in time. Although there are several different explanations to the existence of seasonal anomalies, behavioural finance and its psychological trading patterns represent part of it. Since investors are cognitively affected by certain events that occur at the same time year after year, such as the start of a new tax year, the investment behaviour exhibits a similar repetitive pattern. If an event causes us to react in a certain way one year, we are likely to react in the same way next year, and consequently, the market anomalies are persistent (Thaler, 2005).

The January effect is a good example of a persistent anomaly, and it has been described as the effect of investors selling losers around the turn of the tax year in order to reduce taxes paid on capital gains. In most countries, the new tax year starts in January and consequently, there is a selling pressure around the end of the year, causing negative price developments in the stock market. As investors reinvest their capital in January, the increasing demand pushes prices upwards and results in a positive January effect. Kahneman & Tversky's (1979) prospect theory is in line with this tax-loss hypothesis and suggests that investors tend to be risk averse to capital gains but risk seeking to capital losses. Investors tend to defer the sales of losers until the year-end, hoping that the performance of the stocks will improve. As the end of the year is reached, investors sell the remaining losers to realize losses and reduce tax payments on capital gains. The window-dressing hypothesis is another explanation to the January effect, and it refers to companies selling losing stocks at the end of the year and buying them back in January to make the year-end results look good. In other words, the window-dressing hypothesis suggests that the January effect can be affected by status pressure, which is a purely psychological pitfall (Anderson, Gerlash & Di Traglia, 2007).

The weekend effect has also been explained from a behavioural perspective. Miller (1988) suggests that it exists because traders execute the majority of sell orders after the weekend when investors have had time to analyse their portfolios. After the weekend, worried investors have a latent sales need, resulting in a sudden sales pressure when the stock exchange opens on the following Monday. Kallunki & Martikainen (1997) studied the Finish stock market and found that while small traders increase their sell orders at the beginning of the week, the large traders are more inclined to purchase stocks during the first few days of the week.

Another explanation to the weekend effect is information asymmetry caused by the behaviour of corporations, as they tend to announce good news immediately, and wait with bad news until Friday after the stock exchange is closed. By doing so, they hold back negative information until the weekend, giving investors two non-trading days to absorb the information before reacting on the following Monday. Consequently, all sell orders that results from the bad news get pushed to Monday, causing a downward pressure on prices and negative returns (Kumari & Raj, 2006).

These examples show that individual investment behaviour is too complex to be explained solely by mainstream finance theory. On many occasions, investors do indeed buy and sell securities for purely rational reasons, but on other occasions, psychological factors interfere with the rationality of investors and cause us to buy and sell stocks for less than rational reasons. It is on such occasions that market anomalies occur, and if the triggering event for such irrational behaviour is of repetitive character, seasonal anomalies may be present in the market.

2.8 Review of previous studies

Seasonal anomalies in global stock markets are a topic that has been extensively studied over the last few decades. Researchers generally find that the existence of such phenomena varies widely, both between markets and over time. The following two sections present the results of previous research.

2.8.1 Day-of-the-week effects

Most previous investigations of day-of-the-week effects have been carried out in US markets, particularly on the S&P500 Index. They have generally identified the same effects, observing negative returns on Mondays and abnormally high returns on Wednesdays. Cross (1973) investigated the behaviour of stock prices on Mondays and Fridays in the S&P500 index over the period 1953 to 1970, and found that Fridays offered higher returns than Mondays. French (1980) found further evidence of a negative Monday effect when he studied the S&P500 over the period 1953 to 1977. He divided the sample period into shorter 5-year periods and found evidence of a negative Monday effect in each sub-period while all other trading days of the week offered positive returns. He also found that Wednesday and Friday returns were considerably higher than the average weekday return. Gibbons & Hess (1981) studied the S&P500 index between the years 1962 and 1978, and found that Monday was the only weekday with a negative return, while Wednesdays and Fridays offered returns that significantly exceeded the average weekday return. Keim & Stambaugh (1984) conducted a similar study of the S&P500 over the period 1953 to 1982. Their findings largely support those of Cross (1973), French (1980) and Gibbons & Hess (1981) as they found evidence of a negative Monday effect and abnormally high returns on Wednesdays and Fridays.

Several other US indices have also been studied. Smirlock & Starks (1985) used hourly data when they investigated day-of-the week effects in the Dow Jones Industrial Average (DJIA) between 1963 and 1983. Breaking the sample period into three sub-periods, 1963 to 1968, 1968 to 1974, and 1974 to 1983, they found that that the negative Monday effect has been diminishing over time. In the first sub-period, negative returns occurred during every trading-hour on Mondays, while the return over the weekend period was positive. In the most recent sub-period however, the hourly average returns on Mondays were all positive after noon, and the negative weekend effect was due to negative average returns over the weekend from Friday close to Monday opening. Lakonishok & Smidt (1988) used daily data from the DJIA, and over a 90-year period between 1897 and 1986, they found evidence of substantially negative Monday returns throughout the whole period.

Wang, Li, & Erickson (1997) investigated several US indices over the period 1962 to 1993. Focusing on the NYSE-AMEX equally- and value-weighted return indices, the Nasdaq equally- and value-weighted return indices, and the S&P 500 Index, they found evidence of a negative Monday effect over the entire sample period. They also found that this negative effect occurred primarily in the last two weeks of the month, i.e. the fourth and the fifth weeks of the month. Furthermore, they found that the average Monday return over the first three weeks of the month was not significantly different from zero. Sun & Tong (2002) conducted a similar investigation to that of Wang et al. (1997), but extended the time period to include the years 1962 to 1998. Focusing on the same indices, they also found evidence of a negative Monday effect, but rather than occurring in the last two weeks of the month, negative Monday returns were concentrated to days 18-26 of the month, leading them to suggest that there may exist a 'week-four effect' that can be statistically explained by negative returns on the preceding Friday. Overall, returns during the fourth week were the lowest of the month, with the Monday of that week offering particularly low returns.

In other markets, Condoyanni, O'Hanlon & Ward (1987) studied day-of-the-week effects in Australia, Japan, Singapore, France, UK, Canada and the US over the period 1969 to 1984 and found evidence of a negative Monday effect. Jaffe & Westerfield (1985) studied daily stock returns in the US, UK, Japan, Canada and Australia between 1969 and 1984 and found that positive effects generally occur on Fridays, while Mondays yield the lowest returns. However, in both Japan and Australia, the lowest returns occur on Tuesdays. Dubois & Louvet (1994) conducted one of the most extensive studies when they examined day-of-the-week effects in nine different countries between 1969 and 1992. They concluded that in general, returns were lower during the first few days of the week, but not particularly on Mondays. Furthermore, they found that the day-of-the-week effect has been disappearing in US markets over time, but strong day-of-the-week effects still exist in Europe (Germany, Switzerland, UK and France), Hong Kong and Canada. Overall, Mondays are associated with negative returns, while Wednesday returns tend to be abnormally high. The notable differences are Japan and Australia where Tuesdays rather than Mondays tend to offer significantly low returns. Bursa, Liu, & Schulman (2003) continued on the same track as Dubois & Louvet (1994) when they examined day-of-the-week effects in nine different countries between 1963 and 1995. They found significantly negative returns on Mondays in Brazil, France and Japan, suggesting a traditional weekend effect with Monday returns being the lowest of the week. In the US market, they found evidence of positive Monday returns and suggested a reverse weekend effect, while the markets of Argentina, Chile, UK, Hong Kong and Australia did not show any evidence of day-of-the-week effects. Another extensive study was carried out by Kohers, Kohers, Pandey & Kohers (2004) when they investigated the 12 largest stock markets in the world during a 22-year period in the

1980's and the 1990's. They found that day-of-the-week effects have been gradually diminishing over time, from being highly evident in the 1980's to almost completely disappearing in the 1990's. Consequently, average returns have become more equalized during the different days of the week, which they suggested might be a consequence of improving market efficiency.

Closer to Singapore, a number of Asian studies have focused on the Chinese kets. Mookherjee & Yu (1999) studied the Shanghai and Shenzhen indices over the period 1990 to 1994 and found that, contrary to the findings in many other markets, Thursdays rather than Fridays offered the highest returns in both exchanges. Gao & Kling (2005) investigated the same indices but over an extended time period stretching from 1990 to 2002. Contrary to the findings of Mookherjee & Yu (1999), they found that the highest average returns occurred on Fridays.

Brooks & Persand (2001) studied returns in the markets of South Korea, Malaysia, the Philippines, Taiwan and Thailand between 1989 and 1996. No significant day-of-the-week effects were encountered in South Korea and the Philippines, but contrary to most other studies that suggest a negative Monday effect, they found that both Thailand and Malaysia offered positive Monday returns. They also found that the same markets exhibited significantly negative Tuesday returns, whereas in Taiwan, Wednesday returns were negative. One of the most comprehensive studies of Asian markets was conducted by Hui (2005) who examined day-of-the-week effects in the markets of Hong Kong, South Korea, Singapore and Taiwan along with the US and Japanese markets between 1998 and 2011. He found no evidence of day-of-the-week effects in any of the markets except Singapore where Monday and Tuesday returns are particularly low, while Wednesday and Friday returns are above average.

