An Investigation into the Strength of the 52-week high Momentum Strategy in the United States

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Abstract

This thesis extends the 52-week high momentum literature, which was first published by George and Hwang in 2004, by stressing the parameters of the trading strategy to investigate its robustness. George and Hwang, in their seminal paper, find that the ratio of a stock's close price to its 52-week high price is a good predictor of future returns.

The thesis stresses various parameters of the strategy - such as the percent of total stocks bought and sold each period – and applies the strategy over different time periods – such as bull and bear markets. The study finds that the strategy is more profitable over the later half of the data set due to underperformance in bear markets such as the 1929 market crash and subsequent Great Depression. The results also show a significant difference in profitability between bull and bear market periods.

The second half of the thesis looks at a new area in momentum, the absolute 52-week high. The strategy buys stocks whose price has increased over the previous six months, and who also close to their 52-week high price. Stocks are only bought (sold) if their price has increased (decreased) over the past six months and is close to (far from) the 52-week high price. The aim is to cut out stocks that are considered to be underperforming in the 52-week high momentum strategy, leaving only true winner and loser stocks. This strategy was found to increase the strength of the 52-

week high momentum strategy, and the results show that there is no longer a significant difference between bull and bear market returns.

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1. Introduction

Understanding the psychology of investors is the basis behind behavioural finance. If investor decision making is predictable then the stock market would become predictable. This means that investors who know the formula of the stock market can make money without taking on any risk. Recent literature has focused on devising a method that will allow the maximisation of profit with minimal input and a decreased level of risk.

The highest and lowest price of a stock over the last 52-weeks can act as a resistance barrier. When a stock is close to a trading barrier, traders and investors are less likely to extend the price into territory that is beyond what has previously been regarded a reasonable price for the stock. If this psychology is applied to a stock that is close to/far from its 52-week high, and we assume positive/negative news is announced, we would expect the price to bounce around the resistance barrier until the news is so prevalent that it pushes the stock price through. If this is true, stocks that are close to their 52-week high/low have an increased chance of increasing/decreasing in the short to intermediate term.

In 2004 George and Hwang published their seminal paper *The 52-week high and momentum investing* which created the 52-week high momentum theory and tested it in the U.S. stock market. They found that buying those stocks that were close to their 52-week high price, and selling those furthest from their 52-week high resulted in abnormal monthly returns of 0.45%. The 52-week high momentum strategy has also been tested in an out-of-sample context in the Australian market by Marshall and Cahan (2005), who showed positive abnormal monthly returns of 2.14%. In 1993, Jegadeesh and Titman published *Returns to buying winners and selling losers: Implications for stock market efficiency*. They found that by buying stocks that have performed well in the past and selling stocks that have underperformed they could gain positive abnormal results. This paper and the many that have followed tested the idea that a previous stock price can help determine its future price, making the stock market predictable. As the 52-week high price and a stock's past price are publicly available information, these results present a challenge to weak and semi-strong form of the Efficient Market Hypothesis.

This thesis aims to extend current literature by testing the robustness of the 52-week high strategy, which has previously been completed for price momentum but not for 52-week high momentum. By challenging the underlying assumptions of these strategies, this thesis will provide an in-depth analysis of how this theory performs under different sets of conditions. The percentage of stocks held in each portfolio will be modified, the strategy will be tested in different market conditions and finally absolute momentum will be combined with the strategy to see if it can make the result stronger. These tests will allow the 52-week high momentum to be objectively examined to see if it can legitimately provide a challenge to the Efficient Market Hypothesis.

The remainder of this thesis is organised as follows: the next section contains a review of academic literature to date within the fields of behavioural finance and trading strategies and any implications of these, the following section contains the methodology which details the original 52-week high strategy, the absolute 52-week high strategy and the method behind the robustness tests. The results of the trading strategies will then be shown and then the results of the robustness tests. In the final section some conclusions will be drawn and some suggestions about areas for further research will be made.

2. Literature Review

2.1 Introduction

Technical and momentum trading strategies have gained increasing exposure in recent years due to the challenge they pose to the theory that markets are efficient and no excess return above the market can be made Substantial literature has aimed to build models that allow investors to know exactly when to buy and sell to create positive abnormal returns. Below is a summary of finance literature that discusses the ideas of whether markets are efficient, and if they are not, whether is it possible to profit from these inefficiencies.

2.2 Efficient Market Hypothesis

2.2.1 Background

The Efficient Market Hypothesis is a pivotal concept in finance and one that has been the central focus of academics over 30 years. Fama (1970) defines an efficient market as one in which all available information is reflected in the market price. He states that markets can be efficient at three different levels: weak, semi-strong and strong. If a market is weak form efficient an investor can not profit from information related to the price alone, including past return information and graphical displays. Semi-strong form efficiency would rule out profitability from any publicly available information such as news announcements. Finally if the market is strong form efficient, insider information should also be built into the price so that it would not be possible to profit from this either.

In summary, if a market is efficient the average investor can not hope to consistently outperform the market. Jensen (1978) further defines this statement by showing that a market is efficient if it is not possible to make ‘economic profits’, where economic profits are returns that have accounted for the added risk and costs. The general consensus is that markets should be semi-strong form efficient, however many papers have been written to try to prove this is not so.

2.2.2 Supportive Empirical Studies

Early literature attempts to find a relationship between a stock’s previous price and its future price to try to disprove the theory that markets are efficient. These tests come in two main forms: correlation tests and runs tests.

2.2.2.1 Correlation Tests

Correlation tests use a regression analysis of the below form to determine if there is a relationship between current returns and previous returns.

$$y = a + bx + e$$

The b represents how correlated the previous return x and the future return y are to each other. If this term is close to 1 or negative 1 it shows that there is predictive power in the past return. Fama and Blume (1966) Jennergren (1975) and Paretz (1972) test the theory of correlation of returns over time in the U.S., Australia and Norway respectively. Elton, Gruber, Brown, and Goetzmann (2003) summarise and discount this literature by stating that 'correlation and runs tests seem to show some small positive relationship between today's return and yesterdays return, but on average it is very small and frequently negative for individual securities.' (p.412). They go on to discuss the effect of transaction costs on this already small relationship, explaining that any possible profit would be eliminated by the transaction costs of executing that strategy in the market.

2.2.2.2 Runs Tests

Similar to correlation tests, runs tests look at past returns by examining the sign of the return, positive or negative. If the price changes are related then it would be expected that there would be higher than statistically possible strings of the same sign before a change in sign occurred. As the runs test only uses the change in sign, rather than actual values, it is more robust to extreme observations (Gruber *et al,* 2003). Fama (1965) tests the runs theory and finds only a small positive relationship. This can be discounted when transaction costs are considered and adds to the area of literature that supports the statement that markets are efficient.

2.3. Behavioral Finance and Early Contrarian Literature

2.3.1 Background

The seminal paper by Friedman and Savage (1948) puzzles over the idea that people who are risk averse and buy insurance policies often buy risk seeking lottery tickets. This idea that people are fundamentally not rational has developed into an area of behavioural finance that attempts to explain how investor's reactions affect the outcome of prices in the market.

Uncertainty and unpredictable behaviour in markets can be a result of the inability of agents to process and react in a timely fashion to a diverse range of information (Heiner, 1983). Heiner discusses the idea that behavioural processes do not just arise, but they are developed over time. If the parties contributing to this evolution are 'weak' this may distort the path of the behaviour. Arthur (1994) deduces two reasons for humans to not be perfectly rational. First, because beyond a certain complexity level logic no longer prevails; and second, because in complex situations other agents can not be relied upon to be fully rational and are forced to guess the behaviour of the irrational agent. Haltiwanger and Waldman (1985) discuss a similar notion in their analysis of sophisticated (informed) and unsophisticated (uniformed) agents. They conclude that in repeating game situation both groups have the same chance of being the dominant factor and affecting the equilibrium of the market.

Optimising the decision making process may result in cutting out expensive and less critical information. This results in decisions that are made on imperfect information (Baumol and Quandt, 1964). Baumol and Ouandt discuss the idea of using 6 rules of thumb to set prices in a market. They find the results to be reasonably reflective of the expected profits, with the simplest rule coming out on top. Colisk (1996) looks at bounded rationality and how it is the key to describing economic behaviour. This paper discusses the theory by focusing on four key areas: evidence, success, methodology and scarcity. Becker (1993) analyses behaviour from an economic perspective, using the assumption that 'individuals maximise welfare as they conceive it' (pg. 386). This is saying that people are fundamentally forward looking even in the face of uncertainty; however this is still affected by the lessons learned in the past.

Roll (1984) and Roll (1988) look at how well weather can predict the price of orange juice on the futures market. Roll finds that there is little predictive power in the weather variable, even though it is the largest factor effecting the growth of oranges. Roll also looks at other economic variable and finds that they only explain a small part of the daily price movement, leaving large amounts of unexplainable volatility. In a similar study, Cutler, Porterba and Summers (1991) examine the 50 largest one day stock movements in the US after World War II. They find that many of these movements were not on days with major announcements. This shows that something other than just fundamentals is driving price movements.

Thaler (2000), in his discussion about the future of economics, explains his own biases that make him irrational summing them up in four categories. Optimism: we are fundamentally positive about the future. Overconfidence: thinking that we can predict the future better than we can. The false consensus effect: we assume others are like us. The curse of knowledge: the assumption that everyone knows what we know and that they draw the same conclusions from that knowledge.

The behavioural portfolio theory (BPT) was developed in Shefrin and Statman (2000). They show that to find an optimal BPT an investor needs to hold a combination of risk averse investments like bonds, in the low aspiration portfolio, and risk seeking investments like lottery tickets, in the high aspiration portfolio. This theory is contradictory to the mean-variance efficient frontier, and the capital asset pricing model, CAPM, where investors fall largely into one risk class rather than many.

Contrarian investors aim to profit from overreaction to information in the market, often referred to as the reversal of a trend. They assume that after an initial overreaction, the stock's price will return to its true market value. If a stock under-performs due to negative information they would expect this to generate higher profits to correct the overreaction. The following sections discuss long and short term contrarian effects, and how they attempt to exploit the principles of behavioural finance.

2.3.2 Long-Term Contrarian

Bayes' rule states most people overreact to unexpected and dramatic news events. DeBondt and Thaler (1985, 1987) seek to test whether Bayes' rule is prevalent in stock markets. DeBondt and Thaler (1985) construct portfolios using the 50 most extreme stock returns in the U.S. and test the contrarian effect. They find over a 3 to 5 year period stocks that had performed badly in the past achieve statistically significant higher abnormal returns over the next 3 to 5 year period. They do find that the majority of this excess profit is gained by selling the stocks they expect to depreciate; this generates 25% more profit than the stocks increasing in value. With excess profits concentrated on the stocks decreasing in value this increases the overall risk of investing in this strategy. They also find evidence of excess returns in the January months, even up to 5 years later, which they leave unexplained. Even given these extra risks and unexplained phenomenon, DeBondt and Thaler (1985, 1987) are able to conclude that stock prices overreact to information in the short-term and this overreaction is corrected in the longer term horizon.

Shleifer (1986) looks at the theory of a downward sloping demand curve due to overreaction to a price move in light of new information. Specifically he examines the reaction of a stock price after its inclusion into the Standard and Poor's 500 Index. Shleifer finds that the inclusion of the stock pushes the price up due to funds buying into it even though the underlying fundamentals have not changed - it is no better or worse than it was before it was included in the index. They find that after time has elapsed, the price reverses and returns to a more pertinent market value.

Lakonishok, Shleifier, and Vishny (1994) compare value stocks, stocks which have a low market price relative to their fundamental value, and glamour stocks. The fundamental value is measured by such tools as earnings, dividends and assets. They find a 10-11 percent higher yield per year in value stocks which they say have no extra risk over the glamour stocks. La Porta, Lakonishok, Shleifer, and Vishny (1997) also look at value stocks and investor expectations of stock prices on the NYSE, AMEX and Nasdaq. They state that due to errors in investors' expectations, value stocks tend to over perform in the subsequent period. La Porta, Lakonishok, Shleifer, and Vishny (1997) find stronger returns in the first 2 to 3 years with value stocks earning 25-30 percent more than glamour stocks. This trend continues earning value stocks 15-20 percent more over the 4 to 5 year term.

Lee and Swaminathan (2000) compare price momentum and trading volume on NYSE and AMEX stock between 1965 and 1995. They find that future returns and trading volume are highly correlated. They also use the trading volume as a predictor of the extent of future returns. They find that high volume stocks experience faster reversals downward in the medium term, 3 to 5 year period, and lower volume stocks experience faster reversal upward.

Jegadeesh and Titman (2001) examine beyond the usual holding period of momentum trading and find negative returns in the 13 to 60 months after formation for stocks that had high returns in the previous period. This is consistent with the medium to long term contrarian strategies. Chopra, Lakonishok and Ritter (1992) also find evidence of contrarian effects using a 5 year formation period and a 5 year holding period. Stocks that had performed poorly in the past outperformed those that performed better by 5 to 10 percent. They do find this effect is more prevalent in smaller stocks rather than larger ones.

Brailsford (1992) finds that the contrarian effect is not prevalent in the Australian market. However, Gaunt (2000) examines this more closely and finds that if the portfolio is rebalanced each month, rather than employing the buy and hold strategy, statistically significant abnormal returns result due to contrarian effects. Gaunt (2000) also notes that the effect is strongest in small and possibly illiquid stocks.

