Portfolio structure and optimisation of momentum returns

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Kartick Gupta

Department of Finance

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Abstract

This study analyses momentum returns in 54 countries covering 34 years. It is the first study where optimising programmes are applied to momentum returns and portfolio selection. Momentum returns have remained a contentious topic and a substantial amount of research purports to support and negate this anomaly. Momentum studies have previously concentrated on finding the cause of this anomaly or determining whether abnormal returns are present only in a particular dataset. However, there is no clear consensus regarding how to construct/implement a momentum strategy. To date it has been unclear as to how many portfolios should be created, whether or not the portfolios should be equally-weighted or value-weighted and how the momentum returns will change when a chosen strategy is constructed/implemented compared to an alternative strategy. This lack of precision concerning how to construct/implement momentum strategy potentially leads to confounding results. This current thesis contributes to an understanding of the "structure impact effect" by computing momentum returns for changing portfolio structures and observing the magnitude of the impact on returns on a specially crafted database of 52,593 stocks from 54 countries over the time period 1973-2007.

The two important empirical extensions are the industrial momentum and the 52-week high momentum models. Both the industrial momentum and 52-week high momentum strategies claim that their returns are superior to the traditional momentum return and possess superior explanatory power. Empirical evidence, to date, has not been available to attest to whether the results hold true

when applied in different markets. This gap in knowledge motivated this research investigation of multiple countries addressing how different methods of calculating returns, different approaches to momentum strategy, different portfolio weighting process impact upon the robustness of results.

This research also addresses the question of whether momentum returns can be increased through the use of optimisation algorithms. Traditionally, little attention has been paid to the portfolio weighting with either an equal-weighted or value-weighted approach to allocating funds to the Winner and Loser portfolios. This study proposes an alternative way of allocating money to the Winner and Loser portfolios with the goal of generating increased returns. Eight different algorithms are applied to the share returns to determine whether one method is clearly superior to others in maximising the momentum returns for the synthesised portfolios over a period of time. This is the first study of its type where optimising programmes are applied to momentum returns and portfolio selection and covers several countries.

The results indicate that momentum returns are robust on a global scale and the returns are by and large statistically significant under different portfolio construction approaches. Both the industrial and 52-week momentum strategies remain positive and statistically significant but do not generate the same magnitude of returns as the conventional momentum return model. The optimisation of momentum return shows promising results as a number of optimisation techniques do enhance momentum returns. As the potential to increase returns becomes known, traders will quickly react and there is likely to be a range of new investment products arising.

DEDICATION

To my parents, Gopal Gupta and Krishna Gupta for their continued support, encouragement and love throughout this journey. I would not have succeeded reaching this point without blessings from Maa Kali.

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TABLE OF CONTENTS

LIST OF TABLES

Chapter 1

INTRODUCTION

1.1. Background

The possibility of making significant returns in stock trading based on past price movement of securities has had appeal for a long time. Chartism and other forms of technical analysis continue to attract exponents. The efficient market hypothesis (EMH) debunked these approaches by demonstrating that returns follow a more random walk and that information about future returns is not present in the historical series of returns. This wisdom gained a broad acceptance, at least among academics, although criticisms of the EMH were made. A more serious assault arose from DeBondt and Thaler (1985) who point to a failure of the EMH when they document the possibility of making abnormal profit in the stock market by transacting on the basis of past stock prices using what is known as contrarian strategy. Similarly, momentum strategies, documented by Jegadeesh and Titman (1993), are conceived as a "system" of investing in portfolios of shares in a manner that is more profitable than holding a broadly diversified portfolio while at the same time involving no additional risk. Such a possibility is intriguing and raises a range of issues concerning the sustainability of such profits and whether such strategies can be refined so as to optimise the potential returns in both emerging and developed markets.

One of the concerns always raised in the literature when a new anomaly is documented, momentum returns in this case, is whether it is a one-off or more generalisable phenomenon. In particular, the criticism of data mining may be levied at "events" which are not repeatable in other contexts. It is important to determine if returns significantly deviate when a portfolio structure is applied in a different way, or tested in a different market, or employed in a different time period. These concerns arise because there is no clear explanation as to why momentum returns offer greater returns than a broadly diversified portfolio, i.e., why investors are certain to make a return greater than market return using a pre-defined investment strategy.

To ascertain the source of momentum profitability and whether momentum returns are due to the data mining bias, previous studies of momentum returns have been tested in different markets, using different methods and various time periods. One of the striking results observed in those studies is the inconsistency in results when momentum returns are calculated using different methods, and a lack of general consensus on the affect of portfolio structure on momentum returns. In this situation, momentum strategy will lose credibility if the returns fail to maintain similar levels when tested vigorously. Although some studies address these problems by testing only a part of portfolio structure, a grand picture involving all aspects of the portfolio structure is missing.

This current study addresses the questions of affect of portfolio structure on momentum returns, e.g., equal versus value-weighted approach, Cumulative Abnormal Return (CAR) versus Buy-and-Hold Abnormal Return (BHAR) etc., by documenting momentum returns using several methods and presenting results on a 54-country data set. The results from this study clearly show how momentum returns change with alternative computational methods across 54 countries and the extent to which the portfolio structure is important in the momentum context. The research is also important from practitioners' perspectives as detailed momentum returns are presented for each country under different methods, providing information regarding the most profitable country in which to invest and whether the momentum returns are sustainable under different formative approaches.

The most significant contribution of this research lies in the optimisation of momentum returns. Prior to this study, there has been no consideration of utilising the power of optimising methods to further increase momentum returns. This research is the first of its kind where different optimisation methods are empirically tested systematically documenting whether momentum returns can be further increased above those momentum returns calculated using traditional equal- or value-weighted approach. The process is achieved by allocating weights to each stock in the Winner and Loser portfolios based on return and risk parameters. If the results show further increases in momentum returns are achievable, then this finding will be important for researchers and practitioners. The same optimising scheme can be used to exploit other anomalies observed in the literature and practitioners can take advantage of increased momentum returns.

In short, this dissertation investigates the concept of momentum strategies, reviews prior empirical investigations and then extensively tests the approach on a specially constructed data set covering 54 countries over 34 years. The breadth of the empirical investigation is important in establishing the sustained existence of momentum returns. In addition, factors contributing to and hindering such returns across a significant number of countries are observed. A key contribution to understanding the potential for a sustainable momentum strategy lies in the optimisation of the portfolios. A series of research propositions, listed at the end of the chapter, are formulated and investigated using the 54 country by 34 year monthly return based dataset.

1.2. Momentum returns portfolio structure

EMH in its various forms proposes that a stock's price impounds information relating to its value. All new information concerning a stock's performance is readily incorporated into the stock price and therefore a trader, investor or arbitrageur cannot make a consistent return over the market by employing any investment strategy other than having superior information.

However, the momentum strategy, first documented by Jegadeesh and Titman (1993), suggests an investment strategy based on buying and short-selling the previous 6-months' best performing and worst performing stocks results in a compounded excess average returns of 12.01% per year on US stocks. This is a substantial return above market return and suggests that the weak-form efficient market hypothesis is violated as historical trading data have predictive power in choosing best and worst performing stocks in future.

This momentum strategy generated a huge interest among researchers and a substantial literature evolved devoted to establishing whether or not the returns are commensurate with risk, or are present only in a particular market, or during a particular time-period, or perhaps these observed extra returns are a result of data mining or method bias. The majority of the research focused on uncovering the factors driving these extra returns and why momentum returns are still present even after being documented 16 years ago. No attention has been directed toward the impact of portfolio structure on momentum returns, which is a key issue for this current study. It is surprising that this important topic has been ignored after conflicting results are reported in the extant literature suggesting that the momentum returns may change when the momentum strategy applied uses different methods.

Fama (1998) observes that various anomalies documented in the literature may cease to exist if they are tested using a different approach, e.g., CAR versus BHAR, equal-weighted versus value-weighted, etc. Further, such anomalies should be replicated in different markets to check if the abnormal returns exist in other markets. Given the conflicting results arising from the change in momentum portfolio structure, further empirical evidence is needed to uncover the difference.

Momentum strategy suggests a formation period of 6 months and a holding period of 6 months, i.e., picking best and worst performing stocks by studying 6 months of historical data and then holding those stocks for the next 6 months. This strategy of picking best and worst performing stocks involves a number of steps and can be completed in a several ways that may change the momentum returns. Some of the major differences noted in the context of momentum returns are now discussed.

1.2.1. CAR or BHAR

Should the best and worst performing stocks be screened by using CAR or BHAR approach? The CAR approach proposes monthly rebalancing where the money allocated to a stock remains fixed throughout the formation and holding period. If the stock price increases then an equivalent number of shares are sold to maintain the same allocation. The opposite rule applies when the stock prices drop. The BHAR approach suggests that the number of stocks in a portfolio remains unchanged even when the price fluctuates.

These two approaches may lead to different results and the literature remains divided as to which approach is superior. Jegadeesh and Titman (1993) do not note any difference in results when either the CAR or BHAR approach is used in calculating momentum returns in the US market. However, Demir et al. (2004) find notable differences in the momentum return when the two methods are applied in the Australian stock market. W. Liu and Strong (2008) add that the majority of the anomalies documented in the extant literature may disappear when the BHAR method is applied.

1.2.2. Equal- or value-weighted returns

Once the best and worst performing stocks are identified, the basis for allocating money to each stock in the Winner and Loser portfolio remains unclear. One of the approaches suggested is equal-weighted where the money is equally distributed among the best and worst performing stocks. The second approach is value-weighted where money is allocated in proportion to the market capitalisation of the stocks. Chan et al. (2000) and Demir et al. (2004) find a decline in the momentum returns when the value-weighted approach is employed.

Bird and Whitaker (2003) find a decline in momentum returns with a holding period less than 3 months but an increase in momentum returns with a holding period greater than 3 months. T. Hou and McKnight (2004) propose that a detailed investigation is needed to document the difference arising from the use of equal-weighted or value-weighted method of calculating momentum returns as the extant literature fails to present a clear picture.

1.2.3. Number of stocks in a portfolio

This is another area in which there is a lack of consensus for determining the number of stocks constituting both the Winner and Loser portfolio. Prior studies of momentum returns use between three (Rouwenhorst (1998)) and twenty portfolios (Siganos (2007)) and the results vary across all portfolios. Siganos (2007) asserts that momentum returns in the UK market can be maximised by including only the best and worst stocks in the portfolio with the most extreme returns, i.e., to decrease the number of stocks present in each portfolio. Conversely, Hameed and Kusnadi (2002) do not notice any major change in momentum returns when the momentum strategy is applied in the Pacific-Basin markets. Due to conflicting results, Dahlquist and Broussard (2000, p. 20) observe, "Further research should be done to show how sensitive these results are to the size of the portfolio formed. Since this study, as well as previous studies, focused on portfolios containing 35 stocks, future research might focus on smaller or larger portfolios."

1.2.4. Size effect

The momentum return in size-sorted portfolios is also seen as an important issue on which the literature is divided. It is well documented that various anomalies are present in small-cap stocks and accordingly it may be anticipated that the momentum returns are primarily driven by the small-size stocks. Prior studies compute momentum returns separately for each size-sorted portfolio but the results do not come to the same conclusion. For example, Hameed and Kusnadi (2002) document insignificant momentum returns when the size and turnover factors are controlled in the Pacific Basin countries. Hong et al. (2000) find a gradual decline in the momentum returns when the size of the portfolio is changed from small to big. However, T. Hou and McKnight (2004) and Mengoli (2004) do not find any concrete evidence that the small-size stocks are the sole contributor of the momentum returns in the Canadian and Italian stock market respectively. Therefore, a global analysis taking country-average momentum returns may suggest that size-effect plays an important role in a global context.

Some other topics relating to the portfolio structure of momentum returns also remain unclear and the empirical evidence is not conclusive when tested in different markets. These topics include use of simple or log returns, calculation of momentum returns in a local or foreign currency, whether or not a one-month skip between the formation and holding period is an important factor, and whether the exclusion of extreme return stocks from the Winner and Loser portfolio change momentum returns. A detailed discussion of these topics is presented in the literature review section.

The current study considers issues arising from the lack of any standard way of calculating momentum returns, coupled with the absence of any empirical study documenting the change in momentum returns associated with different approaches. Fama (1998) notes that various anomalies are artefacts of bad modelling and therefore whenever a new anomaly is presented, it should be vigorously tested with a different model in a different market. Although momentum returns are documented in a number of countries, no other studies present momentum returns calculated using different methods and covering all major markets (54-countries) in one study.

One of the important contributions of this study's detailed empirical analysis is presenting results in a global context rather than on a single country basis. The study tests momentum returns in 54 markets. The country-neutral momentums, i.e., average momentum return of 54 markets, are used to compare the difference in momentum returns using alternative computational methods. The 54 countries include developed as well as developing markets. The sample consists of 52,593 stocks and covers nearly 90% of global market capitalisation with a total market capitalisation of USD 52.6 trillion at the end of July 2007.

The decision to study 54 markets instead of just a few countries stems from the conflicting results noted in the prior literature where a different method may seem to be irrelevant in one country but may be important in calculating momentum returns in another. Drawing conclusions from the results from only a few countries may not be helpful, so increased sample coverage is needed to justify the findings. For example, momentum returns calculated using CAR and

BHAR may not differ when compared using developed countries' data, but the results may change when developing countries are included in the sample. Documentation of out-of-sample momentum returns in some countries is an expansion of extant knowledge in this area. Momentum returns have not been tested in all markets prior to this study and hence the results from this study will be helpful in uncovering return patterns in the previously unobserved markets.

1.3. Industrial momentum and 52-week high momentum

The second important topic explored in this study is whether or not the industrial momentum and 52-week high momentum strategies continue to generate positive returns on a global basis and whether they are superior to normal momentum returns. Industrial momentum and 52-week high momentum returns are two extensions to the conventional momentum return. The industrial momentum strategy, first documented by Moskowitz and Grinblatt (1999), suggests that momentum returns are primarily driven by industry factors and therefore the investment strategy should be to buy best and worst performing industries. The 52-week high momentum strategy recommends buying and short-selling stocks based on nearness to 52-week high/low price. Exponents of the 52-week high momentum return (George and Hwang (2004)) claim that the momentum returns under this strategy will yield higher returns than the normal momentum strategy. Both strategies claim that the returns will be higher than the normal momentum strategy primarily based on US market results, but these have not been tested extensively in multiple markets. Industrial momentum has been tested combining stocks from some European countries (Swinkels (2002)) but not on individual countries per se. The current research tests industrial momentum in seven countries.

The remaining 47 countries do not have sufficiently large numbers of stocks to calculate monthly industrial returns. This study also tests industrial momentum in a number of ways to limit the prospect that the strategy is a product of data mining bias. Various methods are employed to calculate industrial momentum returns reporting differences in the returns and the robustness of this strategy in different markets.

Similarly, 52-week momentum return investment strategy documented by George and Hwang (2004) in the US market has been tested in the Australian market as an out-of-sample empirical study. Recently, Du (2008) tested 52-week momentum strategy on international stock indices and documented positive and statistically significant 52-week momentum returns. However, the dataset covers indices rather than stocks listed within a country. The 52-week high momentum return is also subject to the same battery of tests to check the reliability of the returns under different approaches and in different markets. This analysis explores whether the industrial momentum and 52-week high momentum generate superior momentum returns than the normal momentum returns as claimed by Moskowitz and Grinblatt (1999) and George and Hwang (2004) respectively, and whether these returns are consistent under different approaches on a global basis.

1.4. Momentum returns optimisation

The last part of this thesis concentrates on the potential benefits arising from optimising momentum returns. The majority of the extant literature focuses on testing the validity of momentum strategy and implications for market efficiency. It does not consider whether greater momentum returns are achievable through portfolio optimisation techniques. The momentum strategy is implemented by allocating money in a Winner and Loser portfolio using either an equal- or value-weighted approach. The equal-weighted approach follows naïve diversification in which money is allocated equally among all stocks of the portfolio, whereas, the value-weighted approach suggests that a high percentage of money is allocated to stocks with high market capitalisation.

The potential benefit of using optimisation techniques to allocate money to each stock within a portfolio has so far been ignored in the calculation of momentum returns. This lack of advancement is surprising as there is a considerable volume of literature focussing on portfolio optimisation. However, this has not been previously linked with the momentum strategy. Therefore, empirical evidence is needed to establish whether or not the inclusion of an optimisation factor can lead to a further increase in momentum returns vis-*à*-vis the momentum returns computed using the equal- and value-weighted approaches.

This study applies optimisation techniques to momentum portfolios in allocating money to each stock of the Winner and Loser portfolio. The study does not rely on a single optimisation technique as there are a number of ways a portfolio can be optimised and the literature is not clear on which technique is the most suitable. The analysis is completed using data from five big markets to support the findings. The inclusion of five markets rather than 54 markets is necessitated by the need to have a large number of listed companies to form the required portfolios and obtain statistically significant results. Therefore, this part of the thesis aims to bridge the gap between the anomalies present in the market and how optimisation techniques can be effectively used in increasing returns by implementing those strategies, e.g., momentum.

1.5. Research proposition

The analysis proceeds with a number of research propositions. The starting point is to consider current momentum strategies applied to a larger number of markets. In summary, the key research propositions investigated in this research are:

1.5.1. Momentum portfolio structure

Consideration is given to the traditional momentum strategy investigating:

- Whether or not momentum returns are present in all countries
- Whether or not momentum returns are affected by changes in weighting approach, basis of calculating returns, e.g., CAR or BHAR, size of the portfolio, number of stocks in a portfolio, returns calculated in domestic currency or US dollar, and simple or log returns.

1.5.2. Industrial momentum and 52-week high momentum

The next series of issues investigated relates to industrial momentum and 52-week high momentum. The analysis proceeds by testing the following research propositions.

- Whether industrial momentum returns are positive when tested in multiple markets

- Whether 52-week high momentum returns are positive when tested in multiple markets

- Whether industrial momentum and 52-week momentum generate greater returns compared to 'normal' momentum returns

1.5.3. Portfolio optimisation

After investigating the factors impacting upon momentum portfolios, the analysis turns to investigating whether greater momentum returns are achievable through implementation of portfolio optimisation techniques. Several techniques are applied in this current study and the key research proposition is:

- Whether optimisation techniques will lead to an increase in the momentum returns

1.6. Thesis structure

The structure of this thesis will proceed as follows. Chapter 2 will discuss prior research relating to momentum returns portfolio structure, industrial momentum, 52-week high momentum and optimisation techniques. Next, Chapter 3 discusses the methodology outlining methods used for computing various forms of momentum returns. Chapter 4 reviews the specially constructed dataset used in this current study and how a range of problems relating to the dataset are addressed. Chapters 5, 6, 7 and 8 present empirical evidence for momentum returns portfolio structure, industrial momentum, 52-week high momentum, and momentum returns optimisation respectively. Finally, Chapter 9 summarises the main findings of this study.

Chapter 2

PRIOR RESEARCH and TESTABLE PROPOSITIONS

2.1. Momentum returns and portfolio structure

DeBondt and Thaler (1985) document the possibility of making abnormal profit in the stock market by studying past stock prices. Their study observes best and worst performing stocks for a preceding three year period and then subsequently buying (selling) those worst (best) performing stocks as a contrarian strategy. After holding for three years, this strategy yielded a significant abnormal profit above market returns. The authors' reason was that since worst performing stocks are undervalued over a period of time compared to overvalued best performing stocks, it is logical to buy (sell) worst (best) performing stocks.

Since the seminal work of DeBondt and Thaler (1985), considerable research has been undertaken using their "model" and many arguments proposed for and against the contrarian strategy. Jegadeesh and Titman (1993) consider medium-term periods of 3 to 12 months for stock returns, and state that a significant abnormal profit can be made by buying (short selling) best (worst) performing stocks. This strategy, which is popularly known as momentum strategy, is in contrast to the DeBondt and Thaler (1985) hypothesis. The contrarian strategy of DeBondt and Thaler (1985) propose buying loser stocks and short-selling winner stocks; whereas, Jegadeesh and Titman (1993) proposes buying winner stocks and short-selling loser stocks. The main difference in the buying/selling recommendation of these two approaches, which are diametrically opposite, relates to the time period of portfolio formation and holding period. DeBondt and Thaler (1985) prefer a 3 to 5 year period, whereas Jegadeesh and Titman (1993) propose a 3 to 12 month period. In accord with the momentum strategy, stocks are ranked on the basis of their past 3 to 12 months of return and then assigned to different portfolios on the basis of ranking. Each portfolio has a determined cut-off level, e.g., portfolio 1 consists of only those stocks which belong to the top 10% of returns ranking.

Since documentation of these anomalies, the strategies have been widely tested to find the cause of what amounts to a violation of the weak-form efficient market hypothesis. Momentum studies are investigated across markets, using a range of computational methods, contributing to a growing literature. The results relating to the viability of a momentum strategy are mixed. The proponents of contrarian and momentum strategies argue that since profits generated by these respective strategies yield positive returns that are statistically significant, the weak-form of the efficient market hypothesis (EMH) does not hold. Advocates of the alternative view, supporting the EMH, assert that this anomaly may not be robust when factors such as computational method, firm size, transaction costs, etc., are taken into account.

Studies so far have failed to pin-point the exact cause of the anomaly. A short discussion is presented below discussing the main issues pertaining to momentum returns profitability and whether the extra returns commensurate risk and/or are due to other factors not taken into account while computing momentum returns. The issues relating to the momentum strategy are discussed in turn.

2.1.1. Momentum returns

Momentum strategy is first documented by Jegadeesh and Titman (1993). According to their paper, a trader can make significant abnormal returns by buying past 3-12 months winning stocks, short-selling past 3-12 months losing stocks and holding for the next 3-12 months. The paper reports an abnormal return of 1% per month in the US stock market. Compared to contrarian strategy, momentum involves short-term investment and assumes that the persistency of stocks price increases or decreases will continue in the near future. The driving source of momentum returns, however, remains a puzzle and Fama (1998) asserts that momentum is still an open puzzle and thorough research is needed in this area. Four main factors linked to the momentum strategy receive attention in the literature:

(i) returns arise from cross-sectional dispersion rather than time-series predictability,

(ii) behavioural models,

(iii) volume and transaction costs, and

(iv) firm size.

2.1.1.1. Cross-sectional dispersion

Jegadeesh and Titman (1993) promote the time-series pattern of the stock as the main source from which profit arises. However, Conrad and Kaul (1998) argue that the main source of momentum profitability may arise from cross-sectional dispersion rather than the time-series pattern of the stock. By using Monte-Carlo and bootstrap simulation techniques Conrad and Kaul (1998) generate results indicating that the selection of extreme stocks may carry higher/lower risk than other stocks. As a result, the momentum strategy may actually be the product of buying high-risk return generating stocks and short-selling low-risk returns generating stocks. Jegadeesh and Titman (2002), in a subsequent paper, reject this proposition and state that if the cross-sectional dispersion is an important factor in the momentum profitability then the momentum portfolio will continue to generate excess returns in the near future. There is no empirical support for this. The momentum profit starts to disappear after a 12 month holding period.

2.1.1.2. Behavioural models

Behavioural models are also used to explain the sources of momentum profitability. Barberis et al. (1998), Daniel et al. (1998), and Fung (1999) attribute momentum profit to market inefficiency. This form of inefficiency is attributed to a delayed overreaction to information. This delay leads the stock price to deviate from its fundamental value but the price converges back to its fundamental value in the long-term. The behavioural model primarily focuses on the irrational behaviour affecting the decision making process and the different set of information available for different traders leading to momentum returns. The empirical work on momentum returns using these behavioural models are, however, not well documented in the literature. Further, Fama (1998) suggests that there will always be a behavioural explanation for a market anomaly.

2.1.1.3. Volume and transaction cost

Transaction volume is seen by Lee and Swaminathan (2000) as an important element in explaining potential sources of momentum profitability. They document a positive relationship between momentum and value strategies arising from turnover volume. Higher (lower) volume leads to higher (lower) future returns. Hameed and Kusnadi (2002) endorse this finding and note that momentum profit is absent when low-turnover stocks are included in the momentum portfolio. However, the strategy yields positive returns for two out of six countries when only high turnover stocks are considered. Chui et al. (2000) also find evidence of momentum profitability in five out of eight Asian stock markets when high-turnover stocks are included in the portfolio. They demonstrate an increase of five times the profitability when high-turnover stocks are included in place of low-turnover stocks. However, recent results from the Chinese stock market by Naughton et al. (2008) do not suggest volume is an important factor as they find no strong link between past volume and momentum return.

Concerns regarding the economic significance of momentum profitability appear in the literature. Korajczyk and Sadka (2004), using intraday data, recalculate momentum profitability with the inclusion of a trading effect. Their research documents how momentum profits reduce noticeably, or completely disappear, when trading costs are incorporated in momentum profitability. Further, Lesmond et al. (2004) report that a standard momentum trading strategy entails high transaction costs in buying and short-selling stocks. When these costs are properly taken into consideration, the momentum profit almost becomes insignificant. Bettman et al. (2009) find a decrease in momentum returns when transaction and liquidity costs are included, however, the momentum returns remain positive and statistically significant in the Australian stock market.

2.1.1.4. Firm size

Firm size is another factor that may explain momentum returns. Rouwenhorst (1998) shows that the momentum profit is negatively related to small firms but is not completely explained by the small size stocks. Similarly, Hong et al. (2000) find evidence of higher momentum profitability in small size stocks where there tends to be low coverage by analysts.

2.1.2. International studies on momentum strategy

In an effort to shed light on whether the momentum strategy is an artefact of a data-snooping[1] process or whether the strategy is profitable globally, it is necessary to test the strategy in different markets and the results are mixed. Rouwenhorst (1998) studies 12 European stock markets from 1980-1995 and finds that the past winner stock portfolios outperform the past loser stock portfolios by almost 1% per month after adjusting for risk. Rouwenhorst also observes that this profit is present for almost one year and is stronger in smaller firms. However, the sample only includes big companies (covering 60 to 90 percent of each country's market capitalization) which may make it prone to large company sample bias.

[1] Data-snooping refers to finding spurious statistical results which may arise due to chance on repeated use of data more than once for purposes of interference and model selection.

Further work on the statistical significance of momentum returns is presented by Chan et al. (2000) using international equity indices instead of stocks. They find evidence of statistically significant momentum returns and the profitability arises from the time-series predictability of the indices rather than exchange-rate movements. A contrary perspective is provided by Chui et al. (2000) reporting weak evidence of momentum profit in a study of eight Asian markets. Hameed and Kusnadi (2002) also arrive at the same conclusion, documenting small but statistically significant momentum profits in six Pacific Basin stock markets. These momentum returns disappear when firm size and turnover are taken into consideration and it is noted that there is negligible evidence of momentum profitability in the Japanese stock market.

C. Liu and Lee (2001) document negative returns of approximately 0.5% per month in the Japanese stock market. In fact, the results indicate that the Japanese stock market reverses for the momentum strategy, which is mostly confined to the first month of the holding period among small stocks. Du et al. (2009) find an unprofitable momentum strategy when it is applied to the Taiwanese stock market. Bettman et al. (2009) recently investigated momentum return profitability in the Australian stock market after controlling for short-selling restrictions, liquidity constraints and transaction costs and found a decrease in momentum return, however, the momentum return remain positive and statistically significant in the Australian stock market.

2.1.3. Momentum portfolio construction divergence

Prior research is more directed toward ascertaining sources of momentum profit with little attention being given to how momentum portfolios should be constructed. It is puzzling that the extant literature has not addressed the issue directly, given studies have produced a range of results when two different methods are used. One of the important issues explored in this current study is to analyse how momentum profitability changes with small changes in portfolio construction technique. This current study provides wide ranging evidence on the impact of changing portfolio structures.

2.1.3.1. Cumulative Abnormal Return (CAR) or Buy-and-Hold-Abnormal Return (BHAR)?

The two most popular approaches for calculating portfolio returns are CAR and BHAR. Each has distinctive advantages and disadvantages. The CAR approach entails a short-term return interval. Monthly returns are calculated and then summed over the period of formation/holding. Fama (1998) favours this approach as most of the asset pricing models assume a normal distribution and are suitable for short-term intervals. The drawbacks of the CAR approach include high transaction costs. As portfolios need to be rebalanced every month, under this method, a substantial transaction cost is incurred while buying/short-selling stocks. This cost increases the overall cost of constructing the portfolio and raises the question of economic significance. It has also been pointed out that the CAR approach not only accumulates the true return, but also high bid-ask spreads leading to an artificially accumulated return.

BHARs are not calculated for every month, but over the entire holding period. Therefore, the BHAR approach calculates total return for the formation or holding period. For example, if the strategy entails a six month holding period, then the BHAR will be (six month-first month)/first month price. There are two important advantages of using BHAR. First, from the investors' point of view, one is more interested to know about total returns during the holding period. Secondly, since this strategy does not include monthly rebalancing, a considerable amount of transaction cost is avoided.

An important disadvantage of using the BHAR approach is the consequential bias in the return calculation when stocks with extreme returns are included in the portfolio. Another disadvantage relates to the inclusion of new listing bias and delisting bias. Both CAR and BHAR potentially present problems with the stock selection in the portfolio. Loughran and Ritter (1996) give an example of how a stock with very high returns in a month can be allocated to different portfolios using the two methods. As an illustrative example, they discuss Armour & Co which has a calculated CAR for a 36-month holding period of 222%, whereas the raw BHAR is -92%. This large difference is due to a return of more than 500% in a month during the formation period. When the BHAR method is chosen, Armour & Co is not included in the Winner portfolio, whereas it is included in the Winner portfolio under the CAR method.

The seminal article on the contrarian strategy by DeBondt and Thaler (1985) reports abnormal returns on the basis of the CAR method. This approach is rejected by Conrad and Kaul (1993) who find no contrarian profit when the method of calculating returns is changed to BHAR. Therefore, the contrarian strategy may be an artefact of method. Loughran and Ritter (1996) address this point, maintaining that there is no difference in returns when either the CAR or

BHAR method is used in calculating returns. They suggest that the results of Conrad and Kaul (1993) must be handled with caution as the sample has survivorship bias. Support for the Loughran and Ritter (1996) view is found in Brailsford (1992) who uses both CAR and BHAR in a contrarian study on the Australian market from 1958-1987. He employs both the CAR and BHAR approach to calculate abnormal returns and detects no significant difference in the results.

In the context of momentum investing, Jegadeesh and Titman (1993) test both the BHAR and CAR method. The results indicate no significant difference between the two methods, with marginally higher returns under the BHAR method. Rouwenhorst (1998) reaches a similar conclusion for a momentum study on 12 European countries involving 2,190 stocks. However, contrary evidence comes from Demir et al. (2004) reporting a significant difference in momentum profit in the Australian market when the method of calculation is changed. CAR returns are lower than the BHAR return for 11 out of 16 strategies and higher than BHAR in 5 strategies.

There are supporters for using BHAR in calculating contrarian returns. Dissanaike (1994) finds that the contrarian result may change significantly when the method of computing returns is changed. An example of return bias calculated by the CAR method over the BHAR method is used for illustrative purposes. If the price of a stock changes from 100 to 50 to 80, then under the CAR method, cumulative return will be (-50%+60%) = +10%, while under the BHAR method it is -20% ((80-100)/100). Similarly, Otchere and Chan (2003) prefer the BHAR method over the CAR method while documenting short-term contrarian trends in the Hong Kong stock market. Forner and Marhuenda (2003) also report a significant decline in the level of returns when the BHAR method is used in place of the CAR method. W. Liu and Strong (2008) posit that BHAR approach should be always considered over a multiple time horizon. This evidence does suggest that the reliability of obtaining true abnormal returns is an open problem with the possibility existing of different results dependent on the method used.

The literature is divided and there are two groups with their own perspective concerning the correct methodology to be used in calculating returns. Fama (1998) prefers the CAR method as it has strong advantages from the perspective of its statistical properties. Fama also surmises that the various anomalies found within the efficient market hypothesis may disappear once correct methodology or correct statistical testing is used. Nevertheless, the problem remains as a real issue and is more pronounced for studies with a longer time horizon, e.g., contrarian strategy. The proponents of the BHAR method, including Kothari and Warner (1997) and Barber and Lyon (1997), prefer to use the BHAR method over the CAR method based on a number of practical advantages. The resolution of this perplexity may be checked by testing both methods in a global context. The competing views do raise issues about the generalisability of results, suggesting data mining is a problem.

2.1.3.2. Equally-weighted returns or value-weighted returns?

The two most widely used methods of allocating money to stocks in a portfolio are equally-weighted or value-weighted. In an equally-weighted portfolio, the money is equally distributed among all stocks in the portfolio irrespective of its market capitalisation. In a value-weighted portfolio, more money is allocated to high market capitalisation stocks and less to low market capitalisation stocks, i.e., the allocation is proportional to the capitalised value of the stocks. Both methods are used widely in calculating contrarian or momentum profits.

The method of allocating money to a stock in a portfolio assumes a significant role in calculating abnormal profits. It is well known that small capitalisation stocks generate higher returns and at the same time also exhibit higher risk than large capitalisation stocks. An empirical study of the returns and the total market value of New York Stock Exchange from 1936-1975 by Banz (1981), finds that the small capitalisation stocks on average yield higher-risk adjusted returns than large capitalisation stocks. It is also well known that the Capital Asset Pricing Model (CAPM) cannot fully explain returns of small capitalisation stocks.

These return and risk characteristics of the small size stocks pose problems for calculating returns when it is assumed that the risk is the same for all stocks. Fama (1998) explains that various anomalies related to the efficient market hypothesis may disappear once value-weighted returns are used instead of equal-weighted returns. The reasoning may be linked to underlying samples, as most of the anomalies exist only in small market capitalisation stocks. Fama (1998) also suggests that these anomalies may be due to bad-model problems.

It is often noted that small stocks trade infrequently in the market and the bid-ask spread is also very wide. Further, the figures for the infrequently traded small-cap stocks are not readily available and/or are unreliable. Consequently, these small stocks may introduce data problems when included in the sample. Demir et al. (2004) add that momentum investing may not be profitable when high transaction costs and market impact cost, which usually impact small-cap stocks, are included in the sample.

An obvious approach to reducing this bias is to limit the impact of small market capitalisation stocks on the overall sample. This can be done by allocating money to the stocks with higher market capitalisation promoting their respective share of the value of the total portfolio. The DeBondt and Thaler (1985) study on contrarian investment strategy used equally weighted portfolio to calculate returns. The Chang et al. (1995) study of short-term contrarian strategies in the Japanese stock market used equal-weighted and value-weighted returns. The results do not indicate a large difference when the method is changed but there is a decline in the profitability percentage when the value-weighted method is used.

In terms of momentum studies, Jegadeesh and Titman (1993), Jegadeesh and Titman (2001) consider only equal-weighted portfolios. Demir et al. (2004) use both methods of calculating momentum returns on the Australian stock market and report that when the value-weighted method is used in place of the equal-weighted method profits start declining and this may be related to the returns coming mostly from small-cap stocks. Similarly, a study undertaken by Chan et al. (2000) investigating the profitability of momentum strategies in the international equity markets, observed a drop in profits once the buying/selling of international stock indices were calculated on the basis of market capitalisation. Nevertheless, the profit is still statistically significant for short-term investments.

Bird and Whitaker (2003) document the same results for major European stock markets. The use of value-weighted returns diminish the momentum investing profitability over a holding period of 3 months but the value-weighted returns outperform equal-weighted returns with holding periods beyond 3 months. They suggest that reporting value-weighted returns when presenting results is a better approach, noting that some researchers find that the performance has increased when the size factor is handled appropriately. T. Hou and McKnight (2004) propose that a detailed investigation is needed to document the difference arising from the use of equal-weighted or value-weighted methods of calculating momentum returns.

2.1.3.3. How many stocks should be included in a portfolio?

The momentum investing approach entails forming two portfolios to create an arbitrage position. Normally, these two portfolios are formed by selecting the stocks with the highest/lowest returns. Next, the portfolio construction technique involves short-selling one portfolio and buying the other portfolio.

In order to build the highest/lowest return portfolios a choice is required regarding the percentage of the highest/lowest return stocks to be included in the

Winner or Loser portfolio. For instance, if there are 100 stocks and each of them is ranked according to their returns over the observation period and the whole sample is subdivided into 10 portfolios, then each portfolio is made up of (100*10%) or 10 stocks. In these 10 portfolios, portfolio 1 and 10 are made up of stocks with highest/lowest returns and are known as the Winner or Loser portfolio.

From the perspective of effective diversification, it is desirable to have enough stocks in the portfolio to reduce diversifiable risk. In an empirical study, Statman (1987) concludes that 20-30 stocks in a portfolio can lead to substantial decreases in the variability of the portfolio returns as well as reducing the impact of unsystematic risk. Therefore, in a small market, to accommodate the stocks in a portfolio, the number of portfolios formed is generally fewer than for those in a bigger stock market. For example, Mengoli (2004) asserts that quintiles are superior for computing contrarian and momentum returns on the Italian stock market as the number of stocks listed are far less than for the US stock market.

Traditionally, a decile approach is followed when computing momentum returns on the US stock market. Jegadeesh and Titman (1993) divide the whole sample into 10 portfolios. Brailsford (1992), on the other hand, divides the whole sample into 5, 10 and 20 portfolios separately to calculate Winner-Loser returns in the Australian equity market during the period 1958-1987. He suggests that the profitability of an investment strategy may alter with a change in the number of stocks in a portfolio. For the momentum study, the number of portfolios in a given sample start from as low as 3 portfolios, Rouwenhorst (1999), and may go to 20 or more portfolios, Siganos (2007).