Table 2.1 *Review of previous studies: day-of-the-week effects*

Researchers	Period	Market	Findings
Cross (1973)	1953-1970	The US	• Positive Friday effect • Negative Monday effect
French (1980)	1953-1977	The US	• Positive Wednesday and Friday effects • Negative Monday effect
Gibbons & Hess (1981)	1962-1978		
Keim & Stambaugh (1984)	1953-1982		
Smirlock & Starks (1985)	1963-1983	The US	• Negative weekend effect • Diminishing negative Monday effect
Lakonishok & Smidt (1988)	1897-1986	The US	• Negative Monday effect
Wang, Li, & Erickson (1997)	1962- 1993	The US	• Negative Monday effect
Sun & Tong (2002)	1962-1998		
Jaffe & Westerfield (1985)	1969-1984	The US, Canada, United Kingdom, Japan, and Australia	• Overall positive Friday effect • Overall negative Monday effect • Negative Tuesday effect (Japan & Australia)
Condoyanni et al. (1987)	1969-1984	The US, Canada, United Kingdom, France, Japan and Singapore	• Overall negative Monday effect
Dubois & Louvet (1994)	1969-1992	The US, Canada, United Kingdom, France, Switzerland, Germany Japan, Hong Kong and Australia	• Overall positive Wednesday effect • Diminishing positive Friday effect (the US) • Overall negative Monday effect (except Japan & Australia) • Negative Tuesday effect (Australia & Japan) • Diminishing negative Monday effect (the US)
Bursa et al. (2003)	1963-1995	The US, Argentina, Brazil, Chile, United Kingdom, France, Japan, Hong Kong and Australia	• Positive Monday effect (the US) • Negative Monday effect (Brazil, France & Japan)
Mookherjee & Yu (1999)	1990-1994	China	• Positive Thursday effect
Gao & Kling (2005)	1990-2002	China	• Positive Friday effect
Brooks & Persand (2001)	1989-1996	South Korea, Taiwan, Thailand, Malaysia and Philippines	• Positive Monday Effect (Thailand & Malaysia) • Negative Tuesday effect (Thailand & Malaysia) • Negative Wednesday effect (Taiwan)
Hui (2005)	1998-2001	The US, Japan, Hong Kong, South Korea, Taiwan and Singapore	• Positive Wednesday and Friday effects (Singapore) • Negative Monday and Tuesday effects (Singapore)

2.8.2 Month-of-the-year effects

As with day-of-the-week effects, most previous studies of month-of-the-year effects have been carried out in US markets. One of the first US studies was performed by Rozeff & Kinney (1976), who studied data from the NYSE between 1901 and 1974. With the exception of the 1929 to 1940 period, they found significant differences in stock returns among the months of the year. January returns were found to be particularly high, which is mainly due to the high returns that occur in the first two weeks of the month, but they also found evidence of relatively high returns in July, November and December and low returns in February and June.

Keim (1983) investigated the NYSE and AMEX indices between 1963 and 1979. Confirmatory to the findings of Rozeff & Kinney (1976), he found that January returns were higher than returns during the remaining eleven months of the year, while he also found that smaller firms always experience a more pronounced January effect than larger firms. Reinganum (1983) conducted a similar study over the period 1962 to 1979. He further confirmed the existence of a positive January effect that was mainly caused by exceptionally high returns during the first trading days of the month, and suggested that it may be attributable to the tax-loss hypothesis. Haugen & Jorion (1996) also studied data from the NYSE when they were looking for evidence of a weakening January effect between 1926 and 1993. No such evidence was found, and they concluded that the January effect was still strong in the NYSE in 1993. Mehdian & Perry (2002) found further evidence of a positive January effect in the DJIA, the NYSE, and the S&P500 between 1964 and 1998. To deepen the investigation, they divided the sample period into two sub-periods to study the January effect before and after the stock market crash in 1987, concluding that the effect was only significant in the pre-crash period. Imad & Moosa (2007) conducted a study similar to the one of Mehdian & Perry (2002) but focused on the period 1970 to 2005. They found that the January effect existed prior to 1990, but in the period 1990 to 2005, a negative July effect was more prominent.

In non-US markets, Gultekin & Gultekin (1983) conducted one of the most extensive investigations when they studied stock returns in 17 major industrialized countries over the period between 1959 and 1979. They found strong evidence of seasonalities in stock returns, and generally, abnormally high returns were found in the month following the end of the tax year, which in most countries is January. In the UK however, the tax year ends at the beginning of April, and as expected, the highest returns were found in April. In terms of negative returns, August and September were found to be the worst months in most countries. Balaban (1995) investigated the Turkish market over the period 1988 to 1993 and found high returns in January, June and September, and notably, January returns were almost double the size of the combined June and September returns. Rossi (2007) studied the markets of Argentina, Brazil, Chile and Mexico between 1997 and 2006 and found evidence of a January effect in Argentina. Agathee (2008) studied returns in Mauritius from 1989 to 2006 and found that the lowest returns occurred in March while June offered significantly higher returns than the other eleven months of the year.

In Asia, month-of-the-year effects have been studied in a number of countries. Kato & Schallheim (1985) found a January effect in the Tokyo Stock Exchange, but positive effects were also found in June for small-sized enterprises. In India, Pandey (2002) identified a January effect in the Bombay Stock Exchange between 1991 and 2002. Bahadur & Joshi (2005) studied the Nepalese market between 1995 and 2004 and found no evidence of a month-of-the-year effect, but concluded that October returns rather than January returns, as in most international markets, were the highest during the year. They explained the higher October returns with the occurrence of Dashain and Tihar, two of the great festivals of Hindu, as well as the information hypothesis, which suggests that the release of more information could be a reason for the higher October returns. Bepari & Mollik (2009) studied the stock market of Bangladesh between 1993 and 2006. With the Bangladesh tax-year ending in June, they were looking to confirm the existence of a positive July effect, similar to the January effect in many western countries. However, rather than a positive July effect they found evidence of a negative April effect and hence they rejected the idea of a tax-loss selling effect in the Dhaka Stock Exchange. Instead, they explained the negative April effect by the fact that most companies declare dividends and hold their annual general meetings in the month of April. The low returns are a consequence of investors selling their share post-dividend and driving prices downward.

In Chinese markets, Girardin & Liu (2005) discovered that a positive June effect and a negative December effect are present since 1993. Gao & Kling (2005) studied the Shanghai and Shenzhen indices between 1990 and 2002. They found that the highest returns occur in March and April, which are the first two months of the Chinese year, and consequently, an effect similar to the January effect in western markets exists in China. In Malaysia, Nassir & Mohammad (1987) found that January returns were higher than the returns of other months during the period between 1970 and 1986. Wong, Ho & Dollery (2007) also studied the Malaysian market between 1994 and 2006, and they wanted to test if the Asian financial crisis had any implications on the seasonality of Malaysian stock returns. They divided the sample period into three sub-periods, corresponding to the 'pre-crisis' period, the 'crisis' period and the 'post-crisis' period respectively. They found no evidence of a persistent monthly effect over the entire 13-year period, nor in the 'crisis' period. In the 'pre-crisis' period, they found evidence of a positive February effect, while this effect was replaced by a positive January effect in the 'post-crisis' period. In the post-crisis period, they also found evidence of negative effects in March and September, with September returns being the lowest.

Two of the largest studies of month-of-the-year effects were conducted by Ho (1999), and Yakob, Beal & Delpachitra (2005). Ho (1999) found strong evidence of a positive January effect in six of eight Asia-Pacific markets studied between 1975 and 1987, whereas Yakob et al. (2005) found striking evidence of month-of-the-year anomalies in a number of Asia-Pacific markets between 2000 and 2005. Month-of-the-year effects were found in all but the Japanese and Singapore markets, although the traditional January effect was only found in Taiwan and Malaysia. In Malaysia, positive returns also occurred in September and October, while Indian stock returns were highest in November and lowest in April. In Indonesian markets, positive effects were found in the three-month period April-June and in the months of November and December. In Australia, positive effects occurred in August, October and December, and the positive August return may be attributable to the start of the new tax year and hence comparable to the January effect in many western markets. The Hong Kong market showed evidence of a positive November effect and a negative March effect, whereas in China, only a negative March effect was proven. In South Korea, a positive effect was recorded in August while returns in the succeeding month of September were found to be negative.