Fama (1998) argues, in light of all the literature regarding contrarian, that the theory that the market is efficient should not be disregarded. Fama (1998, pg 22) states that the 'anomalies are chance results, apparent overreaction of stock prices to information is about as common as underreaction.' He argues that contrarian effects are not consistent as they vary depending on the way they are measured.

Papers such as Chan (1998) and Ball and Kothari (1989) say that the results obtained by contrarian strategies, in particular DeBondt and Thaler (1985), can be explained by systematic risk, the increased risk undertaken to carry out the strategy, and the size effect.

Fama and French (1996) and Grundy and Martin (2001) use the three factor asset pricing model to explain long-term reversals; however this model cannot be used for short term effects. Fama and French (1996) state that low performing stocks are more likely to do well in the long-term as they have now shifted states to become value stocks, earning higher value level returns.

2.3.3 Short-Term Contrarian

Contrarian, or reversals of a trend, has also been noticed when stocks are held in the short-term between 1 week to 1 month. This idea was first discussed in an economical sense by Cootner (1964) and Fama (1965). Lehmann (1990) tests this theory by examining stocks on the CRSP database to test for trend reversal when using a buy and hold strategy of 1 week. The pervious week's return is used as a guide of which stocks to buy. By buying stocks that had underperformed the previous week they were able to obtain 0.86 to 1.24 percent a week on average. Selling stocks that had performed well the previous week returned 0.35 to 0.55 percent per week on average. He finds that this trend is still statistically significant after testing for bid-ask bounce effects and transaction costs, assuming transaction costs of 0.05 to 0.1 percent per transaction. It is also found that as long as transaction costs per execution were less than 0.2 percent, the results of their study are still statistically significant. He states that due to this apparent arbitrage the idea of the efficient market hypothesis does not hold true. Parisi and Acevedo (2001) use a similar theory, examining the relationship between trading volume resulting in auto-covariances in weekly returns in the Chilean market. They find evidence of a trend and conclude that trading activity is an important predictor of future prices. This result is in support of Conrad, Hameed and Niden (1994).

Jegadeesh (1990) separates portfolios into 10 equal sized bundles based on their past returns when the stocks are held for a 1 month period using data between 1934 and 1987. He finds that the difference between the two most extreme portfolios was an average of 2.49 percent per month. This was achieved by buying the stocks that underperformed in the previous period and selling the ones that over-performed. He also tests the January effect and finds that after excluding the January months they still obtain a statistically significant abnormal return of 2.2 percent per month. The January months achieved 4.37 percent by themselves.

International studies have also been conducted to test data snooping on the contrarian effect. Darren, Lee, Chan and Faff (2003) investigate short term contrarian on the Australian market using weekly data of stocks listed on the All Ordinaries Index from 1994 to 2001. They test both the value-weighted and equally weighted portfolios, achieving statistically significant returns that are uncompromised even when adjusting for risk, bid-ask bounce, seasonality and size. However they do find that the profits dissipate once transaction costs of 0.3 percent or higher are included, making the strategy not practical in the real world.

Mun, Vasconcellos and Kish (1999) examine short, medium and long term contrarian effects on the German and French markets using monthly data from

1991 to 1996. They find that the short term contrarian strategy achieves the highest results and this result decreases on average as the holding period increases. Even though the conclusions are the same on both markets they do find that the German market produces a slightly higher average return, 2.07 percent, compared to the French market, 1.54 percent.

Lo and MacKinlay, (1990) find that the returns documented by contrarian effects are not solely due to overreaction in the market, in fact they attribute less than 50 percent of these profits to overreaction. They find that the bulk of the abnormal profits are due to positive cross-autocorrelations between securities; however they are unable to state what the sources of these cross-autocorrelations are. Conrad and Kaul (1993) argue that the long-term strategies are upwardly biased on single period returns. This is induced by measurement errors such as the bid-ask bounce phenomenon.

2.4 Momentum Literature

Momentum is often defined as the continuation of direction. With regards to momentum trading this would mean that a stock that has increased in price is expected to keep increasing over the subsequent short to medium term. Alternatively a stock that has decreased in the past is expected to keep decreasing in the next period. If this effect holds in the market, we should be able to gain excess abnormal profits and therefore disprove that weak form market efficiency holds in today's stock markets. Fama (1998) dismisses most anomalies; however are unable to dismiss momentum strategies, rather stating that it is an 'open puzzle'. Below is a discussion of the major type of momentum strategies discussed in modern literature.

2.4.1 Individual Stock Price Momentum

The ground breaking paper, Jegadeesh and Titman (1993), define individual stock price momentum as stocks which perform well in the past tend to perform better in the future than those that have performed poorly in the past. They test the theory by ranking stocks by their returns over a period and creating equally weighted portfolios by buying the top ten percent of performers, the 'winners', and selling the bottom ten percent, the 'losers'. This creates a self-financing strategy. They test holding periods of 3 to 12 months. They find significantly positive abnormal returns over all holding periods. However they find that over the first month they find a reversing effect and achieve negative returns. Over all the formation periods and holding periods they find that the 6 month formation period and 6 month holding period generates the highest returns of 12.01% yearly on average.

Chordia and Shivakumar (2002) analyse the NYSE-AMEX stocks with equally weighted portfolios finding statistically significant abnormal returns. They claim that momentum strategy returns show strong robustness and are not due to data mining. They also state that the abnormal profits obtained by momentum strategies can be explained by macroeconomic variables, and once these variables are accounted for there should be no way to profit from this type of strategy.

Chan, Hameed and Tong (2000) look at momentum in international stock indices. They conclude that momentum is prevalent in all markets, not just the emerging markets, and is strongest when the holding period is 4 weeks. They also find that after adjusting for risk the return is substantially reduced. A key finding is that an increase in volume over the formation period leads to higher momentum returns. This result is consistent with the idea of investor herding.

Studies also investigate the price momentum phenomenon in international markets. Demir, Muthuswamy and Walter (2004) investigate individual stock price momentum on the Australian market. They use time horizons of 30, 60, 90 and 180 days to test whether they can gain abnormal returns. They find that stocks with above average past returns tend to perform better in the holding period, and stocks that have lower than average past returns under perform in the next holding period. By buying the performing stocks and selling the underperformers they gain positive statistically significant abnormal returns. The abnormal returns are strongly evident in stocks with a small market capitalization. They follow on to find that more illiquid stocks show the highest correlation to their holding period return. The paper gains a unique angle on momentum by only including stocks that have been approved for short selling on the Australian Stock Exchange.

Rouwenhorst (1998) finds abnormal returns in the intermediate-term, 3 to 12 months, over 12 European countries based on data from 1980 to 1995. Rouwenhorst (1999) examines 20 emerging markets, 1750 individual stocks and also find evidence of momentum using past stock returns. Griffin, Xiuquing and

Martin (2003) examine 40 countries and find statistically significant short term momentum profits. Using the unconditional model of Chen, Roll and Ross (1986) they conclude that this is not due to macroeconomic risks, but may have something to do with country specific risks. Hameed and Kusnadi (2002) test 6 emerging Asian stock markets over 1981 to 1994. They find small and significant abnormal returns over this period using a 6 month holding period. However they find this is not consistent across all the markets and is usually driven by the stocks with low turnover. After adjusting for size and liquidity they find that these returns are no longer significant. They conclude that the Asian markets are not correlated with the U.S. markets in how they react to past information. Muga and Santamaria (2007) examine price momentum in the Spanish market during the 1990s. They find evidence of the effect; however this seems to disappear after the 1997 crisis.

Badrindath and Wafal (2002) and Chan, Jegadeesh and Lakonishok (1999) discuss the idea that the pattern of buying past winners and selling past losers is often exploited by institutional investors such as mutual funds. Hwang and Rubesam (2007) state that due to the hedge fund exploitation momentum profits, from buying stocks whose price has increased in the past and selling stocks whose price has decreased, after the end of 2000 have dissipated.

2.4.2 Industry Momentum

Momentum strategies have also been created using companies industry status to create portfolios of stocks that perform better in the past and stocks that under-perform. Moskowitz and Grinblatt (1999) explain the intricacies of this strategy using value weighted portfolios. By ranking the stocks within each industry by their past returns over a formation period, the top 10% are chosen as the 'winner' portfolio and the bottom 10% in each industry are chosen as the 'loser' portfolio. To formulate the portfolios the 'winners' are brought and 'losers' are short sold. Using a 1 month formation period and 1 month holding period they find abnormal returns. However a lot of this return is gained by the short selling side. Pan, Liano and Huang (2004) also find statistically significant results using industry portfolios which they note is specifically prevalent in the short term of less than 4 weeks. Scowcroft and Sefton (2001), in their paper on understanding momentum, find that momentum is largely an industry phenomenon. By focusing on trends in sectors momentum traders can increase profitability.

Although Moskowitz and Grinblatt (1999) find abnormal profits in the US markets, Fama and French (1997), Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) look at international markets and fail to find similar effects.

2.4.3 Country Momentum

Country momentum strategies is the process of separating stocks into their country classification and buying the stocks in the countries that have performed well over a certain period and selling the stocks in the countries that have underperformed. Using a value weighted model Richards (1997) tests this theory and finds evidence that country rotation strategies can deliver a small excess return in the medium term. Chan *et al* (2000) also look at country momentum factor trading strategies. Using Data Stream market indices and a value weighted portfolio they find positive abnormal returns in the short-term.

In contrast, Rouwenhorst (1999) finds little evidence of country momentum in his study of 20 emerging markets using equally weighted, rather than value weighted, portfolios. They instead suggested that the momentum effects are a result of a common component across all markets.

2.4.4 Directional Momentum/Acceleration Strategies

In recent literature the concept of Directional momentum also known as Acceleration Strategies has arisen. This is the examination of the patterns within the formation periods of the stocks to ascertain if abnormal returns can be gained by using this information.

Ning and Gressis (2006) examine how the movement of stock prices within a quarter can effect the expectations of the market and therefore affect the next quarter's returns. They find that stocks that exhibit accelerated monthly returns are more profitable. Their results reflect that this holds over an 18 year period and is more prominent in the 1990s when the market was more volatile. This is also consistent with the results of Akhbari and Gressis (2007), who state that 'Directional momentum strategies perform best when the stock market is turbulent and prices are declining' Akhbari and Gressis (2007, pg 8). They find that using a directional momentum strategy under these conditions is beneficial to smaller investors, and that there will be large and positive alphas and betas of less than one.

Gettleman and Marks (2006) also look at acceleration strategies within momentum. They compare stocks' rate of change within the formation period, those that are increasing in returns at a higher rate throughout are brought. They find that stocks with low acceleration but the same momentum do not perform as well as stocks with the same momentum but higher acceleration. Specifically they find they can earn 2-3% more than using the conventional momentum strategies.

2.4.5 52-week High Momentum

In more recent literature, George and Hwang (2004) test the idea that the highest price of a stock over the last year, also known as the 52-week high price, relative to its current price, can predict the direction of future price movements. They find that if the stock was near to its 52-week high price it was more likely to increase in the future, over a specified holding period, relative to one that was further away from its 52-week high price. Based on this theory, equally weighted portfolios were created by ranking the stocks, from ones nearest to their 52-week high price to the ones that were furthest away. The top thirty percent became the winner portfolio and the bottom thirty percent the loser portfolio. By buying the stocks in the winner portfolio and selling the stocks in the loser portfolio, creating a self financing strategy, they were able to produce positive abnormal returns. This result was obtained over U.S stocks from 1963 to 2001, assuming a holding period of six months. Being able to profit from this strategy challenges the idea that the market is semi-strong form efficient using the definitions of Fama (1970). George and Hwang also compare their results with the tests of two influential papers within momentum; the individual price movement strategy of Jegadeesh and Titman (1993), and the industry classification of Moskowitz and Grinblatt (1999). They find that the 52-week high strategy outperformed the more conventional momentum ideas over the period tested.

Following the idea of George and Hwang (2004), Marshall and Cahan (2005) test the nearness of a stock's current price to its 52-week high price on the Australian stock market. They also find positive abnormal statistically significant returns even higher than those shown on the U.S. market. This was based on the same holding strategy of six months using data from 1990 to 2003. Again the 52-week high price momentum strategy outperformed the idea of the Jegadeesh and Titman (1993) individual stock price momentum and the Moskowitz and Grinblatt (1999) industry classification momentum. Also built into the strategy was the idea of only using stocks in the portfolio that were approved to be short sold on the Australian market.

On a global scale Visaltanachothi, Wang and Wilson (2007) look at the difference in returns between 'individualistic' cultures - such as the United States, United Kingdom and Germany - and 'collectivistic' cultures - such as Japan and South Korea - using the 52-week high momentum strategy. The results show that the effect is stronger in the individualistic cultures than in the collectivistic cultures. Looking at 45 countries using the 52-week high strategy they find statistically significant abnormal returns in most countries. Comparing these countries they find higher abnormal returns in countries with a higher individualism rating, using a rating system developed by Hofstede (2001). They state that this phenomenon is due to increased participant confidence levels.

2.4.6 Theoretical Explanations

There are various papers that find evidence of abnormal profits using momentum trading strategies, however many authors question how valid these results are. Hong and Stein (1999) discuss the need for a set of criteria that make an explanation credible and suggest the below three to help standardise the process.

> '1. Rest on assumptions about investor behaviour that are either a priori plausible or consistent with casual observation.