The literature so far lacks consensus on determining the optimum portfolio size for calculating momentum returns. The imprecision may affect momentum profit as portfolios may be formed with only extreme return stocks or a large number of stocks. For example, if extreme stocks are chosen to form the portfolio, then the returns are expected to be highly volatile. Therefore, if a portfolio is formed with a limited number of extreme stocks, then the portfolio returns may yield a very high/low return with a large standard deviation.

Siganos (2007) suggests that the previous literature gap concerning the impact of portfolio size is overcome when he calculates the momentum profits on the UK stock market with varying portfolio size. The results suggest that investors can maximise profit by buying/short-selling only a small number of stocks at the same time as the extreme winners and losers yield high returns. Buying and short-selling fewer stocks also lead to lower brokerage and other transaction costs. The study also reports that buying the 10 best large-capitalisation Winners and short-selling the 10 worst large-capitalisation Losers can lead to a momentum profit of 3.45% per month. Potentially, the risk of investing in these extreme stocks also rises with return as expected return increases with an increase in risk and vice-versa.

Conversely, Hameed and Kusnadi (2002) document that the average returns of Pacific Basin stock markets for a momentum strategy remain almost the same when the top 30% and bottom 30% of stocks are included instead of the top

10% and bottom 10% of stocks. Further empirical research is needed to determine the degree to which returns alter with a change in the number of stocks in a portfolio. In the words of Dahlquist and Broussard (2000, p. 20), "Further research should be done to show how sensitive these results are to the size of the portfolio formed. Since this study, as well as previous studies, focused on portfolios containing 35 stocks, future research might focus on smaller or larger portfolios." To date, no systematic investigation across a large number of markets has been compiled, leaving doubts about the generalisability of studies to date.

2.1.3.4. Size effect on momentum profit

Small-cap stocks are prone to a range of problems for the researcher, as noted earlier. Minimising the weighting given to small market capitalisation stocks when creating a portfolio has received attention in the literature. But it appears that in some studies it is more appropriate to document the impact of small-cap stocks in the sample. The change of profit outcomes can be observed when a whole sample is divided into sub-samples on the basis of market capitalisation. If the profits differ significantly among sub-samples, then a detailed investigation is required to find out the cause of the problem. The problem may be related to particular characteristics of a small-cap stock, incorrect data recording, etc. The division of the whole sample into sub-samples also assists in uncovering other puzzles. Lo and MacKinlay (1990) propose that the contrarian profits occur mainly due to a lead-lag structure, i.e., large firms lead small firms.

It is noted in the literature that momentum studies generally break up the whole sample into three sub-samples. Otchere and Chan (2003) sub-divide the whole sample into three sub-samples on the basis of market capitalisation while investigating short-term overreaction in the Hong Kong stock market. Demir et al. (2004) also subdivide the whole sample into three sub-samples on the basis of size while calculating momentum returns on the Australian stock market. All the stocks are then ranked according to the market capitalisation on a particular period and then split into three sub-samples. The momentum strategy is tested separately in each of three sub-samples.

A number of studies report insignificant contrarian/momentum returns when the firm size factor is taken into consideration. Jegadeesh and Titman (1995) document insignificant contrarian profits once size-sorted portfolio returns are calculated. Similarly, Hameed and Kusnadi (2002) document insignificant momentum profit in six Asian stock markets when size and turnover factors are controlled and when calculating country-neutral abnormal returns. Hong et al. (2000) document that return continuation is strong among small-cap portfolios but gradually declines as higher-cap portfolios are tested. The alternative finding is noted by T. Hou and McKnight (2004) where the size factor is irrelevant in explaining momentum returns. Their study shows that the size factor fails to explain any momentum returns in the Canadian stock market. The Mengoli (2004) study of the Italian stock market reports momentum profit in all sub-samples and the small-cap portfolio does not show evidence of being the sole contributor to the momentum profit.

The literature again does not give a precise conclusion of the impact of size sorted portfolios. Few studies document a significant effect on momentum profits when the size effect is considered, while the other group fails to find any significant difference. A clear picture may emerge once the test is taken to a global context with detailed investigation.

2.1.3.5. Simple returns or continuously compounded returns?

For momentum studies, the choice of return metric has been either simple or compounded (log) return. Ignoring dividends, the first approach entails simple returns (closing price/opening price – 1), and the second approach is log returns natural log of (closing price / opening price). In the first approach, i.e., simple returns, it is assumed that the returns are not reinvested over the holding period. In the second approach, i.e., compound returns, it is assumed that the returns are continuously reinvested over the holding period. For example, if the closing price is 110 and opening price is 100, then the simple return is (110/100-1) 10%, and continuously compounded returns is natural log of (110/100) 9.53%. Continuously compounded returns are always less than simple returns when the price of the stock has increased, i.e., positive returns, and higher than simple returns when prices have fallen because it has been assumed that the returns are reinvested continuously. This small bias can lead to serious return calculation problems, especially for the long-term studies using the CAR methodology.

Barber and Lyon (1997) present an example of how returns are changed artificially when continuously compounded returns are used. Suppose, there are two securities, A and B, with simple returns of 20% and 10% respectively, then the average return of the two securities will be 15% and the buy-and-hold abnormal return for securities A and B are +5% (20%-15%) and -5% (10%-15%) with a mean abnormal return of zero for the two securities. However, if continuously compounded returns are used, then the returns will be 18.2% and 9.5% for security A and B respectively. The return on continuously compounded average returns will be 13.85% and the mean abnormal returns of security A and B will be 4.35% and -4.35% respectively. The continuously compounded returns are negatively biased compared to simple returns. Barber and Lyon (1997, p. 350) observe that, "For this reason, we object to the use of continuously compounded returns for analyzing long-run return performance."

In the contrarian/momentum context, a number of studies use continuously compounded returns. Demir et al. (2004) use continuously compounded returns as well as arithmetic returns for computing momentum returns in the Australian stock market. Antoniou et al. (2005) also use continuously compounded returns when calculating contrarian returns for the Athens' stock exchange. The negative bias in continuously compounded returns is apparent in the study by Brailsford (1992) where negative returns for both Winner and Loser portfolios are reported in the Australian stock market. A detailed empirical study on this topic is missing in the literature. A global study using simple returns and continuously compounded returns will promote a better understanding of the implications of choosing one specific metric.

2.1.3.6. Local currency or foreign currency?

The exchange rate can also play an important role in the calculation of momentum returns. There are three main reasons contributing to its importance. First, from the perspective of an international investor, the returns of momentum returns are influenced by the exchange rate movements. For example, if an investor in the US is investing money in the New Zealand stock market and the New Zealand dollar appreciates over a period of time, then the appreciating NZ dollar and depreciating US dollar will bring in extra returns to the US investor and vice-versa. Therefore, an international investor is more interested in knowing total returns (momentum returns + exchange rate returns) while investing in a foreign market. Secondly, the exchange rate movements may have some power in predicting future momentum returns. If one-way or two-way relationships exist between exchange rate movements and momentum returns, then a better strategy can be implemented to achieve greater returns. Thirdly, while undertaking a global study, it can be important to convert all currencies to a single currency to maintain uniformity. This conversion potentially may bring clearer and more accurate results into view. If a study is undertaken in five Asian countries, then it may be better to report all currencies in US dollars at the exchange rate on the corresponding date. Converting local currency into a foreign currency also helps to remove volatility in the local currency, especially when the inflation rate is highly volatile or there is any economic turmoil.

In this study, momentum strategies are subject to testing in a global context to illuminate the impact of potential data-snooping bias in earlier studies. Richards (1997) studies the application of contrarian strategy in 16 countries using only US dollars as the common currency. The study uses national stock indices drawing on the Morgan Stanley Capital International (MSCI) series rather than actual stocks. Rouwenhorst (1998) documents momentum returns in 12 European countries covering 2,190 firms. The study converts all stock prices into Deutsche Marks (DM), sourcing data from the *Financial Times*. In another study on the profitability of momentum strategies in 20 emerging markets, Rouwenhorst (1999) finds momentum returns after converting all stock prices into US dollars. Similarly, Hameed and Kusnadi (2002) undertake momentum studies in six Pacific Basin countries using US dollars as the common currency. Chan et al. (2000) provide an important and extensive study of the interdependence of currency and stock markets in explaining momentum returns in 23 countries. They divide the momentum returns into four components:

(i) profits due to predictability of equity returns based on past equity performance,

(ii) profits due to predictability of exchange rate returns based on past equity performance,

(iii) profits due to predictability of equity returns based on past exchange rate performance, and

(iv) profits due to predictability of exchange rate returns based on past exchange rate performance.

The results show that the exchange rate fails to explain any significant movement in the momentum returns. 90% of the momentum profit can be attributed to the predictability in time-series characteristics of the stock market indices. This suggests a strong support for component one of their four component list and no real support for component two. The evidence concerning component three (equity returns versus past exchange rate performance) presents a negative contribution to the momentum profits.

These results strongly point to the exchange rate not playing an important role in explaining momentum returns. However, a more detailed investigation is needed to consider the change of returns when returns are calculated in foreign currency instead of local currency. This can be done by running the same test on the same data but with a different currency, such as US dollars. One data set should be in local currency and another data set should be in foreign currency converted using date corresponding exchange rate. The difference of returns between two data sets might explain the extent of profit or loss an international investor can expect while investing in a foreign market. The difference in returns may also highlight volatility in the domestic market arising out of inflation, economic crisis or other events.

2.1.3.7. One-month or zero-month skip?

Momentum strategy research, reported in the literature, includes two periods to form Winner or Loser portfolios. The first part is commonly referred to as the formation period. In this period the returns of the whole sample are observed over a period of time and then ranked on the basis of cumulative or buy-and-hold abnormal returns. Based on the ranking of these returns, two extreme portfolios (Winner and Loser) are formed. This completes the portfolio construction stage. In the second stage of the process, the two portfolio returns are calculated over *n* periods (usually six months) and this part is known as the test (holding) period. The returns earned at the end of the test period are the momentum returns.

The majority of studies on momentum returns suggest that there should be a one-month gap between formation and test periods. The rationale for allowing a one-month gap is to attenuate bid-ask spread bounce and/or to address problems related to small stocks. For example, a stock price may be mainly traded as bid price during the formation period but can suddenly bounce back to ask-price during the test period. This price difference may be wrongly recorded as returns when in fact the price has only shifted from bid to ask or vice-versa. This problem is severe in small or illiquid stocks as bid-ask spreads are much wider than is typical for larger, liquid stocks. Leaving a one-month gap between formation and test is thought to limit the impact of this problem. Blume and Stambaugh (1983) document upward bias in long-term performance measures when average short-term returns are used. This upward bias is due to faulty return calculation and bid-ask bounce. Jegadeesh (1990) adds that allowing a gap may also avoid lagged reaction effects.

The suggestion to include a one-month gap is included in some papers on momentum strategies although it is ignored in others. For example, Jegadeesh and Titman (1993) employ a one week skip and a no week skip when calculating returns. Similarly, Rouwenhorst (1998), Griffin et al. (2003) skip one-month and zero-months for their investigations of momentum returns in European countries.

Moskowitz and Grinblatt (1999), Chordia and Shivakumar (2002), Demir et al. (2004) and others choose not to use a skip between formation and holding periods.

An important point is whether skipping a month or other period, or not skipping at all, has a significant impact on holding period returns. Hameed and Kusnadi (2002) report no difference in momentum returns when a one-month gap is used compared to no gap. Similarly, Kang et al. (2002) document that skipping one week or one day while calculating momentum returns in the Chinese stock market does not make a significant difference. However, C. Liu and Lee (2001) notice that leaving a month gap between formation and test periods in the Japanese stock market leads to a decrease in momentum profitability. In their view, this may suggest that there is a reversal element in the first month of the testing period. A broader study of multiple countries considering a range of skip periods will provide more evidence concerning their impact on contrarian and momentum.

2.1.3.8. Extreme returns

It is well known that stocks with extreme returns are, in general, highly volatile. This problem is especially present in small-cap stocks. Sometimes, these extreme returns may arise out of incorrect data records, resulting in such stocks being incorrectly allocated to a Winner or Loser portfolio. Loughran and Ritter (1996) show how a high return spike for a stock in a month can allocate a stock to a different portfolio. This is likely to create a bias in calculating the portfolio returns due to a single/multiple extreme return. One way to mitigate this problem is to exclude extreme stock returns while ranking the stocks. The bottom and top 5% stocks may be excluded when ranking stocks during the formation period. Rouwenhorst (1999) trims extreme 5% stocks for both Winner and Loser portfolios but does not find any significant difference with respect to normal portfolio returns. However, Hameed and Kusnadi (2002) report a change in momentum returns from statistically significant to insignificant in the Pacific Basin countries when extreme 5% ranking period returns are excluded from the portfolio.

Recently, Siganos (2007) noted that momentum returns decline continuously beyond the first few extreme winner and loser stocks. This result is not consistent with the earlier study of Brailsford (1992), who found that decreasing the number of stocks in a portfolio leads to greater price reversal among the Winner portfolio while the Loser portfolio does not change a lot. A multi-country study that specifically targets the importance of outliers will shed more definitive light upon the situation.

The literature expresses opinions on many of these issues but little resolution of conflicting opinions is present to date. Specifically, the focus relates to determining the degree to which momentum profit changes when the portfolio structure alters. In summary, the three main objectives for this study are:

(i) whether the previous momentum profits can be attributed to data mining or small firm effects, currency movements or other methodological flaws,

(ii) to measure the difference in returns when portfolio construction strategy is changed, for example, equal- to value-weighted, and

(iii) to guide future research in this area by correctly identifying the most robust portfolio structure to use when engaging in momentum strategy.

2.2. Industrial momentum

One of the more important explanations for the abnormal return underlying the individual momentum returns is put forward by Moskowitz and Grinblatt (1999). The seminal paper on industry momentum uses industry momentum returns to illustrate how industry factors play an important role in generating individual momentum returns. They use Centre for Research in Security Prices (CRSP) and COMPUSTAT data sources and divide the stocks listed on the NYSE, AMEX and NASDAQ into 20 industries on the basis of first two digits of Standard Industry Classification (SIC) code. Monthly industry returns are value-weighted but the Winner and Loser portfolios are equal-weighted. To minimise the effect of idiosyncratic risk, a big sample, e.g., the US stock market, is chosen where there are enough (about 230) companies within each industry. The result shows that the individual momentum returns are generally not properly diversified as the Winner or Loser portfolio stocks tend to be from the same industry. The small firm effect also seems to be absent in industry momentum as the returns are present even for the largest and most liquid stocks.

According to them, the driving force of the individual momentum returns actually arises from the industry within which the company is positioned. Moskowitz and Grinblattdocument no statistically significant individual momentum returns once the market returns are replaced by the industry returns. Similarly, when the loser and winner portfolios are formed within the same industry, an industry-neutral individual momentum strategy fails to generate positive significant abnormal returns. However, when the investment strategy is changed to buying past winning industry stocks and short-selling past losing industry stocks, the strategy results in significant positive returns.

Moskowitz and Grinblatt conclude that industry factors are the major contributor to individual momentum returns and when applied correctly, the industry momentum strategy can generate higher returns than individual momentum. The results are important as research to date cannot come to a common agreement on finding the driving force for individual momentum. The industry momentum results, however, are not accepted by all. Studies by Lee and Swaminathan (2000) and Lewellen (2002) fail to find any significant role of industry factors in explaining individual momentum returns, while Grundy and Martin (2001) and Chordia and Shivakumar (2002) suggest that the individual and industry momentum returns are a separate phenomenon and should be investigated separately. Further, the industry momentum returns have not received the same attention in the literature as the extensive research documented in the context of individual momentum returns. There are only a few studies testing industry momentum in an international context.

Industry momentum studies across a number of countries are undertaken by Swinkels (2002) and Nijman et al. (2004). However, these studies are limited in the sample coverage. Swinkels (2002) uses Datastream created industry indices, whereas Nijman et al. (2004) choose 1,581 stocks from 15 countries and then sort them into different industries based on the MSCI classification. Iihara et al. (2004) test industry momentum strategy in the Japanese stock market and fail to find evidence of momentum profitability.

Other studies do not find industry momentum as a primary explanatory source of individual momentum returns. Lee and Swaminathan (2000) document only a small decrease (12.5% to 10.1% per year) in the individual momentum profit once the industry factor is taken into consideration. Similarly, Lewellen (2002) finds significant and strong industry momentum returns with size sorted B/M portfolios, but the individual momentum is still present in the sample. Grundy and Martin (2001), Chordia and Shivakumar (2002) claim that the individual and industry momentum are a separate phenomenon and should be investigated separately. Grundy and Martin (2001) further state that the momentum return is not explained by either industry effect or cross-sectional dispersion in mean returns. Hurn and Pavlov (2003) add that no single factor can explain momentum returns. Du and Denning (2005) suggest that momentum returns can be largely explained by contemporaneous and lagged Fama-French factors, rather than industry-specific risk.

In an international context, Swinkels (2002) presents support for industry momentum returns in the European markets but no evidence of the same is noted in the Japanese market**.** Swinkels (2002) uses Datastream industry stock indices as a data sample within various countries to check whether this anomaly is present outside of the US stock market. He adds that Datastream has an advantage over other databases, e.g., CRSP, MSCI, because the coverage is much broader as well as the availability of longer time-series data. A significant difference between

Swinkels (2002) and this current study relates to the database used. Swinkels (2002) uses only industry indices as a source to verify industry momentum returns, whereas this study computes industry monthly returns directly from the stock returns positioned in the industry.

Iihara et al. (2004) do not find evidence of industry momentum returns in the Tokyo stock market. An absence of industry momentum profit in the Japanese stock market is not surprising as previous studies (C. Liu and Lee (2001) and Hameed and Kusnadi (2002)) also find low and not statistically significant individual momentum returns in the Japanese stock market. Nijman et al. (2004) document profitability of individual and industry momentum returns in the European market but individual momentum returns dominate industry momentum returns. Using a sample of 1,581 stocks from 15 countries, they assert that the individual stock effect is the most important factor in explaining momentum returns followed by the industry effect. Nijman et al. (2004) reclassify stocks into 23 industries based on MSCI classification.

The gap of one month between the formation and holding period of the industry momentum return is also seen as an important methodological issue in the recent literature. Grundy and Martin (2001) document insignificant real or random returns when a one-month gap is allowed between the formation and holding period. However, a zero-month gap between the formation and holding period results in positive momentum returns, suggesting that a significant amount of return is generated in the first month of the holding period. These results further indicate that the industry momentum effect can account for almost half of the individual momentum returns. Swinkels (2002) also notes the importance of a one-month gap between the formation and holding period. He reports significant positive returns with a zero-month gap but insignificant returns when a one-month gap is allowed between the formation and holding period.

The contrary view is put forward by Du and Denning (2005) who assert that a one-month gap is not crucial for industry momentum profitability and the returns are almost the same irrespective of a one-month or no gap. Further, the returns do not vary when the portfolio returns are calculated via either equal-weighted or value-weighted method. Several studies, e.g., Grundy and Martin (2001), Lewellen (2002) and Hurn and Pavlov (2003), note that, in general, the industry momentum returns tend to present in a short-term period (around 6 months).

2.3. 52-week high momentum returns

George and Hwang (2004) document how 52-week high momentum returns generate superior returns when the stock selection is made on the proximity to 52-week high/low price rather than the traditional total returns approach utilised in pioneering research by Jegadeesh and Titman (1993). George and Hwang (2004) results show that returns associated with the 52-week high strategy are about twice as large as those associated with the normal momentum returns (Jegadeesh and Titman (1993)) and industrial momentum return (Moskowitz and Grinblatt (1999)). The calendar month anomaly[2] does not also apply to a 52-week momentum strategy as the difference is even larger outside of January. George and Hwang (2004) espouse that the 52-week measure has superior predictive power as stocks trading at 52-week high and low price are readily available from many sources. The authors suggest that when a stock's price has been pushed near or to a new 52-week high, investors are likely to sell the stock even when the information implies a trend of increasing price. But eventually, the information is incorporated into the price and the price goes up, resulting in a price continuation.

George and Hwang (2004) add that the behavioural explanation for momentum returns by Barberis et al. (1998) and Hong and Stein (1999) does not hold for the 52-week high investing metric as return reversal is not present after a 24-month holding period. Earlier literature maintains that short-term or medium-

[2] Calendar anomaly refers to similar patterns in stock return from year to year, month to month.

term momentum is followed by long-term reversals. Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) examine the unconditional mean profits for six-month momentum strategies over a five–year holding period, documenting profit reversals in years two through five inclusive. According to existing behavioural theories, either under-reaction or over-reaction explanations for momentum include the short-term momentum being followed by a long-term reversal. This is fundamental to the whole process whereby information is incorporated into stock prices. George and Hwang (2004) challenge this proposition, finding no long–term reversals for the 52-week high momentum returns as the returns remain positive after 12 months of holding period and accordingly conclude that the short-term momentum and long-term reversals are separate phenomena. Nevertheless, Du (2008) did not find any evidence of continuing 52-week momentum returns when testing this proposition using international equity indices.

Marshall and Cahan (2005) contribute further evidence, presenting an out-of-sample test for the 52-week high strategy using Australian Stock Exchange (ASX) data and find high profitability for the strategy. However, they use a different approach, suggesting their implementation focuses on practical strategies, i.e., returns are calculated on the basis of closing price and invested on next day opening price. The study is also constrained in terms of stocks involved in the sample, using only those stocks which are approved for short-selling by the Australian Stock Exchange. Du (2008) tests a 52-week momentum strategy on international stock indices and documents positive and statistically significant 52-week momentum returns even after adjusting for risk and transaction-cost.

However, the results also show that the 52-week momentum returns follow reversals similar to those of Jegadeesh and Titman (1993) momentum returns.

2.4. Momentum returns optimisation

Momentum studies have previously concentrated on finding the cause of the anomaly, or documenting whether abnormal returns are present only in a particular dataset, e.g., affected by size, volume, etc. Very little attention is paid to the portfolio weighting and the extant literature primarily uses an equal-weighted or value-weighted approach to allocate money to each share of the portfolio. The literature has so far ignored the potential benefits of using portfolio optimisation to determine how money should be allocated in a portfolio to maximise return or minimise risk. This current study proposes an alternative way of allocating money to determine whether momentum returns can be increased by using optimisation techniques.

Major studies, listed in Table 2-1, from 1985 through 2005 indicate that over two-thirds used equal-weighted portfolios.

Table 2-1: Synopsis of weighting method used in the contrarian and momentum strategy

Author, Journal	Topic investigated	Year	Purpose of paper	Weighting method used
DeBondt & Thaler, Journal of Finance	Contrarian	1985	Overreaction in stock market	Equally-weighted
Chan, Journal of Business	Contrarian	1988	Risk factors in contrarian strategy	Equally-weighted
Brailsford, Journal of Business Finance & Accounting	Contrarian	1992	Winner-Loser anomaly in Australian equity market	Equally-weighted
Kryzanowski & Zhang, Journal of Financial & Quantitative Analysis	Contrarian	1992	Profitability of contrarian strategy in Canadian stock market	Equally-weighted
Conrad & Kaul, Journal of Finance	Contrarian	1993	Upward bias in returns calculation	Equally-weighted

Lakonishok et al., Journal of Finance	Contrarian	1994	Risk factor in contrarian strategy	Equally-weighted
Chang et al., Journal of Business Finance & Accounting	Contrarian	1995	Short-term contrarian strategy in Japanese stock market	Equally-weighted & value-weighted
Ball et al., Journal of Financial Economics	Contrarian	1995	Contrarian strategy and low-priced stocks	Equally-weighted
Loughran & Ritter, Journal of Finance	Contrarian	1996	Overreaction in stock market	Equally-weighted
Campbell & Limmack, Applied Financial Economics	Contrarian	1997	Long-term overreaction in UK stock market	Equally-weighted
Dissanaike, Journal of Business Finance & Accounting	Contrarian	1997	Overreaction in stock market	Equally-weighted
Richards, Journal of Finance	Contrarian	1997	Winner-Loser anomaly in international equity market	Value-weighted
Bowman & Iverson, Pacific-Basin Finance Journal	Contrarian	1998	Short-run overreaction in the New Zealand stock market	Equally-weighted
Fung, Global Finance Journal	Contrarian	1999	Overreaction in stock market	Equally-weighted
Assoe & Sy, Canadian Journal of Administrative Science	Contrarian	2003	Profitability of short-run contrarian strategy	Equally-weighted
Jegadessh & Titman, Journal of Finance	Momentum	1993	Seminal paper on momentum	Equally-weighted
Chan et al., Journal of Finance	Momentum	1996	Impact of information on momentum profitability	Equally-weighted & value-weighted
Asness, Financial Analysts Journal	Momentum	1997	Interaction of value and momentum strategies	Value-weighted

Cleary & Inglis, Revue Canadienne des Sciences de l'Administration	Momentum	1998	Impact of risk premium and transaction cost on momentum returns in Canadian market	Considers the four previous quarterly returns with the most recent quarterly returns being weighted twice as heavily as the others
Rouwenhorst, Journal of Finance	Momentum	1998	Momentum profitability in international stock markets	Equally-weighted
Liu et al., Journal of Business Finance & Accounting	Momentum	1999	Profitability of momentum strategies in UK stock market	Equally-weighted
Chan et al., Journal of Financial & Quantitative Analysis	Momentum	2000	Application of momentum strategy in international markets	Determined on the basis of past performance of the asset relative to the average performance of all assets being considered
Hong & Lim, Journal of Finance	Momentum	2000	Impact of information on momentum profitability	Equally-weighted
Lee et al., Journal of Finance	Momentum	2000	Turnover and momentum profitability	Equally-weighted
Jegadessh & Titman, Journal of Finance	Momentum	2001	Delayed overreaction and momentum profitability	Equally-weighted
Chordia & Shivkumar, Journal of Finance	Momentum	2002	Macroeconomic variables and profitability of momentum strategy	Equally-weighted

Hameed & Yuanto, Journal of Financial Research	Momentum	2002	Profitability of momentum strategies in Pacific Basin stock markets	Equally-weighted
Swinkels, Journal of Asset Management	Momentum	2002	Industry momentum profitability in international stock market	Equally-weighted & value-weighted
Bird & Whitaker, Journal of Asset Management	Momentum	2003	Interaction of value and momentum strategies	Equally-weighted & value-weighted
Griffin et al., Journal of Finance	Momentum	2003	Macroeconomic variables and profitability of momentum strategy	Equally-weighted
Hurn & Pavlov, Australian Journal of Management	Momentum	2003	Momentum returns in Australian stock market	Equally-weighted
Aarts & Lehman, Applied Economics Letter	Momentum	2005	Profitability of style momentum strategies	Equally-weighted & value-weighted
Doukas & McNight, European Financial Management	Momentum	2005	Information asymmetry and momentum profitability	Equally-weighted
Kang et al., Pacific-Basin Finance Journal	Contrarian & Momentum	2002	Contrarian and momentum profitability in Chinese stock market	Equally-weighted
Mengoli, International Review of Financial Analysis	Contrarian & Momentum	2004	Contrarian and momentum profitability in Italian stock market	Equally-weighted
Chordia & Shivakumar, Journal of Financial Economics	Momentum	2006	Earnings and price momentum	Equally-weighted
Balvers & Wu, Journal of Empirical Finance	Momentum	2006	Momentum and mean reversion	Equally-weighted

Arena et al., Financial Review	Momentum	2008	Momentum and Idiosyncratic volatility	Equally-weighted
Foster & Kharazi, Journal of Int. Fin. Markets, Inst. & Money	Contrarian & Momentum	2008	Contrarian and momentum returns on Tehran stock market	Equally-weighted

Research during the last 50 years has made significant advances in calculating optimal portfolios. Popular techniques include Markowitz Mean-Variance, Sharpe Single Index Model, Linear programming and Utility theory. Each respective method calculates the optimum allocation in different ways and some involve a large number of calculations. Fortunately, high-speed computers and readily available software packages have simplified the calculation task. Elton et al. (2003) note that during the last 30 years the advances in portfolio optimisation have mainly focused on simplifying the amount and type of data to be used as in computational methods. There has been no obvious advancement in the approach to allocating the weight for stocks when momentum portfolio returns are calculated. The question arises as to whether these sophisticated methods of allocation can be used in momentum strategies to further increase portfolio returns and or decrease portfolio risk.

The first breakthrough in portfolio optimisation was the Mean-Variance (MV) approach developed by Markowitz (1952), providing a method to calculate portfolio risk and allocate optimal weights within a portfolio. In the MV approach, portfolio risk is different from individual stocks' risk. Recognition that portfolio risk is not a simple summation of individual stock risk due to the covariance, which generally means there is a diversification effect reducing overall risk, is fundamental. Markowitz (1952) documents the distinction between market and unique risk in holding a portfolio and shows how unique risk can be eliminated if the number of stocks in a portfolio increases.

Conceptually, the MV approach for finding the optimum allocation among stocks appears appropriate, however there are some problems in implementation. The approach did not rapidly gain acceptance in the investment community (Michaud (1989), Konno and Yamazaki (1991), and Michaud (1998)). Surprisingly, only a few institutions use the MV approach for optimising portfolios even though the approach was first documented 50 years ago. Gray (1983) comments that the prime reason for the investment community failing to adopt the MV approach can be flaws in the calculations or deep-seated resistance to adopting a new method. Michaud (1998) proposes a contrary view, arguing that deep-seated resistance to adopting a new method cannot be cited as a reason for rejecting the MV approach. He cites examples of derivative and fixed income managers who are always open and eager to implement new and sophisticated methods. In particular, new firms in those markets always like to set new standards by adopting a more sophisticated approach.

Potentially, the acceptance problem lies in the calculations and assumptions of the MV approach. A number of problems are identified including the very large number of calculations required, errors in estimating the true mean, variance and covariance computations, distribution of the returns, etc.

One of the key problems of the MV approach relates to corner solutions. Jorion (1985) notes that when the objective of the MV approach is to maximise return, MV often allocates a high percentage of money to a high return stock, thereby ignoring other stocks in the portfolio. Similarly, when the MV objective is set to minimise risk, MV often allocates a high percentage of money to least risky stocks, thereby ignoring other stocks. Hence, some stocks in the portfolio are assigned zero weighting and, as a consequence, the portfolio remains undiversified. This is impractical for the professional investment community as client investors wish to eliminate unique risk through diversification as well as have the benefit of investing in a chosen stock.

Incorrect estimation of inputs is noted as another problem with the MV approach. Jobson and Korkie (1981) observe that MV may fail due to incorrect estimation of mean and standard deviation. Jorion (1985) demonstrates a sharp fall in portfolio performance, accompanied by instability of optimum weights, occurring when past historical returns and risk measures are used as a substitute for expected return and risk. Similarly, Frost and Savarino (1986) note a deterioration in desirable properties in the investment portfolio when historical returns are considered. Michaud (1989) lists eight main problems of the MV approach as:

(i) error maximisation,

(ii) good and bad estimator,

(iii) missing factors and non-financial structure,

(iv) mismatched levels of information,

(v) unstable optimal solutions,

(vi) exact versus approximate MV optimisers,

(vii) inadequate approximation power, and

(viii) default settings of the parameter.

Michaud (1989) propose that a small change in input assumptions can make a big difference in the distribution of the optimum portfolio weights. As a result, MV optimisation is more inclined to maximise effects of error in the input assumptions and thus should be considered as an “error maximisation” approach. Best and Grauer (1991) confirm that there exists high sensitivity among input parameters and optimal portfolio weights. They find that a small increase in the mean of an asset can drive half the securities from the portfolio without any change in the portfolio returns and standard deviation. Gong (2004) notes a contrary view, that the “error maximisation” problem might be avoided if changes in parameter inputs are small, especially considering the impact of transaction cost for a change in portfolio mixture.

Chopra and Ziemba (1993) studied 10 securities listed in DJIA between January 1980 – December 1989, documenting high dispersion in means, variance and covariance. The error increases with the increase in risk tolerance. Similarly, Chow (1995) used another sample to demonstrate the severity of the optimum allocation problem. He shows how a change in expected return from 11% to 13% can lead to a change of 20% in asset weight from a previous 40% to 60% in the optimal portfolio. Amenc and Martellini (2002) suggest a very significant percentage is allocated to an asset which has highest error in the estimated returns.

Kritzman (2006) suggests that the problems associated with MV have been overstated, commenting that even though small input errors may lead to large output errors the return distributions are likely to be the same for correct and incorrect portfolios. Kritzman shows that a massive 56% misallocation of assets led to only a 1.58% increase in exposure to loss. "The hype that mean-variance optimisers are error maximisers seems to be just that hype. Conventional wisdom may be conventional but not always correct" (Kritzman, 2006, p. 69). Michaud (1989) observes that MV is still superior to other ad-hoc methods in terms of properly identifying the portfolio objectives, constraints, investor demand and efficient use of information. The above problems might be checked if certain changes are made in the technique of computation.

One of the most important drawbacks of MV approach repeatedly noted in the literature is "error maximisation", i.e., when a small input error leads to a significant change in the optimum portfolio allocation. To remedy this problem a number of suggestions are proposed. One of the suggestions is that if all inputs (means, variance and covariance) are converged into a grand input, then dispersion will be minimised and hence optimum weighting would be almost same.

Jobson et al. (1979) and Jobson and Korkie (1981) emphasise the importance of the James-Stein estimator in improving traditional MV optimisation. Golosnoy and Okhrin (2005), Jorion (1985) and Jorion (1986) use a shrinkage method in the MV approach and find that significant improvement can be made in the performance of the optimal portfolio. Chopra et al. (1993) study six individual country stock indices, five country bond indices and five cash indices to compare performance of Stein-estimation with a classical MV approach. The results again confirm the dominance of the Stein-estimator in generating higher mean and less variance compared with the classical MV approach.

The James-Stein and Bayes-Stein formulae are accepted methods to compress all inputs into a grand input. James-Stein's estimation shrinks all expected returns to the grand mean, irrespective of sample size. Stein (1955) states that the normal sample means are not fit to calculate returns of a portfolio. Therefore, a simple Bayesian approach can be employed to calculate portfolio return. Stein (1955) employs simulation analysis to compare a classical sample mean and a Bayes-Stein style estimator, obtaining a significantly better performance of the Bayes-Stein estimator in generating extra returns and lowering risk. These findings encouraged Lindley (1962, p. 285) to observe that this method is "one of the most important statistical ideas of the decade…"

Bayes' approach, which is similar to the James-Stein approach, is advocated by Frost and Savarino (1988), Michaud (1989), and Kandel and Stambaugh (1996). Bayes' approach assumes that all securities have the same expected returns, variances, and pairwise correlation. Grauer and Hakansson (1995) contrast portfolio performance when a Bayes-Stein estimator, a James-Stein estimator and CAPM-based estimators are employed.

The constraint approach suggests that extreme return stocks should not be included in the portfolio. This approach is quite similar to the Bayes-Stein method. In the Bayes-Stein method individual inputs are shrunk into a grand input, which implies that a constraint has been applied indirectly. Alternatively, the direct imposition constraints may also improve the portfolio performance. Frost and Savarino (1988) suggest imposing constraints on a portfolio for various reasons. First, error of input estimation may lead to underinvestment or overinvestment in a security. Imposing portfolio weight constraints can minimise the problem. Secondly, as forecasting true means and variances is not possible due to a lack of perfect foresight, imposing weight constraints on each stock can be justified. Frost and Savarino (1988) investigate 200 NYSE securities for the period January 1966 to December 1985, creating six investment strategies starting with no constraints through to a maximum constraint of 5% for each stock. Simulation technique results confirm the superiority of the MV approach when constraints are imposed with the portfolio risk decreasing significantly with an increasing return.

Chopra and Ziemba (1993) state that the portfolios with sensible constraints can outperform the portfolios without any constraints. For example, all expected returns are set to zero (or a non-zero constant) as true expected means are very hard to derive. Jagannathan and Ma (2000) note that imposing weight constraint is as effective as shrinking individual inputs towards a grand input and therefore diminish the uncertainty problem in estimation of inputs. Cohen and Pogue (1967) propose imposing constraints to eliminate the faulty corner solution problem. For a portfolio of stocks between 75 and 150 in number, the authors propose a restriction of 5% and 2.5% respectively on the upper bound. This restriction solves the problem of high percentage allocation towards extreme returns/risky stocks.

Results from other studies are inconsistent with these findings. Grauer and Hakansson (1995) argue that imposing constraints on the stock weights lead to a reduction in risk and a decrease in returns, and accordingly the imposition of constraints is unacceptable as overall performance of the portfolio remains the same. Similarly, Jansen and van Dijk (2002) do not favour imposing constraints on a portfolio since it cannot be optimised when constraints exist. Therefore, in their view, a constrained portfolio will produce inferior results. These views are opposite to the earlier research of Frost and Savarino (1988) who suggest that due to non-availability of true expected means, variance, and covariance, imposing constraints can be justified. They argue that imposing constraints will become irrelevant and distort results only if the true returns and risks are known, which in general is not the case.

Two of the more serious limitations of MV, noted in the literature, are the high sensitivity to input errors and massive number of calculations required. Not surprisingly, there is an increased emphasis on seeking a model where input errors are minimised and the model is easy to calculate. The Single-index model and Stein's method are both examples of addressing these problems. Alternative measures of risk provide another example of portfolio optimisation. The logic for selecting alternative measures of risk are towards investor's placing importance only on downside risk. Most investors are concerned about the risk of return falling below mean return and therefore it is agreed that a classical variance cannot be used as a proper measure for calculating risk of the portfolio. Other methods include utility function optimisation, linear programming, maximising geometric mean, etc. Each approach has its own advantage and disadvantage.