Table 2.2 *Review of previous studies: month-of-the-year effects*

Researchers	Period	Market	Findings
Rozeff & Kinney (1976)	1901-1974	The US	• Positive January effect (except 1929-1940) • Positive July, November and December effects • Negative February and June effects
Keim (1983)	1963-1979	The US	• Positive January effect
Reinganum (1983)	1962-1979	The US	• Positive January effect
Haugen & Jorion (1996)	1926-1993	The US	• Positive January effect
Mehdian & Perry (2002)	1964-1998	The US	• Positive January effect (1964-1987)
Imad & Moosa (2007)	1970-2005	The US	• Positive January effect (1970-1990) • Negative July effect (1990-2005)
Gultekin & Gultekin (1983)	1959-1979	17 major industri-alized countries	• Overall positive January effect • Positive April effect (United Kingdom) • Overall negative August and September effects
Balaban (1995)	1988-1993	Turkey	• Positive January, June and September effects
Rossi (2007)	1997-2006	Argenti-na, Bra-zil, Chile and Mex-ico	• Positive January effect (Argentina)
Agathee (2008)	1989-2006	Mauritius	• Positive June effect • Negative March effect
Kato & Schallheim (1985)	1952-1980	Japan	• Positive January and June effects
Pandey (2002)	1991-2002	India	• Positive January effect
Bahadur & Joshi (2005)	1995-2004	Nepal	• No evidence of a month-of-the-year effect
Bepari & Mollik (2009)	1993-2006	Bangla-desh	• Negative April effect
Girardin & Liu (2005)	1993-2005	China	• Positive June effect • Negative December effect
Gao & Kling (2005)	1990-2002	China	• Positive March and April effects
Nassir & Mohammad (1987)	1970-1986	Malaysia	• Positive January effect
Wong, Ho & Dollery (2007)	1994-2006	Malaysia	• Positive February effect (1994-1997) • Positive January effect (1998-2006) • Negative March and September effects (1998-2006)
Ho (1999)	1975-1987	Asia-Pacific	• Overall positive January effect
Yakob et al. (2005)	2000-2005	Asia-Pacific	• Positive January effect (Taiwan & Malaysia) • Positive April-June effect (Indonesia) • Positive August effect (South Korea) • Positive September and October effects (Malaysia) • Positive August, October and December effects (Australia) • Positive November effect (India, Hong Kong & Indonesia) • Negative March effect (Hong Kong) • Negative April effect (India) • Negative September effect (South Korea)

3 Method

This section presents the methodology that is used throughout the study. First, the delimitations and selection of the study are outlined, followed by a presentation of the data that is used in the statistical investigation. Next, the empirical method is presented together with an introduction to statistical hypothesis testing and significance analysis. Finally, a brief presentation of the method used to develop investment strategies and the limitations of the study concludes the section.

3.1 Delimitation and selection

The investigation is limited to focusing on two types of seasonal anomalies, day-of-the-week effects and month-of-the-year effects. Previous studies of seasonal anomalies have found evidence of different anomalies in different markets, and while a negative Monday effect and a positive Friday effect are the most common day-of-the-week effects, a positive January effect and negative September and October effects are the most frequently identified monthly anomalies in global stock markets. As such, many previous studies have aimed solely at identifying these very specific effects. However, since the Singapore market has been sparsely studied, there is nothing concrete to suggest that these effects should be more common than any other seasonal effects in the Singapore stock market. Therefore, a better approach is to study day-of-the-week effects and month-of-the-year effects instead of focusing on specific days of the week or months of the year. While this approach identifies effects such as the abovementioned Monday and January effects, it does not prevent the identification of other anomalies, such as for example a Wednesday effect or a June effect.

The study is further delimited by focusing on a specific market index, and for the purpose of this study, the STI is the most appropriate index since it is used as the benchmark of the Singapore market as a whole. The index includes companies from a vast number of industries and gives a representative view of the general development on the SGX. Furthermore, the STI is frequently revised to ensure that it measures the market development as accurately as possible.

The sample period is limited to 19 years, stretching from January 1st 1993 to December 31st 2011. Compared to many other studies of seasonal anomalies, this represents an extensive time period that invites an investigation of the changing presence of seasonal anomalies over time. Furthermore, the choice of a unique time period contributes to new research on seasonal anomalies in Southeast Asia and allows for a comparison to studies that have focused on other time periods.

3.2 Data collection

The data used in this study consists of daily closing prices from the STI for the period January 1st 1993 to December 31st 2011. Historical closing prices for every trading day during the sample period have been retrieved from Yahoo! Finance and organized according to dates, weekdays and months. All closing prices are further grouped into five-day weeks and weekends, public holidays and the leap day that occurs every fourth year are excluded.

3.3 Empirical method

Daily historical closing prices are used to compute average daily and monthly returns. Using hypothesis testing, differences in average returns are analysed to determine if seasonal anomalies are present in the Singapore stock market. The investigation first considers the entire sample period, stretching from January 1st 1993 to December 31st 2011, and to investigate if the existence of seasonal anomalies has changed over time, the sample period is then divided into three sub-periods; January 1st 1993 to December 31st 1999, January 1st 2000 to December 31st 2005 and January 1st 2006 to December 31st 2011. The investigation is based on a large number of observations and the significance of the findings is tested through the use of well-proven statistical methods. Therefore, both the reliability[3] and the validity[4] of this study are considered to be high.

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[3] Reliability refers to the trustworthiness of a study and is greatly affected by the method chosen to deal with the data investigation as well as the number of observations in the study (Saunders et al., 2007).

[4] Validity refers to the accuracy of results, and high validity indicates that a study closely measures what it intends to measure (Saunders, Lewis & Thornhill, 2007).

3.3.1 Computation of returns

Daily and monthly returns are computed based on historical closing prices from the STI. In computing the returns, the following formula is used:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{3.1}$$

R_t is the return of day or month *t*

P_t is the closing price of day or month *t*

Daily returns represent the percentage difference between the closing prices of two successive trading days. Monthly returns are calculated in a similar way and represent the percentage difference between the closing prices of two successive months.

Average returns are computed by adding together the returns of a certain weekday or month and dividing by the number of observations in the sample. For example, the average Monday return for the full sample period is calculated as the sum of all Monday returns divided by the number of Mondays in the sample period.

$$\overline{R} = \frac{1}{n}\sum_{t=1}^{n} R_t \tag{3.2}$$

$\overline{R}$ is the average daily or monthly return

n is the number of observations in the sample period

R_t is the return of a certain weekday or month *t*

3.3.2 Null and alternative hypotheses

To investigate day-of-the-week effects and month-of-the-year effects, one sample t-tests are used to test the average return of each weekday or month against the average return of all weekdays or months. The null hypothesis (H_0) suggests that the average return (μ) of a certain day (Monday to Friday) or month (January to December) is equal to the average return of all days or months in the sample. This is tested against an alternative hypothesis (H_A), which suggests that the average return of a certain weekday or month is different from the total average return of all days or months in the sample.

$$\mathbf{H_0:}\ \mu_i = \mu_j$$
$$\mathbf{H_A:}\ \mu_i \neq \mu_j$$

μ_i is the average return of a certain weekday or month *i*

μ_j is the average return of all weekdays or all months in the sample

After this initial test, paired observation t-tests are used to further test for equality in average returns between two particular weekdays or months. The average returns of all weekdays are paired and tested against each other, while the average returns of all months are also paired and tested against each other.

$$\mathbf{H_0:}\ \mu_i = \mu_j$$
$$\mathbf{H_A:}\ \mu_i \neq \mu_j$$

μ_i is the average return of a certain weekday or month *i*

μ_j is the average return of a certain weekday or month *j*

3.3.3 Significance analysis

To test the significance of differences in average returns, statistical t-tests are used. This method is commonly used to determine the probability of two samples belonging to the same underlying population (Aczel & Sounderpandian, 2008).

In the initial phase of the investigation, where the average return of a certain weekday or month is tested against the average return of all weekdays or months, the one sample t-statistic is computed as follows:

$$t = \frac{\overline{X} - \mu}{S\sqrt{n}} \tag{3.3}$$

$\overline{X}$ is the average return of a certain weekday or month

μ is the total average return of all weekdays or months in the sample

S	is the sample standard deviation
n	is the number of observations in the sample

In the second phase of the investigation, where observations are tested pairwise, the t-statistic is computed as follows:

$$t = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)_0}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} \tag{3.4}$$

$\overline{X}_{1,2}$	are the observed average returns of weekdays or months 1 and 2
$\mu_{1,2}$	are the population mean values of weekdays or months 1 and 2 under the null hypothesis
$S_{1,2}$	are the standard deviations of weekdays or months 1 and 2
$n_{1,2}$	are the number of observations of weekdays or months1 and 2

The standard deviation (S) used in equations 3.3 and 3.4 is calculated as follows:

$$S = \sqrt{S^2} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n-1}} \tag{3.5}$$

x_i	is the average return of a certain weekday or month *i*
$\overline{x}$	is the total average return of all weekdays or months in the sample
n	is the number of observations in the sample

The hypotheses are tested at the 1%, 5% and 10% significance levels (α), and critical values from the t-distribution are used to determine whether to accept or reject the null hypothesis. All tests are two-tailed, since both positive and negative deviations from average returns are tested. Consequently, the t-statistic is compared to both a positive and a negative critical value, and the null hypothesis is rejected if the t-statistic is significantly larger than the positive critical value, or significantly smaller than the negative critical value. Accepting the null hypothesis does however not prove that it is true, only that its credibility is above the significance level and hence it cannot be rejected (Aczel & Sounderpandian, 2008). For the purpose of this study, accepting the null hypothesis implies that there is no significant evidence of the effect being investigated, while rejecting the null hypothesis suggests that the effect exists.

3.3.4 Calendar strategies

Statistically significant effects are used to develop two investment strategies, one based on day-of-the-week effects and another based on month-of-the-year effects. The strategies are developed and explained in the analysis section, and the aim of both strategies is to earn returns in excess of the market. To evaluate the performance of the investment strategies, a starting capital of 100 is assumed, although certain strategies will use leverage as a means of increasing returns. The capital is invested in the calendar strategy, and the performance is compared to a buy-and-hold strategy that invests the full capital in the STI over the full sample period from January 1st 1993 to December 31st 2011.

3.4 Limitations

In developing the investment strategies, three main assumptions are made:

1. There are no transaction costs associated with any of the strategies.
2. For the purpose of leveraging, individual investors can borrow at a rate equal to the Singapore Interbank Offered Rate (SIBOR)[5].
3. Investors are not subject to capital gains taxes.