2. Explain the existing evidence in a parsimonious and unified way.

3. Make a number of further predictions that can be subject to "out-of-sample" testing that is ultimately validated.' (p.2144)

Hong and Stein (1999) offer an explanation for the apparent over and under reactions to news announcements that fits within the rules defined. This explanation is based on the behaviour of different sets of traders and how they interact with each other. They test the theory that there are two types of traders: 'newswatchers' and 'momentum traders', making the assumption that newswatchers make their forecast based on actions that affect the fundamentals alone and momentum traders use only simple univariate models based on past price movements to forecast future price movements. One other assumption is added to this, the assumption that news is fed slowly to newswatchers allowing the market to adjust slowly to new announcements. The adjustments made by the newswatcher traders are only ever undereactions rather than overreactions to the new information. Momentum traders then react to this price movement creating a flurry of trading that ends with an overreaction to the announcement.

Using all the stocks on the MSCI world index from 1992 to 2003 Scowcroft and Sefton (2005) brought the best and sold the worst 20 performing stocks over formation periods of 1, 3, 6, 12 24, and 36 months and held the stocks for the same variation of months. They find evidence that an equal weighted portfolio leads to a company specific conclusion, while a portfolio value weighted by market capitalisation shows evidence of country and industry effects. Further, equal weighted portfolios discounted the country and industry phenomenon. They discuss the theory that announcements for bigger firms are being construed as prevailing industry wide, while smaller stock announcements are under-emphasised.

George and Hwang (2004) state that investors are trading based on resistance levels. They test this theory using the 52-week high price. George and Hwang argue that if a stock is near to its 52-week high price that it has recently received good news. Using the 52-week high as a benchmark, they state that traders are able to make judgments on the future direction of the stock. They believe that if a stock is near to its 52-week high price as a result of a positive announcement traders will be reluctant to buy but the new information is eventually incorporated into the price creating a continuation. The same happens with a negative announcement that drives the price away from its 52-week high price. Traders are reluctant to sell at a price they believe is lower than the information suggests it should be, but in time the information is fully reflected in the stock's price, pushing it lower still. George and Hwang compare this scenario to a stock that is neither close to or far from its 52-week high stating that this would mean the information would be reflected in the stock's price in a more timely manner, and therefore be more difficult to predict where it will go in the future.

After investigating a momentum strategy of buying and selling past positive performing and negatively performing mutual funds, Carhart (1997) describes momentum as another risk factor. The strategy of using mutual funds rather than individual stocks gains higher returns. However these returns are reduced after transaction costs are accommodated and the strategy results in below market returns.

Tversky and Kahneman (1974) state that theories tend to view events as either typical or falling into some a particular class and ignore the laws of probability. Barbaris, Shleifer and Vishny (1998) use this knowledge to create their one investor one asset theory. In this model the asset is following a random walk but the investor believes that the asset can be one of two states, mean reverting and trend focused, i.e. increasing or decreasing. The investor then uses the prevalent information about the stock to work out what state it is in. For example, if it increases and then increases again the stock is in a trend, but if it increases and then decreases the investor would believe this was a mean reverting state. Using this model, they show that they are able to predict the returns of stocks.

Daniel, Hirshleifer and Subrahmanyam (1998) look at a similar theory using overconfidence and self-attribution as the parameters for the model, where self-attribution is described as the tendency of investors to attribute positive outcomes to skill and negative outcomes to bad luck. Using this theory investors are more likely to buy more of a stock that they already hold when positive news is announced than they are to sell if a negative one is released. This causes the markets to overreact in the short term and correct themselves in later periods.

De Long, Shleifer, Summers and Waldmann (1990a) and Shleifer and Vishny (1997) attempt to explain why arbitrage opportunities are not completely priced out. They state that investor sentiment is unpredictable which moves prices further from their true fundamental value. This results in loses for arbitrageurs that bet against miss-pricing. Both papers conclude that miss-pricing can exist and are not fully arbitraged away.

2.5 Profitability Issues

Early papers were based around seeing if using a particular strategy resulted in straight abnormal profits. However what is unanswered is whether these strategies would actually be able to gain these returns in the market. Recent papers have looked at critiquing the validity of the abnormal returns that trading strategies have achieved. They examine the areas that would have the most effect on the abnormal profits, namely risk adjustment, liquidity, transaction costs, the January effect and bid-ask bounce.

2.5.1 Adjusting for Risk

A major test of a strategy's ability to make abnormal profits above the market is whether it justifies the additional risk that is created when investing in the stocks picked. Fama and Macbeth (1973) examine the relationship between risk and return using a two parameter portfolio model. Assuming the market is efficient, they find a positive trade off between risk and return. Conrad and Kaul (1998) state that extra profits achieved when looking at investment strategies are only due to the extra risk that the investor encounters when implementing the strategy.

Fama and French (1992, 1993, 1996) and Chan, Jegadeesh and Lakonishok (1996) lead us to question the adequacy of a single index models to explain performance. The Fama and French (1993) three factor model has been considered to give a better understanding of fund behaviour. Besides a value-weighted market proxy, two additional risk factors are used, size and book to market. 'Size and BE/ME are related to systematic patterns in relative profitability and growth that could well be the source of common risk factors in returns.' Fama and French (1993b) pg 55. However they find that the three factor model is not able to explain the cross-sectional variation in momentum-sorted portfolio returns. Cahart (1997) extends the literature by adding a fourth factor that captures the Jegadeesh and Titman (1993) momentum anomaly. The resulting model gives co-efficient values that indicate the portion of the mean return that is attributable to the four basic strategies.

2.5.2 Liquidity

Korajczyk and Sadka (2004) examine the impact of price movements due to heavy trading on the effect of the abnormal returns gained from the strategy. They find that using price impact models the abnormal profits decrease with the portfolio size. They state that the break-even fund size for abnormal profits to not be obtainable is \$4.5 to \$5 billion. They also show that equal weighted portfolios versus value weighted portfolios perform better before transaction costs; however they perform the worst after transaction costs are considered. This is a result of value-weighting investing in more liquid assets. They create liquidity weighted portfolios which they show gain a higher abnormal return than the value weighted strategies after the price impact is considered.

Brennan, Chordia and Subrahmanyam (1998) find a strong correlation between returns of individual securities and the trading volume, which they state as being a liquidity premium in the stock prices. When the stocks have low trading volume, and therefore low liquidity, it results in a higher paper profit when using such strategies.

2.5.3 Transaction Costs

One of the major factors that will influence a strategy's profitability is that of transaction costs. Below is a discussion of some of the key papers that evaluate this relationship. Lehmann (1990) examines portfolios that are rebalanced weekly. This results in large volumes of transactions, typically 2,000 a week. To analyse the effect of these costs on the returns of the portfolio they use six different percentage cost levels, 0.05, 0.1, 0.2, 0.3, 0.4, 1.0. They find that, after adjusting for transaction costs at a reasonable level of 0.1, the abnormal profits still persist.

Lesmond, Schill and Zhou (2004) look at momentum trading strategies that are based on buying stocks that performed well in the past and selling the stocks that have returned the least in the past. They find that large momentum stocks are also those with the highest trading costs. Liu and Strong (2006) compare the transaction costs between a rebalancing portfolio method and a buy and hold method. They find significantly larger transaction costs in the rebalancing portfolio and this effect is large enough to reduce the returns to lower than market returns.

Ali, Hwang and Trombley (2003) look at the reasons why the book-to-market effect exists. One of their key findings is that stocks with higher transaction costs are more likely to exhibit mispricing.

2.5.4 Size

Also related to the issue of the liquidity and transaction costs is that of the size of a stock, as it is often noticed that smaller the size, the less liquid the stock - and therefore less tradable without a price movement - and the higher the transaction costs. Siganos (2007) examines the size of a company outside the usual deciles, quintiles, or triciles method and finds that the momentum effect steadily declines with the increase in size of the stock.

2.5.5 The January Effect

Rozeff and Kinney (1976) find statistically significant differences between the mean returns of the months of the year. They state that this is primarily due to the results of the January month, with January months returning higher results than those of the other 11 months. It is argued that this effect is a result of selling of stocks that underperform in the previous year to realise tax losses. These stocks are then re-bought the following tax year to which provides the illusion of abnormally high returns.

Keim (1983) finds that the January effect phenomenon can be used to explain the high abnormal returns of small stocks found in Banz (1981) and Reinganum (1981). He finds that this is particularly prevalent in the first week of January. Roll (1983) argues that the January effect is a result of tax loss selling at the end of the U.S fiscal year. Roll also finds that the January effect is more evident in smaller stocks. A similar result is found by Reinganum (1983) and Fama (1991).

Gultekin and Gultekin (1983) examine value weighted indices in 18 countries using data from Capital International Perspective from 1959 to 1979. They find significant evidence to show that the January effect theory is prevalent in these markets also. Kato and Shallheim (1985) examine the January effect in the Tokyo markets and find highly significant abnormal returns which are again higher in smaller stocks than their larger counterparts.

This effect is tested outside the U.S. where the tax year does not end in January, for example in Australia which has similar tax laws but a July – June tax year. Brown, Keim, Kleidon and Marsh (1983) and Demir *et al* (2004) show evidence of a January and July effect in this market. This shows that the January effect, like the July effect, is a result of tax-loss selling at the end of the financial year to realise any tax losses. Brailsford and Easton (1991) and Gaunt, Gray and McIvor (2000) also test this theory and find evidence of the July effect in the Australian market.

In a recent paper, Schwert (2002) investigates the phenomenon of small stocks and the January effect. He finds that this anomaly has decreased since the first academic paper was published. However they do find that there is still a small effect evident, but strangely this does not show in portfolios that focus on stocks with a small market capitalisation.

Rather than the end of financial year anomaly, Sias (2007) instead investigates the idea of end of quarter seasonal periods. They find that high abnormal returns are able to be gained at the end of each quarter. Sias argues that this phenomenon is due to the selling off of 'embarrassing' or poor performing stocks at the end of a quarter and buying stocks that have higher past performance, 'winning' stocks, to avoid showing the underperforming stocks on their reports.

2.5.6 Bid-ask Bounce

Lo and Mackinlay (1990) argue that the effect of momentum and contrarian profits is due to the 'bid-ask bounce' as the prices are inconsistently quoted. If the closing price is a bid one week and an ask the next they determine that this may be enough to manipulate the results to a false positive outcome. Conrad, Gultekin and Kaul

(1997) also discuss the theory of bid-ask bounce with their paper reviewing Lehmann (1990).

Market micro-structure bias is discussed in Jegadeesh and Titman's 1995b paper, who find that short term contrarian profits 'can be explained by the way dealers set bid and ask prices, taking into account their inventory imbalances.' This result is consistent with Ho and Stoll (1981) and Madhaven and Smidt (1993) who find that it takes several days to reduce inventory imbalances.

2.6 Conclusion

There is a large body of literature discussing whether markets are efficient, and if it is possible to make money using any knowledge that they may not be efficient. If momentum or contrarian trading strategies were able to consistently gain abnormal returns this would contradict the theory that markets semi-strong form efficient. This area of literature is rapidly growing as academics and the industry debate how plausible these theories and any new theories are with regards to such treatments as liquidity, transaction costs and risk adjustments.

3. Data

Following on from George and Hwang's (2004) seminal paper, this thesis gathers data to extend the analysis of the 52-week high momentum trading strategy. To create this strategy, monthly close price data of stocks is needed over a large sample period. Each month a portfolio of stocks to be brought and a portfolio of stocks to be sold has to be determined.

Daily data was first obtained to calculate the 52-week high price. The date was needed for each price of each stock to create a series of prices. The permno, which is a unique identifier for each company, and the adjusted daily close price, which was used to get the 52-week high and portfolio calculations and as the price to buy and sell at, were also obtained. The share price was adjusted for stock splits and rights issues. The data was collected for all stocks on the CRSP database from December 1925 to December 2005.

The 52-week high was calculated as the highest daily close price over the last 52 weeks. This is only able to be calculated after a stock has been listed for long enough to obtain the information, i.e. 52-weeks of data is needed for each stock to determine its high price. Due to the large volume of daily data over the 1925 to 2005 period, the processing time required to obtain the high price was long.

After calculating the 52-week high price for the stocks, the price data was converted to monthly close price data. The monthly close price was calculated as the last daily closing price for a stock in that month.

To create stock portfolios, the 52-week high price of every stock at the end of each month was compared to its close price at the end of the same month. This calculation was done as a ratio and determined at the time of selection. After selection, a stock could be chosen to be brought or sold at the next month's close price. The stocks are held for a holding period and then they are either sold or bought to close out the position. If a stock de-lists during the holding period it was not included in the portfolio.

Momentum factor (Mom), Small minus Big factor (SMB), High minus Low factor (HML) factor and market data are obtained from Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#BookEquity for the 30 June 1926 to 30 June 2001 period.

As noted on this website, the momentum factor, Mom, is calculated by forming portfolios based first on their prior return, then on their size. Using the two minus twelve months to calculate the formation period return, stocks are ranked and the top 30% are selected as the high return and the bottom 30% are selected as the low return. The high and low portfolios are then split by market equity as a measure of size. Stocks that have a market equity larger than the median market equity on the NYSE are selected for the Big portfolio and stocks that are lower are selected for the

Small portfolio. This creates four portfolios, Bighigh, Smallhigh, Biglow, and Smalllow. The Mom factor is then calculated using the average returns for these portfolios in the below equation:

$$Mom = \tfrac{1}{2}(Smallhigh + Bighigh) - \tfrac{1}{2}(Smalllow + Biglow) \qquad [1]$$

Following on in the same way as the Mom factor, the Small minus Big, SMB, and High minus Low factors are calculated. The SMB is the average return on three small portfolios minus the average return on three big portfolios, and the HML is the average return of the value and growth portfolios.