The Single Index Model (SIM) is the most widely used optimising tool in the investment community according to Elton et al. (2003). For SIM, a significant advantage is in simplifying MV, cutting down unnecessary inputs and reducing problems of "error maximisation". MV needs [n + n + n(n-1)/2] estimates to calculate optimal allocation, whereas only (3n+2) estimates are required for SIM. If 50 stocks are to be optimised using MV approach, then 1325 inputs are needed, whereas, in the SIM only 152 inputs are required.

SIM assumes that stocks vary in relation to a common market aggregate. This assumption is different from MV, where it is assumed that there is co-movement among stocks. In reality, correlations among all stocks are not important as stock prices follow general market trends. SIM simplifies the covariance assumption and reduces estimation errors by focusing on the movement of stock returns with the appropriate market or benchmark.

Sharpe (1963) pioneered SIM suggesting that a small sacrifice of information (correlation structure) may lead to a better outcome than the traditional MV approach. Wallingford (1967) states that the covariance matrix of MV can be simplified as price movements of stocks often rise and fall at the same time with respect to a benchmark.

Linear programming (LP) is an alternative to the MV approach where a portfolio is maximised, given some constraints, but not including portfolio variance. LP involves specifying a number of equality and inequality constraints relating to maximising portfolio returns. A 5% maximum investment in each security can be expressed as an inequality constraint. Further, a constraint might require that the top 30% of securities in a portfolio, by market capitalisation, shall be allocated at least 50% of the weight. An investor has to choose constraints prudently as the success of LP depends upon how wisely the constraints are imposed on the portfolio structure. Sharpe (1967) optimises mutual fund performance using the traditional MV approach and a LP approach, noting that there is limited empirical evidence supporting a close approximation between these approaches. There are limitations to the LP approach and the most significant relate to identifying and imposing each constraint. Michaud (1998) argues that LP has limited acceptance in portfolio optimisation as investors are more interested in returns than risk.

According to Elton et al. (2003), maximisation of the geometric mean (GM) is the most popular alternative approach to the traditional MV approach and includes among the early proponents Elton and Gruber (1974), Hakansson (1971), and Latane (1959). GM approach suggests an investor should choose a portfolio with the highest expected geometric return which Elton et al. (2003) trace to two underlying premises. First, it has the highest probability of attaining expected return over the shortest period of time. Secondly, GM has the highest probability of exceeding wealth over any given period of time. There are dissentions concerning the second proposition, including Breiman (1960), Hakansson (1971), and Roll (1973). If returns are normally distributed, then an MV approach can be used to find the maximum geometric return and, similarly, the Elton and Gruber (1974) approach can be used to locate the efficient frontier when the distribution of returns is lognormal.

Michaud (1998) proposes "resampled efficiency" for calculating optimal portfolio weights. According to the resampled efficiency approach, the weights of the portfolio are statistically tested to check whether any particular stocks contribute most to the portfolio optimisation or which stocks have weights that are deviating significantly from the target efficient portfolio. The analysis is completed by formulating a Monte-Carlo simulation based efficient frontier. A confidence interval is created around the resample frontier and the probability of falling under the true efficient frontier can be readily determined.

In classical MV, the variance of the stock is viewed as a measure of risk recording the dispersion of values below and above the mean. It is suggested that investors do not consider values above the mean as risk. Only possible outcomes below the mean are considered as true risk. Therefore, using classical variance in calculating risk can lead to inappropriate portfolio compositions.

Konno and Yamazaki (1991) propose a mean absolute deviation risk (MAD) function as a measure of optimum asset allocation problem. The advantage of MAD over MV is simplification of the model and easier real time calculation of optimum portfolio allocation for a large number of stocks. Jansen and van Dijk (2002) propose portfolio optimisation with respect to a specific benchmark. This can be achieved by finding the tracking error between the portfolio and a benchmark and then minimising the tracking error. The ex-post tracking error is a good source of information input for the variability between the portfolio and a specified benchmark.

Pioneers of alternative risk measures include Roy (1952), who proposes a safety-first theory. In his theory, probability of a portfolio falling below a certain level is limited to certain disaster. Another popular method is to measure downside risk by using a semi-variance where risk, in this context, is considered a likelihood of outcomes below a specified benchmark or return level.

Harlow (1991) states that the downside-risk measure allows a manager to construct a portfolio more precisely, given investors' risk considerations and constraints on the portfolio. An investigation of optimum asset allocation among a set of international assets indicates the superiority of the downside-risk measure in lowering risk when compared with using a variance approach. Proponents of the downside risk measure include Leibowitz and Kogelman (1991), who consider downside-risk as a ratio of shortfall probability relative to a minimum return threshold.

Roll (1992) proposes a new version of a downside-risk measure known as tracking error variance (TEV), which considers minimisation of volatility between portfolio returns and a benchmark. According to this approach, portfolio managers are expected to find a portfolio with minimum tracking error relative to a specified benchmark on a month-by-month basis. Therefore, the task of the portfolio manager is to find a portfolio where return is higher than a specified benchmark and at the same time is less risky. Chow (1995) also advocates the tracking-error approach to calculate the risk of the portfolio.

The Value-at-Risk (VaR) measure stems from the banking sector where it is used to calculate risk arising from lending money. It has gained broad popularity in the investment community. VaR determines the probability of an increase or decrease in the market value of an asset over a period of time under normal circumstances and involves creating a confidence interval over a period of time. It is expected that the value of an outcome should lie within the confidence interval. Campbell et al. (2001) suggest using VaR as an alternative to the traditional variance approach in calculating portfolio risk. By using VaR as a measure of risk, an assumption of non-normality of the return distribution can be considered and a better risk estimate obtained. Rengifo and Rombouts (2004) state that investors treat losses and gains asymmetrically with skewness and kurtosis pervasive in the data, which violate the assumption of normality and consequentially they advocate using VaR as a risk measure when optimising a portfolio.

Other methods have been proposed to address problems of the MV approach. Jensen and Mercer (2003) find that the performance of MV can be improved substantially if portfolio rebalancing is calculated on the turning point of the monetary cycle as the variance/covariance structure of multiple asset classes depict better estimates. Clarke et al. (2006) support the Bayesian method to calculate a structured covariance matrix procedure for large-scale optimisation. Brocato and Steed (1998) studied nine equity and debt classes and suggest using the NBER business cycle as a reference to calculate in-sample MV. Their approach enhances performance compared to the classical MV approach, as variance/covariance structures are highly influenced by the phase of the business cycle. The MV approach enjoys better diversification during an expansion period compared to during a recession period.

Amenc and Martellini (2002) propose that the covariance matrix structure should be structured to obtain better MV performance. This is achievable by employing methods of constant correlation approach, Elton and Gruber (1973), single factor model, Sharpe (1963), and the multifactor forecast, Chan et al. (1999).

2.5. Testable propositions

2.5.1. Momentum returns and portfolio structure

Several important issues that might lead to differences in momentum profitability have been identified above and are summarised as follows:

(i) should Cumulative Abnormal Returns (rebalanced monthly) or Buy-and-Hold Abnormal Returns be used as the metric over a period of time?

(ii) should portfolios be equally weighted, i.e., money invested equally among stocks in a portfolio or should it be value weighted, i.e., money invested according to the market capitalisation of the stocks?

(iii) what number of portfolios should be used in the momentum strategy, i.e., should the whole sample be divided into 2, 3, 4, 5, 10, or 20 portfolios to calculate momentum returns?

(iv) should momentum returns be calculated using the same firm size, i.e., how does the size effect impact momentum profitability?

(v) should returns be computed as simple returns (single-period returns), i.e., holding period returns or continuously compounded returns, i.e., log returns?

(vi) should returns be calculated in a domestic or foreign currency, e.g., local currency or USD or Euros?

(vii) should one month be skipped between the formation and commencement of the holding period?

(viii) should extreme return stocks in the Winner or Loser portfolio be excluded from the portfolio?

2.5.2. Industrial momentum

The empirical evidence of industrial momentum profitability is limited and not tested extensively in various markets using alternative computational methods. An important reason for little research on industry momentum returns in an international context can be attributed to:

(i) the need for a large number of stocks to be present in each stock market so that each industry within the stock market holds an adequate number of stocks to reduce idiosyncratic risk[3]. For example, if there are 3,000 stocks listed in a stock exchange and these stocks can be assigned to 30 industries, then on an average each industry will have 100 stocks. However, except big markets like US, UK, Japan, etc, only a few stock exchanges hold a large number of stock listings. Thus, a limited number of stocks in small stock markets restricts extensive industry momentum analysis.

(ii) the information relating to the industry to which the stock belongs is not available for all stocks, especially stocks listed outside developed markets. Moskowitz and Grinblatt (1999) use CRSP and SIC codes for US market to reclassify stocks into different industries. The same cannot be done for other stock markets as SIC codes are not available for all stocks outside the US market. On the other hand, Nijman et al. (2004) use MSCI classification

[3] The risk which is present in a small number of securities but can be diversified with a larger sample

to divide stocks into different industries, but they combine stocks from 15 countries in one sample to increase sample size, and

(iii) an international study on industry momentum return comparison is difficult as the data availability and industry classification do not come together with most of the databases. Therefore, the definition of industry classification may be a problem as the criterion for assigning each stock to a particular industry is unlikely to be same for all databases. For example, Microsoft falls under 'Services' industry under the two-digit SIC code, whereas Datastream classify Microsoft as 'Software & Computer Services' industry. This may lead to a serious problem, especially when comparing industry momentum returns between countries. Thus, the best approach is to use a single database holding data for multiple countries when comparing industry momentum returns between countries.

Undertaking an industry momentum returns study on markets outside the US stock market poses various problems. At the same time, it is also important to test a new phenomenon on a global basis to confirm whether the anomaly is not by chance or market confined.

A direct comparison of return across seven markets will illustrate whether the profitability of industry momentum return exceeds *individual* momentum returns and whether industry factors can explain individual momentum returns. This comparison is quite significant as the previous literature lacks substantial evidence of industry momentum profitability outside the US stock market. For example, Nijman et al. (2004) test industry momentum returns by combining data from 15 European countries rather than documenting profitability of each country. Similarly, Swinkels (2002) tests industry momentum returns by using industry indices due to unavailability of stock and industry details for each stock.

There is a focus on increasing the coverage of stocks within a market by directly calculating monthly industry stocks returns from the stock returns positioned within the industry. Unlike industry indices, where only representative companies within an industry are chosen, these data cover all the stocks within an industry, diminishing the potential for selectivity bias. Thus, the data are devoid of survivorship bias as all stocks positioned within the industry are included in calculating monthly returns.

The study also compares individual momentum return with industry momentum returns across seven countries thereby giving an ideal platform to document whether industry momentum returns are superior to individual momentum returns. Although industry momentum is tested in an international context by Swinkels (2002) and Nijman et al. (2004), this current study employs a battery of tests to check whether stock momentum can be explained by industry returns. Swinkels (2002, p. 139) further adds that, “Since individual stock data are not available, it cannot be investigated whether industry momentum subsumes the individual momentum effect”. However, in this study a comparison of the two momentum strategies is feasible. The data used in this study can document the interrelationship between industry momentum returns and individual momentum returns.

An important contribution of this study to the existing literature is the extension of industry momentum strategy to 52-week industry momentum strategy. Industry momentum and 52-week high momentum are the two recent extensions of the stock momentum and both strategies claim to generate higher returns than the traditional stock momentum in the US stock market. George and Hwang (2004) note that the momentum strategy, based on nearness to the 52 week high/low strategy, generates superior risk-adjusted returns. The strategy is also easy to implement as the 52-week high/low prices are readily available from newspaper, internet and other media. Therefore, if 52-week high momentum returns, involving stocks, dominate traditional momentum returns, then do 52-week momentum returns strategy involving industry returns also generate superior returns?

Thus, it is necessary to test the following questions before accepting the validity of industry momentum:

(i) is industry momentum limited only to the US data?

(ii) do industry momentum returns dominate individual momentum?

(iii) is this anomaly specific only to a particular dataset used, e.g., CRSP data for the US stock market

(iv) will industry momentum returns change if the stocks are assigned to a different industry based on classification from other databases?

(v) is industry momentum strategy prevalent only during certain periods of time?

(vi) will changes in portfolio structure, e.g., one-month gap between formation and holding period, etc. render industry momentum profit not statistically significant?

Applying this strategy across seven markets using different dataset and time periods will address the above questions.

2.5.3. 52-week high momentum returns

Empirical analysis of the 52-week high momentum approach is a relatively recent development and lacks widespread empirical support, suggesting further investigation is needed to determine the sources of the profit and to uncover other attributes associated with this investment strategy. The motivation underlying the research reported in this paper is to rigorously test the 52-week high momentum in a global context. Specific issues included are:

(i) data mining bias,

(ii) portfolio construction approach,

- a) CAR versus BHAR,
- b) equal-weighted or value-weighted,
- c) number of stocks in a portfolio, and
- d) size-sorted portfolios.

(iii) data sample, and

(iv) international investing.

2.5.3.1. Data mining bias

It is important to test whether the documented results are a localised anomaly dependent on the sample used or whether they hold more generally across multiple markets. If the results are overall consistent, then the criticism of a data mining bias can be ignored. However, if the results are not consistent and differ significantly from market to market, then a data mining bias cannot be readily rejected. It is important to establish if the results reflect an anomalous chance event which is non-repeatable.

2.5.3.2. Portfolio construction approach

Fama (1998) also surmises that the various anomalies found within the efficient market hypothesis may disappear once correct methodology or correct statistical testing is used. Accordingly, instead of utilising just one method, an alternative approach may be used to check for flaws. This current research uses differing portfolio construction techniques and reports 52-week high momentum investing under each regime. If the changes lead to significant differences in returns, then 52-week high strategy results must be interpreted with caution. The different methods used in the study include:

(i) CAR or BHAR?

The two most popular approaches for calculating portfolio returns are CAR and BHAR. Therefore, if the statistical significance or returns change significantly by swapping between these alternative models, then the strategy is less robust.

(ii) Equal- or value-weighted?

The method for determining how much of each stock will be purchased/sold in specific portfolios is of potential importance. It is well known that small capitalisation stocks generate higher returns and at the same time inherit higher risk than large capitalisation stocks Banz (1981). These return and risk characteristics of the small-cap stocks pose a problem for calculating returns when it is assumed that the risk is same for all stocks. Fama (1998) explains that various anomalies relating to the EMH may disappear once value-weighted returns are used instead of equal-weighted returns. This explanation may be linked to underlying samples, as most of the anomalies exist only in small market capitalisation stocks.

(iii) Number of stocks in a portfolio

The number of portfolios used in a study may assume significant importance. A greater number of portfolios drawn from a stock population will lead to a decreasing number of stocks in any one portfolio. Prior studies of individual momentum returns include portfolio sizes varying from 3 to 20. However, the literature lacks clear guidelines for determining the optimum portfolio size when calculating momentum returns. Although the Dahlquist and Broussard (2000, p. 20) observation dates back some years, the sentiment remains current. "Further research should be done to show how sensitive these results are to the size of the portfolio formed. Since this study, as well as previous studies, focused on portfolios containing 35 stocks, future research might focus on smaller or larger portfolios." The potential that imprecision may affect momentum profit as portfolios are formed with only extreme return stocks or a large number of stocks requires, further research.

Siganos (2007) finds that investors can maximise their profit by buying/short-selling only a small number of stocks as it is the extreme winners and losers that yield the highest returns. Buying and short-selling fewer stocks also leads to lower transaction and other brokerage costs. Therefore, it may be interesting to see how the 52-week high momentum returns change when varying the number of securities in the portfolios. Specifically, investigation reported in this paper considers the impact on 52-week high momentum returns and their standard deviation when more than 3 portfolios are used. This is a first test of the issue for 52-week high momentum returns and will lead to better understanding of the portfolio returns.

(iv) Size-sorted portfolios

Marshall and Cahan (2005) divide the whole sample into 4 sub-samples based on market-capitalisation. Their results indicate that 52-week high momentum returns are highly profitable for the small market-capitalisation stocks but this gradually declines as the market-capitalisation increases. They also report higher volatility in the small-cap portfolio. This may hold an important clue to the sources of 52-week investing. Small-cap stocks, in general, tend to have higher returns and greater variability and this feature may be the predominant source of returns in the 52-week high momentum strategy. However, Marshall and Cahan (2005) study is restricted to the Australian Stock Market, it is appropriate to extend this work to additional markets. This current study investigates the impact of size-sorted portfolio in 54 countries.

2.5.3.3. Data sample

Marshall and Cahan (2005) check for data-snooping bias, extending the coverage of out-of-sample testing. This current research considers 52-week high investing in 54 countries, covering 52,593 stocks. By employing the same investment strategy for all 54 countries, the robustness of this anomaly is tested in depth.

2.5.3.4. International investing

An important contribution of this paper is the inclusion of exchange rate movements in the 52-week calculation of momentum returns. For example, if an investor in the US is using a 52-week momentum investment strategy and invests money in the New Zealand stock market and the New Zealand dollar appreciates over a period of time, then the appreciating NZ dollar and depreciating US dollar will bring extra returns to the US investor. An international investor is quite likely more interested in knowing total returns, i.e., 52-week high momentum return plus exchange rate return, when considering investing in a foreign market.

Since an international investing option is not considered in the context of reported 52-week high investment returns, at least to date, a more detailed investigation is needed to consider the change of returns when they are calculated in a foreign currency instead of local currency. This can be done by running the same test on the same data but with a different common currency, such as Euros, Yen or US dollars. One data set should be in local currency and another data set should be in a common foreign currency reflecting the prices converted using date corresponding exchange rates. The difference of returns between the two data sets might explain the extent of profit or loss an international investor may expect while investing in a foreign market. The difference in returns may also highlight volatility in the domestic market arising out of inflation, economic crises and other events.

2.5.4. Momentum returns optimisation

Portfolio optimisation potentially offers certain advantages. Nevertheless, its application in allocating weights in portfolio construction has so far been ignored in the momentum strategy literature. Researchers are reluctant to accept portfolio optimisation techniques due to researchers:

(i) having ignored the importance of allocating weights among stocks, and the benefits arising from high return and low risk in calculating momentum strategies,

(ii) thinking that including portfolio optimisation techniques in the study will make calculations more complex and difficult to compute.

Construction of optimised portfolios and comparisons with the frequently used methods will provide evidence of any real advantage. If results confirm superiority of optimisation techniques in generating extra returns or decreasing risk compared to the traditional equal- or value-weighted methods, then it is an important finding, with implications for portfolio management, viz., momentum portfolio holders can adopt a portfolio optimisation technique to further improve their portfolio performance. Michaud (1998) notes that effective asset management is not simply a matter of finding attractive investments; it also requires optimally structuring the portfolio of the assets. This is because the investment behaviour of a portfolio is typically different from that of the constituent assets. Several considerations are pertinent:

(i) portfolio optimisation techniques are developed in a manner by which the portfolio return is maximised or risk is minimised. This can be achieved by wisely allocating money among the stocks, given certain inputs. Therefore, instead of using a traditional equal- or value-weighted approach, a portfolio optimisation technique could be applied to allocate weights to the stocks,

(ii) some optimisation techniques provide an option for including risk preferences when calculating the optimum allocation, i.e., an allocation can be made according to investors' risk preference. Risk averse investors prefer less risky portfolios than risk-seeking investors, and a portfolio optimisation technique can calculate the optimal portfolio where risk is minimised. Similarly, risk seekers can use an optimisation technique to allocate money in a portfolio where return is maximised, and

(iii) use of the efficient frontier of return and risk in an optimisation technique provides investors with a range of options for investing in a portfolio. Therefore, the efficient frontier provides a platform where investors with varying risk tolerance can pick an efficient portfolio to meet their requirements.

Chapter 3

METHODOLOGY

3.1. Momentum returns and portfolio structure

The primary aim of this research is to investigate the general applicability of several momentum models and then contribute as to how returns may be further enhanced by the application of portfolio theory. The research is, therefore, empirical drawing on stock price information for 54 countries over 34 years. Several measurement methods are used and a range of portfolio formation algorithms investigated. In the sections below, each of the metrics and each of the algorithms are discussed in turn.

The focus reflected in the prior research, reviewed in the previous chapter, emphasises the method used by Jegadeesh and Titman (1993) and various extensions to test whether momentum returns exist. This study uses alternative methods of buying previous winners and short-selling previous losers to determine 'if their' impact significantly changes the returns. This strategy is constructed by identifying past Winner and Loser stocks' returns. More specifically, each month all stocks are ranked as per the returns over the last *J* months (formation period). These stocks are then ranked into deciles with the Winner portfolio holding stocks generating the most positive returns and the Loser portfolio holding stocks with the most negative returns over the last *J* months respectively. In each month, a self-financing strategy buys the Winner portfolio and short-sells the Loser portfolio. Next, the equally-weighted returns for the Winner and Loser portfolios are calculated for the subsequent K months (holding period).

The return for each stock i is calculated as follows:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$$

where $P_{i,t}$ is the price of the stock i in period t,

Similarly, the return for the broad market index can be calculated as:

$$M_{m,t} = \frac{M_{m,t}}{M_{m,t-1}} - 1$$

where $M_{i,t}$ is the value of market index m in period t.

The formation and holding period returns are calculated in two alternative ways, namely CAR and BHAR.

CAR method follows:

$$AR_{i,t} = R_{i,t} - M_{m,t}$$

where $AR_{i,t}$ is the abnormal return for stock i for period t. The cumulative abnormal return over the period of time is:

$$CAR_{i,t} = \sum_{t=1}^{N} AR_{i,t}$$

where $CAR_{i,t}$ is the cumulative abnormal return for stock i over N months. The portfolio cumulative return can be written as:

$$\overline{CAR}_{W,t} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,t}$$

$$\overline{CAR}_{L,t} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,t}$$

where $\overline{CAR}_{W,t}$ is the cumulative abnormal return for the Winner portfolio, and $\overline{CAR}_{,L,t}$ is the cumulative abnormal return for the Loser portfolio. The momentum returns using the CAR approach for each period *t* are written as:

$$Momentum\ return = \overline{CAR}_{W,t} - \overline{CAR}_{L,t}$$

The second approach to calculating returns over the formation period and holding period is the BHAR method. The method follows:

$$BHAR_{i,t} = \prod_{t=1}^{N}\left[1 + R_{i,t}\right] - \prod_{t=1}^{N}\left[1 + M_{m,t}\right]$$

$$\overline{BHAR}_{W,t} = \frac{1}{N}\sum_{i=1}^{N} BHAR_{i,t}\ for\ the\ Winner\ portfolio, and$$

$$\overline{BHAR}_{L,t} = \frac{1}{N}\sum_{i=1}^{N} BHAR_{i,t}\ for\ the\ Loser\ portfolio$$

$$Momentum\ return = \overline{BHAR}_{W,t} - \overline{BHAR}_{L,t}$$

Momentum returns are calculated using overlapping periods so adjusted standard errors following Newey and West (1987) are used in calculating *t*-statistics. To ignore bias arising from bid-ask spread, price pressure and lagged reaction effects, a one-month gap is allowed between the formation and holding period. The portfolio return is calculated using two weighting approaches, namely equal-weighted and value-weighted. Equal-weighting divides investment equally among all stocks in the portfolio, whereas value-weighted allocates money to each stock based on its respective market capitalisation. The allocation to each stock of the portfolio using value-weighted approach can be written as:

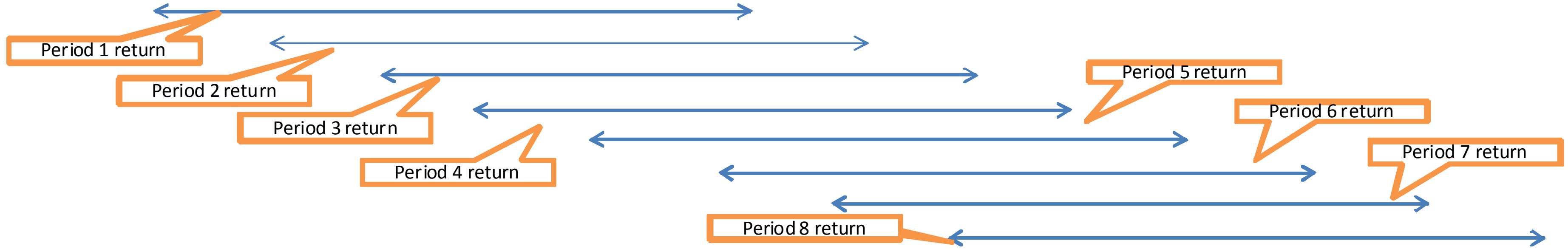
$$\frac{MV_{i,t}}{\sum_{i=1}^{N} MV_{i,t}}$$

where $MV_{i,t}$ is the market value of stock i at the end of formation month t.

As this study uses monthly data, overlapping holding-period returns are calculated to increase the power of statistical reliability. For example, using a formation (J) = 6 months, and a holding (K) = 6 months, consists of 6 parts as shown in Table 3-1. A January 2001 momentum strategy return is determined by 1/6 highest returns of Winners and 1/6 lowest return of Losers from July 2000 to December 2000 (position 6), June 2000 to November 2000 (position 5), May 2000 to October 2000 (position 4), April 2000 to September 2000 (position 3), March 2000 to August 2000 (position 2), and February 2000 to July 2000 (position 1). In the month of February, the Winner and Loser portfolio return from February 2005 to July 2005 will be dropped and the Winner and Loser portfolio return from August 2005 to January 2006 will be added. How the overlapping period is used in calculating momentum returns is schematically presented in Table 3-1.

Table 3-1: Overlapping momentum returns illustration

Momentum period	Aug-00	Sep-00	Oct-00	Nov-00	Dec-00	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01
1	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6							
2		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6						
3			Month 1	Month 2	Month 3	Month 4	Month 5	Month 6					
4				Month 1	Month 2	Month 3	Month 4	Month 5	Month 6				
5					Month 1	Month 2	Month 3	Month 4	Month 5	Month 6			
6						Month 1	Month 2	Month 3	Month 4	Month 5	Month 6		
7							Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	
8								Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
	Average return for Aug-00	Average return for Sep-00	Average return for Oct-00	Average return for Nov-00	Average return for Dec-00	Average return for Jan-01	Average return for Feb-01	Average return for Mar-01	Average return for Apr-01	Average return for May-01	Average return for Jun-01	Average return for Jul-01	Average return for Aug-01



3.2. Industrial momentum

The first step requires computing industry momentum returns for each country under investigation. To identify the industry to which the stocks belong, the Datastream industry classification is used. Datastream maintains 45 industry classifications and each stock is associated with one of these industries. As some industry classifications given by Datastream do not pertain to equity market, only 38 out of the 45 industries are finally chosen to be included in the sample. The details are discussed more fully in Chapter 4 of this thesis. Once the classification is complete and stocks are divided into an industry, then value-weighted monthly industry returns are calculated. This will lead to a time-series of monthly returns for each of the 38 industries.

The monthly industrial returns are then recorded as a descending array of returns over the last six months. Next, equal-weighted Winner and Loser portfolios are formed comprising the top 33% of the ranked industries and bottom 33% respectively. The holding period returns are then calculated for each Winner and Loser portfolio over the next 6 months with the industrial momentum return equal to buying the Winner portfolio and short-selling the Loser portfolio. To increase the power of the test, overlapping portfolios are used as discussed in the previous section.

A second set of data also tests industrial momentum using Datastream maintained indices. The index data can be downloaded from Datastream for each country. This provides the advantage of not identifying stocks associated with a particular industry and therefore skips the step of grouping stocks into monthly value-weighted industry returns.

The industry momentum returns are tested rigorously using several approaches. The first method adjusts the abnormal return of each stock by deducting the industry returns instead of overall market index. Thus, industry-adjusted abnormal returns can be written as:

$$AR_{i,t} = R_{i,t} - M_{m,t}$$

where market index m is equal to the industry to which stock i belongs. Therefore, for example, the abnormal return for the Boeing company is calculated after deducting Aerospace industry, instead of S&P 500 index.

Industry-neutral momentum returns are also calculated to document whether 'normal' momentum returns can generate positive and significant returns once the industry factor is taken out. To complete this analysis, 'normal' momentum returns for each industry, i.e., buying past winning and short-selling past losing stocks within the same industry. Industry-neutral momentum return is the average of the 'normal' momentum returns calculated for each industry.

$$CAR_{i,t,a} = \sum_{t=1}^{N} AR_{i,t,a}$$

where $CAR_{i,t,a}$ is the cumulative abnormal return for stock i, for the period t and industry a. The industry-neutral momentum return is computed as:

$$Industry - neutral\ momentum\ return = \frac{1}{N}\sum_{a=1}^{N}(\overline{CAR}_{W,t,a} - \overline{CAR}_{L,t,a})$$

where CAR_W and CAR_L denotes Winner and Loser portfolio return and a represents the industry to which Winner and Loser portfolio belongs.

3.3. 52-week momentum return

The framework for calculating 52-week momentum returns is based on the current price of the stock to the last 52-week's high/low price. The method is similar to Jegadeesh and Titman (1993), except the ranking of stocks is based on the nearness of current price to its 52-week high. At the end of 12 months of the formation period, all stocks are ranked as per the ratio of current price to 52-week high price. These stocks are ranked and assigned to three portfolios where the Winner portfolio consists of those stocks currently trading close to the last 52-week high price, whereas the Loser portfolio consists of those stocks with a low price when compared to the last 52-week high price. The 52-week momentum return is also subject to rigorous testing with alternative computational methods used to detect any deviation in the returns. The strategy is also computed using formation/holding periods other that the suggested 12 months/6 months formation/holding period, to detect if the returns are due to data mining.

3.4. Momentum returns optimisation

The optimisation of momentum return uses the same framework as Jegadeesh and Titman (1993) to calculate momentum returns. The main difference lies in the allocation of money to each stock in the portfolio where various optimisation techniques are used to allocate money to each stock in the Loser and Winner portfolios. To complete this process, certain inputs are needed to optimise a portfolio, viz., expected mean, standard deviation, correlation, etc.

In reality, true expected return, standard deviation and correlation data are not available and historical estimates are considered a proxy for expected returns, standard deviation and correlation/covariance. This study uses the prior 60 months of historical data for each stock to compute expected return, standard deviation and covariance/correlation. Jobson and Korkie (1981) and Chopra et al. (1993) consider that the prior 60 months of data contribute a reasonable period over which to calculate different inputs needed for an optimisation process. Therefore, availability of data for the previous 60 months[4] becomes another condition in determining whether or not a stock will be included in the Loser or Winner portfolio in any given month.

The implications of requiring 60-months of prior historical data are explained when momentum returns are based on 6-month formation, 1-month gap and next 6-month holding periods. The strategy, as presented below, will calculate momentum return for period 1 starting from January 2000 to January 2001 and momentum return for period 2 will start from February 2000 and end in February 2001. This will continue until the last month of the sample.

```
Jan'00                      Jun'00            Aug'00                       Jan'01
| 1    2    3    4    5    6  |   1   |   1    2    3    4    5   6  |
 -------------------------------------  ---------  -----------------------------------------
          Formation                  Gap               Holding
```

This entails checking whether the stock returns for all companies are available for the previous 5 years, (in this example, from December 1994 to

[4] This constraint is only applicable to momentum return optimisation technique.

December 1999) when period 1 momentum return is considered. Stocks with less than 5 years of historical data will be excluded from period 1 analysis. For example, if stock X data starts from January 1995 (59 months to December 1999), then it will be not be included in the period 1 sample. However, stock X will be included in period 2 (February 2000-February 2001) analysis as the stock now fulfils the requirement of 60 months of prior data.

The various optimisation techniques considered in this study are:

3.4.1. Markowitz method

To understand the Markowitz approach clearly, it is helpful to consider how return and risk in the portfolio are calculated and then optimised. Markowitz analysis requires three inputs to calculate the optimal combination, viz.:

(i) expected return for stock *j*,

(ii) standard deviation or variance of stock *j*, and

(iii) covariance or correlation between stock *j* and *k*.

Portfolio return: $R_p = \sum_{j=1}^{N} X_j R_j$

where, R_p refers to the portfolio return, X_j refers to weight of each stock such that $\sum_{j=1}^{N} X_j = 1$, R_j refers to the return of each security and N refers to the number of securities in the portfolio. Therefore, for two stocks, the portfolio return will be $X_1 R_1 + X_2 R_2$, and $X_1 R_1 + X_2 R_2 + ... + X_N R_N$ for N securities in the portfolio. The expected return of each stock R_j is an average return of stock R_j over the previous 60 months.

Portfolio variance: $\sigma_p^2 = \sum_{j=1}^{N}\sum_{k=1}^{N} X_j X_k \sigma_j \sigma_k$

$$= \sum_{j=1}^{N}(X_j^2\sigma_j^2) + \sum_{j=1}^{N}\sum_{\substack{i=1 \\ k\neq j}}^{N}(X_j X_k \sigma_{jk})$$

$$= \sum_{j=1}^{N}(X_j^2\sigma_j^2) + \sum_{j=1}^{N}\sum_{\substack{k=1 \\ k\neq j}}^{N}(X_j X_k \rho_{jk}\sigma_j\sigma_k)$$

$$\because \text{correlation coefficient } \rho_{jk} = \frac{\sigma_{jk}}{\sigma_j\sigma_k}$$

where, σ_j^2 refers to the variance of stock *j*, and σ_{jk} refers to the covariance between security *j*,*k*. Therefore, the portfolio variance involving 2 stocks will be: $X_1^2\sigma_1^2 + X_2^2\sigma_2^2 + 2X_1X_2\sigma_{12}$ and for *N* securities, the portfolio variance will be: $X_1^2\sigma_1^2 + X_2^2\sigma_2^2 + ... + X_N^2\sigma_N^2 + 2X_1X_2\sigma_{12} + ... + 2X_j X_{\substack{k \\ j<k}} \sigma_{\substack{jk \\ j<k}}$, where k has values in the range 1 to *N*. Variance and covariance/correlation for each stock are computed using the previous 60 months of return and forming a variance-covariance matrix.

The formulation permits an investor to use Sharpe's reward-to-variability ratio to allocate optimum weight in each stock of the Winner and Loser portfolios. Jobson and Korkie (1981) note that the Sharpe reward-to-variability ratio is a common performance measure. They further add that the portfolio weight calculated using Sharpe's ratio substantially dominates the portfolio formed from the traditional Markowitz technique, i.e., to optimise a portfolio by specifying a certain return target or a maximum risk. The Sharpe's reward to variability ratio is:

$$\text{Sharpe's ratio} = \frac{R_p - R_f}{\sigma_p}$$

where,

(i) $R_p = \sum_{j=1}^{N} X_j R_j$,

X_j refers to weight of each stock such that $\sum_{j=1}^{N} X_j = 1$, R_j refers to return of stock j and N refers to number of securities in the portfolio.

(ii) R_f is the 3-monthly risk-free US Treasury Bill,

(iii) σ_p is the portfolio standard deviation.

The objective is to maximise the Sharpe ratio by changing X_j, or the weight of each stock of the portfolio. This means that the optimisation will seek to maximise excess return per unit of risk by changing the weight of each stock in the portfolio.

Sharpe's reward-to-variability ratio is used to find the optimum weight of each security in a portfolio. Several constraints are imposed while maximising Sharpe's reward-to-variability ratio, including:

(i) the sum of all individual stock weights shall be equal to one,

(ii) all the stock weights shall be non-negative, i.e., no short-selling is allowed within the portfolio,

(iii) the maximum percentage allocation to each stock in a portfolio is 5%. This is to avoid the corner solution problem often observed in Markowitz optimisation. Jorion (1985) notes that the Markowitz approach often allocates a high percentage of weight to stocks with high expected returns when the objective of the optimisation is set to maximise returns. Similarly, the Markowitz approach allocates a high percentage of weighting to stocks with low variance when the objective of the optimisation is set to minimise risk. This corner solution problem leads to negligible or no weighting to other stocks of the portfolio and therefore lack desirable diversification properties. Chopra and Ziemba (1993) find that constrained portfolio optimisation outperforms the no constraint approach. Cohen and Pogue (1967) propose a maximum allocation of 2.5% to a stock when there are around 150 stocks in the portfolio and 5% when the number of stocks in the portfolio drops to 75, and

(iv) Jorion (1985) documents corner solution problems in the Markowitz method when some stocks in the portfolio are assigned zero weight. A trial run in this study also exhibits the same pattern where 20 out of 100 stocks are allocated a weight close to 5% each and the remaining 80 stocks are allocated a weight close to or equal to 0%. To minimise this problem and to reduce idiosyncratic risk, another constraint is imposed in the optimisation process where the weight of each stock of the portfolio should be greater than 0.1%. A very minimal filter is applied as there are no prior studies suggesting a consensus level.

These four constraints are imposed in all the optimising techniques considered in this study.

3.4.2. Markowitz method excluding extreme returns

This approach proposes to exclude the extreme 5% of stocks within the Winner and Loser portfolio. For example, if there are 100 stocks within the Winner portfolio, then the five stocks with highest returns during the formation period will be excluded from the Winner portfolio. Likewise, the bottom five stocks of the Loser portfolio with the most negative returns in the formation period will be excluded from the Loser portfolio.

The rationale for excluding the extreme 5% returns is the high sensitivity of the Markowitz approach to inputs used in the optimisation. Michaud (1989) finds that a small change in input estimation can make a big difference in the distribution of the optimum portfolio weights. Best and Grauer (1991) document that a small change in stocks mean return can drive half the securities from the portfolio without any change to the portfolio mean and standard deviation. The problem can be controlled, to some extent, by excluding stocks with extreme high/low returns and placing constraints on the optimisation process as explained above. Further, the test on five different markets will also indicate whether or not the momentum returns substantially change when compared to the Markowitz optimisation method without excluding any stock.