These types of assumptions are commonly made in studies of this nature, mainly for reasons of simplicity and differences between different types of investors and in different countries. The implications of such assumptions are that the results of the investment strategies developed in this study may not be fully representative, and rather they should serve as guidelines for investors seeking to capitalize on seasonal anomalies in the STI. It should also be noted that while this study analyses seasonalities from a be-

[5] The Singapore Interbank Offered Rate (SIBOR) is the rate at which banks in Asian time zones lend to each other. It is widely used as a daily reference rate for borrowers and lenders involved in Asian financial markets. At the time of writing, the one-month rate was 0.31% (The Association of Banks in Singapore, 2012).

havioural perspective, there might exist other, non-psychological and more rational explanations to such effects.

Furthermore, this study uses a methodology based on statistical t-tests. While the same method is used in several other studies of seasonal anomalies, alternative methods, such as Chi-square tests and regression analysis may produce other results.

4 Empirical findings and analysis

This part presents the results of the statistical investigations. Day-of-the-week effects are first identified and analysed, which is followed by a similar investigation of month-of-the-year effects. Finally, the findings are used to develop two investment strategies, a day-of-the week strategy and a month-of-the-year strategy.

4.1 Investigation of day-of-the-week effects 1993-2011

Figure 4.1 shows the average daily returns over the full sample period, stretching from January 1st 1993 to December 31st 2011. Negative returns are recorded in the first two days of the week with Monday returns of -0.0074% being the lowest. With positive returns concentrated to the last three trading days of the week, a positive trend can be identified as the weekend approaches, with a Friday return of 0.0089% being the highest of the week.

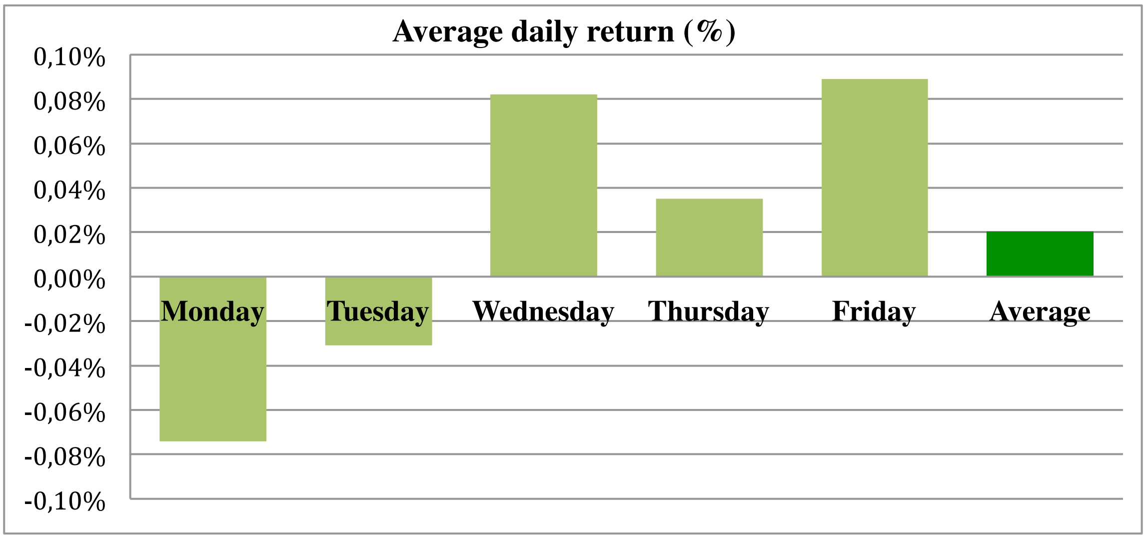

Figure 4.1 *Average daily returns.*

The return distribution found in this investigation largely support the findings of Cross (1973), French (1980), Gibbons & Hess (1981) and Keim & Stambaugh (1984), who all found evidence of negative Monday returns and high Wednesday and Friday returns in the US markets. The study also support the findings of Hui (2005) who found evidence of particularly low Monday and Tuesday returns, and high returns on Wednesdays and Fridays in his study of the Singapore markets between 1998 and 2001.

Table 4.1 summarizes the average returns, standard deviations and t-statistics of each weekday over the full sample period, and the only statistically significant day-of-the-week effect is a negative Monday effect. While a weekend effect cannot be statistically confirmed, the existence of a negative Monday effect supports the idea that individual investors are more active sellers of stocks on Mondays. Behavioural finance offers one possible explanation to such behaviour in the latent selling need that arises partially from negative news releases after the market close on Fridays (Kumari & Raj, 2006). Over the weekend, investors have more time to reflect over bad news and analyse their portfolios, and consequently, a large number of investors are waiting for the stock exchange to open on Mondays to alter their holdings after the weekend.

Table 4.1 *Day-of-the-week effects 1993-2011*

Day	Average return	Std. deviation	t-statistic
Monday	-0.00074	0.0134005	-2.17**
Tuesday	-0.00031	0.0133951	-1.19
Wednesday	0.00082	0.0133951	1.43
Thursday	0.00035	0.0133984	0.33
Friday	0.00089	0.0133937	1.58
*** indicate significance at the 0.05 level.*			

4.1.1 The day-of-the-week effect 2006-2011

Table 4.2 summarizes the average returns, standard deviations and t-statistics for the most recent sub-period in which there is no evidence of a significant day-of-the-week effect.

Table 4.2 *Day-of-the-week effects 2006-2011*

Day	Average return	Std. deviation	t-statistic
Monday	-0.00016	0.0142414	-0.41
Tuesday	-0.00075	0.0142166	-1.13
Wednesday	0.00104	0.0142148	1.06
Thursday	0.00027	0.0142141	0.10
Friday	0.00048	0.0142149	0.36

4.1.2 The day-of-the-week effect 2000-2005

Table 4.3 summarizes the average returns, standard deviations and t-statistics for the period 2000 to 2005, which is the only sub-period in which day-of-the-week effects are proven. Just as over the full sample period, a negative Monday effect is present in this sub-period, while there is also evidence of a positive Friday effect. Consequently, the well-documented weekend effect is proven. Interestingly, the negative Monday effect is also associated with the highest volatility, while the positive Friday effect occurs on the day with the least volatile returns.

Table 4.3 *Day-of-the-week effects 2000-2005*

Day	Average return	Std. deviation	t-statistic
Monday	-0.00117	0.0116311	-1.78*
Tuesday	0.00062	0.0115667	0.89
Wednesday	-0.00064	0.0115547	-1.00
Thursday	0.00014	0.0114676	0.17
Friday	0.00118	0.0114624	1.74*
** indicates significance at the 0.10 level.*			

4.1.3 The day-of-the-week effect 1993-1999

Table 4.4 summarizes the average returns, standard deviations and t-statistics of the earliest sub-period in which there is no evidence of a day-of-a-week effect.

Table 4.4 *Day-of-the-week effect 1993-1999*

Day	Average return	Std. deviation	t-statistic
Monday	-0.00087	0.0404014	-0.57
Tuesday	-0.00074	0.0404022	-0.52
Wednesday	0.00189	0.0404082	0.70
Thursday	0.00059	0.0404063	0.10
Friday	0.00100	0.0404046	0.29

4.1.4 Summarizing analysis: day-of-the-week effects 1993-2011

Over the full sample period, a negative Monday effect is present in the STI. While Fridays historically yield the highest returns and Mondays the lowest, the weekend effect is only statistically proven during the period between 2000 and 2005. By confirming the existence of a day-of-the-week effect, this study suggests that the Singapore stock market is not as efficient as suggested by the EMH, and an irrational trading pattern may exist amongst both individual and institutional investors. Behavioural finance offers a possible explanation to such behaviours, suggesting that sales volumes increase on Mondays as a result of a latent selling need amongst investors after a trading-free weekend. Cross (1973) along with a number of other researchers has found evidence of a negative Monday effect in US markets, while in Singapore, Hui (2005) found a similar effect over the period 1998 to 2001. The EMH suggests that market anomalies should disappear over time (Fama, 1998), and the fact that this study has confirmed the existence of a persistent negative Monday effect over a 19-year period raises further doubts about the validity of the EMH.

This study shows that the presence of day-of-the-week effects in the STI varies over time. While the accumulated results of the full 19-year sample period show evidence of a significant negative Monday effect, only one of the three sub-periods shows evidence of significant day-of-the-week effects. In the second sub-period, 2000 to 2005, both a negative Monday effect and a positive Friday effect are identified and consequently, the weekend effect is present in the Singapore stock market. However, no day-of-the-week effects are confirmed in the first sub-period, 1993 to 1999, nor in the most recent sub-period 2006 to 2011. Despite the varying presence of day-of-the-week effects in the individual sub-periods, the fact that a negative Monday effect is documented over the full sample period is interesting for investors with a long-term investment horizon.

4.2 Investigation of month-of-the-year effects 1993-2011

Figure 4.2 shows the average monthly returns over the full sample period, stretching from January 1st 1993 to December 31st 2011. Negative returns occur in five months of the year, and historically, the period in August and September is a particularly bad period to hold stocks. Interestingly, in contrast to most studies of western markets, a negative January effect is apparent, while other negative returns are recorded in March and May. Seven months offer positive returns, with November and December being two especially good months for investors. April returns of 3.03% are by far the highest, while positive returns are also observed in February, June, July and October.