Table 1a displays a list of the number of different permnos (number of stocks) in the 10 year periods of the CRSP data set.

Table 1a

Number of stocks in the data set over 10 year periods

	Number of Stocks
Jan 1996 - Dec 2005	13996
Jan 1986 - Dec 1995	13175
Jan 1976 - Dec 1985	7736
Jan 1966 - Dec 1975	3558
Jan 1956 - Dec 1965	2422
Jan 1946 - Dec 1955	1110
Jan 1936 - Dec 1945	925
Dec 1925 - Dec 1935	855

4. Method

4.1 Introduction

This thesis analyses the profitability of the 52-week high momentum trading strategy, which was created by George and Hwang (2004). The parameters are stressed to test the robustness of the strategy.

The sections below outline the method behind the 52-week high momentum trading strategy and go on to discuss a new concept called the absolute 52-week high momentum trading strategy. The final sections outline the method behind Fama French three factor regression model and the Carhart multi factor model.

4.2 52-week high momentum trading strategy

The George and Hwang 52-week high momentum trading strategy looks at predicting the profitability of stocks using a stock's nearness to its 52-week high price as a predictor of future performance. The closer (further) a stock is from its 52-week high price (the highest price obtained over the last 52 weeks) the higher (lower) return that is expected, relative to the other stocks, over the holding period.

Using the close price for the month and the calculated highest price over the last 52-weeks, the nearness to the 52-week high price can be calculated:

$$\text{Ratio of nearness to the 52 - week high price} = \frac{p_{i,t}}{high_{i,t}} \qquad [2]$$

Where:

$p_{i,t}$ = The close price of the stock at the end of the month

$high_{i,t}$ = The highest price of the stock during the previous 12-month period (52-week high). The 52-week high period ends on the last day of the month.

Stocks are then ranked from the lowest ratio, closest to the 52-week high price, to highest ratio, furthest from the 52-week high. Equal weighted portfolios are then formed where the top percentage[1] of the ranked stocks constitute the ‘winner’ portfolio, the bottom percentage of the ranked stocks the ‘loser’ portfolio. The remaining percentage constitutes the middle portfolio which is not invested in. The stocks in each portfolio are then brought at the next months close price. Buying all equally weighted stocks in the winner portfolio and selling all equally weighted stocks in the loser portfolio creates a self-financing winner minus loser portfolio. Portfolios are held for six months and sold at the last months close price. Stocks that de-list from the exchange over the holding period are not included in the winner or loser portfolio.

The formula for average monthly stock return is below:

[1] Thirty percent is used as a base percentage as per George and Hwang (2005)

$$\text{average monthly stock return} = \frac{\left(\frac{p_{i,t+1+n}}{p_{i,t+1}} - 1\right) \times 100}{n} \qquad [3]$$

Where:

$p_{i,t+1+n}$ = Close price at the end of the holding period

$p_{i,t+1}$ = End of month close price for a stock one month out

n = Length of the holding period in months

The buy-hold returns on stocks in the winner and loser portfolios are calculated individually and then averaged over a holding period. Stock returns in each portfolio classification are then averaged to create a winner return over the sample period and a loser return over the sample period. The loser return is then subtracted from the winner return, as the winners are brought and the losers are sold, to create a winner minus loser average monthly return.

4.3 Absolute 52-week high momentum

The momentum literature has focused on relative performance. For instance, the 52-week high momentum looks at a stocks status relative to other stocks that could also be invested in. Stocks that meet the criteria to be included in the 52-week high winner or loser portfolios may not have had a price that has increased in the pervious short-term to medium-term period. Absolute 52-week high momentum aims to not only invest in stocks that are near to (far from) their 52-week high price but restrict the stocks so that only ones that have increased (decreased) over a formation period can be included in the winner (loser) portfolio.

Stocks are first ranked by their nearness to their 52-week high price from lowest ratio to highest. The top percentage of stocks on the list is classified as 'could be winners' and the bottom percentage of stocks are classified as 'could be losers' The stocks in the 'could be' portfolios are then tested for past performance. Only stocks that have an increasing (decreasing) past return over the formation period, using close price data, make it into the final winner (loser) portfolio. The stocks in the winner and loser portfolios are then brought at the next months close. Portfolios are held for six months and sold at the last months close price

The process of testing nearness to the 52-week high price is expressed by the below formulae:

$$\text{Ratio of nearness to the 52 - week high price} = \frac{p_{i,t}}{high_{i,t}} \qquad [4]$$

Where:

$p_{i,t}$ = The close price of the stock at the end of the month at time t

$high_{i,t}$ = The highest price of the stock during the previous 12-month period (52-week high). The 52-week high period ends on the last day of the month.

After the stocks are ranked and categorised into 'could be' winners and 'could be' losers the stocks past return is calculated as the close price today as a proportion of the close price at the beginning of the formation period, in this thesis we use a 6 month formation period. The below formula calculates the return over the 6 months before the date of formation:

$$\text{Past return for absolute momentum} = \frac{\left(\dfrac{p_{i,t}}{p_{i,t-n}} - 1\right)}{n} \times 100 \qquad [5]$$

Where:

$p_{i,t}$ = End of month close price of a stock at formation

$p_{i,t-n}$ = End of month close price n months ago

n = Number of months in the formation period

If the result is positive and the stock is a 'could be' winner it qualifies to be in the winner portfolio. If the result is negative and the stock is a 'could be' loser it qualifies to be in the loser portfolio. The rest of the stocks that do not fall under these classifications are not invested in.

4.4 Fama French Three Factor Regression Model

The Fama French three factor regression model has been used as a way of adjusting the 52-week high momentum trading strategy for risk. The model contains three factors that are used for explaining common stock returns, the market factor (market return minus the risk free rate, $R_m - R_f$), size (SMB) and value (HML). The last two factors are designed to mimic "two underlying risk factors or state variables of special hedging concern to investors" (Fama and French, 1996, p.57)

$R_m - R_f$, the excess return on the market, is calculated as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate.

SMB, small minus big, calculated as 1/3 (Small Value + Small Neutral + Small Growth) – 1/3(Big Value + Big Neutral + Big Growth). It is the difference between the returns on small and big stocks with about the same weighted average BE/ME, the SMB is largely clear of BE/ME effects and instead focuses on the different behaviour of small and big stocks. In essence this factor represents the difference in returns between portfolios of small capitalisation firms and big capitalisation firms.

HML, high minus low, calculated as 1/2 (Small Value + Big Value) – 1/2 (Small Growth + Big Growth), is created as a factor representing value. This factor represents the difference in returns between portfolios of high book-to-market and small book-to-market firms.

The regression formula is stated below:

$$r_{52-week} - R_f = \alpha + \beta_1 (R_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \varepsilon \qquad [6]$$

Where:

$r_{52-week}$ = Average monthly return from the 52-week high strategy

R_f = The risk free rate taken as the three month Treasury bill rate[2]

α = intercept

$R_m - R_f$ = The excess return on the market

SMB = Small minus big size factor

HML = High minus low value factor

The excess return, SML and HML data and information has all been taken collected from the Fama French Data Library.

4.5 Carhart Multi-Factor Regression Model

The Fama French three-factor model captures most market anomalies (Fama and French, 1996), except the momentum anomaly. Many papers which were initiated by Jegadeesh and Titman (1993) show that strategies that involve buying (selling) high (low) performing stocks, where performance is measured over 3 to 12 months, tend to produce significant positive abnormal returns when the portfolio is held in the short to medium term. Grundy and Martin (2001) conclude that 'assuming the anomaly (profitability of momentum strategies) endures, then, quite appropriately, it will enter the lexicon of finance as a 'factor' whose economics are as well

[2] Taken from http://www.federalreserve.gov/releases/H15/data/Monthly/discontinued_AH_M3.txt. The three month Treasury bill rate is used as a proxy for the risk free rate as it was the longest continuous data set available at the time.

understood as the SMB and HML factors: If it remains a fact, it remains a factor' (p.72).

The fourth factor is winners minus losers, WML, and is calculated as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. 1/2 (Small High + Big High) – 1/2 (Small Low + Big Low).

The new multi factor regression model is as follows:

$$r_{52-week} - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(WML) + \varepsilon \qquad [7]$$

Where :

$r_{52-week}$ = Average monthly return from the 52-week high strategy

R_f = The risk free rate taken as the three month Treasury bill rate[3]

α = intercept

$R_m - R_f$ = The excess return on the market

SMB = Small minus big size factor

HML = High minus low value factor

WML = Momentum factor

[3] Taken from http://www.federalreserve.gov/releases/H15/data/Monthly/discontinued_AH_M3.txt. The three month Treasury bill rate is used as a proxy for the risk free rate as it was the longest continuous data set available at the time.

The SMB, HML and WML information and data has been collected from the Fama French Data Library.

4.6 Transaction Costs

Many momentum papers do not account for transactions costs and those that do develop a variety of sophisticated techniques to incorporate these costs. An in-depth analysis of transaction costs is beyond the scope of this thesis, but we give this issue brief consideration by determining what the transaction costs would need to be for each stock, as a percentage, to make the return on the strategy zero. This can be calculated using the below formula.

$$TC = \frac{(WLR \times h)}{(4 + (WR \times h) + (LR \times h))} \qquad [8]$$

Where:

TC = The transaction costs for each stock as a percentage that would need to be charged to make the return on the strategy zero.

WLR = Winner minus Loser return given as a percentage

WR = Winner portfolio return as a percentage

LR = Loser portfolio return as a percentage

h = Holding period in months for the strategy

Each winner minus loser return will have four transactions - buying and selling winners and selling and buying losers. The transaction cost formula is adjusting for an increase or decrease in the price of the winner and loser stocks at the end of the holding period. See Appendix one for the derivation

5. Results

5.1 Introduction

The 52-week high momentum trading strategy uses the ratio of a stock's close price to its 52-week high price to predict the direction of the price over the ensuing period. Two portfolios are formed the 'winners' and the 'losers'. The winner portfolio is made up of stocks that are close to their 52-week high price and are expected to increase over the subsequent period, these stocks are brought. The loser portfolio is made up of stocks that are far from their 52-week high price and are expected to decrease, these stocks are sold. Buying the winner portfolio and selling the loser portfolio creates a self-financing trading rule. The portfolios are held for a period and then the positions are closed out.

Following the seminal paper of George and Hwang (2004), the construction of the winner and loser portfolios uses end of month close prices and compares this to the 52-week high price, which is the highest daily close price over the previous 52-weeks. Stocks are ranked with the top stocks being closest to their 52-week high price and the lowest being furthest from it. The top percent of stocks, this thesis is using 30% as a base percent as per George and Hwang (2004), are selected for the 'winner' portfolio and the bottom percent are selected for the 'loser' portfolio. Stocks in the winner portfolio are brought at next month's close price and the stocks in the loser portfolio are sold at next month's close price. The portfolio is closed out after a holding period by selling the stocks in the winner portfolio and buying the stocks in the loser portfolio at the close price of the last month in the holding period. Six months is used as the base holding period. George and Hwang (2004) tested holding period months from one to twelve months and found the six months strategy most profitable. For the sake of convenience, this strategy of buying and selling sets of stocks is referred to as a self-financing portfolio in this thesis as the money from selling the stocks in the loser portfolio is used to buy the winner portfolio. This will not be perfectly self-funded as there are issues around the cost of buying and selling stocks, but these are beyond the scope of this research.

The following tables in Section two analyse the 52-week high momentum strategy over different time periods using a 30% portfolio percentage, a one month lag before entering at the close and a six month holding period. Section three analyses the data using different portfolio percentages. The next section examines the data over different time periods. Finally, absolute momentum and tests around the parameters of absolute momentum followed by the Fama-French three and four factor risk adjustment results.

The first step was running the 52-week high momentum strategy over the same period as George and Hwang (2004) to ensure the code used in this thesis is correct. An identical spread to that of George and Hwang (2004) was obtained and it was also statistically significant at the same level.

5.2 52-Week High Momentum Trading Strategy

Table 2a represents the winner, loser and winner minus loser average monthly returns obtained from investing in the 52-week high strategy over the 1963 to 2005 period and holding the portfolio for six months. This is a rolling strategy so new portfolios are formed every month. T-statistics are shown in parentheses. This is an extension of the original George and Hwang results which only went to 2001.

Table 2a

Winner minus Loser Returns using the 52-week High Momentum Strategy

	Winner	Loser	Winner-Loser
Jul 1963 - Dec 2005	0.0124	0.0090	0.0033
			(1.73)*

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Taking the long winner stocks and the short loser stocks and subtracting the portfolios creates a self financing winner minus loser portfolio. The result shows profitability over the 1963 to 2005 period with a 0.33% average monthly return which is significant at the 10% level. George and Hwang obtained a slightly higher result of 0.45% average monthly return, significant at a 5% level, over the 1963 to 2001 period.

George and Hwang's 52-week High Momentum Strategy paper was published in The Journal of Finance in October 2004. The result using the period after the paper is published is expected to diminish, if markets are efficient, as the 52-week high phenomenon is considered a common knowledge strategy.