3.4.3. Single Index Model

One of the criticisms noted of the Markowitz approach is that a large number of inputs are required to complete the optimisation process. This problem can be reduced by decreasing the number of inputs required to compute the optimised weight of each stock of the portfolio. This reduction of inputs also effectively reduces the "error maximisation" problem noted in the Markowitz approach. For example, 1325 estimates are needed to calculate the optimal portfolio allocation involving 50 stocks. These 1325 estimates consist of 50 estimates of expected return, 50 estimates of variance, and 1225 [n(n – 1)/2] estimates of covariance. However, only 152 inputs (3n+2) are needed to optimise a portfolio of 50 stocks under the Single Index model. The Single Index model assumes that the stock returns generally vary consistently with an overall market aggregate and therefore estimates of correlation/covariance among individual stocks are not required.

The pioneer of this model, Sharpe (1963), proposes that a small sacrifice of information (correlation/covariance among stocks) may actually lead to better results than the traditional Markowitz model. The expected returns, variance and covariance under this model are as following:

(i) Expected returns: $E(R_j) = \alpha_j + \beta_j E(R_m)$,

where, $E(R_j)$ is the expected return of stock j

$E(R_m)$ is the expected market return where the market index of each country is used as a proxy. In this study, the market mean return of the previous 60 months is used as an estimate of market expected return.

α_j and β_j for each stock *j* are computed by linear regression using the prior 60 months of historical stock and market returns data.

(ii) Variance: $\sigma_j^2 = \beta_j^2\sigma_m^2 + \sigma_{ej}^2$,

where, σ_{ej}^2 is unique risk/nonsystematic risk and $\beta_j^2\sigma_m^2$ is the systematic risk of each stock *j*. σ_{ej}^2 is the variance of the residual after regressing stock *j* and market *m* returns over the previous 60 months.

(iii) Covariance between stock *i* and *j*: $\beta_i^2\beta_j^2\sigma_m^2$.

where, β_i is the beta of stock *i* and β_j is the beta of stock *j* calculated by regressing historical 60 months of stock *i* and *j* returns with market *m* return respectively. σ_m^2 is the variance of market return.

Therefore, the new portfolio mean and variance under the Single Index model is:

Portfolio return: $R_p = \sum_{j=1}^{N} X_j R_j$, such that $\sum_{j=1}^{N} X_j = 1$

$$= \sum_{j=1}^{N} X_j \alpha_j + \sum_{j=1}^{N} X_j \beta_j \overline{R_m}$$

Portfolio variance: $\sigma_p^2 = \sum_{j=1}^{N}\sum_{k=1}^{N} X_j X_k \sigma_j \sigma_k$

$$= \sum_{j=1}^{N} X_j^2 \beta_j^2 \sigma_m^2 + \sum_{j=1}^{N}\sum_{\substack{k=1 \\ j\neq k}}^{N} X_j X_k \beta_j \beta_k \sigma_m^2 + \sum_{j=1}^{N} X_j^2 \sigma_{ej}^2$$

3.4.4. Single Index Model with adjusted beta

One of the most important inputs of the Single Index model is the beta of each stock. The reliability of the beta estimate can greatly influence the optimisation results. One of the concerns raised in the literature is whether the past stock beta is an appropriate estimate for calculating expected portfolio mean and variance. Blume (1975) documents how the future beta is closely related to the past data and historical beta can be effective in predicting the next period beta. Regressing beta of one period over the next period, Blume (1975) documents the following result:

$$B_{j,t+1} = \alpha_0 + \alpha_1 \beta_{j,t} + \varepsilon_{j,t+1}$$

$$\text{or,} \qquad \beta_{future} = 1/3 + 2/3\beta_{historical}$$

The adjusted-beta has another advantage of converging all betas toward 1. In reality, true beta coefficients are not available and therefore sampling errors always occur when the beta coefficient is estimated from historical data. This problem can be mitigated by using adjusted-beta as the true beta coefficient is expected to converge toward 1 over a period of time. Three cases are presented in Table 3-2.

Table 3-2: Adjusting historical beta

Case	Historical beta	Adjusted-beta (0.333+0.667*Historical beta)	New adjusted-beta
1	1.00	0.333+0.667*1.00	1.000
2	1.20	0.333+0.667*1.20	1.133
3	0.80	0.333+0.667*0.80	0.866

In the above example, the historical beta of 1.20 decreases to 1.133. Similarly, the historical beta 0.80 increases to 0.866. This is important as Klemkosky and Martin (1975) note that beta are mean reverting and this property can be seen in the adjusted-beta. Accordingly, there may be merit in adjusting the historical betas using the Blume (1975) method. The new set of data in this analysis uses adjusted-betas to investigate whether this optimisation technique is superior to other optimisation techniques discussed above.

3.4.5. Shrinkage method

The prior research notes that Markowitz optimisation results can change significantly with a small change in input estimates. One of the approaches proposed to address this problem is to shrink the historical mean return of each stock to a grand mean return. This will control the dispersion of stock returns within the portfolio and hence the optimisation results will be less sensitive to inputs. This popular technique commonly referred to as the James-Stein shrinkage method after Stein (1955), demonstrates that estimation errors will decrease as the individual mean is converged to the grand mean. A preference for the James-Stein method over the conventional MV approach is advocated by Jobson et al. (1979) and Jobson and Korkie (1981), based on its superior statistical properties. In fact, Lindley (1962) states that this method is, "one of the most important statistical ideas of the decade…"

Jorion (1985), Jorion (1986), and Golosnoy and Okhrin (2005) find superior Markowitz optimisation results when shrinkage means are used as input. Chopra et al. (1993) compare optimisation performance under the Stein-estimator and traditional Markowitz approach and conclude there is a clear dominance by the Stein method. Although there are a number of methods available to calculate the percentage of individual mean shrinkage to global mean, this study proposes three weights:

(i) 25% of individual mean shrinkage to the global mean,

(ii) 50% of individual mean shrinkage to the global mean, and

(iii) 75% of individual mean shrinkage to the global mean.

If the return of stock X for January 2001 is 10% and the market return (in this study market index return is used as a proxy for market return) is 5%, then:

(i) the new expected return of stock X with 25% shrinkage to the global mean is:

0.75 * 10% (stock X return) + 0.25 * 5% (market return) = 8.75%

(ii) the new expected return of stock X with 50% shrinkage to the global mean is:

0.50 * 10% (stock X return) + 0.50 * 5% (market return) = 7.5%

(iii) the new expected return of stock X with 75% shrinkage to the global mean is:

0.25 * 10% (stock X return) + 0.75 * 5% (market return) = 6.25%

The optimisation results under the three different shrinkage estimates will indicate whether the momentum returns can generate greater returns when the new expected mean of individual stock return include a high component of market return (grand mean). The method of computing portfolio mean, portfolio standard deviation and optimum weight for each stock of the portfolio is same as the traditional Markowitz method except for the new individual stock mean as discussed above.

3.4.6. Markowitz method with zero expected return

This is the last optimisation method considered in the study and is another version of the shrinkage method where the expected return of each stock is set to zero. All stocks within the portfolio are converged to a common return (zero in this study). This idea, proposed by Chopra and Ziemba (1993), suggests that in the absence of a true expected return for each stock, the best practice is to set all the stock returns to zero or a non-zero constant. In their view, the optimisation process, which is the same as Markowitz, will yield better results when using sensible constraints (in this case constraining all expected stock returns to zero) than without constraints.

The Winner and Loser portfolio are optimised, for each of the eight methods discussed above, at the end of every formation period. These optimum weights are used in the beginning of the holding period to allocate money among the Winner and Loser portfolio stocks. Altogether, 2,202 months of data are optimised under each optimisation technique to calculate momentum returns for five countries. These optimisation months increase to 17,616 data points when the additional three shrinkage to global mean techniques, effectively eight methods in total, are estimated. A breakdown of the number of months to be optimised for each country is:

(i) Canada = 153 Loser months + 153 Winner months,

(ii) India = 97 Loser months + 97 Winner months,

(iii) Japan = 167 Loser months + 167 Winner months,

(iv) UK = 342 Loser months + 342 Winner months, and

(v) US = 342 Loser months + 342 Winner months.

3.5. Key hypothesis

The analysis proceeds with the investigation of a number of hypotheses. The starting point is to consider the current momentum strategy applied to a larger number of markets. In summary, the key hypotheses tested in this research are:

3.5.1. Momentum portfolio structure

H_0: Momentum returns are present in all countries

H_0: Momentum returns will remain positive using several computing approaches.

3.5.2. Industrial momentum and 52-week high momentum

The industrial momentum and 52-week high momentum issues are investigated with:

H_0: Industrial momentum returns are positive when tested in multiple markets

H_0: 52-week high momentum returns are positive when tested in multiple markets

H_0: Industrial momentum and 52-week momentum do not generate greater returns compared to 'normal' momentum return

3.5.3. Portfolio optimisation

After investigating the factors impacting upon momentum portfolios, the analysis turns to investigating whether greater momentum returns are achievable through implementation of portfolio optimisation techniques. Several techniques are applied in this current study and the key hypothesis is:

H_0: Optimisation techniques will lead to an increase in momentum returns

Chapter 4

DATA

4.1. Introduction

The availability of clean data for this study of 54 countries is important. Thomson Datastream is used as the primary source of data because of its comprehensive coverage of countries and time periods. In this section, the data used are discussed and the cleaning processes are described. The Thomson Datastream website claims:

> Thomson Datastream is the most respected historical financial numerical database, covering an unparalleled breadth of financial instruments, equity and fixed-income securities and indicators for over 175 countries and 60 markets worldwide…. Thomson Datastream's encyclopedic databases of 25 million time-series and 400,000 global economic indicators are now available within Thomson ONE – placing the world's leading source of historic market data alongside the real-time pricing, news, research and fundamental content that you need – all in one single, integrated desktop solution.[5]

Researchers are attracted to this database for reasons like Ince and Porter (2006, p. 463) espouse. "We know of no source comparable to TDS (Thomson

[5] www.thomson.com/content/financial/brand_overviews/Datastream_Advance, retrieved on 29/01/2008.

Datastream) in terms of number of markets covered and number of securities covered in each market."

Many previous studies use Datastream as a source of historical data to present contrarian and momentum results. Chan et al. (2000) use market indices available from Datastream to calculate momentum profitability of international stock market indices. Kang et al. (2002) use weekly stock price data, available from Datastream, to calculate contrarian and momentum profitability in the Chinese stock market. Similarly, Griffin et al. (2003) use Datastream as a data source to investigate the effect of macroeconomic factors on the momentum profitability in an international context. Antoniou et al. (2005) test contrarian profits for the Athens' stock exchange by downloading data from Datastream. T. Hou and McKnight (2004) also use Datastream partially to calculate momentum returns in the Canadian stock market.

Datastream covers a range of data and each of them is divided among the following categories:

(i) Equities,

(ii) Equity indices,

(iii) Constituent lists,

(iv) Unit trusts,

(v) Investment trusts,

(vi) Bonds and Convertibles,

(vii) Bond indices and CDS,

(viii) Warrants,

(ix) Economics,

(x) Economic reports/ charts,

(xi) Exchange rates,

(xii) Interest rates,

(xiii) Futures,

(xiv) Options, and

(xv) Commodities

4.2. Data retrieved

Categories i, ii, xi and xii are primarily used as input data in this study. The types of data retrieved from Datastream include:

(i) stock price (in local and US dollar),

(ii) market value of each stock (in local and US dollar),

(iii) market indices (in local and US dollar),

(iv) corresponding date exchange rate,

(v) risk-free or equivalent interest rates for each country, and

(vi) industry classification given by Datastream.

4.2.1. Stock price

Monthly stock prices from 54 countries are used in the study. All the stock prices are downloaded in the local currency format as well as converted into US dollars at the corresponding date's exchange rate. Altogether, 52,593 stocks are downloaded after removing those stocks that fail to meet certain criteria, as discussed later in the chapter. The remaining stocks include live, dead, merged and suspended companies, ensuring that the sample does not suffer from survivorship bias. The starting date for historical stock prices in this study is January 1973 and the sample period for all countries ends in July 2007, except for Hungary where the listings drop below 40 after July 2005. The length of the period ensures that both bull and bear markets are covered.

A cut off requirement that there be at least 40 stocks available in a month to form a portfolio is less than Griffin et al. (2003) but is considered sufficient to achieve diversification. They propose 50 stocks as a minimum number to be available in a study of momentum investing and business cycle risk in 40 countries. The US has the highest number of stocks within a country, 13,904, which includes dead and live stock, and Lithuania has the lowest with 57.

A list of the number of stocks for each country within the sample period is presented in the following Table 4-1.

Table 4-1: Sample period and sample size

[**Table 4-1** is presented at the end of this chapter in Appendix- Page no. **130**]

This study is only concerned with common class equity returns. Therefore, other equity classes such as real estate investment trusts, preferred stocks, convertible stocks, stocks with restricted voting rights, stocks only for international investors, etc., are not included in the study. This approach is consistent with Chan et al. (1996) and K. Hou et al. (2006) who exclude Closed-end funds, Real Estate Investment Trusts (R.E.I.Ts), trusts, American Depositary Receipts (A.D.Rs), exchange traded funds, etc., from the sample in a study on US stock market returns and cross-sectional, time-series variation in global stock returns. The basis for excluding different classes of stocks is due to the divergence of common class equity prices, which may thereby potentially lead to bias in the calculation of returns.

There are a number of countries where two classes of stock exist. For example, there are two equity classes in the Swedish stock market: Class A stock with full voting rights and Class B with reduced voting rights. An example may explain the basis of excluding low-voting rights stocks from the sample. If the company structure allows two classes of stock and suppose class "A" and class "B" have with different voting rights, then the investors will choose the stock with higher voting rights as higher rights lead to better control over the firm if the price is the same. Zingales (1995) notes investors are ready to pay an extra 11% for higher voting rights class stocks in the US stock market. Lease et al. (1983) investigated 30 US corporations and reported a difference of about 5.4% of the stock price when the same stock with higher voting rights was compared with lower voting rights. Mengoli (2004) used only higher voting class stocks in a study on contrarian and momentum returns in the Italian stock market to avoid any potential bias.

Similarly, R.E.I.Ts stocks are also excluded from the sample as these classes of stock incorporate restrictions in terms of investment. For example, R.E.I.Ts stocks can only invest in real estate and may be tax-free if 95% of the earnings are distributed as dividends. For preferred stock, there are typically restrictions around management control and issues connected with voting rights. Therefore, preferred stocks are excluded from the sample. The only exceptions are the preferred stock listed on the Brazil and Argentina stock exchanges as they are treated as common class stocks.

Also excluded are those stock classes primarily meant for international investors within a domestic market. In China there are two classes of stock, Class A- for domestic investors and Class B- for domestic as well as foreign investors. Chakravarty et al. (1998) show that on average Class B stocks in China trade at a discount of 60% compared to Class A stocks of the same company. The main reason for such a big difference is attributed to foreign investors' lack of information about the Chinese stock market rules and regulations.

The selection of stocks in the Datastream equity category does have some difficulties associated with it. Ince and Porter (2006, p. 464) observe that, "Our most troubling finding is the inability to distinguish easily between various types of securities traded on equity exchanges". Under the Datastream equity category all classes of stock are included in a single group. Stocks with different voting rights are not listed under a separate category but may have a suffix word to indicate a different class. For example, the name of stocks listed in Sweden may end with either “A” or “B” as a suffix. An “A” suffix indicates full voting rights and a “B” suffix indicates reduced voting rights. Similarly, for the Chinese stock market the stocks meant for domestic investors can be identified with a suffix “A” and for foreign investors by suffix “B”. It is, therefore, appropriate for any given sample where different classes of stock are present to first create some restrictions in the Datastream search category and then remove unwanted stock classes manually in those instances where Datastream fails to identify them.

A function, available in Datasteam, - “Does Not Contain” is used to create a list of restrictions. Using this function under the “Name” search, a number of words are given, for example portfolio, rights, R.E.I.Ts, convertible, A.D.Rs, etc., to restrict Datastream from reporting other equity classes in the equity search list. However, for some countries, the classification of stock classes is not readily available. To mitigate this problem, details of different classes of stock are obtained directly from Thomson Financial helpdesk (provider of Datastream). The helpdesk provides information on each equity stock class by giving detailed description of each suffix code. For example, stock names ending with suffix “A” or “I” for the Finnish stock market indicate larger voting rights, whereas names ending with suffix “B”, “C”, “II” and “R” indicate lower voting rights. Once sufficient information is obtained about the different classes of equity within a country the historical stock price as well as historical market value of each stock is downloaded.

There are different types of stock prices available in the Datastream, e.g., opening price, closing price, most traded price, adjusted default price, etc., and some data types may not be available for all stocks under the study. Therefore, the default stock price data type, “Price (Adjusted- Default)” is used as it is available for all stocks and suitable for this study. The Datastream definition of this data type is:

“Datatype (P) represents the official closing price. This is the default data type for all equities.”

The ‘current’ price on Datastream is the latest price available from the appropriate market in primary units of currency (except in the case of the UK where price is given in pence). It is the previous day’s closing price from the default exchange, except where more recent or real-time prices are available, as listed in the Data sources and updating procedure section of the help system. The ‘current’ prices taken at the close of market are stored each day. These stored prices are adjusted for subsequent capital actions, and these adjusted figures then become the default price offered on all Research programs. The actual historical prices can be accessed using the unadjusted price datatype (UP).

Capital events like stock-splits, reverse stock-splits, etc., will be automatically adjusted by Datastream. However, a dividend factor is not included under these data types as this information is available only in a few countries. To maintain data uniformity for all countries, dividend information is ignored and thus may consequentially lead to a small bias in sample construction[6].

The stock price time-series data are downloaded in two sets of currencies for 54 countries. The first set of currencies is the local currency and the second set consists of stock prices converted into US dollars at the exchange rate prevailing on the corresponding date. For instance, if the price of stock X listed on New Zealand stock exchange on 1st February, 2001 is NZ$100, then the stock X should be converted to a US dollar price by using the exchange rate prevailing on 1st February, 2001. The reason for choosing the US dollar as a single foreign currency is arbitrary but mainly stems from the fact that this currency is traded globally and exchange rate information is available for all countries. The only exception is the Russian Federation as Datastream holds the majority of the data from the Russian Trading System stock market reported in US dollars. The prices are not recorded in Russian ruble.

A number of stock exchanges may be present within a single country. The historical information of stocks listed within these exchanges is not always available in Datastream or there may be difficulties with the data, such as low liquidity. Accordingly, the current study focuses only on the main stock exchange within a country. In the US, three stock markets are used to retrieve historical information. These three markets are the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. For Japan, two exchanges

[6] An additional test is conducted documenting results with and without inclusion of dividends. The results are qualitatively similar.

(Tokyo Stock Exchange and Osaka Securities Exchange) are used to download historical information. In China, Shanghai and Shenzhen are the two major markets used to compile historical data. For the remaining 51 countries, only one major stock exchange in each country is the source of download data. A list of countries with their main stock exchange and respective local currency is shown in Table 4-2, showing the stock exchange coding that is used by Datastream.

Table 4-2: Main stock market and local currency

[**Table 4-2** is presented at the end of this chapter in Appendix- Page no. **131**]

4.2.2. Market value of each stock

The time-series market value of each stock is downloaded from Datastream as the input for studying momentum returns. Datastream holds market value (MV) information for all companies for which historical price information is available. Datastream defines market value as:

"Market value on Datastream is the share price multiplied by the number of ordinary shares in issue. The amount in issue is updated whenever new tranches of stock are issued or after a capital change.

§ For companies with more than one class of equity capital, the market value is expressed according to the individual issue.

§ Market value is displayed in millions of units of local currency."

Market value of a stock is not affected by stock-splits and is reported separately for each class of stock, e.g., higher voting rights, lower voting rights, etc. The historical data of market value for a sample period are matched with the same stock price period downloaded previously. For example, if the price of stock X in the sample starts from January 1990 and ends in July 2007, then the market value of stock X should also be downloaded from January 1990 to July 2007.

The market value of each stock is also downloaded in US dollars to match US dollar stock prices downloaded. The conversion rate for MV from local currency to US dollar is the same rate used to convert local currency stock prices to equivalent US dollar stock prices.

4.2.3. Market indices

A market index for each country is downloaded from Datastream. Several alternative indices, representing aggregate market prices by a portfolio of constituent stocks are available in Datastream. In the absence of a suitable market index or lack of historical data, the Datastream "DS" index is used to represent the market. Datastream "DS" is used in a number of studies. Griffin et al. (2003) use Datastream-DS indices to investigate momentum investing in 39 countries and Chan et al. (2000) use France-DS market index to calculate momentum profitability.

A second index, in US dollars, for each country is also downloaded. The conversion rate is the same as that used to convert stock prices and market value from local currency into US dollars. A list of market indices is presented in Table 4-3.

Table 4-3: Main market indices and starting date

[**Table 4-3** is presented at the end of this chapter in Appendix- Page no. **132**]

4.2.4. Corresponding date exchange rate

An important part of this study is to document the difference in returns calculated using US dollars and the local currency. The US dollar calculations are helpful in understanding the position of international investors wanting to invest in a foreign country. Consequently, two sets of data are maintained for each country to document the difference in returns when currency is changed from local to US. These two sets of data hold the following information:

(i) local currency data - stock price, market capitalisation, and market indices are downloaded for 54 countries in the prevailing local currency, and

(ii) foreign currency data - stock price, market capitalisation, and market indices downloaded in US dollars.

The daily exchange rate can be downloaded from Datastream under the "Exchange rates" category. Another option is to change currency from local to US dollars in the Datastream search page.

4.2.5. Risk-free or equivalent interest rates for each country

Risk-free or equivalent interest rates can be downloaded for most of the countries either from Datastream or dXTime. dXTime is a time-series data management database and is available at the University of Waikato. A risk-free rate is needed in the portfolio optimisation calculations where the optimal weighting allocated to each stock is determined by maximising the Sharpe ratio, i.e., (Portfolio return less Risk-free rate)/Portfolio standard deviation. However, as will be seen in the portfolio optimisation chapter, all the results are calculated from the standpoint of a US investor so all the stock prices are converted into US dollars first before calculating momentum returns. Accordingly, only a US risk-free interest rate is required. The 3-month Treasury Bill is chosen as a risk-free reference rate in the US market.

4.2.6. Industry classification as given by Datastream

Industry momentum effect, first documented by Moskowitz and Grinblatt (1999), is investigated later in this study. In order to compute industry momentum returns, monthly value-weighted industry returns need to be calculated. One way of calculating value-weighted industry returns is to download stock returns individually and then group them into various industries, as per Datastream industry classification. Datastream maintains 45 industry classifications and each stock is identified as coming from one of these industries. The industry classification in Datastream is also consistent across all countries, thereby removing problems of conflicting industry classification for each stock under different databases, e.g., Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS).

Of the 45 industry classifications, 38 are chosen as the remaining seven are problematic in terms of their aptness in describing an industry, or their lack of alignment with normal equity stocks category. The seven excluded industries are:

(i) Equity investment instruments,

(ii) Equity warrants,

(iii) Non-equity investment instruments,

(iv) Other equities,

(v) Other warrants,

(vi) Suspended equities, and

(vii) Unquoted equities.

Stocks that fall in the above seven industry classifications are excluded from the sample. The result is that 52,593 stocks from 54 countries are identified with 38 industry classifications as given by Datastream. These 38 industries are:

Table 4-4: Datastream industry classifications

	Sector name		Sector name
1	Aerospace & Defence	20	Industrial Metals
2	Automobiles & Parts	21	Industrial Transportation
3	Banks	22	Leisure Goods
4	Beverages	23	Life Insurance
5	Chemicals	24	Media
6	Construction & Materials	25	Mining
7	Electricity	26	Mobile Telecommunications
8	Electronic, Electrical Equip.	27	Non-life Insurance
9	Fixed Line Telecommunications	28	Oil & Gas Producers
10	Food & Drug Retailers	29	Oil Equipment & Services
11	Food Producers	30	Personal Goods
12	Forestry & Paper	31	Pharmaceuticals, Biotechnology
13	Gas, Water & Multi-utilities	32	Real Estate
14	General Financial	33	Software & Computer Services
15	General Industrials	34	Support Services
16	General Retailers	35	Technology Hardware & Equip.
17	Healthcare Equipment, Services	36	Tobacco
18	Household Goods	37	Travel & Leisure
19	Industrial Engineering	38	Unclassified

There are five types of information to be maintained for each of the 52,593 stocks.

(i) monthly price of each stock,

(ii) monthly market capitalisation of each stock,

(iii) industry to which the stocks belong to,

(iv) country in which the stock is listed, and

(v) currency in which the stock price/market capitalisation is reported.

Swinkels (2002) uses Datastream classified industry indices (not stocks) to calculate industrial momentum returns. Datastream maintains industry indices for various countries. These indices are value-weighted and represent 75-80% of market capitalisation.

As per Datastream Global Indices User Guide Issue 4:

> Datastream Global Equity Indices draw on the wealth of the Thomson Datastream database to provide a range of equity indices across 53 countries, 32 regions and 170 sectors worldwide. They form a comprehensive, independent standard for equity research and benchmarking. For each market, a representative sample of stocks covering a minimum 75 - 80% of total market capitalisation enables market indices to be calculated. By aggregating market indices for regional groupings, regional and world indices are produced. Within each market, stocks are allocated to industrial sectors using the Industry

Classification Benchmark (ICB) jointly created by FTSE and Dow Jones. Sector indices are then calculated. Across the range of Datastream Global Equity Indices, daily data is available for a minimum of five years wherever possible, and from 1973 for the major markets. Datastream Global Equity Indices provide:

- A standard for equity analysis and comparison that draws on the breadth and depth of the Thomson Datastream database.
- Good depth of data for each index, including total returns, price-earnings, dividend yield, market value and more. (p. 3)

However, there are some notable differences between the industry monthly returns (computed directly from stocks positioned within an industry) and Datastream industry indices. One of the most notable differences is the number of companies included in the industry monthly returns. While industry monthly returns include all stocks positioned with the industry, the Datastream industry indices only represent the highest capitalisation stocks within the industry, leading to a large-cap bias. Further, the industry monthly returns allow for continuous addition or exclusion of the stocks within the industry in any month, whereas Datastream industry indices are reviewed only annually for possible addition or deletion of stocks from the industry indices[7].

The inclusion of all stocks positioned within the industry also avoids inflated monthly returns, as returns from distressed or other financially weak firms will still be included in the monthly figure. For example, the returns of company

[7] The reviewing was done on a 3-month interval prior to May 1995

X (say positioned within Utilities industry) will still be included in the industry monthly returns until the last month of delistment. Therefore, computing industry monthly returns directly from stocks avoids survivorship bias. Both the industry monthly returns and Datastream industry indices are value-weighted. The sample period for each country, nevertheless, remains the same.

4.3. Data problems in Datastream

The raw data from Datastream cannot be directly used in the analysis as it suffers from potential biases. Ince and Porter (2006) study Datastream and CRSP data quality and report that ignoring some problems in Datastream data may distort results. Their paper identifies several types of problems in Datastream and likely solutions noting that once these problems are resolved, the Datastream data will be similar to CRSP, which is the most widely used source of data in the academic finance domain. Some of the main problems of Datastream they note are:

(i) it is hard to separate different classes of equity,

(ii) problems lie primarily in smaller size deciles, i.e., small-cap stocks,

(iii) problems relating to delisted stocks,

(iv) data recording errors (high spike returns), and

(v) listing of the same stock in multiple countries.

Cleaning the data of unwanted observations and other biases is very important in ensuring unbiased results. If the data are not properly screened, then the results may not depict a true picture. Care has been taken in this study to investigate each of the problems identified by Ince and Porter in detail and to implement remedial actions to reduce their impact on the results. Some biases may still remain undetected but such occurrences should be few. The actual steps taken to control the impact of the above five problems are now explained in turn.

4.3.1. Screening different classes of equity

Datastream does not separate stocks according to different voting classes, warrants, convertible, etc. The solution to identifying different classes of stock is to obtain the classification code from Datastream helpdesk and then remove them manually or set up some kind of restrictions in the equity search for each category. Setting restrictions in the equity search category can prove difficult. For example, some classes of stocks, such as preferred, warrants, convertibles, etc., do not have a clear identification code. The only clue is a suffix code to the end of the stock name. For example, if the name of stock X ends with "X 'convertible'", then it is likely that the stock is a convertible. The course of action taken is to ignore all those companies whose names end with 'pref', 'preferred', 'deferred', 'convertible'. This can be achieved by setting a restriction in the equity search category of Datastream. Ince and Porter (2006) suggest this procedure for removing unwanted classes from the sample. In the current study, 26 restrictions are set to remove unwanted classes of stock, including preference, warrants, convertible, A.D.Rs, R.E.I.Ts., trusts, units, duplicate, funds, etc. After applying 26 restrictions in the equity search category, Datastream returned a match of 61,640 stocks from 54 countries. These 61,640 stocks are further screened for other problems.

Table 4-5: Restrictions on Datastream equity search

1	preferred	14	american depositary
2	dupl	15	warrants
3	wts	16	real estate
4	%	17	realty investment
5	fund	18	r.e.i.t.
6	convertible	19	real estate investment trust
7	trust	20	adr
8	portfolio	21	a.d.r.
9	rights	22	Suffix b'
10	unit	23	Suffix b
11	restricted	24	Suffix c
12	deferred	25	Suffix c'
13	preference		

4.3.2. Small stock problems

Ince and Porter (2006) find that the equally-weighted returns of smaller decile portfolios are significantly different from CRSP decile portfolios. However, when value-weighted returns are compared with the CRSP database, the correlation increases from 0.66 to 0.998, indicating a significant improvement in comparability. This may suggest that some small-cap stocks in Datastream are not recorded correctly. A simple solution is to use value-weighted returns when reporting results. An alternative approach is to divide the whole sample into three sub-samples on the basis of market capitalisation and test the investment strategies in each of the sub-samples. These two methods may improve the quality of results and limit the bias of small-cap stocks. Therefore, the main results for the momentum returns are presented separately using value-weighted method and size-sorted sub-samples identifying whether the anomaly is primarily arising from small-cap stocks.

4.3.3. Screening for dead stocks

One of the more serious problems in Datastream lies in the faulty data recording method. Datastream continues to record dead stocks' price at the last traded price from the date of delisting through to the end of the sample. For example, if stock X is delisted on 15th July 2000, and the last price traded was $100, then Datastream will continue to record stock X price as $100 after 15 July 2000. Carter Holt Harvey stock remained showing as listed on the New Zealand stock market as at July 2007 although it was delisted on April 2006. The stock price continued to be recorded at the last trading price of NZ$2.74.

Table 4-6: Datastream dead stock illustration

Stock name	Carter Holt Harvey Dead - Delisted 05/04/06	
Date	Actual data recorded in Datastream	Data should be
Jan-2006	2.53	2.53
Feb-2006	2.73	2.73
Mar-2006	2.75	2.75
Apr-2006	2.74	2.74
May-2006	2.74	.
Jun-2006	2.74	.
Jul-2006	2.74	.
Aug-2006	2.74	.
Sep-2006	2.74	.
Oct-2006	2.74	.
Nov-2006	2.74	.
Dec-2006	2.74	.
…	…	…
Jul-2007	2.74	.

For some stocks, Datastream gives the exact date they are delisted, as is in the case of Carter Holt Harvey (05/04/06), but this is not true for all dead stocks. For some stocks, Datastream only adds the words "Dead, Delisted, Suspended, etc.” at the end of the stock name but no information relating to the delisting date[8]. Arnotts Limited, an Australian company, was taken over by Campbell Soup Company on 5/12/1997 but no date for this event is given in Datastream. The only information in Datastream is “Arnotts (Australian) Dead – Take-Over”. This complicates the problem as a correct takeover date should be selected and all future entries for prices are set to missing.

In some cases, the problem is exacerbated when Datastream continues to identify dead/delisted, etc., stocks as live stocks and hence no words like dead, delisted, etc., are added to the stock name. An example of this is Baillie Farmers, a stock listed on the New Zealand Stock Exchange which delisted in the late 1980s but no information is incorporated in Datastream. The name of the stock continues to be shown as “Baillie Farmers” and the last trading price is NZ$0.18 in December 1989. Detection of these types of stocks is very difficult but steps are necessary to remove stocks no longer active in the stock exchange. A three phase screening process is implemented to remove unwanted observations from the sample.

4.3.3.1. When exact date of delisting is given

If Datastream identifies a stock as dead/delisted/suspended, etc., and the exact date of this event is given, then the computer will automatically detect the date and set all observations to missing through to July 2007. The program searches for two kinds of information. First, to match similar words, e.g., ‘dead’, ‘delisted’, ‘suspended’, ‘merge’, ‘amalgamated’, etc., in the stock name. A

[8] Delisting date is synonymous for the dead/delisting/suspended/merged/amalgamated, etc. date.

combination of words is used to detect dead stocks, as sometimes Datastream may report stock “X ‘suspended’” as “X `susp’” and similarly uses a range of notations for other events. The second stage commences once this word matching is completed for all stocks searching for the date of the event. Thirdly, if this information is also available, then the program will automatically set the rest of the observations starting from the “delisting” date to missing.

4.3.3.2. When the exact date of delisting is not given

If the exact date for the event is not given, then only the first stage of the process is completed. Ince and Porter (2006) suggest that in the absence of any information regarding the event date, then a plausible solution is to set all observations to missing, starting from the end of the time series, e.g., for this study July 2007, and proceed toward the beginning of the series until returns are not equal to zero. However, a small number of valid zero returns may be lost in this process. An illustrative example is to assume that stock X is delisted in June 2005 if it shows zero returns for each period after this date even though no information is given in Datastream except that it is delisted. Following the Ince and Porter (2006), approach observations are set to missing from July 2005 through to July 2007.

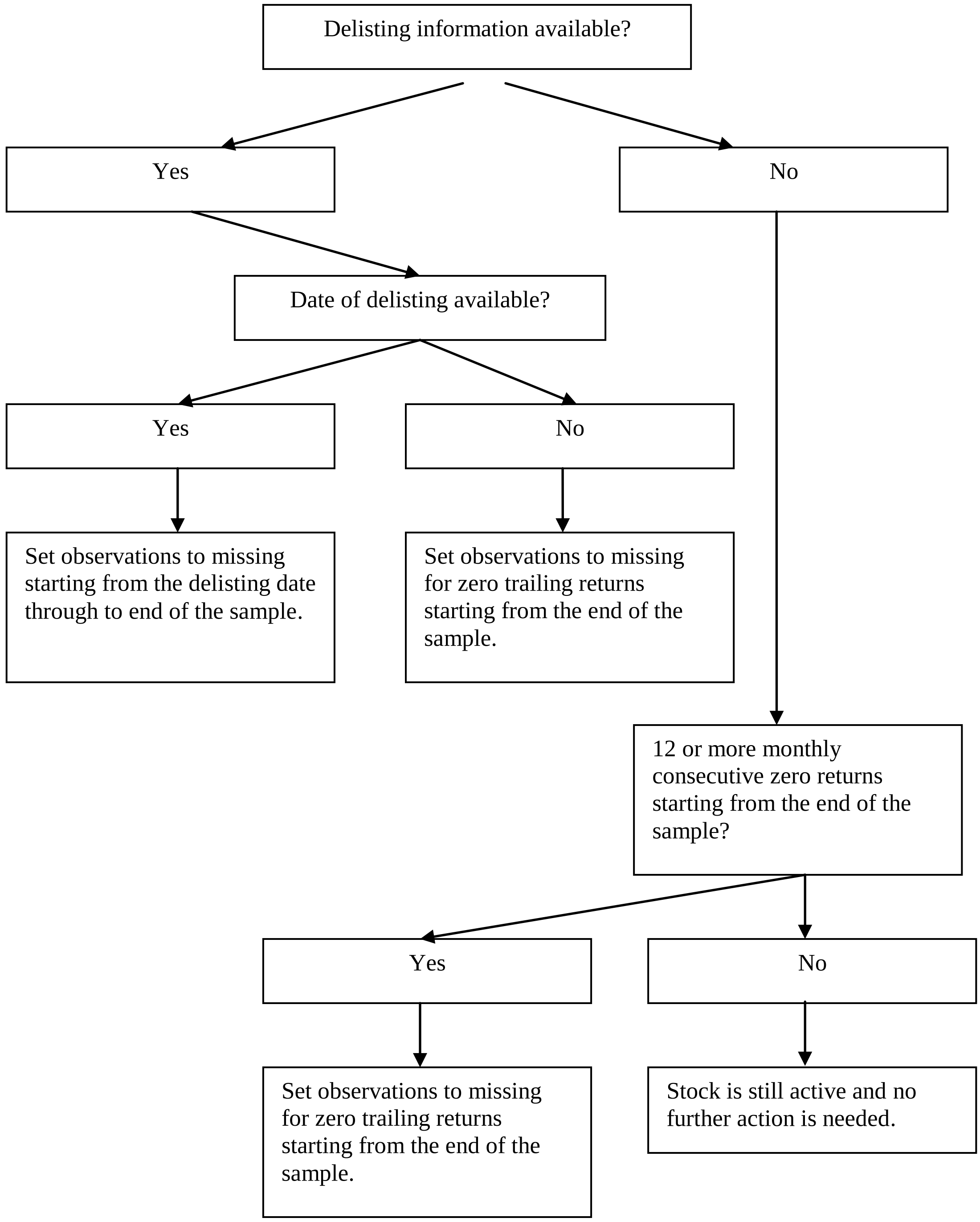
Table 4-7: Correcting stock price illustration

Month	Stock price	Stock returns		Corrected stock price
Jan-2005	100			100
Feb-2005	110	10.00%		110
Mar-2005	110	0.00%		110
Apr-2005	105	-4.55%		105
May-2005	110	4.76%		110
Jun-2005	105	-4.55%		105
Jul-2005	105	0.00%	trailing zero returns	.
Aug-2005	105	0.00%		.
Sep-2005	105	0.00%		.
…	…	…		…
Jul-2007	105	0.00%		.