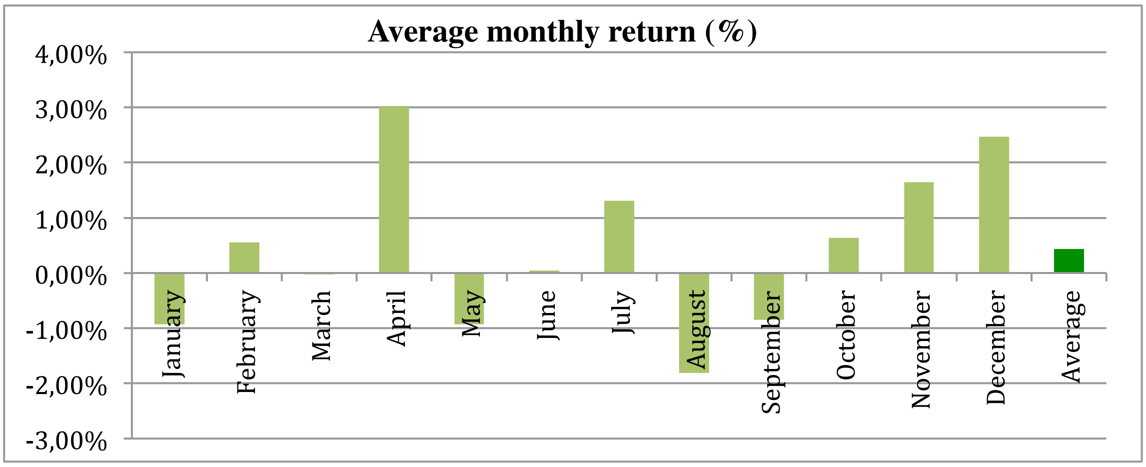

Figure 4.2 *Average monthly returns.*

The findings of this study are largely in line with those of Rozeff & Kinney (1976) who found evidence of high returns in July, November and December in their study of the US markets. The investigation also supports the findings of Gultekin & Gultekin (1983), who found negative August and September effects when studying the markets of 17 industrialized countries.

Table 4.5 shows the average returns, standard deviations and t-statistics for the full sample period 1993 to 2011. Statistically significant month-of-the-year effects are recorded in a number of months, with negative effects observed in January, May, August and September, and positive effects in April, July, November and December. The lowest returns are earned in August, while April is the best month for investors with higher return and lower volatility than both November and December.

Table 4.5 *Month-of-the-year effects 1993-2011*

Month	Average return	Std. deviation	t-statistic
January	-0.00935	0.0134712	-4.42***
February	0.00551	0.0134745	0.39
March	-0.00025	0.0134829	-1.47
April	0.03028	0.0134864	8.40***
May	-0.00927	0.0134887	-4.38***
June	0.00047	0.0134807	-1.24
July	0.01309	0.0134777	2.84**
August	-0.01811	0.0135323	-7.22***
September	-0.00843	0.0135662	-4.09***
October	0.00642	0.0135979	0.68
November	0.01647	0.0136192	3.90***
December	0.02472	0.0136274	6.53***
****and ** indicate significance at 0.01 and 0.05 levels, respectively.*			

4.2.1 The month-of-the-year effect 2006-2011

Table 4.6 shows the average returns, standard deviations and t-statistics for the period 2006-2011. Negative month-of-the-year effects are found in January, February, August, October and November, while positive effects occur in March, April, July and December. Just as over the full sample period, the lowest returns are earned in August and the highest in April. Worth noting, the November effect, which is significantly positive in the full sample period and in the other two sub-periods, is negative between 2006 and 2011.

Table 4.6 *Month-of-the-year effects 2006-2011*

Month	Average return	Std. Deviation	t-statistic
January	-0.02226	0.0146014	-4.37***
February	-0.01640	0.0146215	-3.38**
March	0.03534	0.0146580	5.27***
April	0.04954	0.0146839	7.63***
May	0.01519	0.0147037	1.9
June	-0.00360	0.0146096	-1.24
July	0.03500	0.0145281	5.27***
August	-0.03676	0.0146798	-6.76***
September	-0.00201	0.0147830	-0.96
October	-0.01587	0.0149167	-3.23**
November	-0.01239	0.0149690	-2.65**
December	0.01953	0.0150007	2.57**
****and ** indicate significance at 0.01 and 0.05 levels, respectively.*			

4.2.2 Month-of-the-year effects 2000-2005

Table 4.7 summarizes the average returns, standard deviations and t-statistics for the period 2000 to 2005. Negative month-of-the-year effects are found in February, March, May and September, while positive effects occur in June, July, October, November and December. The highest returns are earned in June, while September returns are by far the lowest. The low September returns can partially be explained by the events on September 11th in 2001, after which the STI tumbled by 15.33% during the remainder of the month (Yahoo! Finance, 2012, a).

Table 4.7 *Month-of-the-year effects 2000-2005*

Month	Average Return	Std. Deviation	t-statistic
January	0.00969	0.0123327	1.79
February	-0.01491	0.0120485	-3.16**
March	-0.01593	0.0119736	-3.39**
April	0.00102	0.0118280	0.08
May	-0.03521	0.0114358	-7.68***
June	0.03709	0.0112763	7.92***
July	0.01850	0.0111396	3.92**
August	0.00250	0.0111111	0.41
September	-0.04903	0.0110647	-11.0***
October	0.02159	0.0110374	4.65***
November	0.01308	0.0108226	2.81**
December	0.01946	0.0106746	4.32***
**** and ** indicate significance at 0.01 and 0.05 levels, respectively.*			

4.2.3 Month-of-the-year effects 1993-1999

Table 4.8 shows the average returns, standard deviations and t-statistics for the period 1993 to 1999. This is the period with the largest number of significant effects, and October is the only month in which no effect is recorded. Negative month-of-the-year effects are found in January, March, May, June, July and August, while positive returns are recorded in February, April, September, November and December. Similar to the other sub-periods, April and December exhibit positive returns with the highest volatility again concentrated to the last two months of the year. Interestingly, the July effect, which is positive over the full sample period and in the other two sub-periods, is negative in this sub-period. Furthermore, the September effect, which is negative over the full sample period, is positive in this sub-period.

Table 4.8 *Month-of-the-year effects 1993-1999*

Day	Average Return	Std. Deviation	t-statistic
January	-0.01461	0.0140809	-4.22***
February	0.04179	0.0142096	6.32***
March	-0.01731	0.0142201	-4.68***
April	0.03885	0.0143840	5.70***
May	-0.00799	0.0144507	-2.90**
June	-0.02742	0.0144678	-6.45***
July	-0.01034	0.0146091	-3.30**
August	-0.01980	0.0146982	-4.98***
September	0.02087	0.0147195	2.34*
October	0.01254	0.0147916	0.84
November	0.04411	0.0148175	6.47***
December	0.03367	0.0148520	4.60***

****, ** and * indicate significance at 0.01, 0.05 and 0.10 levels, respectively.*

4.2.4 Summarizing analysis: month-of-the-year effects 1993-2011

Over the full sample period, January, May, August and September offer significantly negative returns whereas positive effects are recorded in April, July, November and December.

While a large number of previous studies have found evidence of a positive January effect in global stock markets (Rozeff & Kinney, 1976; Mehdian & Perry, 2002), this study identifies a negative January effect in the STI over the period 1993 to 2011. Positive January effects are often explained by the tax-loss hypothesis, but such investor behaviour cannot explain the reverse January effect identified in this study. In most cases, the positive January effect is found in countries where investors have to pay taxes on capital gains, and the fact that no such taxes are payable in Singapore (IRAS, 2011) offers a possible explanation as to why no such effect is present in the STI. Instead, the reverse January effect can possibly be explained by the upcoming Chinese New Year. According to Jacobs & Levy (1988) calendar anomalies occur at turning points in time. The Chinese New Year constitutes one such turning point, and while it is not associated with the start of a new tax year or any tax benefits, the negative price development may be caused by investors clearing out their portfolios ahead of the New Year.

Over the full sample period, and in two of the three sub-periods, April returns are the highest. The abnormally high April returns may be attributable to the start of the new tax year, as Singapore's fiscal year runs from April 1st to March 31st (Blöndal, 2006). This explanation is further supported by Gultekin & Gultekin's (1983) findings of a similar effect in the UK, where the fiscal year also starts in April. As previously mentioned, the first month of the new tax year is often found to be one of the best months for investors, which is often explained by the tax-loss and window-dressing hypotheses. While the former is not applicable to the Singapore context, the window-dressing hypothesis may offer a possible explanation to the positive April effect in both Singapore and the UK. Interestingly, Gao & Kling (2005) also found evidence of a positive April effect in China, and with almost 75% of the Singapore population being of Chinese origin (Singapore Department of Statistics, 2010), seasonal anomalies in these two markets may be correlated.

While some explanations to seasonal anomalies, such as the abovementioned tax-loss and window-dressing hypotheses, are widely accepted and valid in most countries, other possible explanations are more limited and applicable only to a few countries. For example, Singapore society, just as many other Asian societies, is widely influenced by traditions, superstitions and folklore, and while certain events, such as National Day on 9th August are widely celebrated by most people, other events are concentrated to certain ethnical or religious groups. Singapore is a melting pot of different cultures and religions, and this wide diversity may help explain the large number of seasonal effects identified in this investigation. Despite being a widely diverse society, the majority of the Singapore population have roots in China, and interestingly, several monthly anomalies clearly coincide with significant events in the lunar calendar.