Table 2b shows the average monthly return to buying the winner portfolio and selling the loser portfolio where the winners are the top 30% of stocks, when they are ranked by their nearness to their 52-week high price to the furthest from the 52-week high price, and the losers are the bottom 30% of the ranked list. Stocks are brought and sold at the next month's close price and held for six months. This is strategy is run on all data in the CRSP from November 2004 to December 2005. The T-statistics are shown in parenthesis.

Table 2b

52-week High Momentum Strategy - after GH was published 2004-2005

	Winner	Loser	Winner-Loser
Nov 2004 - Dec 2005	0.0112	0.0056	0.0057
			(1.13)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

The winner minus loser return over the 2004 to 2005 period resulted in a stronger average monthly return of 0.57% however this result was not significant at a 10% level. The result was more positive, but not as significant. The low significance is not surprising as the sample size is small at only 8. The winner minus loser return for each month is used in the t-statistic calculation resulting in only 8 data points. The evidence suggests that the 52-week high momentum strategy still works even after publication.

Table 2c shows the result of the 52-week high winner, loser and winner minus loser average monthly portfolio returns using all months available on CRSP. The first year, December 1925 to November 1926, is not in Table 1c as this period was used to obtain the 52 week high price. The winner portfolio is formed by taking the close price of a stock each month and comparing it to the stocks 52-week high price. All stocks are ranked by how close they are to their 52-week high price from the closest to the furthest. The top 30% of stocks (the closest to their 52-week high prices) are brought and the bottom 30% are sold creating a self-financing portfolio. Stocks are held for six months and then the positions are closed out. The winner and loser portfolios are created each month and the results are averaged. Significance levels are shown in the brackets below the results.

Table 2c

52-week High Momentum Winner Minus Loser Returns Using All Data

	Winner	Loser	Winner-Loser
Dec 1926 - Dec 2005	0.0107	0.0100	0.0007
			(0.41)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

The resulting winner minus loser return for the 1926 to 2005 period is small, less than 0.1% per month, and not significant at a 10% level. Results for the later half of the data are large and significant as shown in Table 1a which means that the first half of the data could be driving the small insignificant result. Section 5.4 investigates this phenomenon in more depth.

5.3 Portfolio percentage

The next section varies the portfolio formation percentage parameter. George and Hwang use 30%. Winner and Loser portfolios are created by ranking stocks on how close they are to their 52-week high price. A certain percentage of the top (bottom) ranked stocks are brought (sold) for the winner (loser) portfolio. Stocks are held for six months and then the positions are sold (brought) for the winner (loser) portfolio. Winner and loser portfolios are created each month. Table 2a tests the 52-week momentum strategy using 1%, 2%, 3%, 4%, 5%, 10%, 20%, 30%, 40% and 50%, where 50% uses all eligible stocks in that period, half in the winner portfolio and half in the loser portfolio. The change in portfolio percentages is tested over July 1963 to December 2005. Significance is shown in the brackets below. Results are expected to not be significant at the lower portfolio percentage levels as the smaller the number of stocks in each portfolio the larger the variability in the results, this is also known as a large amount of noise in the data.

Table 3a

52-week high momentum using different portfolio percentages Jul 1963 - Dec 2005

	Winner	Loser	Winner-Loser
1%	0.017	0.016	0.001
			(0.22)
2%	0.0161	0.0123	0.0038
			(1.24)
3%	0.0152	0.0106	0.0046
			(1.62)
4%	0.0146	0.0090	0.0056
			(2.14)*
5%	0.0142	0.0087	0.0055
			(2.21)*
10%	0.0132	0.0084	0.0049
			(2.14)*
20%	0.0126	0.0086	0.0040
			(1.94)*
30%	0.0124	0.0090	0.0033
			(1.73)*
40%	0.0123	0.0094	0.0029
			(1.57)
50%	0.0121	0.0098	0.0024
			(1.35)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Figure 1a

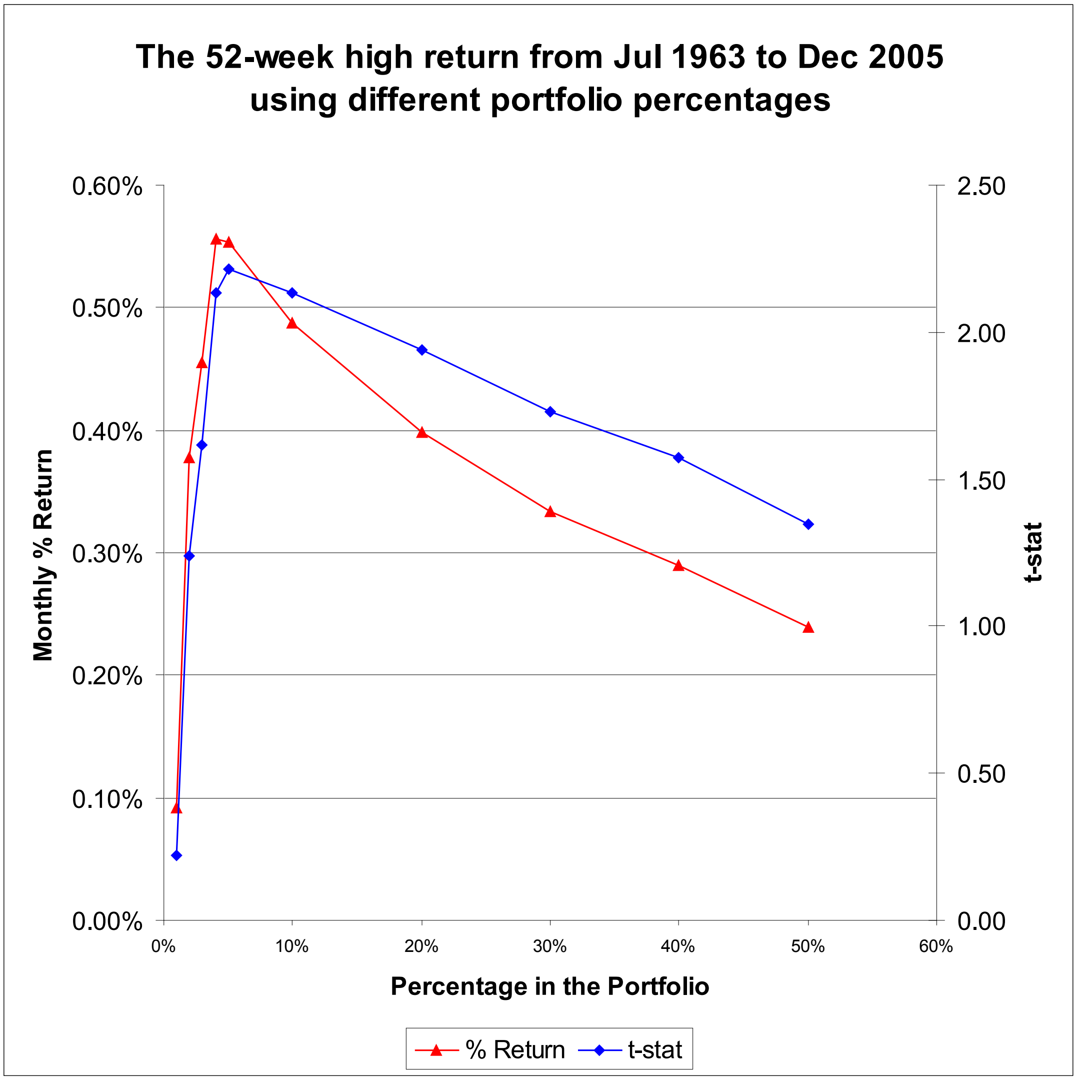

Figure 1a shows a clear peak with a downward trend as the portfolio percentage increases for both the average monthly return and the t-statistic used as a measure for significance. As the portfolio percentage moves down from 5% to 1% the strategy loses strength and significance. It is expected that as the portfolio percentage decreases, the number of stocks decreases which increases the opportunity for noise in the data. As the portfolio percentage increases and therefore the number of stocks the 52-week high momentum signal strengthens.

Both Table 3a and Figure 1a show that highest return is actually obtained when using a 4% portfolio, 0.56%, and the highest significance when the portfolio formation is 5%. The 30% chosen by George and Hwang seems to be an average return. They could have chosen a different percentage to show off the new strategy. As the 30% demonstrates to not be a result of data mining the remaining portfolios will be formed using this percentage unless otherwise stated.

The significance of a result can be affected by the amount of stocks in a portfolio as the smaller the number of stocks the larger the variance in returns. The minimum, maximum, median and average number of stocks for the winner and loser portfolios for the same period, 1963 to 2005, is shown in Table 3b, for analysis.

Table 3b

Statistics on the number of stocks in the winner and loser portfolios at different percentage levels

	Winners				Losers			
	Min	Max	Median	Average	Min	Max	Median	Average
1%	9	78	41	40	10	56	22	27
2%	25	153	84	80	30	120	52	62
3%	44	229	126	121	51	187	96	99
4%	61	305	169	162	72	257	136	139
5%	81	383	217	203	92	326	187	179
10%	175	763	462	415	187	696	426	388
20%	364	1519	976	851	383	1478	931	821
30%	560	2298	1496	1293	577	2272	1441	1262
40%	761	3079	2016	1737	771	3076	1962	1707
50%	956	3882	2533	2182	965	3877	2472	2152

Table 3b shows that when the sample is cut down to 1% the sample size is small but not too small to create a meaningful result. There is a minimum of 9 but an average 40 stocks in each winner portfolio and a minimum of 10 and average of 27 stocks for each loser portfolio. When the 52-week high momentum strategy is run using half of the data in each of the winner and loser portfolios, 50%, the maximum number of stocks is 3882 (3877) the average is 2182 (2152) for the winner (loser) portfolio. As the portfolios are equally weighted it does not matter if the winner and loser portfolios have the same amount of stocks in each. This can happen if a stock does not have enough data to be held for the full six month period.

5.4 52-Week High Momentum in 10 Year Increments

After analysing the full CRSP data set, 1926 to 2005, in Section 5.2, it became apparent that their are large differences in results when using the full CRSP data set compared to the 1963 to 2005 subset. Table 3a shows an analysis of the 52-week high momentum strategy over data sets that have be split to only contain 10 years of information from CRSP. Winner and loser portfolios are created by ranking the stocks that are closest to their 52-week high price, using the monthly close price as a comparison, to stocks that are furthest from it. The top 30% are brought (winners) and the bottom 30% are sold (losers) and both are held for six months. Buying winners and selling losers is an almost self financing portfolio. This is repeated each month over the data set period and the results are averaged. The significance of the average monthly return is shown below in brackets.

Table 4a

52-week high momentum strategy over 10 year periods

	Winner	Loser	Winner-Loser
Jan 1996 - Dec 2005	0.0133	0.0116	0.0017
			(0.39)
Jan 1986 - Dec 1995	0.0105	0.0066	0.0039
			(1.23)
Jan 1976 - Dec 1985	0.0177	0.0106	0.0071
			(2.18)**
Jan 1966 - Dec 1975	0.0071	0.0049	0.0022
			(0.45)
Jan 1956 - Dec 1965	0.0105	0.0071	0.0035
			(1.29)
Jan 1946 - Dec 1955	0.0080	0.0036	0.0045
			(1.73)*
Jan 1936 - Dec 1945	0.0087	0.0176	-0.0089
			(-1.67)*
Jan 1926 - Dec 1935	0.0102	0.0180	-0.0078
			(-0.78)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Figure 2a

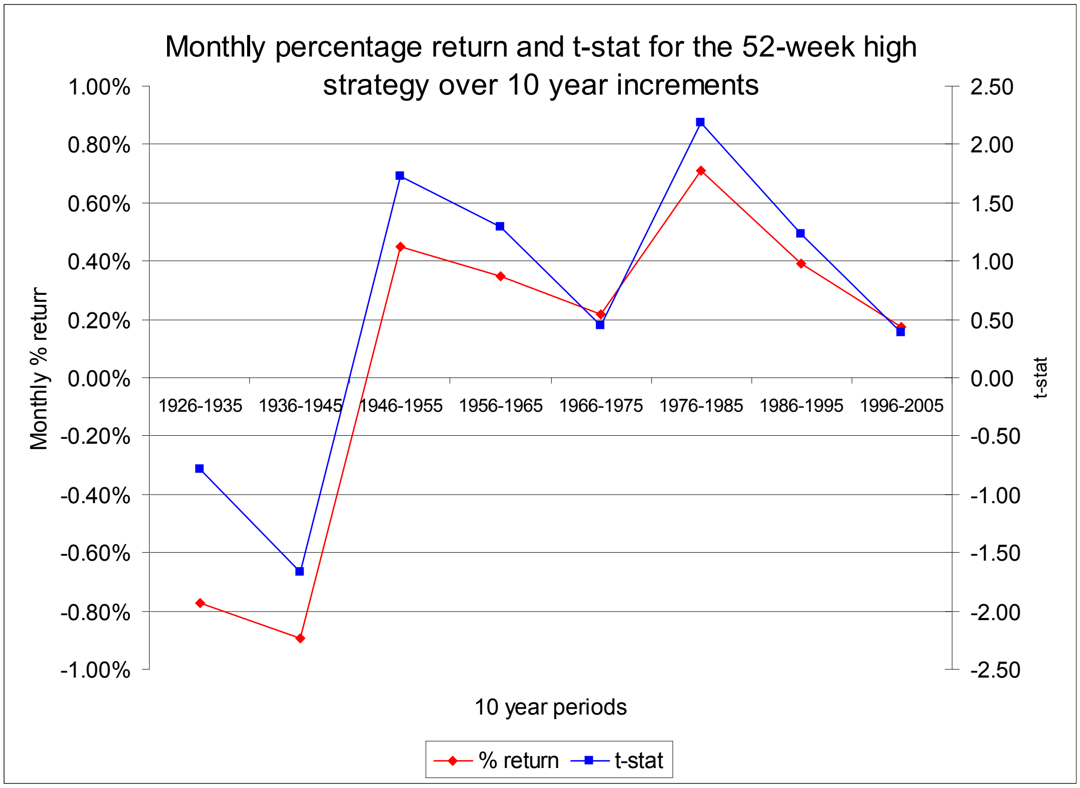

Table 4a and Figure 2a display a negative trend in returns and significance, measured by the t-statistic, for the 52-week high momentum strategy over the first part of the CRSP data series from 1926 to 1945, with returns of -0.78% and -0.89% for the first two 10 year data periods. It is interesting to note that over the 1926 to 1945 period the stock market went through the 1929 stock market crash and then through the great depression both creating a extreme bear market conditions. The later half of the dataset, 1946 to 2005, shows positive average monthly returns and significance. The results displayed could be for a number of reasons one of which is the market conditions mentioned earlier and this is examined further in Section 5.5.