4.3.3.3. When neither delisting information nor exact date of delisting is given

For some companies, like Baillie Farmers of New Zealand, no information is provided by Datastream regarding the current status, such as the delisting date etc. This lack of information precludes implementation of the two stage process. This paper proposes an alternative modified process to address this problem. For any given stock, starting from the end period of the sample, i.e., July 2007, if there are 12 months or more of consecutive zero returns, then it is assumed that the particular stock is dead. Accordingly, the stock prices starting from the end will be set to missing until the return is not equal to zero. The main conditions for this additional process are that the zero returns should be taken into account from the end of the sample period and there must be 12 or more consecutive zero returns. Again, a small number of valid zero returns may be lost under this process. Stocks delisted within the last 11 months (September 2006 to July 2007) of the study will not be detected under this process. The basis for choosing 12 months or more is arbitrary. In some illiquid markets, stock prices do not change for months; hence a period of 1 year is chosen to allow enough time to distinguish live and dead stocks.

A flow chart is presented to depict the overall process of identifying dead stocks and removing unwanted observations from the sample.



4.3.4. High spike returns

There are a number of poor data recording instances in Datastream where stock prices are recorded as suddenly increasing when in fact this did not happen. Allis-Chalmers Energy, listed on the NYSE, was trading at US$0.625 in August 1995 but suddenly increased to US$19.375 in September 1995, a gain of about 3000% in a month! Eventually the stock price reverted to US$1.875 in October 2005. Ince and Porter (2006) and K. Hou et al. (2006) suggest a trigger point of 300% for any monthly stock return. If the stock price is wrongly recorded for more than one month, but finally scaled down to original price, then all those incorrect recordings will be set to missing. An example may help clarify the method. In the table below, stock X's price rose from 11 to 44 (month 2 to 3). This increase is 300% and therefore the program will automatically put a missing observation for stock X price until the price returns to the same level. In this case, the wrong recording of stock X price was present for months 3 and 4 but returned to its original price in month 5. The computer will automatically set months 3 and 4 price as missing.

Table 4-8: High spike returns illustration

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Stock X price	10	11	**44**	**46**	9	8
Return %		10.00%	**300.00% trigger point**	**4.55%** -> continue	-80.43%	-11.11%
Corrected price	10	11	.	.	9	8

4.3.5. Multiple-listing of stocks and unavailability of any information

A single stock may be listed in the domestic market as well as in a foreign market. For example, Air New Zealand is primarily a New Zealand company but it is traded in four markets. This study is only interested in including stocks domiciled within the domestic country so listings other than on the domestic stock exchange are excluded from the sample. An example from Datastream may illustrate this problem. If only "Air New Zealand" is typed in the Datastream equity search category, then an output similar to Table 4-9 will appear on the screen.

Table 4-9: Multiple listings

Expanded Name	Name	Market	Currency	Exchange
Air New Zealand	AIR NEW ZEALAND	New Zealand	New Zealand Dollar	New Zealand
Air New Zealand (Australian)	AIR NEW ZEALAND (ASX)	New Zealand	Australian Dollar	Australian
Air New Zealand (Berlin)	AIR NEW ZEALAND (BER)	New Zealand	Euro	Berlin
Air New Zealand (Non-NASDAQ OTC)	AIR NEW ZEALAND (OTC)	New Zealand	United States Dollar	Non NASDAQ OTC

Note: Output edited to fit into this page

To address the issue of multiple listings, three restrictions are set into Datastream before downloading any data for a country. These three restrictions are:

(i) market is equal to the country for which data are to be downloaded,

(ii) currency is equal to local currency prevailing in the same market, e.g., New Zealand dollar for New Zealand, and

(iii) exchange is equal to the stock exchange within the country. For example, Tokyo, Osaka in Japan.

These three restrictions will exclude foreign cross-listings of stocks from the sample.

A further difficulty arises when Datastream does not provide historical information for some stocks. The approach adopted is to exclude automatically stocks from the sample for which no observations are available through the entire sample period.

The above screening processes are mainly achieved using Stata version 10 Special Edition. Stata is a statistical research software and there are a number of reasons for choosing Stata over other packages. The first and most important advantage of using Stata is the ease of good data management options. Since this study involves significant amounts of data management in various stages of the project, ranging from screening data to calculating different investment returns, Stata executes the whole process with relative ease. Secondly, Stata is much faster in executing results, and big datasets can be handled by increasing RAM. Programs for each section have been written in Stata to accomplish the above objectives. In addition to Stata, programs such as Microsoft Excel VBA Macros and Premium Solver are used especially for optimising momentum returns.

Appendix

Table 4-1: Sample period and sample size

	Country	Sample period	Total number of stocks
1	Argentina	February 1993 - July 2007	135
2	Australia	January 1973 - July 2007	2,627
3	Austria	July 1990 - July 2007	194
4	Bangladesh	January 1992 - July 2007	284
5	Belgium	January 1986 - July 2007	280
6	Brazil	January 1994 - July 2007	1,145
7	Canada	January 1973 - July 2007	2,904
8	Chile	July 1989 – July 2007	292
9	China	January 1993 – July 2007	1,495
10	Colombia	January 1993 – July 2007	174
11	Cyprus	March 2000 – July 2007	115
12	Czech Republic	November 1993 – July 2007	357
13	Denmark	April 1988 – July 2007	309
14	Egypt	May 1997 – July 2007	147
15	Finland	May 1994 – July 2007	191
16	France	January 1973 – July 2007	1,454
17	Germany	January 1973 – July 2007	1,316
18	Greece	February 1988 – July 2007	393
19	Hong Kong	January 1973 – July 2007	1,164
20	Hungary	November 1997 – **July 2005**	72
21	India	January 1990 – July 2007	2,102
22	Indonesia	April 1990 – July 2007	482
23	Ireland	March 1990 – July 2007	105
24	Israel	January 1986 – July 2007	874
25	Italy	August 1974 – July 2007	431
26	Japan	January 1973 – July 2007	3,364
27	Kenya	January 1996 – July 2007	58
28	Lithuania	August 2001 – July 2007	57
29	Malaysia	January 1986 – July 2007	772
30	Mexico	March 1988 – July 2007	222
31	Morocco	January 1995 – July 2007	90
32	Netherlands	January 1973 – July 2007	272
33	New Zealand	January 1988 – July 2007	311
34	Norway	September 1980 – July 2007	521
35	Pakistan	August 1992 – July 2007	373
36	Peru	January 1992 – July 2007	305
37	Philippines	May 1990 – July 2007	239
38	Poland	January 1997 – July 2007	382
39	Portugal	July 1992 – July 2007	99
40	Romania	June 1998 – July 2007	98
41	Russian Federation	January 1997 – July 2007	336
42	Singapore	January 1983 – July 2007	613
43	South Africa	January 1975 – July 2007	902
44	South Korea	July 1984 – July 2007	1,054
45	Spain	June 1987 – July 2007	194
46	Sri Lanka	June 1987 – July 2007	298
47	Sweden	January 1982 – July 2007	688
48	Switzerland	January 1973 – July 2007	316
49	Taiwan	July 1989 – July 2007	820
50	Thailand	January 1987 – July 2007	649
51	Turkey	April 1988 – July 2007	380
52	UK	January 1973 – July 2007	6,161
53	US	January 1973 – July 2007	13,904
54	Venezuela	January 2001 – July 2007	73
	Total		**52,593**

Table 4-2: Main stock market and local currency

	Country	Main Market	Local Currency
1	Argentina	Buenos Aires	Argentine peso
2	Australia	Australian	Australian Dollar
3	Austria	Vienna	Euro
4	Bangladesh	Dhaka	Bangladesh Taka
5	Belgium	Brussels	Euro
6	Brazil	Sao Paulo	Brazilian Real
7	Canada	Toronto	Canadian Dollar
8	Chile	Santiago	Chilean Peso
9	China	Shanghai, Shenzhen	Chinese Yuan Renminbi
10	Colombia	Bogota	Colombian Peso
11	Cyprus	Cyprus	Euro
12	Czech Republic	Prague	Czech Koruna
13	Denmark	Copenhagen	Danish Krone
14	Egypt	Cairo	Egyptian Pound
15	Finland	Helsinki	Euro
16	France	Paris-SBF	Euro
17	Germany	Frankfurt	Euro
18	Greece	Athens	Euro
19	Hong Kong	Hong Kong	Hong Kong Dollar
20	Hungary	Budapest	Hungarian Forint
21	India	Bombay	Indian Rupee
22	Indonesia	Jakarta	Indonesian Rupiah
23	Ireland	Dublin	Euro
24	Israel	Tel Aviv	Israeli Sheqel
25	Italy	Milan	Euro
26	Japan	Tokyo , Osaka	Japanese Yen
27	Kenya	Nairobi	Kenyan Shilling
28	South Korea	Korea	South Korean Won
29	Lithuania	Lithuania	Lithuanian Lita
30	Malaysia	Kuala Lumpur	Malaysian Ringgit
31	Mexico	Mexico	Mexican Peso
32	Morocco	Casablanca	Moroccan Dirham
33	Netherlands	Euronext Amsterdam (AEX)	Euro
34	New Zealand	New Zealand	New Zealand Dollar
35	Norway	Oslo	Norwegian Krone
36	Pakistan	Karachi	Pakistani Rupee
37	Peru	Lima	Peruvian Nuevo Sol
38	Philippines	Philippine	Philippine Peso
39	Poland	Warsaw	Polish Zloty
40	Portugal	Lisbon	Euro
41	Romania	Bucharest	Romanian Leu
42	Russian Federation	Russian Trading System	United States Dollar
43	Singapore	Singapore	Singaporean Dollar
44	South Africa	Johannesburg	South African Rand
45	Spain	Madrid	Euro
46	Sri Lanka	Colombo	Sri Lankan Rupee
47	Sweden	Stockholm	Swedish Krona
48	Switzerland	Swiss	Swiss Franc
49	Taiwan	Taiwan	Taiwanese Dollar
50	Thailand	Bangkok	Thai Baht
51	Turkey	Istanbul	Turkish Lira
52	United Kingdom	London	United Kingdom Pound
53	United States	NYSE, AMEX, NASDAQ	United States Dollar
54	Venezuela	Caracas	Venezuelan Bolivar

Table 4-3: Main market indices and starting date

	Country	Index Name	Starting from
1	Argentina	ARGENTINA- DS	Feb-93
2	Australia	ASX ALL ORDINARIES	Jan-73
3	Austria	ATX - AUSTRIAN TRADED INDEX	Jul-90
4	Bangladesh	BANGLADESH SE ALL SHARE	Jan-92
5	Belgium	BRUSSELS ALL SHARE	Jan-86
6	Brazil	BRAZIL BOVESPA	Jan-94
7	Canada	S&P/TSX COMPOSITE INDEX	Jan-73
8	Chile	CHILE GENERAL (IGPA)	Jul-89
9	China	SHANGHAI SE A SHARE	Jan-93
10	Colombia	COLOMBIA- DS	Jan-93
11	Cyprus	CYPRUS- DS	Mar-00
12	Czech Republic	CZECH REPUBLIC- DS	Nov-93
13	Denmark	DENMARK- DS	Apr-88
14	Egypt	EGYPT EFG	May-97
15	Finland	OMX HELSINKI (OMXH)	May-94
16	France	FRANCE- DS	Jan-73
17	Germany	DAX 30 PERFORMANCE	Jan-73
18	Greece	GREECE- DS	Feb-88
19	Hong Kong	HANG SENG	Jan-73
20	Hungary	BUDAPEST(BUX)	Nov-97
21	India	INDIA BSE (100) NATIONAL	Jan-90
22	Indonesia	JAKARTA SE COMPOSITE	Apr-90
23	Ireland	IRELAND SE OVERALL (ISEQ)	Mar-90
24	Israel	TEL AVIV SE GENERAL	Jan-86
25	Italy	MILAN COMIT GLOBAL	Aug-74
26	Japan	NIKKEI 225 STOCK AVERAGE	Jan-73
27	Kenya	KENYA NAIROBI SE	Jan-96
28	Lithuania	NOMURA LITHUANIA	Aug-01
29	Malaysia	KLCI COMPOSITE	Jan-86
30	Mexico	MEXICO IPC (BOLSA)	Mar-88
31	Morocco	MOROCCO SE CFG 25	Jan-95
32	Netherlands	NETHERLAND- DS	Jan-73
33	New Zealand	NEW ZEALAND- DS	Jan-88
34	Norway	NORWAY- DS	Sep-80
35	Pakistan	KARACHI SE 100	Aug-92
36	Peru	LIMA SE GENERAL(IGBL)	Jan-92
37	Philippines	PHILIPPINE SE I(PSEi)	May-90
38	Poland	WARSAW GENERAL INDEX	Jan-97
39	Portugal	PORTUGAL- DS	Jul-92
40	Romania	NOMURA ROMANIA	Jun-98
41	Russian Federation	RSF EE MT(U$) INDEX	Jan-97
42	Singapore	SINGAPORE STRAITS T. DS	Jan-83
43	South Africa	SOUTH AFRICA- DS	Jan-75
44	South Korea	KOREA SECOMPOSITE (KOSPI)	Jul-84
45	Spain	MADRID SE GENERAL	Jun-87
46	Sri Lanka	COLOMBO SE ALL SHARE	Jun-87
47	Sweden	OMX STOCKHOLM (OMXS)	Jan-82
48	Switzerland	SWITZERLAND- DS	Jan-73
49	Taiwan	TAIWAN SE WEIGHTED	Jul-89
50	Thailand	BANGKOK S.E.T.	Jan-87
51	Turkey	ISE NATIONAL 100	Apr-88
52	UK	FTSE ALL SHARE	Jan-73
53	US	DOW JONES WILSHIRE 5000	Jan-73
54	Venezuela	VENEZUELA SE GENERAL	Jan-01

Chapter 5

FINDINGS: MOMENTUM RETURNS AND PORTFOLIO STRUCTURE

Analysis

The analysis of momentum returns requires a series of computational approaches regarding the appropriate metric for calculating a series of stock returns. Choices need to be made concerning whether the stock returns are computed using CAR or BHAR approach or whether the portfolio returns are equal-weighted or value-weighted. Similarly, the number of stocks in a portfolio and the effect of the size of the portfolio on the momentum returns are also important. The effect of simple versus log returns, local currency versus US dollar, one-month and zero-month gap and excluding extreme return issues are also discussed in this chapter in turn.

5.1. CAR versus BHAR

The two most popular alternative methods of calculating momentum returns are Cumulative Abnormal Return (CAR) and Buy-and-Hold Return (BHAR). Each method has advantages and disadvantages and previous studies of momentum returns have used BHAR and CAR methods. The seminal paper on momentum by Jegadeesh and Titman (1993) finds little difference between the momentum returns computed using BHAR and CAR methods. Rouwenhorst (1998) also reports no significant difference for CAR and BHAR momentum returns in a study of 12 European countries. Demir et al. (2004) find contrary results reporting a significant difference of returns in the Australian stock market between the methods.

Table 5-1 presents a comparison of the results obtained using CAR and BHAR methods for 54 countries. The actual numbers reported are calculated by dividing the respective market portfolios into 5 groups where the top and bottom groups are the conventional Winner and Loser portfolios. Value-weighted returns are used to calculate the 5-portfolio returns and the stocks prices of all countries are denominated in US dollars. The momentum formation and holding formation periods are 6 months each with a one-month skip between formation and holding periods.

Table 5-1: Momentum returns

[**Table 5-1** is presented at the end of this chapter in Appendix- Page no. **155**]

The results presented in Table 5-1 show higher returns under the CAR method than the BHAR approach. The country-neutral average-monthly momentum profit under CAR is 0.67% compared with 0.64% for the BHAR method. Both BHAR and CAR country-neutral returns are highly statistically significant. The earlier analysis of Demir et al. (2004) suggesting higher returns under the BHAR method in the Australian stock market, is not supported by these results. To investigate further why CAR returns are higher than BHAR returns, these momentum returns are presented separately for Winner and Loser portfolios.

Table 5-2: Winner and Loser portfolio returns

6 x 6 months, Value-Weighted, 1-month gap, 5 portfolios, US Dollar

	Loser (L)	**t-stat**	**Winner (W)**	**t-stat**	**W – L**	**t-stat**
BHAR returns	-0.36%	-2.54	0.28%	2.69	0.64%	3.45
CAR returns	-0.45%	-3.67	0.22%	2.49	0.67%	4.54

The results presented in Table 5-2 indicate that the Winner portfolio returns under the BHAR method are higher than the CAR method, whereas the Loser portfolio returns generate greater negative returns under the CAR method. The results show that an increase of Winner portfolio returns for BHAR relative to the CAR method (0.28%-0.22%=0.06%) is less than the extra returns on a Loser portfolio using CAR compared to the BHAR method (-0.36%+0.45%=0.09%). The momentum profit difference between the BHAR and CAR arbitrage portfolio is (0.09%-0.06%=0.03%) representing a 0.03% increase in the arbitrage profit when the metric changes from BHAR to CAR. An interesting point to observe is that the Winner and Loser portfolios do not increase at the same rate. The Loser portfolio returns generate greater negative returns, whereas the Winner portfolio is lower in the CAR method compared to the BHAR method. The reason for this difference is due to the underlying calculation technique. An illustration of share price upward and downward movements using both CAR and BHAR methods is examined using the numbers in Table 5-3.

Table 5-3: Share price upward and downward movement

	with NO reversal		with reversal	
Price	**X**	**Y**	**X**	**Y**
Initial Investment	100,000	100,000	100,000	100,000
Month 1	100	100	100	100
Month 2	110	90	110	90
Month 3	120	80	120	80
Month 4	130	70	125	75
Month 5	140	60	120	80
Month 6	150	50	110	90
	Using BHAR method			
Terminal Value	150,000	50,000	110,000	90,000
Profit	50,000	-50,000	10,000	-10,000
Momentum Profit	50,000-(-)50000=	**100,000**	10,000-(-)10,000=	**20,000**
	Using CAR method			
Terminal Value	142,259	35,436	110,924	91,806
Profit	42,259	-64,564	10,924	-8,194
Momentum Profit	42,259-(-)64,564=	**106,823**	10,924-(-)8,194=	**19,119**
Difference (BHAR - CAR) profit		**-6,823**		**881**

In the above example, it is assumed that stock X belongs to the Winner portfolio and stock Y belongs to the Loser portfolio. According to the momentum investing strategy, the price of stock X is supposed to increase and stock Y price is supposed to decrease over the holding period. The above example is illustrated assuming two scenarios. The first scenario assumes that the stock price continues to increase or decrease during the holding period. The second scenario assumes that the stock price increases or decreases at the end of holding period but this increase or decrease is not continuous, i.e., the stock prices are assumed to fluctuate during the holding period.

The example indicates that the momentum returns will be higher under the CAR approach when there are no reversals during the holding period. The momentum returns, however, are higher under the BHAR approach when a reversal or fluctuation is noted during the holding period.

The illustration indicates that the momentum profit under BHAR and CAR may be higher or lower depending on the continuation of Loser and Winner portfolio returns. Momentum returns will be higher under the CAR approach when the returns follow a trend. Conversely, when a market is fluctuating in the absence of a trend, the BHAR approach is expected to generate greater momentum returns than the CAR approach. The results also confirm that the momentum returns are not confined to a particular country. The country-neutral results from the 54 markets report statistically significant positive returns for both BHAR and CAR methods.

The results of BHAR and CAR analysis also demonstrate that a country with negative momentum returns can change to positive returns if the metric is changed from BHAR to CAR or vice-versa. The significance level may also change when an alternative method is chosen. For example, the average-monthly momentum return for Austria under BHAR is 0.36% but this drops to -0.16% when the CAR method is used. The results for Indonesia are not statistically significant using BHAR but become statistically significant when CAR is employed. A careful analysis is necessary before drawing any conclusion relating to momentum profitability and significance.

5.2. Equal- versus value-weighted

In the 54-country analysis reported in Table 5-1, all the country-neutral momentum returns are calculated using value-weighted returns, i.e., the contribution of each stock to the portfolio is dependent on its market capitalisation. Extant literature suggests that a value-weighted approach is the correct method for calculating momentum returns as it substantially controls the bias arising from the small-cap stocks. Fama (1998) adds that various anomalies may become irrelevant once a value-weighted approach is used to calculate returns. The results from previous momentum studies indicate a lower return when value-weighted returns are used (Demir et al. (2004), Chan et al. (2000)). T. Hou and McKnight (2004) present a detailed study of momentum returns arising from the use of equal-weighted and value-weighted portfolio returns. The 54-country portfolios are recomputed using an equal-weighted construction approach for both CAR and BHAR metrics and are presented in Table 5-4.

Table 5-4: Effect of equal- or value-weighted approach on momentum returns

[**Table 5-4** is presented at the end of this chapter in Appendix- Page no. **156**]

An initial inspection of the results from Table 5-4 suggests that the equal-weighted momentum returns are more volatile, and this is especially seen in Brazil and Russia. The equal-weighted country-neutral momentum returns are negative and not statistically significant. However, to remove any bias arising from outlier observations, Brazil and Russia are excluded and the country-neutral returns are re-computed. The re-computed results show that value-weighted returns are greater than equal-weighted returns indicating that the equal-weighted portfolio returns are not as volatile as first indicated. Bird and Whitaker (2003) also note increase in momentum returns with a holding period greater than 6 months when value-weighted returns are used instead of equal-weighted returns. This observation runs contrary to the results observed in previous studies where value-weighted returns are expected to be smaller than equal-weighted returns. The breakdown of momentum profit may present a more comprehensive picture of the low returns associated with an equal-weighted approach compared to the value-weighted approach.

Table 5-5: Country-neutral returns (excluding Brazil and Russia) using equal- and value-weighted returns

6 x 6 months, 1-month gap, 5 portfolios, US Dollar

	Loser(L)	t-stat	Winner(W)	t-stat	W-L	t-stat
BHAR:						
Value-Weighted	-0.39%	-2.67	0.29%	2.68	0.68%	3.54
Equal- Weighted	0.66%	3.67	0.73%	6.00	0.07%	0.34
CAR:						
Value-Weighted	-0.44%	-3.47	0.22%	2.45	0.66%	4.33
Equal-Weighted	0.48%	2.56	0.66%	6.33	0.18%	0.91

A breakdown of momentum returns can be seen when the arbitrage portfolio is divided into Winner and Loser portfolios in Table 5-5. The Loser and Winner portfolio stocks have higher returns under the equal-weighted method than the value-weighted method. The profit for an equal-weighted average-monthly momentum Loser portfolio (excluding Brazil and Russia) is 0.66% compared to -0.39% for value-weighted Loser portfolio using the BHAR method. Similarly, the average-monthly return for the Winner portfolio under equal-weighted returns is 0.73% compared to 0.29% for value-weighted Winner portfolio using the BHAR method. The same order of results is noticed when the CAR method is employed. These observations suggest that the Loser stocks under the equal-weighted method do not follow momentum and/or there may be some problems related to the data.

The value-weighted method appears superior and less problematic than the equal-weighted approach. For example, the average-monthly momentum returns for Brazil and Russia are -136.39% and -82.38% respectively under equal-weighted BHAR returns. But when the method is changed to value-weighted, the returns substantially alter to a more realistic -0.03% and -0.58% for Brazil and Russia respectively. Overall, the results point to the adoption of value-weighted returns to avoid potential data bias, especially for small-cap stocks.

5.3. Number of stocks in a portfolio

To investigate whether portfolio returns vary significantly when the number of stocks in a portfolio are increased or decreased, the momentum returns are calculated for portfolios containing varying number of stocks. The different size portfolios will shed further light on momentum return patterns when portfolios vary from a broad number of stocks to a small number of extreme return stocks. For example, if there are 100 stocks in the whole sample, then there will be 50 stocks in each portfolio when two portfolios are chosen to differentiate between Winners and Losers. Similarly, there will be five stocks in each Winner and Loser portfolio when the sample is divided into 20 portfolios. The country-neutral returns for this analysis are calculated using the BHAR method with value-weighted portfolio returns.

In this study, the minimum number of stocks present in a country in any given month is 40. When 40 stocks are divided into 20 portfolios, there are two stocks in each Winner and Loser portfolio. Therefore, the results must be interpreted cautiously for 20 portfolio momentum returns, especially for developing markets where there are a small number of stocks. In Venezuela, Russia and other countries with few stocks in the market portfolio, dividing them into 20 portfolios may result in high volatility resulting in questionable findings.

Table 5-6: Number of stocks in a portfolio

[**Table 5-6** is presented at the end of this chapter in Appendix- Page no. **157**]

The results presented in Table 5-6 show an upward moving momentum return, starting at two portfolios to five portfolios, and then a gradual decline as the number of portfolios increases to 20. The returns for two to five are highly significant, and 10 portfolio momentum returns are significant at the 5% level. The results also show high volatility in small markets, such as Venezuela and Russia, where returns are extremely negative, particularly for 10 and 20 portfolios. These large negative returns are the primary contributors to the negative returns for the 20 portfolio country-neutral momentum returns. If the momentum returns for Venezuela and Russia are excluded, then the country-neutral average-monthly momentum returns for 10 portfolios is 0.79% (t-stat 4.98) and 0.59% (t-stat 2.90) for 20 portfolios. This suggests that, after excluding countries with small markets, the country-neutral returns are generally positive for all portfolios. The portfolio returns continue to increase as the number of stocks decrease in a portfolio.

Table 5-7: Country-neutral returns (excluding Russia and Venezuela) for different portfolios

6 x 6 months, Value-Weighted, 1-month gap, US dollar, BHAR

	2 portfolios	**3 portfolios**	**4 portfolios**	**5 portfolios**	**10 portfolios**	**20 portfolios**
Loser	-0.46%	-0.47%	-0.48%	-0.50%	-0.42%	-0.17%
t-stat	-6.05	-5.96	-5.86	-5.7	-3.44	-1.08
Winner	-0.01%	0.14%	0.23%	0.30%	0.37%	0.43%
t-stat	-0.11	1.59	2.39	2.87	3.10	3.40
W-L	0.45%	0.61%	0.71%	0.80%	0.79%	0.60%
t-stat	6.53	6.10	6.10	6.17	5.00	2.92

To gain further insights, the returns for Winner and Loser portfolios are checked for each country. Venezuela and Russia are excluded while calculating country-neutral Winner and Loser portfolio returns. The results reported in Table 5-7 show a clear upward trend in Winner portfolios when the number of portfolios increases from two to 20. This indicates that as the number of stocks present in the Winner portfolio declines the move extreme past high returns stocks are included and they continue to generate the high returns in the holding period. The returns for the Loser portfolio are statistically significant and initially negative for two portfolios and this increases up to five portfolios and then slowly becoming less negative as the number of portfolios increases to 20. However, past extreme Loser stocks do not continue to generate the same magnitude of returns. The reduction in the negative returns of Loser portfolios from -0.46% (2 portfolios) to

-0.17% (20 portfolios) indicates that the extreme Loser stocks may have low momentum or there may be reversals.

The significance level of the Winner portfolio from two to three portfolios is also not statistically significant at 5% level. This means that the Winner stocks with low Buy-and-Hold return during the formation period do not continue to generate the same momentum during the holding period. On the contrary, the Loser portfolio stocks are statistically significant from two to 10 portfolios at 5% significance level, but not significant at 5% level for 20 portfolios. This indicates a high dispersion among extreme Loser stocks.

The overall analysis of the portfolio results indicates that average monthly momentum profit can almost double from 0.45% (2 portfolio) to 0.80% (5 portfolio) while excluding Venezuela and Russia. However, the difference in returns between five portfolios and 10 portfolios are not very pronounced on a country-neutral basis. Previously, most of the studies have used five or 10 portfolios when calculating momentum returns. The unreported country-neutral average monthly standard deviation (excluding Russia and Venezuela) also jumps from 2.06% for two portfolios to 5.24% for 20 portfolios. This steep increase in the standard deviation indicates higher volatility of momentum returns as the number of stocks in the portfolio decrease. Therefore, the risk of holding a momentum portfolio also increases as the number of stocks within such a portfolio decreases.

5.4. Size-sorted portfolio

An effect of stock size on the momentum returns has been reported in the literature where a number of studies document non-statistically significant momentum returns when the size effect is taken into account. For example, Hameed and Kusnadi (2002) find non-statistically significant momentum returns when size and turnover factors in the six Asian markets are controlled. Hong et al. (2000) show decreasing momentum profitability for momentum returns when they are calculated for small-cap stocks through to large-cap stocks. Conflicting results are apparent in the study by T. Hou and McKnight (2004) where the size effect in the Canadian stock markets does not seem to be an important factor. The potential impact of a particular size effect on particular countries and on a global basis warrants investigation.

The 54-country sample is subdivided into three sub-samples on the basis of market capitalisation. The first month of the formation period is taken as a basis to rank stocks from large firms to small firms. The whole sample is divided into three sub-samples with the top 33% constituting the high market capitalisation group of stocks, the bottom 33% constituting the small-cap stocks and the remaining 33% constituting the medium market capitalisation stocks.

The momentum returns within each sample are further calculated using equal-weighted and value-weighted methods which provide further insight into a potential size effect. The basis for including value-weighted returns within the size-sorted portfolio is to illustrate the marginal effect of stock returns within the size-sorted portfolio. If a portfolio's return is volatile when calculated using equal-weighted returns but becomes less volatile when value-weighted returns are used, then this suggests that the small-cap stocks within the portfolio are the primary source of volatility. On the other hand, equal-weighted size-sorted portfolios will show variations across size. The analysis is undertaken using the BHAR method and each size-sorted sample is divided into three portfolios to calculate the momentum returns.

Table 5-8: Momentum size-sorted portfolio returns

[**Table 5-8** is presented at the end of this chapter in Appendix- Page no. **159**]

The results recorded in Table 5-8 show the presence of high volatility in small-cap portfolios. In particular, there are large negative returns for the Brazilian and Russian stock markets when an equal-weighted portfolio return method is used. The value-weighted small-cap portfolio returns exhibit lower volatility when compared with equal-weighted portfolios. Further, the returns of Brazil and Russia are substantially controlled when value-weighted returns are employed. The size-sorted equal- and value-weighted momentum returns breakdown into Winner and Loser portfolios is reported in Table 5-9.

Table 5-9: Country-neutral size-sorted momentum returns

6 x 6 months, 1-month gap, US dollar, BHAR, 3 portfolios within each size-sorted sample

	Portfolio size	Loser (L)	t-stat	Winner (W)	t-stat	W - L	t-stat
	Small	33.94%	1.19	1.26%	5.98	-32.68%	-1.14
Equal-	Medium	0.42%	1.07	0.39%	4.45	-0.03%	-0.06
Weighted	Large	0.07%	0.19	0.31%	1.83	0.24%	0.62
	Small	0.96%	4.03	0.67%	5.52	-0.29%	-1.29
Value-	Medium	0.28%	0.61	0.27%	2.89	-0.01%	0.01
Weighted	Large	-0.45%	-6.39	0.10%	1.08	0.55%	5.02

The size-sorted equal-weighted momentum returns are not statistically significant for all categories. Similarly, when value-weighted returns are used, the country-neutral momentum returns are not statistically significant for small and medium sized portfolios but are highly significant for the large sized portfolios. The country-neutral momentum returns increase from the small-cap portfolio to the large-cap portfolio. The average monthly momentum return for a value-weighted portfolio increases from -0.29% (small size) to 0.55% (large size). The negative return in the small-cap value-weighted portfolio is primarily propelled by a positive return from the Loser portfolio (0.96%). With the increase in portfolio size the Loser portfolio returns drop from 0.96% to -0.45%. The return for the Winner portfolio is also high for the small-cap portfolio at 0.67% but drops to 0.10% for the large-cap portfolio. This suggests that the small-cap loser stocks have a tendency toward low momentum or reversal. The results also suggest that the magnitude of returns for both Loser and Winner portfolio stocks decrease as the market cap of the stock increases. The results also align with the findings of

Bird and Whitaker (2003) who note that after adjusting for size affect, the value-weighted returns improves the performance of momentum strategy.

5.5. Simple versus log returns

Log returns in place of simple returns have been used in some previous momentum studies. The continuous compounding properties of the log return results in lower figure than those computed as simple returns when the stock prices are increasing. However, the log return is greater than the simple return when stock prices are falling. This creates a negative bias and momentum returns may be higher with log returns compared to simple return measures. To investigate the significance of this bias, the whole sample is divided into five value-weighted portfolios to calculate momentum returns using the CAR method. The BHAR method is not used in this analysis as it would not be theoretically correct to multiply (1+monthly log returns) to arrive at a 6-month holding period return due to the continuous compounding effect of the log function.

Table 5-10: Momentum returns under simple and log returns

[**Table 5-10** is presented at the end of this chapter in Appendix- Page no. **161**]

The results displayed in Table 5-10 show higher country-neutral average monthly momentum returns when log returns are used compared to simple returns. The log-return based country-neutral momentum returns is 0.95% (t-stat 6.51) compared to a simple return 0.67% (t-stat 4.54). The underlying reason for a higher log based return can be attributed to large negative returns for country-neutral Loser portfolios. The breakdown of country-neutral momentum profit into separate Loser and Winner portfolios with log and simple returns presented in Table 5-11 indicates a negative bias arising from the use of log returns over simple returns.

Table 5-11: Country-neutral momentum returns under simple and log returns

6 x 6 months, Value-Weighted, 1-month gap, 5 portfolios, US dollar, CAR

	Loser(L)	t-stat	Winner(W)	t-stat	W-L	t-stat
Simple returns	-0.45%	-3.67	0.22%	2.49	0.67%	4.54
Log returns	-1.43%	-13.07	-0.49%	-3.20	0.95%	6.51

The impact of using log returns is so strong that even a positive Winner portfolio return changes to a negative return. Further, even though the Winner portfolio using log return is negative, the arbitrage portfolio returns increases from 0.67% to 0.95% primarily due to a strong negative return from the Loser portfolio. The results also confirm the finding of Barber and Lyon (1997) who note that the continuously compounded returns are negatively biased compared to simple returns. Therefore, a careful analysis needs to be undertaken prior to choosing the method of calculating return as it may substantially change the momentum return.

5.6. Local versus US dollar

The momentum returns computed in the previous section use the stock prices converted to US dollars using the corresponding date exchange rate. However, it may be important to check the difference between momentum return computed in local currency and US dollars as the exchange rate plays a significant role for an international investor wanting to invest in another country. With the markets slowly becoming integrated, it is possible for an investor to take advantage of the anomalies still present in other markets. The difference in return when momentum returns are calculated in local currency compared to US dollar is now investigated. The choice of US dollar rather than Euro or Yen, etc., is due to the ready availability of exchange rates for all countries included in this study.

The relationship between the US dollar and each local currency is not fixed, i.e., the US dollar may be appreciating with respect to local currency X but at the same time depreciating with respect to local currency Y. Consequently, any US dollar investment exchanged into currency Y will have a higher momentum returns than those calculated in local currency due to extra returns from appreciating currency Y. The similar but opposite impact can occur depending on the exchange rate effect. The study of 54 countries portrays an average difference of returns for US dollar investments on a global basis. The results reported in Table 5-12 are calculated using both BHAR and CAR for value-weighted 5 portfolios.

Table 5-12: Local currency momentum returns versus US dollar momentum returns

[**Table 5-12** is presented at the end of this chapter in Appendix- Page no. **162**]

The findings reported in Table 5-12 indicate contradictory results between BHAR and CAR methods. The BHAR method computes the local currency country-neutral average monthly momentum return as 0.59% compared to US dollar results of 0.64%. CAR method findings run contrary to BHAR with local currency country-neutral momentum return of 0.68% decreasing to 0.67% for the US dollar. These inconsistencies indicate that the returns will be higher under

BHAR method but lower under CAR method when the currency is changed from local to US dollar. The difference between BHAR and CAR results arise predominantly from the interaction of momentum returns. For example, if the momentum profit is arising from the short-selling of a Loser portfolio and the US exchange rate is depreciating with respect to the domestic currency during the holding period, then the CAR momentum returns will be higher than BHAR momentum returns and vice-versa. The Loser portfolio's negative returns under the CAR method are magnified when the local currency is depreciating against the US dollar. The explanation of the different BHAR and CAR effects on the momentum returns, discussed above, noted that the returns in US dollars are quite sensitive to the choice of either BHAR or CAR. The exchange rate movements constitute an additional factor to be considered.

5.7. One-month and zero-month skip

The literature notes the existence of a bid-ask spread bounce between the formation and holding period when constructing momentum returns. To avoid this problem, some studies allow a one-month gap between the formation and holding period. Chordia and Shivakumar (2002), and Demir et al. (2004) choose not to skip a month. The results of skipping and not skipping a month are mixed, with Kang et al. (2002) and Hameed and Kusnadi (2002) finding little evidence of momentum return difference between skipping a time period and not skipping a period.

The potential differences from including and excluding a one-month skip are investigated using the 54-country data set. All results are calculated using US dollar stock prices with a value-weighted returns approach, thus avoiding any bias arising from the small-cap stocks. The bid-ask spread problem is more pronounced in the small-cap stocks. Kaul and Nimalendran (1990) report that bid-ask error (measurement error in prices) can explain over 50% of the daily variances in small-cap stocks. The whole sample is divided into 5 portfolios and the returns are calculated using BHAR and CAR methods.