The high July returns is one example of an anomaly that can possibly be explained by traditions and the mood of Singaporeans in anticipation of the highly celebrated National Day on August 9th. During the month leading up to the celebrations, trading volumes and stock prices tend to increase (CNBC, 2012) in response to the general market sentiment. During periods of strong positive development, it is not unlikely that irrational investor behaviour increases, as more people want to make the most of the occasion.

The positive July returns are historically followed by negative price developments in August and September, which could be explained by superstitions associated with the 'hungry ghost month'. The 'hungry ghost month' occurs during the seventh month of the lunar year, and with the new lunar year starting around the January-February turn-of-the-month, it falls sometime in the period August-September. During this period, which is associated with bad luck, Chinese people are superstitious and risk averse, hence discouraged from taking part in major events and activities (Chinese Culture, 2012). With three out of four Singaporeans being of Chinese descent, the 'hungry ghost month' plays a significant role in Singaporean society, and it is also likely that such effects are correlated to the stock market and the negative returns that occur at that time of the year.

Notably, the successive months of November and December constantly exhibit high stock returns with the exception of negative November returns in the sub-period 2006 to 2011. According to the expression "sell in May and go away", November through April is the best period to invest in stocks (Bouman & Jacobsen, 2002). This study finds evidence in support of the expression, as the total average returns for the months November to April totals 6.74%, whereas the equivalent returns between May and October totals -1.58%.

4.3 Development of investment strategies

The statistical investigation shows evidence of several seasonal anomalies in the Singapore stock market. While a negative Monday effect is the only significant day-of-the-week effect, several monthly anomalies are present in the STI. Positive effects are recorded in April, July, November and December, while negative effects occur in January, August and September. These effects are used to develop two investment strategies, one based on the day-of-the-week effects, and another based on the month-of-the-year effects. The strategies are evaluated by comparing the returns to a buy-and-hold strategy that invests the full capital in the STI on the first day of the sample period and retains the initial position over the entire period from January 1st 1993 to December 31st 2011. Consequently, the buy-and-hold strategy completely tracks the performance of the STI.

4.3.1 The day-of-the-week strategy

The findings of this study suggest significant evidence of one day-of-the-week effect, a negative Monday effect. The day-of-the-week strategy is therefore designed to take advantage of this negative effect by avoiding exposure to the STI on Mondays.

The day-of-the week strategy is based on two actions[6]:

1. During days when there is no evidence of a significant effect, the strategy takes a 100% exposure towards the STI.
2. During Mondays, where a negative effect has been identified, the full position is sold and the strategy takes a 0% exposure towards the STI.

The day-of-the-week strategy is derived using the following equation:

$$\mathrm{Strategy}_t = \mathrm{Strategy}_{t-1} * \left(1 + \frac{\mathrm{STI}_t - \mathrm{STI}_{t-1}}{\mathrm{STI}_{t-1}}\right) * x(t)$$

x(t) is the proportion of own capital invested in the STI (0 on Mondays, 1 Tuesday to Friday)

[6] A detailed illustration of the actions involved with the day-of-the-week strategy is presented in appendix 2.

Figure 4.3 plots the development of the day-of-the-week strategy and a buy-and-hold strategy with 100% exposure towards the STI. From the figure, it is evident that the day-of-the-week strategy has significantly outperformed the market over the course of the sample period.

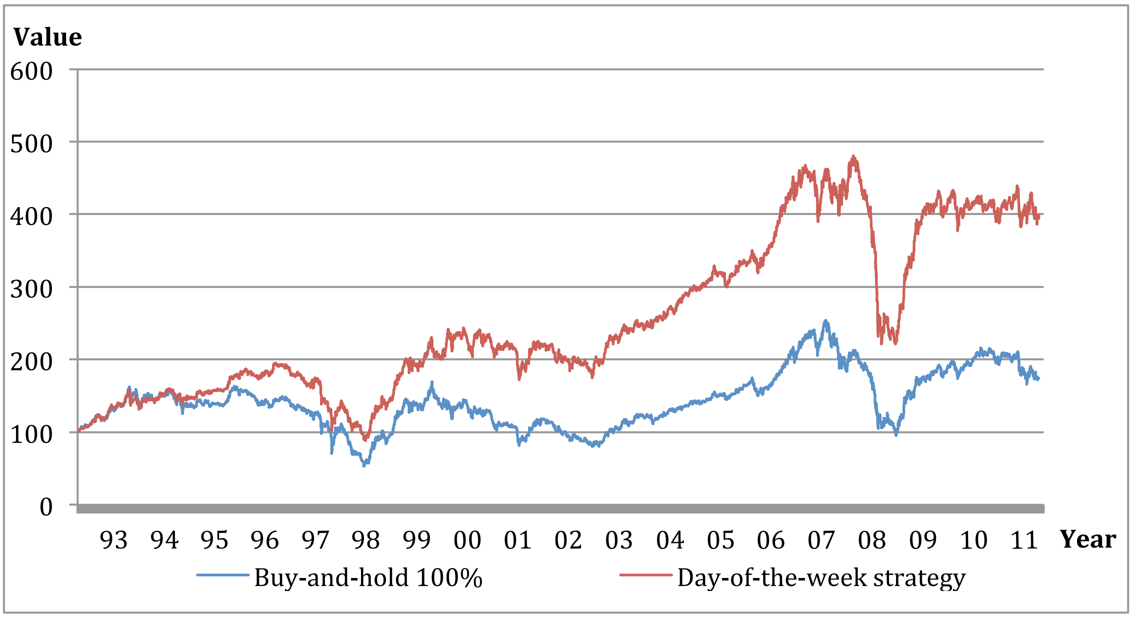

Figure 4.3 *The day-of-the-week strategy.*

Table 4.9 further illustrates the superiority of the day-of-the-week strategy. It summarizes the development of both strategies over the full sample period, and while the return on the buy-and-hold strategy was 73.63%, the day-of-the week strategy earned a positive return of 294.23%, an excess return of 220.6% over the period January 1st 1993 to December 31st 2011.

Table 4.9 *The day-of-the-week strategy*

Strategy	Jan. 1st 1993	Dec. 31st 2011	Return (%)
Buy-and-hold	100	173.633	73.63%
Day-of-the-week	100	394.230	294.23%

Figure 4.4 compares the yearly performance of the STI and the day-of–the-week strategy. While the accumulated return of the day-of-the-week strategy clearly exceeds the return on the buy-and-hold strategy, the former has also outperformed the market in 12 of 19 years. The STI rose during 10 of the 19 years in the sample period, but the day-of-the-week strategy was particularly preferable during the years of negative development.

The strategy outperformed the index during 8 of 9 years, and only in 1997, the day-of-the-week strategy fell more than the index, while in both 1996 and 1998, the strategy yielded positive returns while the STI fell. Only once, in 2010, the strategy has earned a negative return while the STI has risen. However, during the 10 years of positive development, the strategy has outperformed the index on 4 occasions.

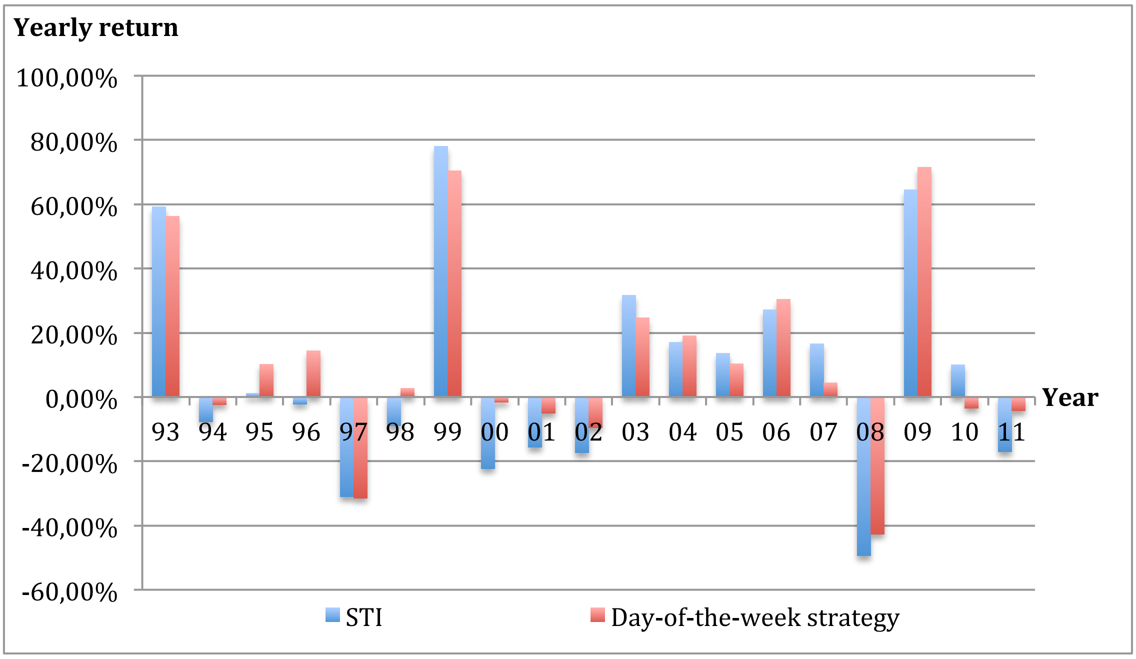

Figure 4.4 *Comparison: STI vs. Day-of-the week strategy.*

4.3.2 The month-of-the-year strategy

This study suggests statistical evidence for a number of monthly anomalies in the STI. Significantly positive returns occur in April, July, November and December, while significantly negative returns are recorded in January, May, August and September. The most efficient strategy is one that takes advantage of both positive and the negative effects, and in order to do so, the month-of-the-year strategy uses leverage to take advantage of positive effects. Leveraging does however involve an interest cost, which in this study is assumed equal to the one-month Singapore Interbank Offered Rate (SIBOR).