Table 4b displays the minimum, maximum, median and average number of stocks used to create the winner and loser portfolios in the different 10 year data sets.

Table 4b

Statistics on the number of stocks in the winner and loser portfolios over the 10 year periods

	Winners				Losers			
	Min	Max	Median	Average	Min	Max	Median	Average
Jan 1996 - Dec 2005	1789	2298	2063	2056	1757	2272	1954	1991
Jan 1986 - Dec 1995	1540	2132	1795	1804	1460	2160	1704	1741
Jan 1976 - Dec 1985	618	1634	679	866	644	1528	710.5	862
Jan 1966 - Dec 1975	560	770	659	668	586	757	650	666
Jan 1956 - Dec 1965	299	598	314.5	379	302	597	314	382
Jan 1946 - Dec 1955	247	309	294	288	246	308	294	288
Jan 1936 - Dec 1945	202	246	230.5	229	201	247	228.5	227
Jan 1926 - Dec 1935	141	213	205	191	139	211	201	189

In what is expected to be the smallest dataset 1926 to 1935 the minimum number of stocks in a winner (loser) portfolio was 141 (139) and the average number of stocks was 191 (189). These are large enough numbers to create a meaningful result. In comparison the 1996 to 2005 dataset, which is the most current and therefore expected to have the most stocks, has a minimum of 1789 (1757) for the winner (loser) portfolio an average of 2056 (1991). The larger the sample size, the higher the significance of a result, assuming a constant level of variability.

The next section examines the 52-week high strategy over Bull, contraction, and Bear, expansion, market conditions to see if the 52-week high momentum strategy reacts differently.

5.5 Bull and Bear Market Analysis

Previously in Section 5.4 it is shown that the 52-week high momentum trading strategy achieves diverse results when analyzed over time. The data was split into 10 year increments and the average monthly return was vastly different at the beginning of the data set to the result at the end of the data set. This phenomenon requires further examination. One possible explanation is that the strategy is being affected by different market conditions, Bull and Bear markets.

Table 5a splits the CRSP dataset that contains all the stocks to 2005 into sub-periods based on market conditions. This is achieved by creating subsets using a switch between a Bull (expansion market) and a Bear (contraction market) as the indicator to stop the current set[4].

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[4] Bull and Bear market period definitions have been taken from http://www.nber.org/cycles.html

Winner and loser portfolios are created by ranking a stock by how close its current monthly close price is to its 52-week high price. The top 30% are brought at next months close price and called the winner portfolio and the bottom 30% are sold and called the loser portfolio. The portfolios are held for six months before being closed out. Each month a new winner and loser portfolio are created and the result is the average of all the monthly returns over the period. Buying the winner portfolio and selling the loser portfolio is a self-financing strategy. The significance of the average monthly return is shown in brackets.

Table 5a

52-week high momentum strategy split between bull and bear market conditions

	Bull/Bear	Exp/Cont	Winner	Loser	Winner-Loser
Dec 1926 - Nov 1927	Bear	Contraction	0.0240	0.0313	-0.0073
					(-0.89)
Dec 1927 - Jul 1929	Bull	Expansion	0.0152	-0.0091	0.0244
					(2.19)*
Aug 1929 - Mar 1933	Bear	Contraction	-0.0033	0.0202	-0.0235
					(-1.00)
Apr 1933 - Apr 1937	Bull	Expansion	0.0132	0.0236	-0.0104
					(-1.02)
May 1937 - Jun 1938	Bear	Contraction	-0.0066	-0.0059	-0.0007
					(-0.03)
Jul 1938 - Jan 1945	Bull	Expansion	0.0095	0.0189	-0.0095
					(-1.57)
Feb 1945 - Oct 1945	Bear	Contraction	0.0404	0.0543	-0.0139
					(-2.09)**
Nov 1945 - Oct 1948	Bull	Expansion	-0.0050	-0.0146	0.0095
					(2.13)**
Nov 1948 - Oct 1949	Bear	Contraction	0.0169	0.0207	-0.0038
					(-0.49)
Nov 1949 - Jun 1953	Bull	Expansion	0.0081	0.0033	0.0048
					(1.52)
Jul 1953 - May 1954	Bear	Contraction	0.0273	0.0232	0.0040
					(0.91)
Jun 1954 - Jul 1957	Bull	Expansion	0.0065	0.0024	0.0040
					(0.94)
Aug 1957 - Apr 1958	Bear	Contraction	0.0268	0.0339	-0.0071
					(-0.95)
May 1958 - Mar 1960	Bull	Expansion	0.0108	0.0041	0.0067
					(1.25)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

52-week high momentum strategy split between bull and bear market conditions - Cont

	Bull/Bear	Exp/Cont	Winner	Loser	Winner-Loser
Apr 1960 - Feb 1961	Bear	Contraction	0.0231	0.0180	0.0050
					(0.60)
Mar 1961 - Nov 1969	Bull	Expansion	0.0095	0.0088	0.0007
					(0.16)
Dec 1969 - Nov 1970	Bear	Contraction	0.0172	0.0225	-0.0053
					(-0.33)
Dec 1970 - Oct 1973	Bull	Expansion	-0.0023	-0.0179	0.0156
					(2.91)***
Nov 1973 - Mar 1975	Bear	Contraction	0.0065	0.0113	-0.0048
					(-0.26)
Apr 1975 - Dec 1979	Bull	Expansion	0.0154	0.0165	-0.0011
					(-0.25)
Jan 1980 - Jul 1980	Bear	Contraction	0.0398	0.0361	0.0037
					(0.32)
Aug 1980 - Jun 1981	Bull	Expansion	0.0020	-0.0031	0.0052
					(0.60)
Jul 1981 - Nov 1982	Bear	Contraction	0.0322	0.0283	0.0039
					(0.30)
Dec 1982 - Jun 1990	Bull	Expansion	0.0086	-0.0058	0.0143
					(4.12)***
Jul 1990 - Mar 1991	Bear	Contraction	0.0277	0.0469	-0.0192
					(-1.60)
Apr 1991 - Feb 2001	Bull	Expansion	0.0137	0.0102	0.0035
					(1.09)
Mar 2001 - Nov 2001	Bear	Contraction	0.0149	-0.0012	0.0161
					(1.49)
Dec 2001 - Dec 2005	Bull	Expansion	0.0141	0.0232	-0.0090
					(-1.03)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 5a shows mixed results between the periods with only a few results showing any significance, but this is not unexpected as the significance is affected by the small number of portfolios formed in each bear and bull market period. The results shown in Table 5a are summarised in Table 5b by using all the Bear time periods and all the Bull time periods separately. The Bull and Bear time periods are then compared to see if there is a difference between the two results.

Table 5b

52-week high momentum strategy for Bull and Bear markets 1926-2005

	Winner	Loser	Winner-Loser
Bear	0.0152	0.0222	-0.0070
			(-1.12)
Bull	0.0098	0.0069	0.0030
			(1.87)*
Bull-Bear			0.0099
			(2.99)***

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

The Bear market result although not significant at a 10% level is negative, -0.7%, whereas the Bull market spread between the winner and loser portfolios is positive, 0.3%, and significant at a 10% level. Using a difference between two means test, we find that the Bull and Bear market results are different from each other and this result is statistically significant at a 1% level. This shows that 52-week high momentum trading strategy works better in Bull, expansion, markets than it does in Bear, contraction, markets.

Previously we noted that the CRSP dataset reacted differently to the 52-week high momentum strategy in the first years of the data compared to the later years of the data. For this reason the dataset has been split in half to see if the first years produce different results to the later years when they are also split for Bull and Bear markets. The next two tables display the results for the Bull and Bear markets over the December 1926 to February 1961 period and the March 1961 to December 2005 period. The same parameters as Table 5a and b have been used, a 30% portfolio percentage, a one month lag before buying at the close price and a six month holding period. The split in the data at the 1961 year was chosen, rather than using the previous 1963 period, as there was a switch between a contracting market and an expanding market at this time.

Table 5c

52-week high momentum strategy for Bull and Bear markets 1926-1961

	Winner	Loser	Winner-Loser
Bear	0.0116	0.0219	-0.0104
			(-1.15)
Bull	0.0082	0.0079	0.0003
			(0.11)
Bull-Bear			0.0107
			(2.12)**

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 5d

52-week high momentum strategy for Bull and Bear markets 1961-2005

	Winner	Loser	Winner-Loser
Bear	0.0215	0.0226	-0.0011
			(-0.17)
Bull	0.0109	0.0062	0.0046
			(2.45)**
Bull-Bear			0.0058
			(1.90)*

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

There is a statistically significant difference between the Bull and Bear market periods in both the 1926 to 1961 and the 1961 to 2005 data sets. The 1926 to 1961 resulted in significance at a 5% level and 1961 to 2005 has significance at a 10% level. The results show that the 52-week high momentum trading strategy performed well in the Bull markets over the 1961 to 2005 period resulting in a 0.46% monthly average return which is significant at a 1% level. George and Hwang (2004) obtained an average monthly return of 0.45% over the 1963 to 2001 period.

It is interesting to note that in the 1926 to 1961 period the Bear market produced an average monthly return of -1.04% although not statistically significant at a 10% level, even though the result is negative it still has a stronger t-statistic than the average monthly return of 0.03% for the Bull markets over the same period. The Bull market is also not significant at a 10% level. However the in the 1961 to 2005 period the Bull market seems to be the driver with an average monthly return of

0.46% which is significant at a 5% level, compared to the Bear markets average monthly return over the same time period of -0.11% which is not significant.

In summary, using the 52-week high momentum strategy in Bull markets obtains positive average monthly returns. In contrast the Bear market finds negative average monthly returns. The returns from the Bull and the Bear markets are significantly different from each other showing a clear trend in the way the 52-week high momentum trading strategy reacts in different market conditions.

Appendix two Table I and Table II show the results of the 52-week high momentum strategy over the entire data from December 1926 to February 1961 and March 1961 to December 2005 for the respective tables. This information is a useful comparison to the Bull and Bear market split results.

5.6 Absolute 52-Week High Momentum

The Bear market results in Section 5.5 shows that when the market is declining the 52-week high momentum strategy results in more negative average monthly returns. As the 52-week high is a comparison ratio between the other stocks in the market at a given point in time it can be choosing the best of the worst stocks in these markets. The below test looks at investing in only stocks that have increased over a formation period to be accepted into the winner portfolio and only stocks that have decreased over a formation period are to be chosen for the loser portfolio. This strategy is referred to as the Absolute 52-week high momentum strategy. This is the first time that the author is aware that absolute momentum has been analysed. Momentum is about relative strength, buying strong stocks and selling weak stocks. The reasoning behind absolute momentum is to buy stocks that are truly strong (have actually increased) and sell stocks that are truly weak (have actually decreased) over a past period.

To form portfolios, stocks are ranked by how close their monthly close price is to the 52-week high from the closest to the furthest stocks are then selected for preliminary winner and loser portfolios. The top 30% are selected for the winners and the bottom 30% for the losers. The return that each stock has gained over the formation period, which is the previous 1, 3, 6, or 12 months, is calculated. If a stock in the winner (loser) portfolio has a negative (positive) return over the formation period selected it is excluded from the portfolio. Stocks are then brought (sold) for the final winner (loser) portfolio at the next months close price and held for six months. Stocks are required to have data for the entire formation and holding period to be included in a portfolio. These portfolios are created each month over the 1963 to 2005 period. Buying the winner portfolio and selling the loser portfolio is a self-financing strategy. The significance of the average monthly returns, measured by the t-statistic, is shown below the result in brackets.

Table 6a

Absolute 52-week high momentum over the Jul 1963 - Dec 2005 period

	Winner	Loser	Winner-Loser
1 month formation period	0.0130	0.0089	0.0041
			(2.10)**
3 month formation period	0.0132	0.0088	0.0044
			(2.29)**
6 month formation period	0.0135	0.0085	0.0050
			(2.61)***
12 month formation period	0.0132	0.0095	0.0037
			(1.93)*

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

All the results in Table 6a are positive and statistically significant. The six month formation period, which is commonly used in momentum literature, obtained the highest average monthly return, 0.5%, and was also statistically significant at a 1% level. This 6 month result is more prevalent than the 52-week high strategy without the absolute component over the same period which resulted in 0.33% average monthly return. The formation period will remain at 6 months for the remainder of this paper unless otherwise stated with the results.