Table 5-13: Effect of one-month versus zero-month gap on momentum returns

[**Table 5-13** is presented at the end of this chapter in Appendix- Page no. **163**]

The results presented in Table 5-13 show country-neutral momentum low returns, calculated with and without a one-month skip. The low returns associated with the zero-month skip between the formation and holding period is an indicator of possible reversals in the first month of the holding period. The BHAR for zero-month skip country-neutral average monthly momentum returns are 0.57% increasing to 0.64% for one-month skip. Both returns are statistically significant. A significant amount of variation can also be seen in the Venezuelan market with the momentum return almost doubling when portfolio construction is changed from zero-month skip to one-month skip.

Table 5-14: Country-neutral momentum returns with and without a month gap

6 x 6 months, Value-weighted returns, 5 portfolios, US dollar

	Loser (L)	t-stat	Winner (W)	t-stat	W - L	t-stat
BHAR:						
1 month gap	-0.36%	-2.54	0.28%	2.69	0.64%	3.45
0 month gap	-0.34%	-3.40	0.23%	2.02	0.57%	3.68
CAR:						
1 month gap	-0.45%	-3.67	0.22%	2.49	0.67%	4.54
0 month gap	-0.42%	-5.25	0.16%	1.85	0.58%	4.99

The momentum returns are also divided into Winner and Loser portfolios to examine the continuation or reversal in the first month of the formation period. The returns of Winner and Loser portfolios, presented in Table 5-14, show lower returns in the zero-month skip compared to the one-month skip. This means that there is a reversal in both Winner and Loser portfolios in the first month of the holding period. The same patterns emerge when the momentum returns are calculated using the CAR method.

5.8. Excluding extreme returns

The potential impact of extreme returns on Winner and Loser portfolios is to distort the average result. Extreme stock returns tend to be volatile and this may arise as a result of incorrect data recording. Rouwenhorst (1999) excludes the extreme 5% of stocks from the Winner and Loser portfolios but finds little difference in the momentum return. Hameed and Kusnadi (2002) also trim 5% of extreme stocks from both portfolios and report an insignificant momentum return when the extreme return stocks are excluded from the portfolio. These conflicting results suggest that an examination of the extreme returns in the 54-country portfolio will shed further light on their impact.

For each portfolio, 5% of the stocks is taken as an arbitrary measure to exclude extreme stocks. This means, for example, out of 100 stocks in a Loser portfolio, only 95 stocks will be included and the bottom five stocks with the most negative returns will be excluded. Similarly, for the Winner portfolio, the top five stock returns during the formation period will be excluded. The results are calculated using both BHAR and CAR methods. All the stock prices are in US dollars and the whole sample is divided into five value-weighted portfolios.

Table 5-15: Momentum returns excluding extreme Winner and Loser stocks
[**Table 5-15** is presented at the end of this chapter in Appendix- Page no. **164**]

The results from Table 5-15 suggest that excluding the extreme 5% of the Winner and Loser portfolios does not significantly change average monthly momentum returns. The country-neutral momentum return increases from 0.64% (without excluding extreme stocks and using the BHAR method) to 0.66% after excluding extreme stocks. The null hypothesis that the means are the same is not rejected at the 5% level under either BHAR or CAR methods.

Table 5-16: Country-neutral momentum returns calculated using BHAR and CAR method after excluding extreme Winner and Loser stocks

	Loser(L)	t-stat	Winner(W)	t-stat	W - L	t-stat
BHAR:						
After excluding extreme stocks	-0.37%	-2.64	0.29%	2.73	0.66%	3.57
Without excluding extreme stocks	-0.36%	-2.54	0.28%	2.69	0.64%	3.45
CAR:						
After excluding extreme stocks	-0.44%	-3.63	0.23%	2.62	0.67%	4.59
Without excluding extreme stocks	-0.45%	-3.67	0.22%	2.49	0.67%	4.54

Table 5-16 reports momentum returns separately for Winner and Loser portfolios. The returns of the Winner and Loser portfolios before and after the excluding extreme 5% are almost same. This suggests that excluding 5% of extreme Winner and Loser portfolios does not significantly change country-neutral average monthly momentum returns.

Appendix

TABLE 5-1: Momentum returns

6 x 6 months, Value-weighted returns, 1-month gap, 5 portfolios, US dollar

	BHAR		CAR	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.41%	-0.54	-0.22%	-0.42
Australia	1.30%	4.92	1.45%	5.45
Austria	0.36%	1.04	-0.16%	-0.41
Bangladesh	5.29%	2.24	3.39%	2.53
Belgium	1.00%	4.20	0.95%	4.06
Brazil	-0.03%	-0.04	0.34%	0.55
Canada	1.40%	4.97	1.41%	5.28
Chile	0.15%	0.40	0.12%	0.38
China	0.88%	3.03	0.89%	3.14
Colombia	1.04%	2.03	0.72%	1.57
Cyprus	0.89%	1.68	0.61%	1.05
Czech Republic	1.10%	2.25	1.04%	2.38
Denmark	0.91%	3.79	0.83%	3.40
Egypt	1.91%	2.50	1.63%	2.35
Finland	2.38%	4.37	2.02%	3.75
France	0.82%	3.94	0.78%	4.29
Germany	0.82%	4.35	0.84%	4.82
Greece	1.81%	2.77	1.37%	2.67
Hong Kong	0.95%	3.72	0.86%	3.37
Hungary	2.14%	4.10	0.85%	2.02
India	1.62%	3.94	1.78%	4.12
Indonesia	0.21%	0.56	0.69%	1.99
Ireland	0.97%	1.72	1.49%	2.41
Israel	-0.15%	-0.34	-0.31%	-0.64
Italy	1.05%	3.73	0.96%	3.68
Japan	0.36%	1.56	0.26%	1.19
Kenya	1.19%	1.37	1.41%	1.99
Lithuania	1.38%	2.06	1.33%	2.54
Malaysia	0.24%	0.78	0.16%	0.54
Mexico	1.27%	2.90	1.26%	2.87
Morocco	0.76%	2.34	0.63%	2.05
Netherlands	0.64%	2.44	0.66%	2.85
New Zealand	0.64%	2.02	0.59%	1.89
Norway	0.95%	3.04	1.19%	4.39
Pakistan	-0.28%	-0.63	-0.10%	-0.24
Peru	-0.08%	-0.16	0.83%	1.52
Philippines	-0.48%	-1.14	-0.38%	-0.88
Poland	1.85%	3.52	1.68%	3.84
Portugal	0.54%	1.45	0.65%	1.90
Romania	0.13%	0.18	-0.04%	-0.04
Russian Federation	-0.58%	-0.45	1.52%	1.35
Singapore	0.09%	0.27	0.27%	0.99
South Africa	1.15%	3.83	1.19%	4.53
South Korea	-0.27%	-0.49	-0.19%	-0.52
Spain	0.36%	1.52	0.29%	1.27
Sri Lanka	-0.59%	-1.57	-0.31%	-1.05
Sweden	0.02%	0.03	0.33%	0.79
Switzerland	0.78%	3.85	0.79%	4.29
Taiwan	0.10%	0.26	-0.03%	-0.08
Thailand	0.78%	2.09	0.89%	3.02
Turkey	0.04%	0.05	0.36%	0.65
UK	0.87%	3.99	0.89%	4.44
US	0.73%	4.16	0.77%	4.40
Venezuela	-6.50%	-1.95	-5.27%	-1.85
Country Neutral Momentum returns	**0.64%**	3.45	**0.67%**	4.54

Table 5-4: Effect of equal- or value-weighted approach on momentum returns

6 x 6 months, 1-month gap, 5 portfolios, US Dollar

	BHAR				CAR			
	Equal Weighted		Value Weighted		Equal Weighted		Value Weighted	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.46%	-0.83	-0.41%	-0.54	-0.24%	-0.72	-0.22%	-0.42
Australia	0.40%	1.32	1.30%	4.92	0.95%	3.83	1.45%	5.45
Austria	-0.30%	-0.46	0.36%	1.04	-0.17%	-0.28	-0.16%	-0.41
Bangladesh	4.82%	1.65	5.29%	2.24	3.64%	1.73	3.39%	2.53
Belgium	1.10%	4.33	1.00%	4.20	1.32%	6.19	0.95%	4.06
Brazil	-136.39%	-1.32	-0.03%	-0.04	-18.83%	-2.25	0.34%	0.55
Canada	0.12%	0.29	1.40%	4.97	0.96%	4.40	1.41%	5.28
Chile	0.44%	1.34	0.15%	0.40	0.40%	1.30	0.12%	0.38
China	0.51%	2.16	0.88%	3.03	0.41%	1.82	0.89%	3.14
Colombia	-0.51%	-0.83	1.04%	2.03	-0.77%	-1.02	0.72%	1.57
Cyprus	-1.56%	-2.91	0.89%	1.68	-1.55%	-3.51	0.61%	1.05
Czech Republic	0.52%	1.43	1.10%	2.25	0.35%	1.06	1.04%	2.38
Denmark	0.82%	3.38	0.91%	3.79	0.75%	3.39	0.83%	3.40
Egypt	1.09%	1.94	1.91%	2.50	1.02%	1.98	1.63%	2.35
Finland	1.07%	3.05	2.38%	4.37	0.93%	3.63	2.02%	3.75
France	0.83%	3.90	0.82%	3.94	0.78%	4.51	0.78%	4.29
Germany	0.55%	3.13	0.82%	4.35	0.54%	3.66	0.84%	4.82
Greece	2.16%	3.37	1.81%	2.77	1.49%	3.71	1.37%	2.67
Hong Kong	0.53%	2.06	0.95%	3.72	0.66%	3.17	0.86%	3.37
Hungary	0.27%	0.47	2.14%	4.10	0.77%	1.66	0.85%	2.02
India	-0.31%	-0.68	1.62%	3.94	0.33%	0.91	1.78%	4.12
Indonesia	-0.87%	-2.68	0.21%	0.56	-0.17%	-0.78	0.69%	1.99
Ireland	0.24%	0.44	0.97%	1.72	0.76%	1.91	1.49%	2.41
Israel	-0.08%	-0.42	-0.15%	-0.34	0.00%	-0.02	-0.31%	-0.64
Italy	1.02%	5.46	1.05%	3.73	0.89%	5.26	0.96%	3.68
Japan	0.03%	0.16	0.36%	1.56	-0.01%	-0.03	0.26%	1.19
Kenya	0.67%	0.90	1.19%	1.37	0.80%	1.32	1.41%	1.99
Lithuania	1.00%	1.65	1.38%	2.06	1.11%	2.53	1.33%	2.54
Malaysia	0.18%	0.64	0.24%	0.78	0.14%	0.56	0.16%	0.54
Mexico	0.50%	1.63	1.27%	2.90	0.51%	1.65	1.26%	2.87
Morocco	0.16%	0.39	0.76%	2.34	0.08%	0.23	0.63%	2.05
Netherlands	0.77%	2.93	0.64%	2.44	0.79%	3.91	0.66%	2.85
New Zealand	0.89%	3.21	0.64%	2.02	0.99%	3.82	0.59%	1.89
Norway	0.44%	0.93	0.95%	3.04	0.68%	1.94	1.19%	4.39
Pakistan	-0.85%	-2.24	-0.28%	-0.63	-0.37%	-1.18	-0.10%	-0.24
Peru	-5.34%	-1.83	-0.08%	-0.16	-4.61%	-1.58	0.83%	1.52
Philippines	-0.77%	-1.56	-0.48%	-1.14	-0.32%	-0.74	-0.38%	-0.88
Poland	1.83%	5.21	1.85%	3.52	1.71%	5.98	1.68%	3.84
Portugal	-2.83%	-1.42	0.54%	1.45	-4.93%	-1.42	0.65%	1.90
Romania	0.17%	0.27	0.13%	0.18	0.18%	0.34	-0.04%	-0.04
Russian Federation	-82.38%	-1.69	-0.58%	-0.45	-55.19%	-1.04	1.52%	1.35
Singapore	0.33%	1.14	0.09%	0.27	0.44%	2.00	0.27%	0.99
South Africa	0.86%	3.34	1.15%	3.83	1.22%	5.52	1.19%	4.53
South Korea	-0.47%	-0.84	-0.27%	-0.49	-0.31%	-0.97	-0.19%	-0.52
Spain	0.54%	2.13	0.36%	1.52	0.44%	1.75	0.29%	1.27
Sri Lanka	-1.03%	-2.48	-0.59%	-1.57	-0.65%	-2.18	-0.31%	-1.05
Sweden	0.03%	0.05	0.02%	0.03	0.32%	0.98	0.33%	0.79
Switzerland	0.91%	4.89	0.78%	3.85	0.87%	5.49	0.79%	4.29
Taiwan	0.01%	0.02	0.10%	0.26	-0.07%	-0.20	-0.03%	-0.08
Thailand	0.14%	0.45	0.78%	2.09	0.35%	1.18	0.89%	3.02
Turkey	-1.42%	-2.14	0.04%	0.05	-0.47%	-1.34	0.36%	0.65
UK	0.93%	4.39	0.87%	3.99	0.96%	5.26	0.89%	4.44
US	-0.69%	-1.40	0.73%	4.16	-0.14%	-0.36	0.77%	4.40
Venezuela	-5.58%	-1.94	-6.50%	-1.95	-4.41%	-1.66	-5.27%	-1.85
Country Neutral Momentum returns	**-3.98%**	-1.36	**0.64%**	3.45	**-1.20%**	-1.09	**0.67%**	4.54
Country Neutral Momentum returns ex Brazil, Russia	**0.07%**	0.339	**0.67%**	3.5404	**0.18%**	0.91	**0.66%**	4.33

TABLE 5-6: Number of stocks in a portfolio

6 x 6 months, Value-Weighted, 1-month gap, US dollar, BHAR

	2 portfolios		3 portfolios		4 portfolios		5 portfolios		10 portfolios		20 portfolios	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	0.44%	1.30	0.11%	0.22	-0.22%	-0.35	-0.41%	-0.54	0.02%	0.01	0.71%	0.60
Australia	0.37%	2.67	0.91%	4.58	1.12%	4.70	1.30%	4.92	1.71%	4.80	2.05%	4.44
Austria	0.31%	1.06	0.25%	0.77	0.14%	0.39	0.36%	1.04	0.10%	0.22	0.93%	1.53
Bangladesh	2.30%	2.23	3.74%	2.30	4.73%	2.38	5.29%	2.24	4.66%	2.25	1.53%	2.30
Belgium	0.36%	3.47	0.55%	3.48	0.81%	4.00	1.00%	4.20	1.28%	3.60	2.14%	4.62
Brazil	-0.14%	-0.22	-0.19%	-0.32	-0.24%	-0.40	-0.03%	-0.04	-0.70%	-0.87	-1.47%	-2.03
Canada	0.60%	3.96	0.96%	4.67	1.20%	4.94	1.40%	4.97	1.81%	5.05	2.05%	4.31
Chile	0.28%	1.17	0.23%	0.69	0.10%	0.26	0.15%	0.40	0.23%	0.61	0.12%	0.23
China	0.67%	2.92	0.75%	2.79	0.89%	3.08	0.88%	3.03	1.06%	3.48	1.30%	4.06
Colombia	0.91%	3.16	0.88%	2.55	0.88%	2.04	1.04%	2.03	0.65%	1.21	1.28%	1.94
Cyprus	1.75%	3.98	2.00%	3.30	1.37%	2.65	0.89%	1.68	-0.53%	-0.69	-1.60%	-1.91
Czech Republic	0.82%	2.40	1.31%	3.10	1.25%	2.60	1.10%	2.25	0.77%	1.63	0.63%	1.11
Denmark	0.42%	2.73	0.53%	2.56	0.65%	2.94	0.91%	3.79	1.46%	3.92	2.00%	4.30
Egypt	1.12%	2.18	1.41%	2.21	1.73%	2.45	1.91%	2.50	2.62%	2.22	2.90%	2.04
Finland	1.53%	2.72	1.96%	3.53	2.21%	4.05	2.38%	4.37	2.60%	3.94	2.11%	3.04
France	0.43%	3.75	0.61%	3.80	0.79%	4.17	0.82%	3.94	0.94%	3.35	1.20%	3.50
Germany	0.35%	3.62	0.54%	3.90	0.71%	4.10	0.82%	4.35	1.08%	4.12	1.54%	4.51
Greece	0.83%	2.47	1.11%	2.23	1.51%	2.58	1.81%	2.77	2.14%	3.18	2.12%	4.08
Hong Kong	0.43%	3.13	0.52%	2.57	0.75%	3.28	0.95%	3.72	1.22%	3.84	1.52%	3.80
Hungary	0.84%	2.07	1.03%	2.62	1.18%	2.30	2.14%	4.10	2.38%	2.72	0.23%	0.20
India	0.71%	2.96	1.19%	3.69	1.49%	3.99	1.62%	3.94	1.84%	3.17	2.32%	3.83
Indonesia	-0.05%	-0.19	-0.26%	-0.73	0.00%	0.00	0.21%	0.56	0.20%	0.48	-0.56%	-0.55
Ireland	0.82%	2.67	1.00%	2.40	1.13%	2.18	0.97%	1.72	0.01%	0.01	-0.38%	-0.44
Israel	0.15%	0.48	0.17%	0.46	-0.12%	-0.30	-0.15%	-0.34	-0.18%	-0.36	-0.33%	-0.65
Italy	0.53%	2.88	0.72%	3.17	0.94%	3.52	1.05%	3.73	1.38%	3.80	1.35%	3.17
Japan	0.09%	0.64	0.16%	0.85	0.25%	1.19	0.36%	1.56	0.38%	1.37	0.42%	1.20
Kenya	0.79%	2.05	1.02%	1.58	1.29%	1.59	1.19%	1.37	1.56%	1.29	0.37%	0.33
Lithuania	1.14%	2.62	1.38%	2.84	1.63%	2.84	1.38%	2.06	-0.19%	-0.13	2.01%	1.24

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	2 portfolios		3 portfolios		4 portfolios		5 portfolios		10 portfolios		20 portfolios	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Malaysia	0.19%	1.01	0.19%	0.76	0.26%	0.87	0.24%	0.78	0.37%	1.08	0.08%	0.20
Mexico	0.57%	1.61	0.78%	1.93	1.02%	2.41	1.27%	2.90	1.78%	3.71	1.88%	2.27
Morocco	0.37%	2.26	0.78%	3.54	0.75%	2.49	0.76%	2.34	0.52%	1.15	-0.59%	-0.66
Netherlands	0.18%	1.17	0.37%	1.74	0.53%	2.28	0.64%	2.44	0.86%	2.68	0.85%	1.83
New Zealand	0.30%	1.50	0.42%	1.75	0.41%	1.41	0.64%	2.02	0.73%	1.30	0.08%	0.11
Norway	0.11%	0.66	0.37%	1.81	0.66%	2.51	0.95%	3.04	1.70%	3.89	1.50%	2.43
Pakistan	0.14%	0.53	0.06%	0.17	-0.17%	-0.42	-0.28%	-0.63	-0.42%	-0.77	-1.22%	-2.10
Peru	0.02%	0.05	0.43%	0.99	0.57%	1.16	-0.08%	-0.16	-1.09%	-1.69	-2.73%	-2.86
Philippines	0.00%	0.00	-0.22%	-0.66	-0.44%	-1.03	-0.48%	-1.14	-1.08%	-1.63	-2.77%	-3.33
Poland	0.81%	3.25	1.22%	3.39	1.46%	3.34	1.85%	3.52	2.77%	3.96	2.50%	3.74
Portugal	0.11%	0.62	0.29%	1.16	0.35%	1.09	0.54%	1.45	-0.52%	-0.40	-2.73%	-0.90
Romania	-0.19%	-0.27	-0.71%	-1.02	-0.26%	-0.34	0.13%	0.18	0.24%	0.31	-0.48%	-0.49
Russian Federation	0.48%	0.54	0.07%	0.07	-0.84%	-0.60	-0.58%	-0.45	-5.03%	-1.15	-24.75%	-1.13
Singapore	-0.14%	-0.72	-0.11%	-0.44	0.02%	0.05	0.09%	0.27	0.63%	1.85	1.11%	3.17
South Africa	0.40%	2.30	0.64%	2.64	1.06%	3.86	1.15%	3.83	1.33%	4.18	2.16%	5.26
South Korea	-0.35%	-1.05	-0.40%	-0.89	-0.39%	-0.78	-0.27%	-0.49	0.38%	0.72	0.52%	0.91
Spain	0.25%	1.74	0.33%	1.73	0.35%	1.56	0.36%	1.52	0.50%	1.40	0.92%	2.04
Sri Lanka	0.01%	0.04	-0.14%	-0.55	-0.40%	-1.27	-0.59%	-1.57	-1.68%	-2.59	-2.34%	-3.19
Sweden	0.09%	0.42	0.00%	0.00	-0.10%	-0.22	0.02%	0.03	0.07%	0.07	0.73%	1.11
Switzerland	0.45%	3.42	0.67%	4.06	0.72%	3.79	0.78%	3.85	0.92%	3.63	1.23%	3.39
Taiwan	-0.19%	-0.81	-0.15%	-0.48	-0.01%	-0.03	0.10%	0.26	0.45%	0.92	0.63%	0.98
Thailand	0.49%	2.02	0.64%	1.84	0.81%	1.99	0.78%	2.09	0.62%	1.33	0.75%	1.56
Turkey	0.27%	0.42	0.42%	0.57	0.37%	0.43	0.04%	0.05	-0.89%	-1.29	-2.66%	-1.93
UK	0.32%	3.33	0.48%	3.36	0.70%	3.77	0.87%	3.99	1.36%	4.40	1.80%	4.92
US	0.26%	2.94	0.43%	3.19	0.62%	3.85	0.73%	4.16	1.08%	4.72	1.38%	4.43
Venezuela	-1.38%	-1.06	-3.22%	-1.62	-6.00%	-1.90	-6.50%	-1.95	-10.29%	-2.05	-19.16%	-1.73
Country-Neutral Momentum Returns	**0.41%**	**5.58**	**0.52%**	**4.39**	**0.56%**	**3.30**	**0.64%**	**3.45**	**0.48%**	**1.73**	**-0.24%**	**-0.38**

TABLE 5-8: Momentum size-sorted portfolio returns

6 x 6 months, 1-month gap, 3 portfolios, 3 portfolios within each size-sorted sample, US dollar, BHAR

	Equal-weighted						Value-weighted					
	Small Size Portfolio		Medium Size Portfolio		Large Size Portfolio		Small Size Portfolio		Medium Size Portfolio		Large Size Portfolio	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	7.05%	1.10	-0.11%	-0.24	-0.27%	-0.40	0.80%	1.64	0.23%	0.43	-0.22%	-0.28
Australia	-1.05%	-2.54	0.87%	4.61	1.10%	6.09	-0.42%	-1.07	1.19%	5.84	0.54%	3.30
Austria	-1.73%	-1.19	0.96%	4.72	0.52%	2.42	0.50%	1.42	1.00%	4.75	0.25%	0.73
Bangladesh	-1.34%	-1.83	1.11%	2.95	9.13%	1.62	-0.66%	-0.95	1.10%	2.57	5.12%	2.10
Belgium	0.82%	2.07	0.92%	4.98	1.04%	5.27	0.74%	3.19	1.09%	5.31	0.56%	3.73
Brazil	-1533.43%	-1.19	-2.84%	-1.32	0.17%	0.48	-9.60%	-1.51	-1.66%	-1.03	-0.12%	-0.21
Canada	-1.11%	-2.38	0.79%	3.81	0.88%	5.08	-0.28%	-0.64	1.10%	5.02	0.75%	3.85
Chile	-0.85%	-1.08	1.17%	5.28	0.48%	1.81	0.12%	0.23	0.97%	4.55	0.33%	1.06
China	-0.65%	-3.00	0.20%	0.77	0.80%	3.46	-0.64%	-2.87	0.19%	0.77	0.98%	3.26
Colombia	-0.31%	-0.37	0.30%	0.59	0.89%	2.52	-1.82%	-0.49	0.79%	1.73	1.03%	2.77
Cyprus	-2.80%	-4.36	-0.74%	-1.51	0.91%	2.43	-1.41%	-2.80	-0.71%	-1.89	1.94%	3.22
Czech Republic	-0.21%	-0.52	0.75%	1.67	0.74%	1.99	-0.41%	-1.09	0.97%	2.22	0.93%	1.92
Denmark	0.43%	1.33	0.74%	3.58	0.91%	4.99	1.02%	3.56	0.73%	3.75	0.49%	2.24
Egypt	0.42%	0.53	0.42%	1.13	0.99%	2.40	0.34%	0.28	0.51%	1.48	1.61%	2.20
Finland	0.81%	2.25	1.09%	3.88	0.66%	2.07	1.06%	3.28	0.80%	2.56	1.70%	2.71
France	0.49%	2.03	0.67%	3.92	0.79%	4.33	0.99%	4.19	0.73%	4.20	0.64%	3.87
Germany	0.04%	0.18	0.65%	4.20	0.60%	3.82	0.45%	2.41	0.72%	4.54	0.48%	3.47
Greece	1.40%	2.36	0.37%	0.75	1.28%	4.57	-0.04%	-0.07	0.10%	0.19	0.94%	2.74
Hong Kong	-0.47%	-1.55	0.59%	2.15	0.76%	3.89	-0.19%	-0.63	0.66%	2.75	0.62%	3.40
Hungary	-0.26%	-0.31	0.73%	1.05	0.59%	1.79	0.69%	0.68	0.80%	1.82	1.24%	2.18
India	-2.10%	-4.39	0.67%	1.89	0.85%	2.86	-0.71%	-1.54	1.18%	2.91	1.02%	3.37
Indonesia	-2.12%	-3.85	-0.70%	-2.20	-0.45%	-1.31	-1.65%	-3.09	-0.39%	-1.26	0.05%	0.16
Ireland	-0.38%	-0.55	0.77%	1.72	1.00%	3.51	0.07%	0.10	0.67%	1.47	0.77%	2.14
Israel	-0.39%	-1.54	-0.17%	-0.78	-0.04%	-0.17	-0.21%	-0.91	-0.15%	-0.59	-0.05%	-0.11
Italy	0.77%	4.03	0.65%	4.23	1.03%	3.41	0.79%	4.08	0.66%	3.82	0.88%	3.05
Japan	-0.25%	-1.79	0.03%	0.23	0.11%	0.68	-0.30%	-2.10	0.05%	0.35	0.12%	0.63
Kenya	0.34%	0.32	1.27%	2.05	0.36%	0.38	1.32%	1.54	1.14%	1.93	0.56%	0.68
Lithuania	1.79%	1.23	1.72%	3.14	0.70%	1.66	0.50%	0.29	2.24%	3.80	0.98%	2.21

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	Equal-weighted						Value-weighted					
	Small Size Portfolio		Medium Size Portfolio		Large Size Portfolio		Small Size Portfolio		Medium Size Portfolio		Large Size Portfolio	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Malaysia	-0.23%	-0.86	0.25%	1.24	0.47%	1.98	-0.22%	-0.86	0.27%	1.35	0.26%	1.12
Mexico	0.66%	1.78	0.06%	0.16	0.71%	2.98	1.45%	3.15	0.38%	1.10	0.89%	2.35
Morocco	-0.73%	-1.00	0.70%	2.75	0.71%	2.65	-0.57%	-0.76	0.93%	2.29	0.54%	2.69
Netherlands	0.34%	1.07	1.08%	5.11	0.44%	2.82	0.88%	3.90	1.06%	5.37	0.16%	0.78
New Zealand	0.31%	0.84	0.85%	3.68	1.00%	4.18	1.24%	3.59	0.82%	3.54	0.40%	1.57
Norway	-0.24%	-0.47	0.89%	2.26	0.57%	2.45	0.48%	1.34	1.07%	3.60	0.23%	1.18
Pakistan	-0.66%	-1.13	-0.45%	-1.47	0.22%	0.71	-0.65%	-1.46	-0.17%	-0.52	0.16%	0.43
Peru	-4.24%	-3.40	0.98%	0.62	-6.06%	-1.28	-3.76%	-2.63	0.19%	0.26	-0.19%	-0.33
Philippines	-0.76%	-1.50	-0.45%	-0.98	-0.04%	-0.10	-0.85%	-1.33	-0.41%	-0.86	-0.02%	-0.05
Poland	0.75%	1.12	1.46%	3.96	1.04%	3.79	0.57%	0.80	1.63%	5.09	1.02%	3.02
Portugal	-6.70%	-1.46	0.87%	1.92	0.33%	1.21	0.18%	0.18	1.11%	2.27	0.23%	0.87
Romania	-0.41%	-0.31	-0.01%	-0.01	0.03%	0.04	-1.81%	-2.26	0.12%	0.14	-0.17%	-0.21
Russian Federation	-212.91%	-1.37	-2.16%	-2.28	-16.11%	-1.14	-2.57%	-2.59	-1.50%	-2.05	0.13%	0.18
Singapore	-0.12%	-0.39	0.56%	2.62	0.38%	1.56	0.02%	0.07	0.67%	3.25	-0.18%	-0.62
South Africa	0.26%	0.92	1.14%	4.47	0.67%	3.20	0.91%	3.02	1.10%	4.19	0.52%	2.33
South Korea	-0.92%	-1.71	-0.23%	-0.49	0.05%	0.15	-0.74%	-1.49	-0.22%	-0.59	-0.21%	-0.48
Spain	0.27%	0.70	0.67%	3.39	0.06%	0.28	0.45%	1.22	0.53%	2.62	0.12%	0.61
Sri Lanka	-0.66%	-1.43	-0.74%	-2.59	-0.64%	-1.71	-0.82%	-2.04	-0.69%	-2.53	0.01%	0.04
Sweden	-0.40%	-0.68	0.86%	3.24	0.17%	0.58	0.33%	0.72	0.93%	3.20	0.09%	0.31
Switzerland	0.71%	4.56	0.80%	4.09	0.63%	3.98	0.79%	4.87	0.72%	3.75	0.57%	3.44
Taiwan	0.06%	0.16	-0.11%	-0.33	0.24%	0.82	0.03%	0.07	-0.08%	-0.23	-0.08%	-0.26
Thailand	-0.79%	-1.79	0.38%	1.12	0.29%	1.02	-0.88%	-1.69	0.45%	1.51	0.48%	1.21
Turkey	-0.50%	-1.10	-2.39%	-1.53	-0.10%	-0.25	-1.21%	-1.97	-1.88%	-1.53	0.26%	0.31
UK	0.38%	2.48	1.09%	6.41	0.74%	5.12	0.75%	4.94	1.17%	6.92	0.37%	2.80
US	-2.64%	-2.42	0.56%	3.86	0.45%	3.79	0.41%	2.78	0.72%	5.76	0.32%	2.66
Venezuela	-0.69%	-0.73	-21.04%	-1.50	0.15%	0.35	-1.24%	-1.30	-26.00%	-1.52	-0.31%	-0.72
Country-Neutral Momentum Returns	**-32.68%**	**-1.14**	**-0.03%**	**-0.06**	**0.24%**	**0.62**	**-0.29%**	**-1.29**	**-0.01%**	**0.01**	**0.55%**	**5.02**

TABLE 5-10: Momentum returns under simple and log returns

6 x 6 months, Value-Weighted, 1-month gap, 5 portfolios, US dollar, CAR

	Simple Returns		Log Returns	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.22%	-0.42	0.11%	0.22
Australia	1.45%	5.45	1.94%	5.38
Austria	-0.16%	-0.41	0.79%	2.40
Bangladesh	3.39%	2.53	1.99%	2.58
Belgium	0.95%	4.06	1.03%	4.08
Brazil	0.34%	0.55	0.69%	0.80
Canada	1.41%	5.28	1.95%	6.47
Chile	0.12%	0.38	0.46%	1.85
China	0.89%	3.14	0.83%	3.26
Colombia	0.72%	1.57	1.40%	3.05
Cyprus	0.61%	1.05	1.97%	3.52
Czech Republic	1.04%	2.38	1.48%	3.40
Denmark	0.83%	3.40	1.00%	4.06
Egypt	1.63%	2.35	1.08%	1.35
Finland	2.02%	3.75	2.45%	4.31
France	0.78%	4.29	0.99%	5.46
Germany	0.84%	4.82	1.05%	4.69
Greece	1.37%	2.67	2.00%	4.01
Hong Kong	0.86%	3.37	1.29%	4.70
Hungary	0.85%	2.02	2.53%	4.79
India	1.78%	4.12	1.71%	3.88
Indonesia	0.69%	1.99	0.82%	2.16
Ireland	1.49%	2.41	2.03%	2.48
Israel	-0.31%	-0.64	-4.04%	-1.80
Italy	0.96%	3.68	1.06%	4.42
Japan	0.26%	1.19	0.34%	1.61
Kenya	1.41%	1.99	1.63%	3.09
Lithuania	1.33%	2.54	1.29%	2.34
Malaysia	0.16%	0.54	0.31%	1.21
Mexico	1.26%	2.87	3.08%	2.56
Morocco	0.63%	2.05	0.85%	2.90
Netherlands	0.66%	2.85	0.84%	3.39
New Zealand	0.59%	1.89	1.09%	3.60
Norway	1.19%	4.39	1.61%	5.46
Pakistan	-0.10%	-0.24	0.57%	1.21
Peru	0.83%	1.52	0.90%	2.03
Philippines	-0.38%	-0.88	0.32%	0.90
Poland	1.68%	3.84	1.95%	3.77
Portugal	0.65%	1.90	0.84%	2.47
Romania	-0.04%	-0.04	-0.19%	-0.21
Russian Federation	1.52%	1.35	0.91%	1.17
Singapore	0.27%	0.99	0.31%	1.07
South Africa	1.19%	4.53	1.36%	4.59
South Korea	-0.19%	-0.52	0.58%	1.44
Spain	0.29%	1.27	0.63%	2.54
Sri Lanka	-0.31%	-1.05	0.00%	0.00
Sweden	0.33%	0.79	0.91%	1.80
Switzerland	0.79%	4.29	0.94%	4.97
Taiwan	-0.03%	-0.08	0.23%	0.64
Thailand	0.89%	3.02	1.17%	3.24
Turkey	0.36%	0.65	0.30%	0.65
UK	0.89%	4.44	1.19%	4.83
US	0.77%	4.40	0.89%	5.29
Venezuela	-5.27%	-1.85	-2.26%	-1.81
Country Neutral Momentum returns	**0.67%**	4.54	**0.95%**	6.51

TABLE 5-12: Local currency momentum returns versus US dollar momentum returns

6 x 6 months, Value-Weighted, 1-month gap, 5 portfolios

	BHAR				CAR			
	Local Currency		US Currency		Local Currency		US Currency	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.28%	-0.42	-0.41%	-0.54	-0.17%	-0.33	-0.22%	-0.42
Australia	1.29%	4.88	1.30%	4.92	1.48%	5.55	1.45%	5.45
Austria	0.19%	0.46	0.36%	1.04	-0.17%	-0.43	-0.16%	-0.41
Bangladesh	4.61%	2.53	5.29%	2.24	3.41%	2.57	3.39%	2.53
Belgium	1.00%	4.37	1.00%	4.20	0.95%	4.06	0.95%	4.06
Brazil	-0.04%	-0.06	-0.03%	-0.04	0.39%	0.65	0.34%	0.55
Canada	1.43%	4.98	1.40%	4.97	1.40%	5.24	1.41%	5.28
Chile	1.12%	1.61	0.15%	0.40	0.22%	0.77	0.12%	0.38
China	0.89%	3.05	0.88%	3.03	0.86%	3.07	0.89%	3.14
Colombia	1.23%	2.46	1.04%	2.03	1.13%	2.74	0.72%	1.57
Cyprus	0.25%	0.57	0.89%	1.68	0.41%	0.89	0.61%	1.05
Czech Republic	1.06%	2.21	1.10%	2.25	1.04%	2.43	1.04%	2.38
Denmark	0.85%	3.59	0.91%	3.79	0.82%	3.45	0.83%	3.40
Egypt	1.85%	2.49	1.91%	2.50	1.53%	2.23	1.63%	2.35
Finland	2.36%	4.23	2.38%	4.37	2.00%	3.69	2.02%	3.75
France	0.80%	4.05	0.82%	3.94	0.80%	4.47	0.78%	4.29
Germany	0.79%	4.28	0.82%	4.35	0.82%	4.73	0.84%	4.82
Greece	1.90%	2.84	1.81%	2.77	1.39%	2.71	1.37%	2.67
Hong Kong	1.02%	3.83	0.95%	3.72	0.91%	3.59	0.86%	3.37
Hungary	2.00%	3.89	2.14%	4.10	0.48%	1.13	0.85%	2.02
India	1.63%	3.94	1.62%	3.94	1.80%	4.06	1.78%	4.12
Indonesia	0.28%	0.63	0.21%	0.56	0.65%	1.63	0.69%	1.99
Ireland	0.89%	1.65	0.97%	1.72	1.49%	2.52	1.49%	2.41
Israel	-0.21%	-0.44	-0.15%	-0.34	-0.40%	-0.81	-0.31%	-0.64
Italy	1.05%	3.62	1.05%	3.73	0.90%	3.53	0.96%	3.68
Japan	0.35%	1.58	0.36%	1.56	0.28%	1.26	0.26%	1.19
Kenya	1.85%	2.56	1.19%	1.37	1.82%	3.07	1.41%	1.99
Lithuania	1.15%	1.67	1.38%	2.06	1.13%	2.27	1.33%	2.54
Malaysia	0.13%	0.39	0.24%	0.78	0.14%	0.49	0.16%	0.54
Mexico	1.21%	2.43	1.27%	2.90	1.33%	3.15	1.26%	2.87
Morocco	0.74%	2.32	0.76%	2.34	0.62%	2.04	0.63%	2.05
Netherlands	0.59%	2.27	0.64%	2.44	0.63%	2.74	0.66%	2.85
New Zealand	0.64%	2.03	0.64%	2.02	0.57%	1.83	0.59%	1.89
Norway	0.84%	2.65	0.95%	3.04	1.20%	4.59	1.19%	4.39
Pakistan	-0.31%	-0.68	-0.28%	-0.63	-0.10%	-0.22	-0.10%	-0.24
Peru	0.25%	0.43	-0.08%	-0.16	0.78%	1.33	0.83%	1.52
Philippines	-0.37%	-0.84	-0.48%	-1.14	-0.33%	-0.78	-0.38%	-0.88
Poland	1.76%	3.39	1.85%	3.52	1.71%	3.90	1.68%	3.84
Portugal	0.55%	1.41	0.54%	1.45	0.73%	2.02	0.65%	1.90
Romania	-0.04%	-0.04	0.13%	0.18	0.16%	0.21	-0.04%	-0.04
Russian Federation	-0.58%	-0.45	-0.58%	-0.45	1.52%	1.35	1.52%	1.35
Singapore	0.08%	0.24	0.09%	0.27	0.23%	0.81	0.27%	0.99
South Africa	1.16%	3.78	1.15%	3.83	1.05%	3.76	1.19%	4.53
South Korea	-0.24%	-0.46	-0.27%	-0.49	-0.11%	-0.30	-0.19%	-0.52
Spain	0.34%	1.39	0.36%	1.52	0.24%	1.07	0.29%	1.27
Sri Lanka	-1.61%	-1.72	-0.59%	-1.57	-0.38%	-1.24	-0.31%	-1.05
Sweden	0.00%	0.00	0.02%	0.03	0.32%	0.76	0.33%	0.79
Switzerland	0.76%	3.62	0.78%	3.85	0.77%	4.12	0.79%	4.29
Taiwan	0.11%	0.28	0.10%	0.26	-0.02%	-0.04	-0.03%	-0.08
Thailand	0.77%	1.99	0.78%	2.09	0.93%	2.94	0.89%	3.02
Turkey	-1.95%	-1.97	0.04%	0.05	-0.11%	-0.17	0.36%	0.65
UK	0.82%	3.85	0.87%	3.99	0.86%	4.37	0.89%	4.44
US	0.73%	4.16	0.73%	4.16	0.77%	4.40	0.77%	4.40
Venezuela	-6.01%	-1.94	-6.50%	-1.95	-4.21%	-1.65	-5.27%	-1.85
Country Neutral Momentum returns	**0.59%**	3.22	**0.64%**	3.45	**0.68%**	5.08	**0.67%**	4.54