The month-of-the-year strategy is based on three actions[7]:

1. During months in which there is no evidence of a significant effect, the strategy takes a 100% exposure towards the STI.
2. During months where a negative effect has been identified, the full position is sold and hence the strategy takes a 0% exposure towards the STI.
3. During months where a positive effect has been proven, the capital is leveraged by 50%, and consequently, the strategy takes a 150% exposure towards the STI.

The month-of-the-year strategy is derived using the following equation:

$$\mathrm{Strategy}_t = \mathrm{Strategy}_{t-1} * \left[1 + \frac{\mathrm{STI}_t - \mathrm{STI}_{t-1}}{\mathrm{STI}_{t-1}} * [x(t) + y(t)] - y(t) * r(t)\right]$$

x(t) is the proportion of own capital invested in the STI (1, except in January, May, August and September when it is 0)

y(t) is the leverage factor (0, except in April, July, November and December when it is 0,5)

r(t) is the one-month SIBOR rate (0, except in April, July, November and December when it is 0.0031)

During good times, a high exposure towards the market is desirable, and comparing a strategy that at times takes a 150% exposure towards the market against a strategy that only takes a 100% exposure may lead to an unfair evaluation. Therefore, the month-of-the-year strategy is evaluated against both a traditional buy-and-hold strategy and a buy-and-hold strategy that takes a 150% exposure towards the STI over the full sample period.

Figure 4.5 plots the development of a buy-and-hold strategy with 100% exposure towards the STI, a buy-and-hold strategy with 150% exposure towards the STI, and the

[7] A detailed illustration of the actions involved with the month-of-the-year strategy is presented in appendix 2.

month-of-the-year strategy. While the buy-and-hold strategies show a similar development, with the leveraged strategy exhibiting the higher volatility, the month-of-the-year strategy is far superior to both the leveraged and the unleveraged buy-and-hold strategies.

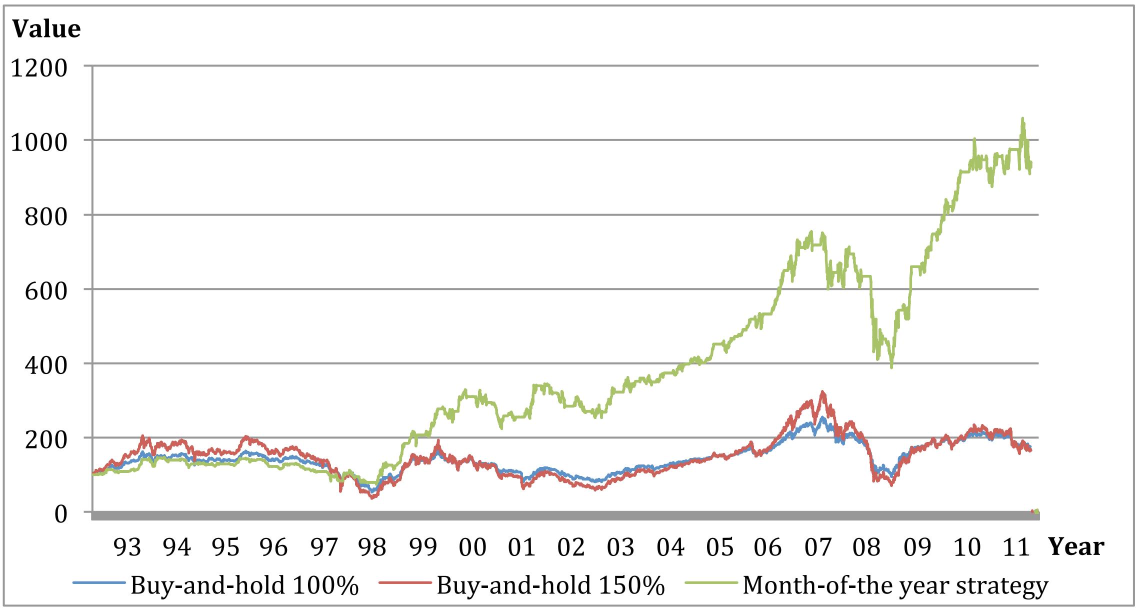

Figure 4.5 *The month-of-the-year strategy.*

The tremendous performance of the month of-the-year strategy is further evident in table 4.10, which summarizes the development of all three strategies over the full sample period. Interestingly, the leveraged buy-and-hold strategy performed worse than the unleveraged strategy, earning a total return of only 66.10%, as compared to 73.63% total return on the unleveraged buy-and-hold strategy. Over the same period, the month-of-the-year strategy yielded a return of 826%, an impressive 752.37% in excess of the market.

Table 4.10 *The month-of-the-year strategy*

Strategy	Jan. 1st 1993	Dec. 31st 2011	Return (%)
Buy-and-hold (100%)	100	173.633	73.63%
Buy-and-hold (150%)	100	166.097	66.10%
Month-of-the-year	100	926.002	826.00%

Figure 4.6 compares the yearly performance of the STI and the month-of–the-year strategy. While the month-of-the-year strategy has earned an incredible excess return over

the full sample period, it has also outperformed the STI during 10 of the 19 years included in the sample period. Whereas the day-of-the-week strategy performed particularly well during bad times, the month-of-the-year strategy is more or less equally preferable during good and bad times, outperforming the market in 5 of the 10 years of positive development, and in 5 of the 9 years of negative development. The benefits of leverage and higher exposure towards the market are particularly evident during the best year, 1999, when the STI rose by 78.04% while the month-of-the-year strategy yielded a return of 120.98%. During years of negative development, the month-of-the-year strategy performed less badly than the market on 5 out of 9 occasions. In 1998, 2000 and 2001, the strategy earned positive returns when the index fell, while in 2007, the reverse happened as the strategy yielded a small negative return when the STI rose by 16.63%.

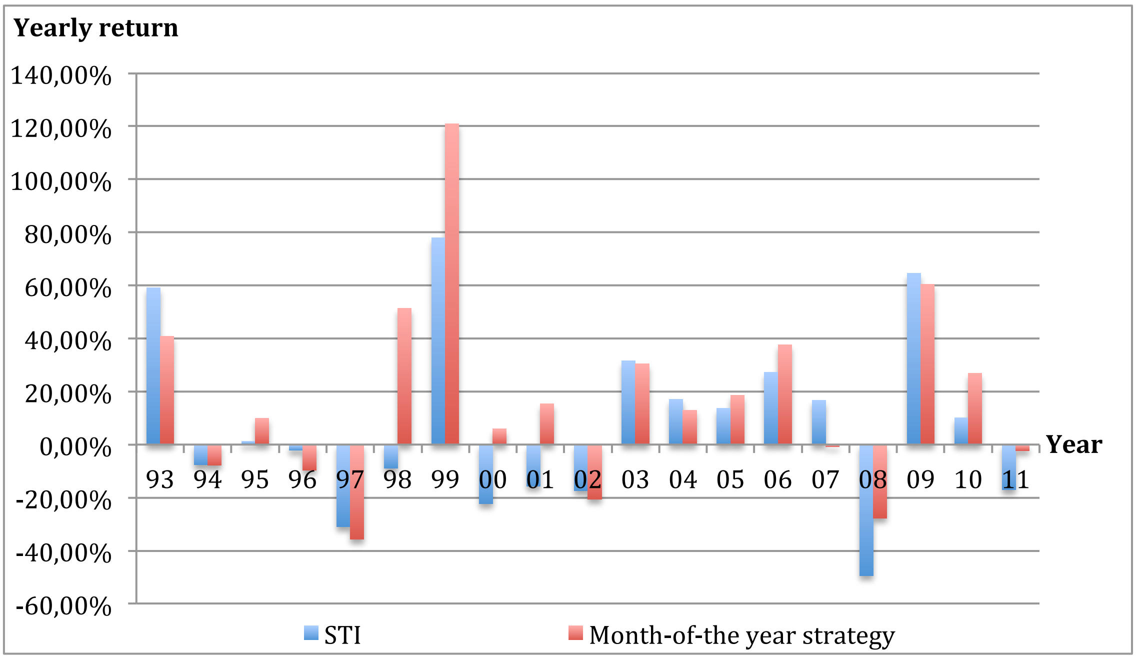

Figure 4.6 *Comparison: STI vs. Month-of-the-year strategy.*

4.3.3 Risk and return comparison of investment strategies

Investment strategies should not be evaluated solely on returns. Higher returns may come at the cost of higher volatility, and these two components must both be considered in order to make a fair evaluation of any investment strategy. According to the EMH, investors cannot earn higher returns without assuming a higher level of risk (Fama, 1965), and accordingly, any investment that increases the return should also imply a higher level of risk. From the average daily returns and volatilities in table 4.11, no such risk-return relationship is evident between the calendar strategies and the buy-and-hold strategies, and consequently, the findings contradict one of the key fundamentals of mainstream finance theory, the risk-return relationship.