Tables 6b to 6g examine the absolute 52-week high momentum strategy in the same way as the 52-week high strategy for comparison purposes. The portfolio percentage, 10 year periods and market conditions are all analysed.

Table 6b shows the average monthly return using different portfolio percentages when portfolios are created using the absolute 52-week high momentum strategy. Stocks are first ranked by how near the monthly close price at the time is to its 52-

week high price. Stocks that are closest are listed at the top and stocks that are furthest are listed at the bottom. The top (bottom) portfolio percentage 1%, 2%, 3%, 4%, 5%, 10%, 20%, 30%, 40% or 50% of stocks are included in the winner (loser) portfolio. Stocks in the winner (loser) portfolio are then tested to see if their past return is positive (negative) over the previous 6 months. Only stocks that meet both criteria are included in the winner and loser portfolios. Once these stocks are finalised the winners are brought and the losers sold at next months close price. Stocks are held for 6 months and then the positions are closed out. Buying winners and selling losers is a self-financing portfolio. Significance using the t-statistic is shown below in brackets.

Table 6b

Absolute 52-week high momentum for different portfolio percentages 1963 - 2005

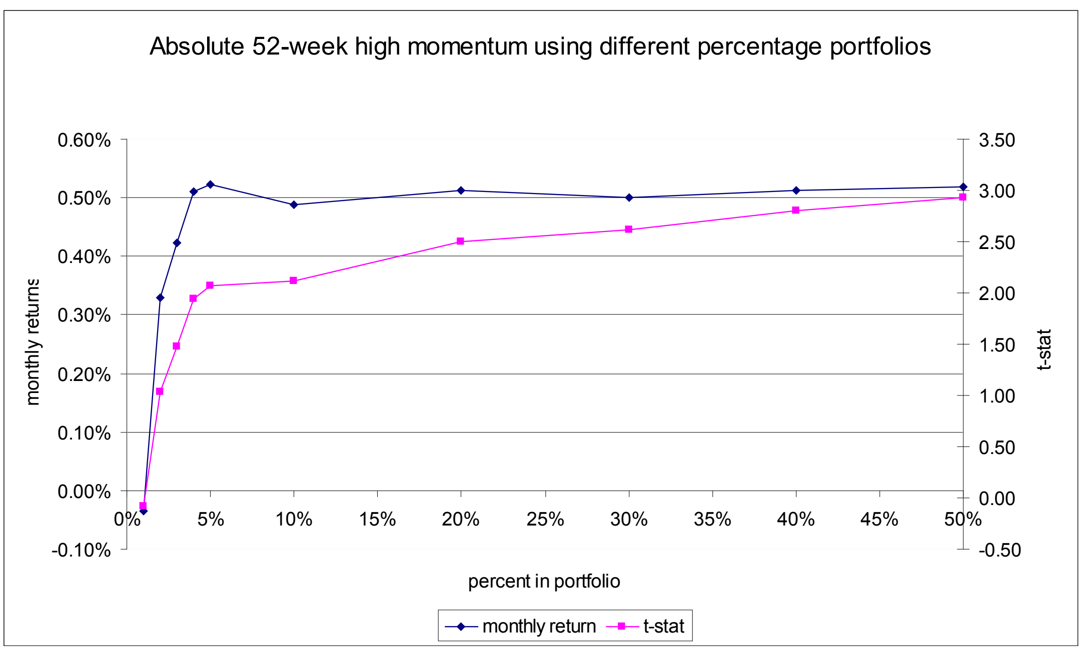
	Winner	Loser	Winner-Loser
1%	0.0175	0.0178	-0.0003
			(-0.08)
2%	0.0164	0.0131	0.0033
			(1.04)
3%	0.0154	0.0112	0.0042
			(1.48)
4%	0.0149	0.0097	0.0051
			(1.94)*
5%	0.0145	0.0093	0.0052
			(2.06)**
10%	0.0137	0.0088	0.0049
			(2.12)**
20%	0.0134	0.0083	0.0051
			(2.50)**
30%	0.0135	0.0085	0.0050
			(2.61)***
40%	0.0136	0.0084	0.0051
			(2.80)***
50%	0.0136	0.0084	0.0052
			(2.93)***

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 6b shows the average monthly returns with significance levels for the absolute 52-week high momentum trading strategy over the 1963 to 2005 period using different portfolio percentages. There is a relatively flat trend between monthly returns and statistical significance and the size of the portfolio percentage. The largest result is gained by investing in the 50% portfolio percentage, 0.52% significant at a 1% level, where all stocks are considered for the winner and loser portfolio. These stocks are first separated into the two classifications by how close they are to their 52-week high price and then stocks that have not got a positive, for the winners, or negative for the losers, past return over the previous 6 months are discarded from the portfolio. An investigation into whether in fact the absolute part of the strategy was the binding factor is examined more in Section 5.7.

In summary, it is found that the smaller the percentage of stocks in the winner and loser portfolios which are close to and far from to the 52-week high price the smaller the average monthly return and statistical significance of the winner minus loser self financing portfolio. This is best represented by Figure 3a.

Figure 3a



Comparing Figure 3a to Figure 1a we notice that the returns and significance levels do not taper off instead they stay pretty flat. As the portfolio percentage nears 50 the absolute component of the strategy becomes more binding and this makes the strategy stronger. This result is expected as with an increase in the size of portfolios only stocks that are truly winners, have increased in the past, and stocks that are truly losers, have decreased in the past, are allowed to be included in the portfolios. This is in contrast to momentum papers such as Jegadeesh and Titman (1993) whose winner portfolio could have decreased over the preceding period as stocks are selected based on how they perform relative to other stocks in that period.

If theory holds we would expect to see at a high portfolio percentage stocks that are chosen by how close they are to their 52-week high price and have increased over the previous six month period would be the same list of stocks as the stocks chosen in the next portfolio percentage up. The absolute component is not, however, completely influencing the 40% and below portfolio percentages as there is still a difference between the 40% and 50% average monthly returns. To fully analyse this Absolute Momentum would need to be tested as a strategy in its own right. Testing absolute momentum in isolation is however, beyond the scope of this research. The remainder of the thesis will continue to use a 30% portfolio percentage as per George and Hwang (2004) unless specified.

Previous sections have shown that the performance of the dataset varies over different time periods so the Table 5c analyses the absolute 52-week high momentum trading strategy over 10 year subsets.

Stocks are first ranked by there nearness to their 52-week high price relative to their monthly close price. The top 30% are classified as winners and the bottom 30% as losers. The past return over the last six months is then calculated and only stocks that have a positive (negative) past return may be included in the winner (loser) portfolio. Stocks are then brought, for winners and sold, for losers, at the next months close price and held for 6 months. This is repeated each month and the results are averaged. Buying the winners and selling the losers creates a self-financing portfolio. The significance of the results is represented by the t-statistic in the brackets below.

Table 6c

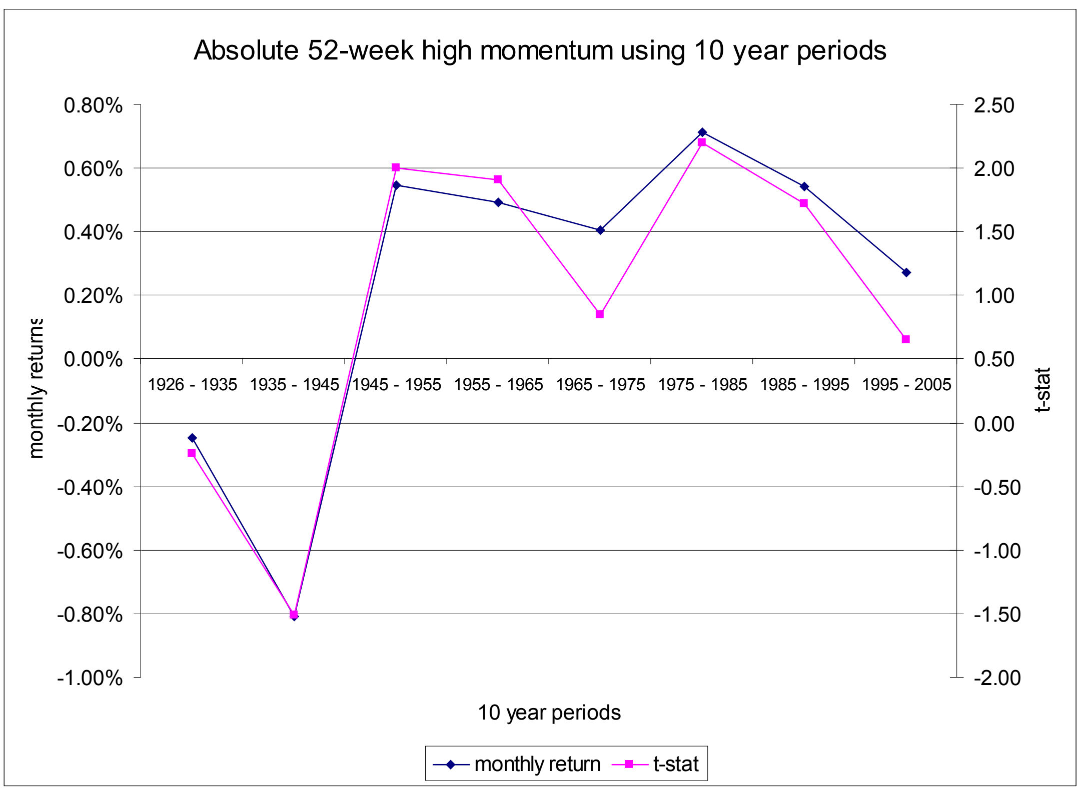
Absolute 52-week high momentum - over 10 year periods

	Winner	Loser	Winner-Loser
Dec 1995 - Dec 2005	0.015	0.0123	0.0027
			-0.65
Dec 1985 - Dec 1995	0.0128	0.0074	0.0054
			(1.72)*
Dec 1975 - Dec 1985	0.0193	0.0122	0.0071
			(2.19)**
Dec 1965 - Dec 1975	0.0093	0.0053	0.004
			-0.85
Dec 1955 - Dec 1965	0.0109	0.006	0.0049
			-1.9
Dec 1945 - Dec 1955	0.0097	0.0043	0.0055
			(2.00)**
Dec 1935 - Dec 1945	0.0106	0.0187	-0.0081
			(-1.52)
Dec 1926 - Dec 1935	0.0117	0.0141	-0.0025
			(-0.25)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 6c represents the winner, loser and winner minus loser average monthly returns and significance of the absolute 52-week high momentum strategy using a 30% portfolio percentage and a six month formation period. The highest yielding period is 1975 to 1985 with a monthly return of 0.71% which is significant at the 5% level. The first two decades are negative which was the trend noted previously in Section 5.4 which analysed the 52-week high strategy without the absolute component. It is interesting to note that these results are less negative in the first two decades and more positive on the remaining decades than the results in Section 5.4. Table 6c is summarised using Figure 3b.

Figure 3b



The statistical significance and the average monthly returns for the separate 10 year periods exhibit the same trends as Section 5.4.

Table 6d displays the results obtained by running the absolute 52-week high momentum strategy over bull, expansion, and bear, contraction, markets[5]. Stocks are ranked by how close the monthly close price is to the 52-week high price of a stock. The top (bottom) 30% stocks are stocks are selected for the winner (loser) portfolio, then the return for the previous 6 month period is calculated, if the return is positive (negative), the stock remains in the winner (loser) portfolio. Stocks that make it to the final winner (loser) portfolio are brought (sold) at the next months close price and held for a six month period. Buying the winners and selling the losers creates an almost self financing portfolio. This process is repeated every month to create anew set of portfolios and the monthly returns are averaged. The significance is represented by the t-statistic shown in parenthesis.