TABLE 5-13: Effect of one-month versus zero-month gap on momentum returns

6x6 months, Value-Weighted, 5 portfolios, US dollar

	BHAR				CAR			
	1 month gap		0 month gap		1 month gap		0 month gap	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.41%	-0.54	0.03%	0.04	-0.22%	-0.42	0.13%	0.26
Australia	1.30%	4.92	1.35%	4.88	1.45%	5.45	1.48%	5.19
Austria	0.36%	1.04	0.13%	0.32	-0.16%	-0.41	-0.31%	-0.79
Bangladesh	5.29%	2.24	5.00%	2.07	3.39%	2.53	3.09%	2.26
Belgium	1.00%	4.20	1.01%	4.53	0.95%	4.06	0.91%	4.28
Brazil	-0.03%	-0.04	-0.40%	-0.63	0.34%	0.55	-0.10%	-0.15
Canada	1.40%	4.97	1.46%	5.08	1.41%	5.28	1.38%	5.22
Chile	0.15%	0.40	-0.07%	-0.16	0.12%	0.38	0.14%	0.44
China	0.88%	3.03	0.84%	2.59	0.89%	3.14	0.80%	2.82
Colombia	1.04%	2.03	0.94%	1.81	0.72%	1.57	0.50%	1.02
Cyprus	0.89%	1.68	1.17%	2.40	0.61%	1.05	0.82%	1.48
Czech Republic	1.10%	2.25	0.82%	1.65	1.04%	2.38	0.78%	1.69
Denmark	0.91%	3.79	1.04%	4.13	0.83%	3.40	0.96%	3.84
Egypt	1.91%	2.50	1.50%	1.93	1.63%	2.35	1.20%	1.73
Finland	2.38%	4.37	2.11%	3.69	2.02%	3.75	1.69%	2.88
France	0.82%	3.94	0.72%	3.08	0.78%	4.29	0.65%	3.23
Germany	0.82%	4.35	0.81%	4.29	0.84%	4.82	0.86%	4.73
Greece	1.81%	2.77	1.41%	1.80	1.37%	2.67	1.12%	1.86
Hong Kong	0.95%	3.72	0.90%	3.37	0.86%	3.37	0.77%	2.89
Hungary	2.14%	4.10	2.20%	4.25	0.85%	2.02	0.92%	2.07
India	1.62%	3.94	1.41%	3.47	1.78%	4.12	1.53%	3.59
Indonesia	0.21%	0.56	-0.52%	-1.11	0.69%	1.99	-0.01%	-0.04
Ireland	0.97%	1.72	1.12%	2.00	1.49%	2.41	1.72%	2.74
Israel	-0.15%	-0.34	-0.34%	-0.72	-0.31%	-0.64	-0.50%	-0.96
Italy	1.05%	3.73	1.08%	3.59	0.96%	3.68	1.02%	3.74
Japan	0.36%	1.56	0.26%	1.04	0.26%	1.19	0.16%	0.68
Kenya	1.19%	1.37	1.02%	1.37	1.41%	1.99	1.45%	2.38
Lithuania	1.38%	2.06	1.72%	2.22	1.33%	2.54	1.50%	2.68
Malaysia	0.24%	0.78	0.17%	0.54	0.16%	0.54	0.09%	0.28
Mexico	1.27%	2.90	0.93%	2.32	1.26%	2.87	0.97%	2.40
Morocco	0.76%	2.34	0.58%	1.77	0.63%	2.05	0.53%	1.78
Netherlands	0.64%	2.44	0.60%	2.28	0.66%	2.85	0.64%	2.74
New Zealand	0.64%	2.02	0.71%	2.20	0.59%	1.89	0.73%	2.30
Norway	0.95%	3.04	1.00%	3.25	1.19%	4.39	1.18%	4.41
Pakistan	-0.28%	-0.63	-0.43%	-0.94	-0.10%	-0.24	-0.25%	-0.63
Peru	-0.08%	-0.16	-0.71%	-1.56	0.83%	1.52	0.06%	0.11
Philippines	-0.48%	-1.14	-0.75%	-1.76	-0.38%	-0.88	-0.57%	-1.30
Poland	1.85%	3.52	2.11%	3.87	1.68%	3.84	2.00%	4.26
Portugal	0.54%	1.45	0.42%	1.10	0.65%	1.90	0.59%	1.71
Romania	0.13%	0.18	-0.34%	-0.48	-0.04%	-0.04	-0.59%	-0.78
Russian Federation	-0.58%	-0.45	-1.21%	-0.90	1.52%	1.35	0.76%	0.67
Singapore	0.09%	0.27	0.16%	0.47	0.27%	0.99	0.27%	0.97
South Africa	1.15%	3.83	0.82%	2.76	1.19%	4.53	0.87%	3.28
South Korea	-0.27%	-0.49	-0.34%	-0.66	-0.19%	-0.52	-0.43%	-1.24
Spain	0.36%	1.52	0.15%	0.60	0.29%	1.27	0.08%	0.31
Sri Lanka	-0.59%	-1.57	-0.81%	-2.44	-0.31%	-1.05	-0.61%	-2.28
Sweden	0.02%	0.03	0.23%	0.48	0.33%	0.79	0.52%	1.28
Switzerland	0.78%	3.85	0.74%	3.64	0.79%	4.29	0.72%	3.88
Taiwan	0.10%	0.26	-0.04%	-0.10	-0.03%	-0.08	-0.17%	-0.42
Thailand	0.78%	2.09	0.67%	1.66	0.89%	3.02	0.69%	2.11
Turkey	0.04%	0.05	-0.43%	-0.54	0.36%	0.65	0.04%	0.06
UK	0.87%	3.99	0.79%	3.74	0.89%	4.44	0.81%	3.99
US	0.73%	4.16	0.49%	2.63	0.77%	4.40	0.58%	3.22
Venezuela	-6.50%	-1.95	-3.49%	-2.34	-5.27%	-1.85	-2.69%	-2.07
Country Neutral Momentum returns	**0.64%**	3.45	**0.57%**	3.68	**0.67%**	4.54	**0.58%**	4.99

TABLE 5-15: Momentum returns excluding extreme Winner and Loser stocks

6 x 6 months, Value-Weighted, 1-month gap, 5 portfolios, US dollar

	BHAR		CAR	
	excluding extreme W & L		excluding extreme W & L	
Country	**W - L**	**t-stat**	**W-L**	**t-stat**
Argentina	-0.33%	-0.43	-0.16%	-0.30
Australia	1.29%	4.98	1.47%	5.58
Austria	0.41%	1.17	-0.12%	-0.29
Bangladesh	5.57%	2.16	3.54%	2.47
Belgium	0.97%	4.09	1.03%	4.56
Brazil	-0.04%	-0.06	0.39%	0.63
Canada	1.44%	5.11	1.41%	5.34
Chile	0.19%	0.50	0.14%	0.47
China	0.88%	2.85	0.85%	2.97
Colombia	1.08%	2.12	0.76%	1.64
Cyprus	0.87%	1.64	0.67%	1.17
Czech Republic	1.13%	2.24	1.03%	2.35
Denmark	0.79%	3.38	0.72%	2.99
Egypt	1.43%	2.26	1.24%	2.10
Finland	2.40%	4.80	2.16%	4.25
France	0.86%	4.28	0.81%	4.57
Germany	0.81%	4.32	0.82%	4.77
Greece	1.89%	2.88	1.45%	2.77
Hong Kong	0.97%	3.89	0.87%	3.50
Hungary	2.08%	3.93	0.81%	1.90
India	1.59%	3.94	1.69%	3.98
Indonesia	0.23%	0.62	0.71%	2.01
Ireland	0.97%	2.09	1.41%	2.68
Israel	-0.02%	-0.03	-0.22%	-0.43
Italy	1.05%	3.73	0.99%	3.81
Japan	0.37%	1.64	0.27%	1.29
Kenya	1.19%	1.37	1.41%	1.99
Lithuania	1.39%	2.09	1.31%	2.52
Malaysia	0.22%	0.72	0.15%	0.51
Mexico	1.07%	2.66	1.05%	2.54
Morocco	0.73%	2.28	0.63%	2.06
Netherlands	0.67%	2.57	0.70%	3.08
New Zealand	0.77%	2.47	0.61%	2.00
Norway	0.93%	3.00	1.17%	4.33
Pakistan	-0.25%	-0.56	-0.06%	-0.13
Peru	-0.14%	-0.28	0.91%	1.68
Philippines	-0.33%	-0.77	-0.22%	-0.51
Poland	1.81%	3.38	1.65%	3.63
Portugal	0.49%	1.36	0.63%	1.85
Romania	0.07%	0.09	-0.06%	-0.07
Russian Federation	0.35%	0.38	1.62%	1.51
Singapore	0.03%	0.07	0.15%	0.55
South Africa	1.13%	3.75	1.15%	4.42
South Korea	-0.28%	-0.53	-0.17%	-0.47
Spain	0.33%	1.49	0.22%	1.02
Sri Lanka	-0.46%	-1.24	-0.25%	-0.80
Sweden	0.03%	0.05	0.33%	0.80
Switzerland	0.74%	3.79	0.75%	4.19
Taiwan	0.10%	0.28	-0.05%	-0.12
Thailand	0.85%	2.24	0.96%	3.20
Turkey	0.17%	0.23	0.53%	0.94
UK	0.85%	3.94	0.87%	4.37
US	0.73%	4.17	0.76%	4.36
Venezuela	-6.50%	-1.95	-5.27%	-1.85
Country Neutral Momentum returns	**0.66%**	**3.57**	**0.67%**	**4.59**

Chapter 6

FINDINGS: INDUSTRIAL MOMENTUM

Analysis

The analysis of industrial momentum proceeds by testing industrial momentum returns using the specially crafted monthly value-weighted industry returns and the Datastream provided industry indices. To test whether 'normal' momentum returns arise due to industry factors, two analyses are undertaken where the industry-adjusted and industry-neutral momentum returns are calculated. The industry momentum returns are then compared to other versions of momentum returns to document if industry momentum returns generate superior returns. The final section of this chapter shows the applicability of industry momentum returns to the recently documented 52-week high momentum returns.

The industry momentum strategy cannot be tested in all 54 countries as the number of companies within an industry is not sufficient in some stock markets. To avoid idiosyncratic risk, it is necessary to have enough companies within an industry to permit proper diversification. Adoption of an arbitrary minimum number of 1000 stocks within any given month results in only seven out of 54 countries satisfying the above condition. The final seven markets are Australia, Canada, China, Japan, India, UK and US. The data used in this study are divided into 38 industries. Therefore, on average there will be around 25 companies within each industry to increase statistical reliability and reduce idiosyncratic risk from monthly industry returns[9].

The sample period for some countries also changes as a result of a restriction on the minimum number of stocks. For example, the sample starting date for Canada changes from January 1973 to October 1988 as there are fewer than 1000 stocks in the sample prior to October 1988. Similarly, the starting date for the Australian stock market becomes March 2000, China is October 2000, India is June 1993 and Japan is August 1987 to ensure the number of stocks is 1000 in each respective market.

CAR is selected as the appropriate method to compute abnormal returns. The BHAR method is not considered as an approach in this study, as the allocation to each industry should be kept fixed at the start of the portfolio holding period. The data for this study uses monthly rebalanced industry returns and, therefore, are not suitable for the BHAR method.

All the tests in the following section are calculated from the perspective of a US investor. The relevant price and capitalisation figures are converted to US dollars at the daily prevailing exchange rate. The industry momentum return strategy is tested with a 6-month formation and holding period. Grundy and Martin (2001), Lewellen (2002), Swinkels (2002), and Hurn and Pavlov (2003) report that the industry momentum returns are generally a medium-term effect (about 6 months). The analyses reported below include a one-month gap between

[9] Some industries, e.g., Oil & Gas producers, may have fewer than 25 companies, potentially creating a degree of idiosyncratic risk in the returns.

the formation and holding period, unless otherwise stated. The industry monthly returns for each industry are value-weighted but the returns of the Winner and Loser portfolios are equal-weighted. Du and Denning (2005) find no difference in industry momentum returns when either equal- or value-weighted methods are used to calculate the portfolio return.

6.1. Profitability of industry momentum

The results from Table 6-1 document positive industry momentum returns in six out of seven countries. The self-financing industry momentum return from the Japanese stock market is very low and not statistically significant. The highest profitability is observed in the Indian stock market with an average monthly return of 0.60% above market. The return in the US market is comparatively lower, vis-à-vis other markets, but still profitable with a market excess return of 0.32% per month. Moskowitz and Grinblatt (1999) report an average monthly return of 0.43% in the US stock market. The loser portfolio returns are negative for all countries except Japan, suggesting a reversal pattern in the Loser portfolio. The results of Iihara et al. (2004) also fail to find evidence of industry momentum profitability in the Japanese stock market.

Table 6-1: Industry momentum returns using monthly stock returns

6 x 6 months, 1-month gap, 3 portfolios, CAR, US dollar

Country	Loser(L)	t-stat	Winner(W)	t-stat	W - L	t-stat
Australia	-0.76%	-2.12	0.42%	3.27	1.18%	3.30
Canada	-0.18%	-1.10	0.43%	3.43	0.61%	4.01
China	-0.62%	-2.42	0.32%	2.13	0.94%	4.88
India	-0.40%	-1.12	1.20%	4.44	1.60%	4.68
Japan	0.20%	1.33	0.24%	1.68	0.04%	0.19
UK	-0.11%	-1.14	0.27%	3.89	0.38%	3.02
US	-0.01%	-0.05	0.31%	4.77	0.32%	3.24

The above results reported are calculated by assigning each stock to an industry and then calculating value-weighted monthly returns for each industry. However, implementing this strategy may be difficult given there are so many stocks within an industry. For example, if there are 1000 stocks within a stock market and 30 identifiable industry sectors within that market, then the 1000 stocks need to reclassified into 30 industries to compute monthly industry returns.

An alternative approach is to utilise this investment strategy by considering different industry index data published by a number of financial institutions, e.g., Datastream, MSCI, etc. Industry indices are considered to be a good proxy for the overall performance of the specific industry sector. MSCI and Datastream provide industry index data for a number of countries. The availability of industry indices greatly reduces the time required as compared to calculating individual stock returns and then assigning them to an industry. Accordingly, an industry momentum strategy can be simply implemented by directly buying and short-selling top and bottom performing industry indices respectively, resulting in a huge saving of time, computation effort and transaction costs.

Although potentially compelling arguments have been presented for the use of industry indices, a comparison with the monthly industry returns computed directly from the stock returns will be illuminating in terms of the closeness of result. The different returns from industry indices and monthly industry returns can further shed light on the impact of the size effect on industry momentum returns. Datastream industry indices include large, well-established and surviving firms, whereas monthly industry returns include all stocks assigned to an industry. Table 6-2 reports industry momentum returns for seven countries under investigation. The results suggest that the returns change when indices are used. There is an increase in returns for Canada, Japan, UK and US when using indices and a decline in industry momentum returns for Australia, China and India. The results again indicate high industry momentum profitability in the Indian stock market and the major contribution of this profit is from the Winner portfolio. Industry momentum returns are again not statistically significant for the Japanese stock market. Swinkels (2002) also finds statistically non-significant industry return profitability in the Japanese stock market when Datastream industry indices are used.

The results of this study are consistent with those of Swinkels (2002). He reports a return of 0.44% per month for the US stock market, 0.63% per month for the European market, and 0.28% per month for the Japanese stock market. The returns of the US stock market are statistically significant at a 10% level, whereas the industry momentum returns are not statistically significant for the Japanese stock market. Overall, the results from this study suggest that the industry momentum returns are profitable in six of the seven markets studied when industry indices are used.

Table 6-2: Industry momentum returns using Datastream indices

6 x 6 months, 1-month gap, 3 portfolios, CAR, US dollar

Country	Loser(L)	t-stat	Winner(W)	t-stat	W - L	t-stat
Australia	-0.11%	-0.89	0.57%	8.13	0.68%	4.82
Canada	-0.12%	-0.58	0.71%	3.61	0.83%	5.45
China	-0.44%	-1.90	0.23%	1.05	0.67%	4.10
India	-0.37%	-1.35	1.01%	3.57	1.38%	3.63
Japan	0.12%	0.81	0.35%	2.44	0.23%	1.17
UK	-0.22%	-2.22	0.29%	3.81	0.52%	4.12
US	-0.05%	-0.52	0.32%	4.15	0.37%	3.59

6.2. Are industry-returns adjusted significantly positive?

When determining individual stocks' momentum return, the market return is usually deducted from the individual stock return to arrive at the *AR*. Moskowitz and Grinblatt (1999) suggest that if industry return is deducted from the individual return stocks, instead of market returns, then the return from the momentum strategy would be almost negligible. They report a marginally significant profit of 13 basis points per month after monthly industry returns are deducted instead of market returns. The above proposition stems from the industry momentum idea that if a company within an industry is generating higher returns, then the rest of the companies within the same industry are also likely to generate positive returns due to momentum within the whole industry. Therefore, if all companies within an industry are generating higher returns, then the abnormal returns will be absent as high industry returns are subtracted instead of overall market return.

To test the above idea, the individual momentum returns for the seven countries are now adjusted for the same industry-market return instead of the overall market return. The initial hypothesis is that the momentum return will be very low as the industry return is expected to be the driving factor of momentum. However, the results presented in Table 6-3 do not support this proposition. Although the returns decrease when industry-adjusted abnormal returns are taken into consideration, the returns from individual momentum returns are still high and statistically significant. The exception is the UK where the returns increase with the use of industry-adjusted returns. This result suggests that not all the companies within an industry are following momentum trends.

Table 6-3: Industry adjusted individual momentum returns

6 x 6 months, 1-month gap, 3 portfolios, US dollar

	Individual industry-return adjusted momentum returns						Market returns adjusted	
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Australia	-0.90%	-2.96	0.46%	4.90	1.37%	4.48	1.50%	3.75
Canada	-0.45%	-5.11	0.56%	4.33	1.01%	5.52	1.36%	4.48
China	-0.21%	-1.43	0.32%	4.36	0.54%	2.56	0.80%	2.92
India	-0.56%	-2.78	0.36%	2.99	0.92%	3.67	1.47%	3.60
Japan	-0.06%	-0.52	0.06%	0.82	0.12%	0.70	0.19%	0.75
UK	-0.30%	-5.05	0.23%	4.80	0.52%	5.90	0.50%	3.73
US	-0.19%	-3.73	0.23%	4.84	0.42%	4.87	0.46%	3.38

6.3. Industry-neutral returns

Moskowitz and Grinblatt (1999) also illustrate superiority of industry momentum returns by calculating industry-neutral individual momentum returns. According to this hypothesis, Winner and Loser portfolios are formed within each industry and a similar strategy is used across other industries within the sample. Therefore, if the market has 30 industries, then there will be individual momentum returns for each of the industry, and an average of 30 industries will be industry-neutral momentum. By creating an industry-neutral portfolio, the industry effect can be controlled. Moskowitz and Grinblatt (1999) report a not-statistically significant 0.11% per month when the industry effect is removed from individual momentum returns.

The results reported in Table 6-4 do not support the Moskowitz and Grinblatt (1999) hypothesis. The returns, though decreasing with industry-neutral returns, are still high and statistically significant for all markets except Japan. A significant drop in profit is also noticed in the Indian stock market when industry-neutral momentum returns are used. The results from the industry-adjusted returns also show a significant decline in the profitability for the Indian stock market. This means that a major portion of industry momentum profitability is coming from a particular industry and this profit disappears when an average of all industries is taken together, suggesting that an industry effect may be present in the Indian stock market.

The results indicate that stocks within an industry tend not to rally together. Stocks within an industry can move in opposite directions and a momentum strategy can still be profitable by buying/short-selling Winner and Loser stocks within the same industry. This is contrary to the proposition of Moskowitz and Grinblatt (1999) where the majority of the Winner or Loser portfolio stocks are expected to be positioned within a particular group of industries.

Table 6-4: Industry-neutral momentum returns

6 x 6 months, 1-month gap, 3 portfolios, CAR, US dollar

	Industry-neutral momentum returns						Normal momentum	
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Australia	-0.84%	-3.98	0.44%	2.26	1.28%	5.09	1.50%	3.75
Canada	-0.61%	-6.27	0.53%	6.61	1.14%	10.29	1.36%	4.48
China	-0.68%	-8.46	-0.14%	-1.11	0.54%	4.41	0.80%	2.92
India	0.39%	0.77	0.76%	2.51	0.37%	1.16	1.47%	3.60
Japan	0.21%	6.35	0.22%	4.32	0.01%	0.33	0.19%	0.75
UK	-0.27%	-4.66	0.27%	7.15	0.53%	8.52	0.50%	3.73
US	-0.05%	-1.53	0.38%	9.66	0.43%	9.53	0.46%	3.38

Further, the results exhibit statistically significant positive returns for industry momentum but the individual momentum returns still dominate. The industry-adjusted returns and industry-neutral returns indicate statistically significant positive returns for six out of seven countries, indicating a less important role of industries in explaining individual momentum returns.

6.4. Do industry momentum returns dominate?

Moskowitz and Grinblatt (1999) claim that industry momentum return dominates individual stock momentum return. However, the results from this study do not confirm their claim. The results from Table 6-5 clearly show dominance of individual momentum returns over industry momentum returns. The returns, except for China and India, indicate higher individual momentum returns than industry momentum returns. The results for China and India offer a mixed result with a higher industry momentum return when industry monthly returns are calculated using individual stock returns and a lower return when industry indices are used. Momentum return for the Japanese stock market is not statistically significant when assessed using all three strategies.

Table 6-5: Comparing industry momentum returns versus individual momentum returns

	Industry momentum-using stock returns		Industry momentum-using industry indices		Individual momentum returns	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Australia	1.18%	3.30	0.68%	4.82	1.50%	3.75
Canada	0.61%	4.01	0.83%	5.45	1.36%	4.48
China	0.94%	4.88	0.67%	4.10	0.80%	2.92
India	1.60%	4.68	1.38%	3.63	1.47%	3.60
Japan	0.04%	0.19	0.23%	1.17	0.19%	0.75
UK	0.38%	3.02	0.52%	4.12	0.50%	3.73
US	0.32%	3.24	0.37%	3.59	0.46%	3.38

6.5. 52-week industry momentum returns

George and Hwang (2004) recently documented an investment strategy that involves buying stocks trading close to a 52-week high, short-selling 52-week low stocks and holding for a period of 6 months. This investment strategy resulted in a positive abnormal return of 1.23% per month (excluding January). This anomaly is quite remarkable as 52-week high/low price is readily available and the strategy can be easily implemented. Further, price reversals are also absent after 12 months of holding period in the 52-week high/low momentum return. The non-reversal of 52-week momentum profitability is inconsistent with the behavioural explanation put forward by Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999).

This study extends the above analysis of the industry 52-week high/low strategy to test whether the abnormal return exists at industry level. For example, if a certain number of stocks within the same industry are trading at a 52-week high price, and a certain number of stocks within other industries are trading at 52-week low price, then there are potential opportunities for profit to be made by buying industry/ (short selling) stocks which are trading at a 52-week high price/(52-week low price). This can be done by forming an investment strategy that will calculate 52-week high/low in the industry context and forming the Winner and Loser portfolio from the top and bottom 33% ranking industries. The initial hypothesis is that the returns generated from the 52-week high/low industry momentum returns will generate positive significant profits. The method for calculating the 52-week *industry* momentum strategy is the same as George and Hwang (2004) except the industry monthly returns are used instead of individual stock returns when calculating returns.

There are some underlying reasons for testing the 52-week high/low industry return as a substitute for 52-week high/low stock returns. Moskowitz and Grinblatt (1999) explain that much of the individual momentum returns are subsumed in the industry return. They also add that the industry momentum return generates higher returns compared to the individual stock momentum returns. Therefore, if this is true, then a 52-week high/low individual stock return can be replicated as a 52-week high/low industry momentum return. Further, George and Hwang (2004) add that 52-week high return dominates individual stock momentum returns. Therefore, if the two extensions to the traditional momentum strategy are combined, then will a 52-week industry momentum strategy generate significant positive return? The 52-week industry momentum return incorporates investment strategy ideas from all three forms of momentum investing, i.e., individual, industry and 52-week.

The above investment strategy is tested in seven markets and the results are largely devoid of data-snooping as the sample represents developing and developed markets. This test cannot be extended to 54 countries as there are too few companies within an industry in some countries which will lead to idiosyncratic risk.

The results from Table 6-6 clearly show positive returns when the 52-week high/low strategy is applied in the context of industry returns. The return, however, is not statistically significant for the Japanese and US markets with an average monthly return of about 0.19%. When the same strategy is applied with Datastream maintained industry indices, the results presented in Table 6-7, show weak support for this strategy for Japan, US and Australia. A sharp drop in return is also noted for the Canadian stock market. The overall results do not suggest a strong profit from 52-week high/low industry momentum compared to other momentum strategies available.

Table 6-6: 52-week high/low industry momentum returns (using monthly returns)

12 x 6 months, 1-month gap, 3 portfolios, CAR, US dollar

Country	Loser(L)	t-stat	Winner(W)	t-stat	W - L	t-stat
Australia	-0.45%	-1.48	0.39%	3.54	0.84%	2.95
Canada	-0.16%	-1.10	0.33%	2.18	0.49%	2.82
China	-0.66%	-3.00	0.27%	1.21	0.93%	5.28
India	-0.09%	-0.25	0.78%	3.04	0.87%	2.61
Japan	0.13%	0.91	0.21%	1.52	0.09%	0.47
UK	-0.11%	-0.98	0.19%	3.01	0.30%	2.10
US	0.00%	0.03	0.19%	2.72	0.19%	1.93

Table 6-7: 52-week high/low industry momentum returns (using industry indices)

12 x 6 months, 1-month gap, 3 portfolios, CAR, US dollar

Country	Loser(L)	t-stat	Winner(W)	t-stat	W - L	t-stat
Australia	0.04%	0.26	0.26%	3.92	0.22%	1.61
Canada	-0.02%	-0.08	0.46%	2.30	0.48%	3.04
China	-0.54%	-2.25	0.14%	0.63	0.68%	4.98
India	-0.34%	-1.05	0.98%	3.77	1.32%	3.44
Japan	0.07%	0.51	0.29%	2.16	0.22%	1.30
UK	-0.29%	-2.35	0.26%	3.82	0.54%	3.68
US	0.05%	0.45	0.16%	2.26	0.11%	1.14

6.6. Gap of one month between the formation and holding period

The gap of one month between the formation and holding period also attracts attention in the literature concerning industry momentum profitability. Grundy and Martin (2001) do not find statistically significant returns when a gap of one-month is allowed between the formation and holding period. However, these not significant returns turned to positive returns when the one-month gap was removed between the formation and holding period. Swinkels (2002), among others, also notes the importance of a one-month gap between the formation and holding period in industry momentum profitability. On the contrary, Du and Denning (2005) assert that a one-month gap does not make any significant difference to the industry momentum profitability. The current study investigates the issue of whether a one-month or zero-month gap can significantly change momentum returns using the country data discussed above.

The results presented in Table 6-8 do not show a significant difference for the stock industry momentum and the 52-week industry momentum when a one-month gap is or is not included. The returns marginally change when a one-month gap is changed to a zero-month gap. The most notable difference is seen in the Chinese stock market where the industry momentum return decreases by more than 0.18% when no gap of a month is allowed between the formation and holding period. The statistical reliability is also poor for the US stock market when no gap of a month is allowed when calculating 52-week industry momentum returns. Overall, the results do not suggest a significant difference in returns when a one-month gap is allowed between the formation and holding period but there are country differences. This suggests that the first month after the formation period is not the sole contributor to industry momentum profitability.

Table 6-8: Momentum profitability with a gap and no gap of one month

	Industry momentum returns				52-week industry momentum returns			
	0 month gap		1 month gap		0 month gap		1 month gap	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Australia	1.23%	3.27	1.18%	3.30	0.97%	3.33	0.84%	2.95
Canada	0.60%	3.96	0.61%	4.01	0.51%	2.82	0.49%	2.82
China	0.76%	3.74	0.94%	4.88	0.89%	4.86	0.93%	5.28
India	1.65%	4.89	1.60%	4.68	0.94%	2.76	0.87%	2.61
Japan	0.06%	0.28	0.04%	0.19	0.07%	0.38	0.09%	0.47
UK	0.40%	3.33	0.38%	3.02	0.31%	2.18	0.30%	2.10
US	0.25%	2.39	0.32%	3.24	0.15%	1.60	0.19%	1.93

6.7. Momentum returns comparison

Table 6-9 presents a comparison of the momentum returns using different investment strategies, highlighting which momentum strategy is comparatively better in terms of investing. Returns from the 52-week individual stock momentum are higher than the 52-week industry momentum returns for five out of seven countries, suggesting an inferior performance of the 52-week industry momentum returns compared to the 52-week individual stock momentum returns. Similarly, industry momentum returns dominate the 52-week industry momentum returns. All the country returns, except Japan, are higher than the 52-week industry momentum returns. Finally, out of all four strategies tested, individual stock momentum generates the most impressive returns.

Table 6-9: Comparison of momentum returns

	52-week industry		52-week stock		Industry momentum		Stock momentum	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Australia	0.84%	2.95	1.20%	2.52	1.18%	3.30	1.50%	3.75
Canada	0.49%	2.82	1.67%	3.75	0.61%	4.01	1.36%	4.48
China	0.93%	5.28	0.89%	3.16	0.94%	4.88	0.80%	2.92
India	0.87%	2.61	1.18%	2.83	1.60%	4.68	1.47%	3.60
Japan	0.09%	0.47	0.04%	0.16	0.04%	0.19	0.19%	0.75
UK	0.30%	2.10	0.50%	2.71	0.38%	3.02	0.50%	3.73
US	0.19%	1.93	0.28%	1.99	0.32%	3.24	0.46%	3.38

The above analysis suggests that the individual stock momentum return is superior to other momentum strategies available. Nijman et al. (2004) also arrive at the same conclusion on testing the industry momentum strategy in the European market. The significant positive profits arising from other investment strategies also supports rejection of the presence of data-snooping, as returns are significantly profitable in almost all markets except Japan. This study provides an out-of-sample test for the different momentum strategies, as the database used for this research has not been used extensively before to test either 52-week industry or industry momentum strategies for a number of stock markets. Swinkels (2002) uses Datastream industry indices to check industry momentum returns in an international context, emphasising that the industry returns, after aggregating stock returns, may provide a better picture for industry momentum returns.

Chapter 7

FINDINGS: 52-WEEK HIGH MOMENTUM RETURNS

Analysis

The analysis of the 52-week high momentum return is based on value-weighted returns unless otherwise stated. The value-weighted approach substantially controls observations for some specific problems that are more pronounced in small capitalisation stocks, e.g., outliers, incorrect data recording etc. The whole sample is divided into three portfolios where the top 33% belong to Winner stocks and the bottom 33% to Loser stocks. All tests include a one-month gap between formation and holding period.

7.1. Data mining

7.1.1. 52-week high momentum profitability

The initial results from Table 7-1 indicate that the 52-week high momentum return is profitable on a global basis. The country-neutral average monthly return is 0.34% (t-stat 2.81) using the BHAR method, which is statistically significant at 1% level. The highest 52-week high momentum return is seen in the Bangladesh stock market with an average monthly return of 4.39% and the lowest return is observed in the Venezuela market with an average monthly holding period return of -2.37%.

Table 7-1: 52-week high momentum returns

[**Table 7-1** is presented at the end of this chapter in Appendix- Page no. **195**]

The results obtained for this 52-week high momentum return are low compared to those documented by George and Hwang (2004) and Marshall and Cahan (2005) in the US and Australian markets respectively. In the US market, George and Hwang (2004) report a 52-week high momentum monthly return of 1.23% (excluding January returns), whereas Marshall and Cahan (2005) report a monthly return of 2.14% for the Australian stock market (using only approved securities). The big difference between the results documented in the previous studies and this study are attributable to two reasons:

(i) George and Hwang (2004) report strong dominance of 52-week high momentum results when the January effect is excluded. Similarly, Marshall and Cahan (2005) report profitable 52-week high momentum only for the stocks which are approved for short-selling by the Australian stock exchange. This current study, however, does not consider returns excluding January and the sample includes all the stocks listed in the stock exchange irrespective of whether or not the Loser portfolio stocks are approved for short-selling by the stock exchange.

(ii) The two previous studies of the US and Australian markets use an equal-weighted approach to calculate portfolio returns. The current study uses a value-weighted approach to calculate momentum returns as it provides a superior measure of returns as discussed above.

The 52-week momentum return also fails to generate a high return compared to a traditional momentum return as documented by Jegadeesh and Titman (1993), using the same formation/ holding period. Table 7-2 shows the average monthly return of traditional momentum strategies using three portfolios. The value-weighted BHAR approach is 0.52% compared to this study's 52-week high momentum returns of 0.34%. The low return of the 52-week high momentum does not support the hypothesis that 52-week high momentum return generates higher momentum returns than those of the Jegadeesh and Titman (1993) approach on a country-neutral global basis. The results also show negative Winner portfolio returns for 52-week high momentum against the expected positive returns. The major contribution to the 52-week momentum return arise primarily through the short-selling of the Loser portfolio stocks. Again, this observation differs from the result of George and Hwang (2004) and Marshall and Cahan (2005) where the Loser portfolio is not noted as the sole contributor to the 52-week momentum returns.

Table 7-2: Country-neutral returns showing Loser and Winner portfolio returns separately using BHAR method

12 x 6 months, Value-weighted returns, 1-month gap, 3 portfolios, US dollar

	Loser (L)	**t-stat**	**Winner (W)**	**t-stat**	**W - L**	**t-stat**
J&T Momentum	-0.41%	-4.56	0.11%	1.25	0.52%	4.39
52-week returns	-0.37%	-4.30	-0.03%	-0.29	0.34%	2.81

7.1.2. Using different holding periods

George and Hwang (2004) and Marshall and Cahan (2005) primarily rely on a 6-month holding period to illustrate the superiority of the 52-week high momentum return. However, different holding period returns may be calculated to check if the 52-week high momentum return is consistent over differing periods or whether the profit is only present for a specific holding period. Momentum returns for various holding periods can be computed and 3, 9, 12, 24 and 36 months are tested.

Table 7-3: 52-week profitability with different holding periods

[**Table 7-3** is presented at the end of this chapter in Appendix- Page no. **196**]

The results in Table 7-3 exclude Peru, Russia and Venezuela as they report significantly high volatility in returns which may distort a country-neutral 52-week momentum return. The results indicate a profitable 52-week high momentum strategy up to the first 12 months of a holding period followed by a gradual decline with non-statistically significant returns thereafter. These findings are similar to the pattern seen in the traditional momentum returns of Jegadeesh and Titman (1993) who also report significant momentum profits only during the first 12 months of a holding period. The average 52-week momentum return decreases from 0.47% (3-month holding period) to 0.23% (12-month holding period). The results for 24-month and 36-month holding periods do not indicate a profitable investment strategy.

7.1.3. Using alternative formation/holding periods

George and Hwang (2004) base the selection of stocks for computing the 52-week high momentum return on the basis of nearness to the last 52-weeks' high/low stock price. Their algorithm may represent an example of data-snooping, so alternative time frames, considering nearness to last 24 months (104 weeks) and 36 months (156 weeks) high/low price are investigated. The returns on equities in Peru, Russia and Venezuela are again excluded from this analysis to avoid any bias arising from those relatively much more volatile stock returns.