Table 4.11 *Average daily return and volatility of the strategies*

Strategy	Average daily return	Daily volatility
Buy-and-hold 100%	0.02%	1.34%
Buy-and-hold 150%	0.01%	2.01%
Day-of-the-week	0.06%	1.13%
Month-of-the-year	0.17%	1.32%

Despite being subject to higher volatility, the leveraged buy-and-hold strategy offers a lower return than its unleveraged equivalent, making it the least appealing strategy discussed in this thesis. Both the day-of-the-week strategy and the month-of-the-year strategy offer returns that are significantly higher than the return of the buy-and-hold strategy. The return of the day-of-the-week strategy is 3 times higher than the return of the buy-and-hold strategy, while the month-of-the-year strategy offers a return of more than 8 times the buy-and-hold strategy. Despite this, both the day-of-the-week strategy and the month-of-the-year strategy offer returns that are less volatile than the return of the buy-and-hold strategy. This makes both strategies preferable to a traditional buy-and-hold strategy, and in particular the month-of-the-year strategy looks very appealing to the investor.

The lower volatility of the day-of-the-week strategy is a result of investing in four rather than five days of the week. By taking a shorter exposure to the market, the strategy is subject to fewer fluctuations and consequently to lower volatility. The same explanation is valid for the volatility of the month-of-the-year strategy, which despite taking a 150% exposure to the market during months of statistically positive returns completely avoids exposure to the market during four months each year.

It is important to point out that while both the day-of-the-week strategy and the month-of-the-year strategy look attractive, they are both developed under certain assumptions. Before deciding on the most appropriate strategy, additional costs, including transaction costs, interest rates and capital gains taxes must be considered from the perspective of each individual investor since such costs may prevent investors from capitalizing on seasonalities.

5 Conclusions

The purpose of this thesis has been to study the possible existence of day-of-the-week effects and month-of-the-year effects in the Singapore stock market. The findings have been analysed with the intention of developing investment strategies and to investigate if behavioural finance can help to explain the existence of such anomalies.

The investigation shows statistical evidence of several seasonal anomalies in the Straits Times Index over the period January 1st 1993 to December 31st 2011. A day-of-the-week effect has been identified on Mondays, during which returns are abnormally negative. Furthermore, several month-of-the-year effects have been identified, and positive effects occur in April, July, November and December, while negative effects are recorded in January, May, August and September. While these effects have been observed over the full 19-year sample period, the existence of seasonal anomalies has been proven to vary over time.

Based on these seasonal effects, two investment strategies have been developed. The day-of-the-week strategy, which avoids exposure to the STI on Mondays, has been proven to outperform the STI by 220.6% over the course of the sample period. The month-of-the-year strategy, which avoids exposure to the STI in January, May, August and September, and takes a 150% exposure towards the index during April, July, November and December, has earned returns of 752.37% in excess of the market over the same period. Despite clearly outperforming the market, the returns of both strategies are less volatile than the returns of a simple buy-and-hold strategy, making both the day-of-the-week strategy and the month-of-the-year strategy highly preferable to the investor. It should however be noted that the investment strategies have been developed under certain assumptions, and the inclusion of transaction costs, capital gains taxes and interest costs other than the SIBOR rate would have a depreciative effect on the results.

Having proven the existence of seasonalities, this study also shows that the Singapore stock market is not efficient in accordance with the efficient market hypothesis. Consequently, mainstream finance theory is not sufficient to explain such anomalies and must be complemented with alternative frameworks. Behavioural finance offers one such framework, and many of the anomalies identified in this study can be explained by investor irrationality.

To conclude, this thesis proves that a number of seasonal anomalies are present in the Straits Times Index, many of which can be explained by the theories of behavioural finance. It is further proven that these anomalies can be used to develop investment strategies that clearly outperform the market and reduce the risk by avoiding exposure to the market during periods in which negative effects have been confirmed.

6 Suggestions for further research

This investigation identifies a number of seasonal anomalies in the Straits Times Index, which raises several questions that would benefit from future research. By focusing exclusively on the STI, an index composed of companies from a number of different industries, no industry-specific seasonalities are identified in this study. A study of specific industry indices would allow for a more detailed analysis of seasonalities in the Singapore equity market, and consequently, the investment strategies developed in this study could be further refined.

Furthermore, the diverse and multi-cultural population of Singapore means that a study of investment patterns amongst specific ethnical groups could further help explain and understand why anomalies occur at certain times of the year.

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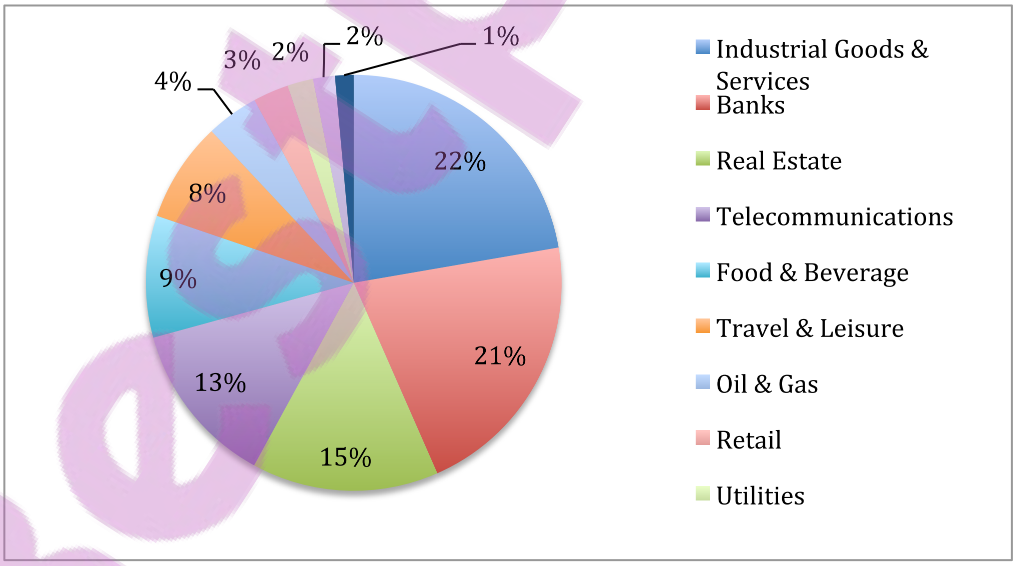
Appendix 1 – STI constituents and supersector classifications

STI Constituents (Ranked after Market Capitalization)	ICB Supersector Classification	Index Weight (%)
1. Singapore Telecommunications	Telecommunications	11.52
2. DBS Group Holdings	Banks	7.28
3. Wilmar International	Food & Beverage	7.20
4. Oversea-Chinese Banking Corporation	Banks	7.07
5. United Overseas Bank	Banks	6.74
6. Genting International PLC	Travel & Leisure	4.79
7. Jardine Strategic Holdings	Industrial Goods & Services	4.65
8. Keppel Corporations	Industrial Goods & Services	4.59
9. Jardine Cycle & Carriage	Oil & Gas	4.06
10. Jardine Matheson Holdings	Industrial Goods & Services	3.60
11. Hongkong Land Holdings	Real Estate	3.27
12. Capitaland	Real Estate	3.03
13. Singapore Airlines	Travel & Leisure	2.98
14. Sembcorp Marine	Industrial Goods & Services	2.55
15 City Development	Real Estate	2.31
16. Global Logistic Properties	Real Estate	2.30
17. Golden Agri-Resources Ltd	Food & Beverage	2.25
18. Singapore Technologies Engineering	Industrial Goods & Services	2.24
19. Sembcorp Industries	Utilities	2.20
20. Fraser and Neave	Real Estate	2.19
21. Noble Group	Industrial Goods & Services	2.00
22. Singapore Exchange	Financial Services	1.69
33. CapitaMalls Asia	Retail	1.45
24. Singapore Press Holdings	Media	1.45
25. Capitamall Trust	Real Estate	1.41
26. Olam International	Retail	1.32
27. Starhub	Telecommunications	1.25
28. SIA Engineering Company	Industrial Goods & Services	1.01
29. Neptune Orient Lines	Industrial Goods & Services	0.86
30. Comfortdelgro Corporation	Industrial Goods & Services	0.74



(Yahoo! Finance, 2012 b)

Appendix 2 – Investment strategies

The day-of-the-week strategy

Day	Effect	Action
Monday	Negative	-
Tuesday	No effect	Invest 100% at opening price
Wednesday	No effect	-
Thursday	No effect	-
Friday	No effect	Sell full position at closing price

The month-of-the-year strategy

Month	Effect	Action 1	Action 2
January	Negative	-	-
February	No effect	Invest 100% at opening price first trading day	-
March	No effect	-	-
April	Positive	Invest additional 50% lever-aged capital at opening price first trading day	Sell full position at clos-ing price last trading day
May	Negative	-	-
June	No effect	Invest 100% at opening price first trading day	-
July	Positive	Invest additional 50% lever-aged capital at opening price first trading day	Sell full position at clos-ing price last trading day
August	Negative	-	-
September	Negative	-	-
October	No effect	Invest 100% at opening price first trading day	-
November	Positive	Invest additional 50% lever-aged capital at opening price first trading day	-
December	Positive	-	Sell full position at clos-ing price last trading day