[5] Bull and Bear market period definitions have been taken from http://www.nber.org/cycles.html

Table 6d

Absolute 52-week high momentum split between Bull and Bear markets

	Bull/Bear	Exp/Cont	Winner	Loser	Winner-Loser
Dec 1926 - Nov 1927	Bear	Contraction	0.0237	0.0276	-0.0039
					(-0.49)
Dec 1927 - Jul 1929	Bull	Expansion	0.0178	0.0033	0.0145
					(1.49)
Aug 1929 - Mar 1933	Bear	Contraction	-0.0004	0.0045	-0.0050
					(-0.27)
Apr 1933 - Apr 1937	Bull	Expansion	0.0259	0.0467	-0.0209
					(-1.38)
May 1937 - Jun 1938	Bear	Contraction	-0.0153	-0.0163	0.0009
					(0.06)
Jul 1938 - Jan 1945	Bull	Expansion	0.0119	0.0178	-0.0058
					(-1.08)
Feb 1945 - Oct 1945	Bear	Contraction	0.0325	0.0453	-0.0128
					(-2.30)**
Nov 1945 - Oct 1948	Bull	Expansion	0.0029	-0.0053	0.0082
					(1.34)
Nov 1948 - Oct 1949	Bear	Contraction	0.0045	0.0041	0.0004
					(0.04)
Nov 1949 - Jun 1953	Bull	Expansion	0.0105	0.0067	0.0038
					(1.16)
Jul 1953 - May 1954	Bear	Contraction	0.0153	0.0073	0.0080
					(1.17)
Jun 1954 - Jul 1957	Bull	Expansion	0.0105	0.0056	0.0049
					(1.17)
Aug 1957 - Apr 1958	Bear	Contraction	0.0094	0.0078	0.0017
					(0.16)
May 1958 - Mar 1960	Bull	Expansion	0.0154	0.0109	0.0045
					(0.80)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Absolute 52-week high momentum split between Bull and Bear markets – Cont

	Bull/Bear	Exp/Cont	Winner	Loser	Winner-Loser
Apr 1960 - Feb 1961	Bear	Contraction	0.0150	0.0055	0.0096
					(1.38)
Mar 1961 - Nov 1969	Bull	Expansion	0.0114	0.0081	0.0034
					(0.87)
Dec 1969 - Nov 1970	Bear	Contraction	0.0025	0.0001	0.0023
					(0.17)
Dec 1970 - Oct 1973	Bull	Expansion	0.0065	-0.0061	0.0125
					(1.85)
Nov 1973 - Mar 1975	Bear	Contraction	0.0055	0.0006	0.0049
					(0.36)
Apr 1975 - Dec 1979	Bull	Expansion	0.0188	0.0194	-0.0006
					(-0.12)
Jan 1980 - Jul 1980	Bear	Contraction	0.0294	0.0131	0.0163
					(1.67)*
Aug 1980 - Jun 1981	Bull	Expansion	0.0186	0.0096	0.0090
					(0.96)
Jul 1981 - Nov 1982	Bear	Contraction	0.0215	0.0149	0.0066
					(0.61)
Dec 1982 - Jun 1990	Bull	Expansion	0.0125	0.0005	0.0120
					(2.94)***
Jul 1990 - Mar 1991	Bear	Contraction	0.0109	0.0077	0.0032
					(0.22)
Apr 1991 - Feb 2001	Bull	Expansion	0.0158	0.0131	0.0027
					(0.85)
Mar 2001 - Nov 2001	Bear	Contraction	0.0145	-0.0026	0.0171
					(2.07)**
Dec 2001 - Dec 2005	Bull	Expansion	0.0161	0.0202	-0.0041
					(-0.54)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 6d finds that of the 14 bull markets 10 have a positive winner minus loser portfolio spread. From the 14 bear market periods only 3 exhibit a negative winner minus loser spread, compared to the 9 in the basic 52-week high momentum strategy, so adding the absolute component is helping the strategy choose more successful stocks to create a positive overall return in Bear markets. Much like Table 6a which analysed the 52-week high strategy over Bull and Bear market sub period the results are sparsely significant which is expected due to the small sample size for each sub-period. Table 6e quantifies the difference between Bull and Bear markets over the 1926 to 2005 period.

Table 6e

52-week high absolute momentum Bull and Bear markets summary 1926-2005

	Winner	Loser	Winner-Loser
Bear	0.0098	0.0072	0.0026
			(0.61)
Bull	0.0138	0.0114	0.0023
			(1.35)
Bull-Bear			-0.0003
			(-0.11)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

The result of splitting the data into Bull and Bear markets for the absolute 52-week high momentum strategy proves to be interesting. Unlike the straight 52-week high strategy the result of difference between the two markets is not significant at a 10% level and is outputting a negative result. This is consistent with Table 6d results which show that out of 14 sub periods 10 for the Bull and 11 for the Bear markets obtained positive winner minus loser spread returns.

Table 6f and Table 6g show the Bull and Bear market condition summary analysis when the dataset is split in half, 1926 to 1961 and 1961 to 2005. As noted before the first half of the dataset exhibits negative results for both the 52-week high and the absolute 52-week high so it is necessary to see if this is driving the lack of significance in Table 6e.

Table 6f

52-week high absolute momentum Bull and Bear markets summary 1926-1961

	Winner	Loser	Winner-Loser
Bear	0.0074	0.0082	-0.0008
			(-0.13)
Bull	0.0135	0.0146	-0.0011
			(-0.34)
Bull-Bear			-0.0003
			(-0.09)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table 6g

52-week high absolute momentum Bull and Bear markets summary 1961-2005

	Winner	Loser	Winner-Loser
Bear	0.0134	0.0056	0.0077
			(1.50)
Bull	0.0140	0.0093	0.0046
			(2.49)**
Bull-Bear			-0.0031
			(-1.32)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

The 1926 to 1961 period still shows no significance with even smaller bull and bear average monthly returns, -0.11% and -0.08% respectively. However in the 1961 to 2005 dataset the bull markets shows statistically significant returns of 0.46% at the

5% level but the difference between the bull and bear markets still shows no significance. The lack of significance between the bull and bear markets could prove that the absolute part of the strategy is working, as stocks that would normally decrease (increase) in a bear (bull) market are not being entered into the winner (loser) portfolio during those periods. This result strengthens the theory that the 52-week high momentum strategy works differently in Bull versus Bear market conditions. It shows that in a Bear market the substantial amount of stocks that are decreasing are pulling down the performance of the original strategy.

It is shown in these results that by adding Absolute Momentum different stocks are chosen for each portfolio giving different average monthly returns. It is difficult to determine if Absolute Momentum is a binding constraint and further research would be needed to understand this further but that is outside the scope of this research.

5.7 Fama-French Three Factor Regression Model

The below regression analysis is examining how much of the 52-week high momentum trading strategy average monthly return can be explained away by the factors; return above the market, size and value.

Table 7a

Fama French Three Factor Risk Adjustment over Jul 1963 to Dec 2001

	Intercept	R_m-R_f	SMB	HML
Parameter	0.02037	0.01795	-0.12729	0.03265
t-stat	(0.23)	(0.81)	(-4.22)***	(1.09)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

All the coefficients are not significant except SMB which is significant at the 10% level. The results are showing that the larger the difference between the small cap returns and large cap returns the less profitable the 52-week high momentum strategy becomes. As the intercept is not significant it appears that the 52-week high momentum strategy is not profitable after adjustment for risk. Further investigation into these results is needed to understand the impact that size has on the stocks chosen in the 52-week high strategy.

5.8 Cahart Multi-Factor Regression Model

In the Cahart Multi-factor regression the same factors are used as the three factor model with an addition of a Momentum factor.

Table 7b

Cahart Multi - Factor Risk Adjustment over Jul 1963 to Dec 2001

	Intercept	R_m-R_f	SMB	HML	Mom
Parameter	0.00870	0.01922	-0.12578	0.03827	0.00996
t-stat	(0.09)	(0.86)	(-3.72)***	(1.22)	(0.27)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Like the three factor model the SMB co-efficient is negative and significant at a 10% level but the new factor momentum is not significant showing that the basic past return momentum is not explaining the average monthly return obtained by the 52-week high strategy.

5.9 Transaction Costs

Table 8a shows the amount of transaction costs that would need to be charged to make the 52-week high momentum trading strategy average monthly returns amount to zero. This result is shown for the different portfolio percentages that were tested in this thesis.

Table 8a

Transaction costs to make the returns from the 52-week high momentum strategy equal zero using different portfolio percentage Jul 1963 - Dec 2005

Portfolio Percentage	Winner	Loser	Winner-Loser	Transaction Costs
1%	0.017	0.016	0.001	0.14%
2%	0.0161	0.0123	0.0038	0.55%
3%	0.0152	0.0106	0.0046	0.66%
4%	0.0146	0.009	0.0056	0.81%
5%	0.0142	0.0087	0.0055	0.80%
10%	0.0132	0.0084	0.0049	0.71%
20%	0.0126	0.0086	0.004	0.58%
30%	0.0124	0.009	0.0033	0.48%
40%	0.0123	0.0094	0.0029	0.42%
50%	0.0121	0.0098	0.0024	0.35%

The lower the winner minus loser average monthly return the lower the transaction costs that would need to be charged to make the 52-week high momentum trading strategy return zero. For the 30% portfolio percentage which was used in the majority of this thesis and in George and Hwang (2004) the transaction costs would need to be higher than 0.48% on the buy and the sell side to return a negative winner minus loser result after transaction costs have been accounted for. This seems like a reasonable level of transaction costs that need to be charged before the 52-week high momentum trading strategy can be discounted as unprofitable. There are also costs associated with short selling but it is hard to quantify all the costs a trader would be faced with.

6. Conclusion

The 52-week high momentum strategy was first published by George and Hwang in 2004. The paper found positive abnormal returns in the US market by buying stocks that are close to their 52-week high price and selling stocks that are far from their 52-week high price. George and Hwang's result was found to be stronger than previous price momentum strategies such as Jegadeesh and Titman (1993), but unlike price momentum the 52-week high strategy has not had many robustness checks. Marshall and Cahan (2005) perform the first out of sample test also finding positive abnormal returns on the Australian market. Further investigation into the strength of the strategy is needed to determine if this is a way of making consistent positive abnormal returns.

This thesis uses the same CRSP data set as the George and Hwang paper but over a longer period of 1925 to 2005. It is found that the 52-week high momentum trading strategy can not be ruled out as possibly having positive abnormal returns after the George and Hwang paper was published in 2004. Changing the portfolio percentage, the portion of stocks allocated to the winner and loser portfolio, to 1%, 2%, 3%, 4%, 5%, 10%, 20%, 30%, 40%, 50% found as expected that the monthly return decreases as the portfolio percentage gets really small and the number of stocks in the portfolios gets small. This occurs as there is greater opportunity for noise in the data. After the optimal percentage of 4% the returns start to flatten with an increase in portfolio percentage as the 52-week high momentum signal gets stronger. This is a test of the strength of the signal versus the noise in the data. As per George and Hwang for the base portfolio percentage for the results is 30%.

Running the 52-week high strategy over all the data, 1925 to 2005 obtained a small insignificant return of 0.07%, but the return over the 1963 to 2005 period was 0.33% and significant at the 10% level. This substantial drop in return required further analysis. The data was sliced into 10 year blocks to see how the strategy performs over time. The results found that the first two decades, around the time of the great depression and the 1929 stock market crash, exhibit negative returns affecting the all data result.

To further analyse the negative returns the data is split between bull and bear market periods and it is found that 10 of 14 bull market periods having a positive spread between winner and loser portfolio returns and 9 of 14 bear market periods having negative spread between the winner and loser returns. As the sample size is small for each period the significance levels are not examined. It is found that there is a significant difference between the Bull and Bear market winner minus loser portfolio spreads. This shows that there is a difference in the way the 52-week high strategy performs in bull and bear markets.

Negative returns are obtained over bear markets showing that the strategy is choosing stocks that are not 'true' winners and 'true' losers. Instead the strategy is picking stocks that are the 'best of the worst'. It is found that the absolute 52-week high combats this issue by buying only stocks that are close to their 52-week high and have positive past returns and selling stocks that are far from their 52-week high and have negative past returns. The absolute 52-week high obtained a higher average monthly return 0.5% that is significant at a 1% level. This is the first time that absolute momentum has been studied as far as the author is aware.

Examining the Absolute 52- week high momentum trading strategy over different portfolio percentages it was found that the strategy exhibits a flatter return over the larger portfolio percentage. The flatness shows that the absolute component may be binding the strategy.

Analysing the absolute 52-week high momentum trading strategy over the separate bull and bear markets found that the absolute component increases the success rate over bear markets with a drop from 9 out of 14 winner minus loser spreads being negative to only 3 out of 14. The difference between the bull and bear markets is no longer significant showing that the bear market is now exhibiting as much positive return as the bull market. Adding absolute to the 52-week high momentum strategy strengthens the average monthly returns when used over different market conditions.

All these results are interesting and they help strengthen the theory of the 52-week high; however more research still needs to be completed especially in the area of absolute momentum to gain a more solid understanding of the area. Future research should also look more closely at whether the 52-week high momentum strategy can add value after adjusting for risk.

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8. Appendix one

Transaction cost derivation

The below derives the formula used to calculate what percentage value of transaction costs would need to be charged on each transaction to make the 52-week high momentum strategy return equal zero. Four transactions are needed to form each portfolio, buying and then selling stocks in the winner portfolio and selling and then buying stocks in the loser portfolio. It is not possible to divide the final winner minus loser return by four as the winner and loser stocks change value over time. The formulae below accounts for the change, either increase or decrease, in value of stocks between the formation date and the final close out date by adding in the TC(1+WR) and TC(1+LR) terms. These terms adjust the level of transaction costs by the proportional value difference in the individual winner and loser portfolios at the end of the holding period.

$$0 = \left[2TC + TC(1+WR) + TC(1+LR)\right] - WLR$$

$$0 = 2TC + TC + TC(WR) + TC + TC(LR) - WLR$$

$$WLR = 4TC + TC(WR + LR)$$

$$WLR = TC(4 + WR + LR)$$

$$TC = \frac{WLR}{(4 + WR + LR)}$$

Where:

TC = Percentage of transaction costs

WLR = Winner minus loser average monthly return $\times$ the holding period in months (h)

WR = Winner average monthly return $\times$ the holding period in months (h)

LR = Loser average monthly return $\times$ the holding period in months (h)

9. Appendix two

Table I

52-week high momentum strategy over Dec 1926 – Feb 1961

	Winner	Loser	Winner-Loser
Dec 1926 - Feb 1961	0.0092	0.0121	-0.0029
			(-0.85)

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level

Table II

52-week high momentum strategy over Mar 1961 - Dec 2005

	Winner	Loser	Winner-Loser
Mar 1961 - Dec 2005	0.0119	0.0084	0.0035
			(1.90)*

*** significance at a 1% level; ** significance at a 5% level; * significance at a 10% level