Table 7-4: 52-week momentum returns with different combination of formation/holding period (all country-neutral portfolios)

Value-weighted returns, 1-month gap, 3 portfolios, US dollar

	Loser (L)	**t-stat**	**Winner (W)**	**t-stat**	**W - L**	**t-stat**
Holding period	24 months formation period					
3 months	0.05%	1.40	-0.13%	-3.28	-0.18%	-3.78
6 months	0.07%	0.90	-0.23%	-3.51	-0.30%	-3.78
12 months	0.04%	0.25	-0.49%	-3.35	-0.53%	-3.41
24 months	-0.13%	-0.28	-1.34%	-2.96	-1.21%	-3.64
Holding period	36 months formation period					
3 months	0.06%	1.35	-0.11%	-3.61	-0.17%	-3.96
6 months	0.08%	0.85	-0.21%	-3.02	-0.29%	-3.11
12 months	0.06%	0.26	-0.47%	-2.78	-0.53%	-2.82
24 months	-0.23%	-0.39	-1.29%	-2.61	-1.06%	-2.65
36 months	-1.61%	-1.07	-2.56%	-2.05	-0.95%	-1.54

The country-neutral momentum returns for various combinations of formation and holding periods are reported in Table 7-4. The results indicate that a momentum strategy based on the nearness to 24- or 36-month high is not a profitable investment strategy. All returns are negative and show reversals instead of momentum. The country-neutral Loser portfolios show positive returns in the short-term instead of negative returns. The Winner portfolios are negative for all combinations of formation-holding periods.

The results from Table 7-4 confirm that 52-week high momentum return is present only within a one-year holding period. Further, a longer period of stock price nearness, i.e., 24 months or 36 months does not show any evidence of momentum profitability. However, the results from Table 7-2 do not indicate 52-

week high momentum generating higher returns compared to traditional momentum strategies as documented by Jegadeesh and Titman (1993).

7.2. Portfolio construction approach

7.2.1. CAR or BHAR?

The results reported earlier in this study are calculated using the BHAR method, which is consistent with the George and Hwang (2004) and Marshall and Cahan (2005) studies of 52-week high momentum. As discussed above, the method of calculating returns may be important in terms of results, and the choice of either BHAR or CAR methods may substantially impact on the computed return.

Research regarding traditional momentum returns supports as well as rejects the impact of different return metrics. Conrad and Kaul (1993) maintain that contrarian returns documented by DeBondt and Thaler (1985) disappear when the manner of calculating returns changes from CAR to BHAR. Loughran and Ritter (1996) fail to detect any difference between the approaches, which is similar to the momentum studies of Jegadeesh and Titman (1993) and Rouwenhorst (1998) who find little evidence of significant differences when either BHAR or CAR are used. However, Demir et al. (2004) report contrary evidence as the momentum returns in the Australian stock market are lower under CAR method compared to the BHAR method.

Table 7-5: 52-week momentum returns using BHAR and CAR

[**Table 7-5** is presented at the end of this chapter in Appendix- Page no. **198**]

The 52-week high momentum returns are re-calculated using the CAR approach, instead of the BHAR approach and the results are presented in Table 7-5. The numbers suggesting a slight increase in average monthly returns from 0.34% (BHAR) to 0.38% (CAR) arise due to higher negative Loser stock returns under the CAR method. The returns under both methods are highly statistically significant. The results indicate that the 52-week high momentum returns do not change significantly when the method of calculating return changes from BHAR to CAR on a country-neutral global basis. The apparent method-based bias highlighted by Conrad and Kaul (1993) does not apply in this study of 52-week high momentum returns.

7.2.2. Equal-weighted or value-weighted?

The previous studies of the 52-week high momentum returns calculate equal-weighted portfolio returns, i.e., all the stocks within the portfolio are given the same weight. Another popular approach is to allocate weighting to individual stocks pro rata to their market capitalisation. The stocks with higher market capitalisation are allocated a greater weighting, and vice-versa. This approach is particularly effective in controlling various anomalies that arise in small-cap stocks as most of the anomalies are present in small-cap stocks. As this study investigates 52-week high momentum across 54 markets, including developed and impacts developing markets, the impacts of the more pronounced developing market fluctuations are also reduced by using a value-weighted approach.

In this section, the returns are calculated using both equal-weighted and value-weighted methods to investigate differences in returns arising from the change of metric. The results for the equal- and value-weighted returns exclude Brazil, Peru, Russia and Venezuela.

Table 7-6: 52-week momentum returns (equal- versus value-weighted)
[**Table 7-6** is presented at the end of this chapter in Appendix- Page no. **199**]

The results in Table 7-6 exhibit a non-statistically significant 52-week momentum return when an equal-weighted portfolio approach is used. The primary reason for the low 52-week high momentum return is attributable to the high positive average monthly return in the Loser portfolio (0.49%). The country-neutral Loser portfolio return, under a value-weighted method is -0.39%, suggesting that the small-size stocks in the Loser portfolio reverse during the holding period while the high market cap stocks in the Loser portfolio follow the momentum and further decline during the holding period. The change in the country-neutral Loser portfolio return from -0.39% (under value-weighted) to +0.49% (under equal-weighted) indicates a significant number of high positive Loser stock returns.

The country-neutral Winner portfolio also exhibits high positive and statistically significant returns under equal-weighted approach with an average monthly return of 0.55% compared to a non-statistically significant 0.08% under value-weighted approach. This suggests that the small-cap stocks under the Winner portfolio generate higher returns than the large-cap stocks. The country-neutral self-financing portfolio (Winner-Loser) portfolio is also not statistically significant with an average monthly return of 0.07% under an equal-weighted method, largely due to positive returns from the country-neutral Loser portfolio.

7.2.3. Number of stocks in a portfolio

George and Hwang (2004) and Marshall and Cahan (2005) divide their samples into three portfolios (Winner, Middle, Loser), calculating 52-week high momentum returns for each. The self-financing momentum profit is calculated by deducting the return for the bottom 30% of stocks (Loser portfolio) from that of the top 30% stocks (Winner portfolio). This method contrasts with the traditional momentum return approach, which typically divides the whole sample into five or 10 portfolios when calculating returns. This analysis recalculates the 52-week high momentum return using two, five and 10 portfolios, investigating how the returns change as the number of stocks decrease in a portfolio.

The results presented in Table 7-7 need to be interpreted carefully, especially for small countries having a smaller number of stock market listings. When the stock market performs well during a period a high number of stocks trade at their 52-week high price. For example, if there are 100 stocks and there are five portfolios, then each portfolio should have 20 stocks. However, if 50 stocks are trading at 52-week high price, then not all of these 50 stocks can be allocated to the Winner portfolio as only 20 stocks are included in the Winner portfolio. Therefore, dividing the whole sample into five or 10 portfolios may be a problem in countries with a smaller number of listed securities in periods when most of the stocks are trading at a 52-week high/low price.

Table 7-7: 52-week momentum returns (number of stocks in a portfolio)

[**Table 7-7** is presented at the end of this chapter in Appendix- Page no. **200**]

The results suggest a decline in 52-week momentum profitability from 0.30% for two portfolios to 0.15% for 10 portfolios. The statistical significance also declines when the number of portfolios is increased to 10. However, this observation is not noted when Brazil, Peru, Russia and Venezuela are excluded from the sample. The 52-week high momentum return remains the same at 0.40% for two and 10 portfolios. Similarly the results, excluding Brazil, Peru, Russia and Venezuela, do not change substantially on a country-neutral basis as the number of portfolios is increased when calculating the 52-week high momentum return.

7.2.4. Size-sorted portfolios

Marshall and Cahan (2005) investigate size effects on 52-week high momentum returns in the Australian stock market, dividing the whole sample into four sub-samples on the basis of market capitalisation. They report a higher profitability as well as higher volatility in the smaller capitalisation value sample. This current study divides the whole sample into three sub-samples on the basis of their respective market capitalisation in the last month of the formation period to provide a country-neutral size-neutral comparison. The stocks with the highest market capitalisation are allocated to a large-cap portfolio, whereas the stocks with the smallest market capitalisation are allocated to a small-cap portfolio. The 52-week high momentum return for each of the size-sorted samples is value-weighted to control potential problems arising from very small-cap stocks.

Table 7-8: 52-week momentum returns (size-sorted portfolio)

[**Table 7-8** is presented at the end of this chapter in Appendix- Page no. **201**]

The results reported in Table 7-8 exhibit a low 52-week high country-neutral, size-neutral momentum profit when the small-cap sample is chosen and a comparatively high profit when the large-cap sample is selected. This is contrary to the findings of the Australian study of Marshall and Cahan (2005) who report high profit in the small-cap stocks and a gradual decline of returns as stock size increases. The country-neutral Winner and Loser portfolio returns are also presented below, showing the change in Winner and Loser portfolio returns as the portfolio size increases.

Table 7-9: 52-week country-neutral returns showing Loser and Winner returns separately

12x6 months, Value-Weighted, 3 portfolios within each sub-sample, 1-month gap, US dollar, BHAR

	Loser (L)	t-stat	Winner (W)	t-stat	W - L	t-stat
Small Size	0.59%	4.50	0.75%	3.05	0.16%	0.59
Medium Size	-0.12%	-1.08	0.17%	1.78	0.29%	2.08
Large Size	-0.40%	-4.12	0.01%	-0.04	0.39%	3.16

The results in Table 7-9 show positive returns for both the Loser and Winner portfolios when the small-cap portfolio is chosen. The positive profit from the Loser portfolio is primarily responsible for a low 52-week high momentum return within the small-cap portfolio. The result for the large-cap portfolio, on the other hand, suggests that both the Loser and Winner portfolios generate negative returns. This means that low market capitalisation Loser stocks follow a reversal pattern during the holding period. These findings are consistent with the results presented previously in the discussion covering the choice of equal- versus value-weighted portfolios. The 52-week high momentum returns under an equal-weighted approach are lower than those under a value-weighted approach, resulting from positive Loser portfolio stock returns. The returns of the Loser and Winner portfolios are negative when a small-cap portfolio is chosen but the returns for both portfolios change to positive when the portfolio size increases to large.

7.3. 52-week return reversals

Jegadeesh and Titman (1993) document profitable momentum strategies that persist for the first 12 months of the holding period. After this period, the momentum return becomes negative. In support of this observation, Barberis et al. (1998) and Hong and Stein (1999) propose a behavioural theory where the short-term momentum is expected to be followed by a long-term reversal. However, George and Hwang (2004) show that the existing behavioural theories do not work with a 52-week high momentum strategy as the return does not reverse after a 12 month holding period. To support their results, George and Hwang (2004) leave a gap of 12 to 48 months between formation and holding period, still finding a positive 52-week high momentum return.

A 12 to 24 month gap between formation and holding period is investigated using the 54-country dataset. If the 52-week momentum returns are positive after allowing a 12 or 24 month gap, then behavioural theory is not a likely explanation for momentum returns, as the momentum return does not reverse even after allowing a gap of 12 or 24 months.

Table 7-10: 52-week momentum returns (return reversals)

[**Table 7-10** is presented at the end of this chapter in Appendix- Page no. **202**]

The results, presented in Table 7-10, differ from the findings of George and Hwang (2004) as the 52-week high momentum return is negative when either a 12 or 24 month gap is allowed between formation and holding period. The country-neutral Loser and Winner portfolio return reported in Table 7-11 shows reversals against expected momentum during the holding period. Overall, the results do not align with the findings of George and Hwang (2004), suggesting that the reversal pattern, documented previously in the traditional momentum strategies, does seem to be present in the 52-week high momentum.

Table 7-11: 52-week country-neutral returns showing Loser and Winner portfolio returns separately

12x6 months, Value-Weighted, 3 portfolios, US dollar, BHAR

	Loser (L)	t-stat	Winner (W)	t-stat	W - L	t-stat
With a gap of:						
12 months	0.10%	1.14	-0.30%	-4.08	-0.40%	-3.94
24 months	0.07%	0.80	-0.19%	-1.84	-0.26%	-2.09

7.4. International investing

The research findings of this study fill a gap in the extant literature, documenting the differences when returns are calculated in local currency as well as foreign currency. The increasing globalisation of stock markets makes it possible for investors to trade in the share market of more than one country.

International investing potentially alters the 52-week high momentum return to an investor when any exchange rate effect is brought to account. For example, if the currency of the foreign country appreciates with respect to the domestic currency of the investor, then the total returns will be higher when stock prices are converted back at a higher price and vice-versa. The US dollar (USD) is chosen as the base currency to reflect a total return movement.

Table 7-12: 52-week momentum returns (local versus US dollar)
[**Table 7-12** is presented at the end of this chapter in Appendix- Page no. **203**]

The results reported in Table 7-12 do not indicate a substantial difference in return compared to local currency for 52-week high momentum return. The country-neutral 52-week high average monthly momentum return under local currency is 0.39% compared to 0.34% using USD. These results show an increase in the 52-week high momentum return for 27 countries when USD is used, and a decrease in returns for the other 27 countries in the sample. Significant changes in return are noticed in Brazil, Chile, Lithuania, Turkey and Venezuela, possibly arising from their respective volatile foreign exchange rates.

APPENDIX

TABLE 7-1: 52-week high momentum returns

12x 6 months, Value-weighted returns, 1-month gap, 3 portfolios, US dollar

Country	Loser (L)	t-stat	Winner (W)	t-stat	W - L	t-stat
Argentina	0.08%	0.13	-0.01%	-0.04	-0.09%	-0.12
Australia	-0.71%	-3.40	0.04%	0.48	0.75%	3.05
Austria	-0.36%	-1.28	-0.45%	-2.21	-0.09%	-0.25
Bangladesh	-1.13%	-3.14	3.26%	1.62	4.39%	2.12
Belgium	-0.33%	-2.00	0.15%	1.79	0.48%	2.51
Brazil	-1.34%	-2.03	-1.64%	-2.38	-0.30%	-0.42
Canada	-0.75%	-3.25	0.18%	3.20	0.94%	3.45
Chile	0.01%	0.06	0.06%	0.29	0.05%	0.17
China	-0.34%	-1.39	0.49%	1.71	0.83%	3.09
Colombia	-0.04%	-0.17	0.17%	1.17	0.21%	0.81
Cyprus	-1.47%	-2.79	0.08%	0.80	1.55%	2.81
Czech Republic	-1.00%	-3.10	0.23%	1.07	1.23%	3.08
Denmark	-0.52%	-3.11	0.12%	0.91	0.64%	2.75
Egypt	-2.16%	-3.00	-0.88%	-2.34	1.28%	2.12
Finland	-0.74%	-1.54	0.51%	2.10	1.25%	2.07
France	-0.50%	-3.53	0.20%	2.78	0.69%	3.55
Germany	-0.50%	-3.48	-0.03%	-0.37	0.46%	2.60
Greece	-1.32%	-3.23	-0.04%	-0.12	1.29%	3.23
Hong Kong	-0.34%	-1.47	0.09%	1.27	0.43%	1.90
Hungary	-0.41%	-0.92	-0.12%	-0.87	0.29%	0.57
India	-0.46%	-1.12	0.25%	2.03	0.71%	1.60
Indonesia	0.08%	0.18	-0.06%	-0.28	-0.14%	-0.24
Ireland	0.39%	0.72	0.27%	2.44	-0.12%	-0.18
Israel	-1.26%	-4.83	-1.30%	-3.21	-0.04%	-0.10
Italy	-0.38%	-2.31	0.36%	3.39	0.73%	3.00
Japan	0.05%	0.39	0.14%	1.63	0.09%	0.49
Kenya	0.81%	1.20	1.71%	6.99	0.90%	1.22
Lithuania	-0.35%	-0.69	-0.30%	-0.94	0.05%	0.07
Malaysia	-0.05%	-0.21	0.15%	1.64	0.21%	0.81
Mexico	-1.12%	-2.46	-0.36%	-1.57	0.76%	1.84
Morocco	-0.76%	-3.82	0.32%	2.92	1.07%	4.02
Netherlands	-0.20%	-1.12	0.10%	1.05	0.30%	1.42
New Zealand	-0.35%	-1.66	0.09%	0.67	0.44%	1.52
Norway	-0.42%	-1.56	-0.24%	-1.85	0.18%	0.60
Pakistan	-0.37%	-1.12	-0.28%	-1.48	0.10%	0.23
Peru	-0.90%	-1.39	-1.68%	-3.12	-0.79%	-1.39
Philippines	0.60%	1.64	-0.33%	-1.87	-0.93%	-2.31
Poland	-0.77%	-2.52	0.07%	0.32	0.83%	2.06
Portugal	-0.14%	-0.66	0.09%	0.66	0.23%	0.82
Romania	-1.39%	-1.68	-0.95%	-1.82	0.44%	0.51
Russian Federation	-0.18%	-0.29	-1.90%	-2.08	-1.73%	-1.82
Singapore	0.19%	0.73	-0.18%	-1.10	-0.36%	-1.23
South Africa	-0.43%	-1.84	0.09%	0.78	0.51%	1.78
South Korea	-0.13%	-0.34	-0.20%	-1.39	-0.07%	-0.14
Spain	-0.08%	-0.37	0.15%	1.01	0.22%	0.90
Sri Lanka	0.48%	2.22	-0.19%	-1.25	-0.67%	-2.59
Sweden	0.33%	0.87	0.00%	0.00	-0.33%	-0.73
Switzerland	-0.44%	-2.61	0.24%	1.88	0.68%	3.55
Taiwan	-0.08%	-0.34	-0.21%	-1.85	-0.13%	-0.38
Thailand	-0.01%	-0.02	0.35%	1.64	0.36%	0.68
Turkey	-0.13%	-0.20	0.21%	0.59	0.34%	0.38
UK	-0.40%	-2.41	0.07%	1.44	0.47%	2.39
US	-0.18%	-1.48	0.09%	1.78	0.27%	1.81
Venezuela	1.81%	1.11	-0.55%	-1.15	-2.37%	-1.47
Country-Neutral 52-week return	**-0.37%**	-4.30	**-0.03%**	-0.29	**0.34%**	2.81

TABLE 7-3: 52-week profitability with different holding periods
12 months formation period, Value-Weighted, 3 portfolios, 1-month gap, US dollar, BHAR

	3 months		9 months		12 months		24 months		36 months	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	0.04%	0.05	-0.08%	-0.12	-0.39%	-0.60	-0.66%	-1.48	-1.03%	-2.40
Australia	0.96%	3.12	0.57%	2.67	0.34%	1.82	-0.08%	-0.70	-0.26%	-2.38
Austria	-0.23%	-0.50	0.12%	0.42	-0.02%	-0.09	-0.55%	-2.80	-0.04%	-0.48
Bangladesh	4.16%	1.81	4.09%	2.51	3.19%	3.00	1.50%	4.13	0.73%	2.89
Belgium	0.51%	2.17	0.43%	2.87	0.35%	2.57	0.23%	1.85	0.09%	0.88
Brazil	-0.54%	-0.69	-0.02%	-0.02	0.10%	0.18	-0.07%	-0.19	-0.57%	-1.85
Canada	1.15%	3.57	0.75%	3.24	0.51%	2.47	0.26%	2.04	0.21%	1.99
Chile	0.03%	0.08	-0.19%	-0.77	-0.29%	-1.36	-0.33%	-2.03	-0.18%	-1.68
China	0.97%	2.06	0.72%	3.70	0.45%	2.99	-0.21%	-1.34	-0.23%	-1.95
Colombia	0.34%	0.83	-0.14%	-0.65	-0.38%	-1.90	-0.08%	-1.07	-0.70%	-3.77
Cyprus	1.30%	1.63	1.93%	4.47	1.95%	4.81	2.07%	6.59	1.59%	5.55
Czech Republic	1.17%	2.33	1.40%	4.91	1.36%	6.61	0.63%	3.89	-0.06%	-0.56
Denmark	0.70%	2.61	0.54%	2.79	0.43%	2.56	0.40%	5.13	0.18%	3.75
Egypt	0.96%	1.42	0.85%	1.75	0.59%	1.40	-0.53%	-1.73	-1.79%	-3.84
Finland	1.20%	1.62	1.25%	2.30	1.09%	2.12	1.01%	3.21	0.50%	2.08
France	0.84%	3.42	0.60%	3.70	0.43%	2.99	0.14%	1.76	0.06%	1.15
Germany	0.51%	2.46	0.47%	3.00	0.42%	2.94	0.12%	1.34	0.06%	0.70
Greece	0.99%	1.77	0.97%	2.98	0.42%	1.32	-0.69%	-1.23	-1.19%	-1.94
Hong Kong	0.38%	1.50	0.42%	2.30	0.39%	2.46	0.24%	2.24	0.20%	1.93
Hungary	0.39%	0.58	0.29%	0.66	0.26%	0.62	0.45%	1.19	0.65%	1.46
India	0.55%	1.00	0.60%	1.93	0.44%	1.94	0.39%	3.13	-0.09%	-1.46
Indonesia	-0.84%	-0.90	-0.16%	-0.27	-0.20%	-0.35	-0.06%	-0.20	0.07%	0.54
Ireland	0.73%	1.12	-0.54%	-0.94	-0.81%	-1.46	-1.28%	-2.10	-0.14%	-0.50
Israel	-0.13%	-0.24	-0.12%	-0.34	-0.27%	-0.85	-0.12%	-0.96	-0.25%	-2.74
Italy	0.75%	2.93	0.82%	3.59	0.83%	3.78	0.43%	2.69	0.23%	1.80

P.T.O.

	3 months		9 months		12 months		24 months		36 months	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Japan	0.00%	0.00	0.13%	0.90	0.08%	0.65	0.12%	1.61	0.12%	1.78
Kenya	1.53%	2.11	0.10%	0.13	-0.07%	-0.11	-0.59%	-1.35	-1.99%	-2.88
Lithuania	0.51%	0.67	-0.42%	-0.61	-0.84%	-1.52	-0.56%	-1.31	-0.94%	-1.25
Malaysia	-0.02%	-0.06	0.01%	0.03	-0.23%	-0.91	-0.38%	-1.98	-0.23%	-1.79
Mexico	1.14%	2.40	0.74%	2.12	0.83%	3.14	0.88%	5.62	0.64%	5.04
Morocco	1.17%	3.38	0.89%	4.36	0.70%	4.82	0.04%	0.23	-0.37%	-1.49
Netherlands	0.42%	1.73	0.17%	0.96	0.09%	0.59	-0.17%	-1.70	-0.08%	-1.08
New Zealand	0.42%	1.13	0.54%	2.45	0.52%	3.35	0.32%	3.44	0.07%	0.95
Norway	0.49%	1.54	-0.10%	-0.32	-0.25%	-0.85	-0.16%	-0.97	-0.09%	-0.55
Pakistan	-0.25%	-0.51	0.24%	0.78	0.31%	1.27	0.10%	0.64	0.01%	0.07
Philippines	-1.19%	-2.27	-0.95%	-2.45	-0.88%	-2.82	-0.89%	-4.17	-0.75%	-4.31
Poland	1.00%	2.00	0.67%	1.81	0.21%	0.52	-0.40%	-1.82	-0.33%	-3.29
Portugal	0.22%	0.61	0.16%	0.74	0.05%	0.23	-0.18%	-1.31	-0.17%	-2.07
Romania	-0.09%	-0.08	0.70%	1.10	0.72%	1.53	0.74%	1.21	-0.26%	-0.63
Singapore	-0.43%	-1.26	-0.38%	-1.36	-0.45%	-1.79	-0.18%	-1.44	-0.38%	-3.41
South Africa	0.66%	2.15	0.34%	1.40	0.15%	0.67	-0.11%	-0.58	-0.35%	-1.94
South Korea	-0.04%	-0.06	0.06%	0.16	-0.08%	-0.28	-0.03%	-0.15	-0.39%	-1.93
Spain	0.16%	0.51	0.21%	0.99	0.16%	0.87	-0.01%	-0.07	-0.05%	-0.55
Sri Lanka	-0.37%	-1.36	-0.60%	-2.57	-0.70%	-2.82	-0.95%	-3.66	-0.91%	-3.48
Sweden	-0.04%	-0.09	-0.40%	-0.94	-0.41%	-1.10	-0.29%	-2.16	-0.33%	-3.37
Switzerland	0.67%	2.96	0.65%	4.14	0.51%	3.79	0.24%	3.07	0.23%	4.32
Taiwan	-0.24%	-0.57	-0.04%	-0.15	-0.13%	-0.71	0.02%	0.31	-0.04%	-0.78
Thailand	0.28%	0.42	0.27%	0.51	0.20%	0.40	0.41%	1.55	0.39%	2.38
Turkey	0.47%	0.58	-0.01%	-0.01	-0.43%	-0.64	-0.96%	-2.32	-1.25%	-3.09
UK	0.50%	2.25	0.44%	2.74	0.35%	2.62	0.04%	0.46	-0.07%	-1.31
US	0.25%	1.34	0.24%	1.88	0.14%	1.23	-0.10%	-1.20	-0.28%	-3.53
Country-Neutral 52-week return excluding Peru, Russia & Venezuela	**0.47%**	**4.33**	**0.38%**	**3.60**	**0.23%**	**2.40**	**0.00%**	**0.04**	**-0.19%**	**-2.26**

TABLE 7-5: 52-week momentum returns using BHAR and CAR

12x6 months, Value-Weighted, 3 portfolios, 1-month gap, US dollar

	BHAR		CAR	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.09%	-0.12	0.40%	0.68
Australia	0.75%	3.05	0.85%	3.15
Austria	-0.09%	-0.25	-0.02%	-0.05
Bangladesh	4.39%	2.12	3.34%	2.22
Belgium	0.48%	2.51	0.38%	2.01
Brazil	-0.30%	-0.42	-0.19%	-0.27
Canada	0.94%	3.45	1.07%	3.78
Chile	0.05%	0.17	0.07%	0.27
China	0.83%	3.09	0.76%	3.35
Colombia	0.21%	0.81	0.15%	0.57
Cyprus	1.55%	2.81	1.68%	3.18
Czech Republic	1.23%	3.08	1.29%	3.54
Denmark	0.64%	2.75	0.67%	2.85
Egypt	1.28%	2.12	0.82%	1.47
Finland	1.25%	2.07	1.26%	2.17
France	0.69%	3.55	0.70%	3.81
Germany	0.46%	2.60	0.48%	2.80
Greece	1.29%	3.23	1.14%	3.08
Hong Kong	0.43%	1.90	0.42%	1.91
Hungary	0.29%	0.57	0.35%	0.73
India	0.71%	1.60	0.68%	1.61
Indonesia	-0.14%	-0.24	-0.14%	-0.24
Ireland	-0.12%	-0.18	0.08%	0.12
Israel	-0.04%	-0.10	-0.19%	-0.39
Italy	0.73%	3.00	0.68%	3.27
Japan	0.09%	0.49	0.09%	0.54
Kenya	0.90%	1.22	1.19%	1.97
Lithuania	0.05%	0.07	0.28%	0.60
Malaysia	0.21%	0.81	0.13%	0.48
Mexico	0.76%	1.84	0.98%	2.57
Morocco	1.07%	4.02	0.99%	3.92
Netherlands	0.30%	1.42	0.33%	1.65
New Zealand	0.44%	1.52	0.38%	1.27
Norway	0.18%	0.60	0.37%	1.30
Pakistan	0.10%	0.23	0.21%	0.55
Peru	-0.79%	-1.39	-0.75%	-1.24
Philippines	-0.93%	-2.31	-0.83%	-2.12
Poland	0.83%	2.06	1.00%	2.63
Portugal	0.23%	0.82	0.28%	1.04
Romania	0.44%	0.51	0.23%	0.27
Russian Federation	-1.73%	-1.82	-1.39%	-1.75
Singapore	-0.36%	-1.23	-0.29%	-1.14
South Africa	0.51%	1.78	0.57%	2.05
South Korea	-0.07%	-0.14	0.07%	0.18
Spain	0.22%	0.90	0.32%	1.24
Sri Lanka	-0.67%	-2.59	-0.49%	-2.05
Sweden	-0.33%	-0.73	-0.05%	-0.12
Switzerland	0.68%	3.55	0.72%	4.01
Taiwan	-0.13%	-0.38	-0.17%	-0.55
Thailand	0.36%	0.68	0.48%	1.07
Turkey	0.34%	0.38	0.01%	0.02
UK	0.47%	2.39	0.50%	2.71
US	0.27%	1.81	0.28%	1.99
Venezuela	-2.37%	-1.47	-1.83%	-1.46
Country-Neutral 52-week return	**0.34%**	2.81	**0.38%**	3.66

TABLE 7-6: 52-week momentum returns (equal- versus value- Weighted)

12x6 months, 3 portfolios, 1-month gap, US dollar, BHAR

Country	Loser	t-stat	Winner	t-stat	W - L	t-stat
Argentina	0.57%	0.81	0.87%	2.24	0.30%	0.57
Australia	1.54%	4.15	0.95%	6.95	-0.60%	-1.98
Austria	0.14%	0.28	-0.36%	-1.65	-0.50%	-1.15
Bangladesh	-0.12%	-0.22	3.12%	1.47	3.24%	1.44
Belgium	-0.05%	-0.22	0.62%	2.99	0.67%	3.49
Canada	2.13%	3.60	1.20%	4.08	-0.94%	-1.47
Chile	0.35%	1.21	0.66%	2.27	0.32%	1.17
China	0.04%	0.13	0.64%	1.92	0.60%	2.89
Colombia	0.58%	1.91	0.70%	1.38	0.11%	0.21
Cyprus	0.01%	0.01	-1.15%	-2.46	-1.16%	-2.01
Czech Republic	-0.25%	-0.64	-0.04%	-0.12	0.21%	0.68
Denmark	-0.09%	-0.31	0.45%	1.77	0.53%	1.86
Egypt	-0.71%	-0.74	-1.71%	-2.24	-0.99%	-1.86
Finland	-0.51%	-0.85	0.23%	0.36	0.73%	1.93
France	0.09%	0.45	0.49%	3.58	0.40%	2.07
Germany	-0.38%	-1.62	0.10%	0.64	0.47%	2.07
Greece	0.03%	0.02	1.32%	1.36	1.30%	2.87
Hong Kong	0.61%	1.50	0.44%	2.11	-0.17%	-0.54
Hungary	0.26%	0.42	-0.40%	-1.14	-0.66%	-1.18
India	2.03%	2.45	0.87%	2.29	-1.16%	-1.81
Indonesia	1.74%	2.40	0.21%	0.65	-1.53%	-2.51
Ireland	1.00%	1.59	0.69%	3.33	-0.31%	-0.53
Israel	0.27%	0.84	-0.32%	-1.33	-0.59%	-3.01
Italy	-0.16%	-0.88	0.58%	4.71	0.74%	3.99
Japan	0.44%	2.00	0.42%	3.21	-0.02%	-0.11
Kenya	1.58%	2.73	1.48%	4.98	-0.11%	-0.14
Lithuania	-0.24%	-0.58	-0.23%	-0.56	0.02%	0.02
Malaysia	0.45%	1.17	0.57%	2.31	0.12%	0.50
Mexico	-0.43%	-1.11	-0.63%	-1.86	-0.20%	-0.55
Morocco	0.01%	0.02	0.47%	2.00	0.46%	1.05
Netherlands	-0.07%	-0.27	0.41%	2.78	0.48%	1.98
New Zealand	0.43%	1.46	0.82%	3.56	0.39%	1.79
Norway	0.48%	1.02	0.28%	1.15	-0.20%	-0.42
Pakistan	1.06%	2.07	0.20%	0.48	-0.86%	-1.61
Philippines	1.88%	3.52	0.56%	1.64	-1.32%	-2.54
Poland	1.25%	1.39	1.51%	2.72	0.26%	0.55
Portugal	1.33%	1.62	4.07%	1.56	2.74%	1.23
Romania	-0.18%	-0.18	0.55%	0.71	0.73%	1.60
Singapore	0.28%	0.76	0.33%	1.35	0.05%	0.17
South Africa	0.50%	1.81	0.48%	2.93	-0.03%	-0.09
South Korea	0.83%	1.50	0.30%	1.16	-0.53%	-0.99
Spain	0.25%	0.87	0.47%	2.87	0.23%	0.83
Sri Lanka	1.41%	4.51	0.56%	1.73	-0.85%	-2.12
Sweden	0.46%	0.95	0.33%	1.89	-0.13%	-0.25
Switzerland	-0.39%	-2.00	0.26%	1.79	0.65%	3.61
Taiwan	0.19%	0.49	0.18%	0.84	-0.01%	-0.03
Thailand	0.86%	2.26	0.78%	2.59	-0.08%	-0.18
Turkey	1.30%	2.08	0.91%	2.14	-0.39%	-0.83
UK	-0.05%	-0.20	0.53%	2.92	0.58%	2.89
US	1.56%	4.68	1.92%	5.32	0.35%	0.77
Country Neutral 52-week return	**0.49%**	4.77	**0.55%**	4.43	**0.07%**	0.55
(using equal-weight)						
Country Neutral 52-week return	**-0.39%**	-4.92	**0.08%**	0.96	**0.47%**	4.40
(using value-weight)	above results excluding Brazil, Peru, Russia, Venezuela					

TABLE 7-7: 52-week momentum returns (number of stocks in a portfolio)

12x6 months, Value-Weighted, 1-month gap, US dollar, BHAR

	2 portfolios		5 portfolios		10 portfolios	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.12%	-0.21	-0.24%	-0.25	-0.95%	-0.66
Australia	0.39%	2.37	0.75%	2.44	0.51%	1.42
Austria	-0.15%	-0.40	-0.03%	-0.07	0.55%	1.09
Bangladesh	3.29%	2.10	4.08%	2.00	5.43%	1.90
Belgium	0.33%	2.70	0.78%	2.57	0.59%	1.47
Brazil	-0.14%	-0.25	-0.18%	-0.24	-0.83%	-0.91
Canada	0.72%	3.73	1.03%	3.11	0.61%	1.01
Chile	0.24%	1.10	0.05%	0.12	-0.14%	-0.28
China	0.55%	2.87	1.03%	3.06	1.10%	2.77
Colombia	0.13%	0.61	0.08%	0.21	0.06%	0.10
Cyprus	1.80%	4.46	0.85%	0.92	1.22%	0.93
Czech Republic	0.82%	2.68	1.44%	3.85	1.05%	2.19
Denmark	0.45%	2.87	0.63%	1.82	0.81%	1.77
Egypt	1.02%	2.30	1.33%	1.63	0.56%	0.58
Finland	1.22%	2.05	0.91%	1.40	0.90%	1.19
France	0.48%	3.34	0.81%	3.02	0.89%	2.77
Germany	0.38%	3.03	0.54%	2.35	0.71%	2.12
Greece	0.91%	2.53	1.83%	4.09	1.67%	2.91
Hong Kong	0.35%	2.14	0.67%	2.39	0.84%	1.87
Hungary	0.68%	1.65	0.37%	0.41	0.99%	0.65
India	0.68%	2.03	0.69%	1.21	0.61%	0.84
Indonesia	-0.11%	-0.29	-0.06%	-0.09	-0.81%	-0.62
Ireland	0.54%	1.39	-0.98%	-1.06	-0.59%	-0.62
Israel	-0.13%	-0.34	0.03%	0.07	0.30%	0.63
Italy	0.71%	3.41	0.97%	3.58	0.99%	2.93
Japan	0.09%	0.69	0.12%	0.55	0.24%	0.82
Kenya	1.01%	2.11	0.56%	0.56	0.22%	0.18
Lithuania	0.08%	0.12	0.12%	0.09	1.39%	1.00
Malaysia	0.13%	0.63	0.28%	0.89	0.47%	1.36
Mexico	0.60%	1.94	1.10%	2.41	0.61%	0.75
Morocco	0.80%	4.58	1.34%	4.07	0.26%	0.33
Netherlands	0.17%	0.98	0.46%	1.70	0.40%	1.13
New Zealand	0.39%	1.62	0.96%	2.67	0.99%	1.74
Norway	0.11%	0.42	0.11%	0.25	0.20%	0.27
Pakistan	0.11%	0.42	-0.06%	-0.09	-1.03%	-1.15
Peru	-0.31%	-0.76	-0.93%	-1.43	-2.69%	-2.94
Philippines	-0.72%	-2.36	-1.30%	-2.53	-1.90%	-2.37
Poland	0.67%	1.94	0.77%	1.32	0.15%	0.19
Portugal	0.16%	0.81	0.32%	0.60	-2.32%	-0.99
Romania	0.22%	0.28	1.04%	1.11	1.45%	1.46
Russian Federation	-1.30%	-1.55	-3.05%	-2.66	-5.52%	-4.92
Singapore	-0.19%	-0.75	-0.37%	-1.04	-0.46%	-0.94
South Africa	0.33%	1.62	0.48%	1.43	0.70%	1.95
South Korea	-0.24%	-0.61	0.29%	0.52	0.27%	0.41
Spain	0.15%	0.79	0.28%	0.95	0.30%	0.79
Sri Lanka	-0.29%	-1.72	-0.78%	-2.25	-1.10%	-2.51
Sweden	-0.21%	-0.69	-0.27%	-0.33	-0.12%	-0.12
Switzerland	0.52%	3.51	0.65%	2.65	0.79%	2.08
Taiwan	-0.20%	-0.77	-0.06%	-0.15	0.17%	0.30
Thailand	0.46%	1.21	0.66%	1.43	0.99%	2.47
Turkey	0.30%	0.36	-0.95%	-1.35	-1.81%	-1.74
UK	0.29%	2.18	0.85%	3.01	1.04%	2.83
US	0.17%	1.64	0.33%	1.66	0.40%	1.48
Venezuela	-2.08%	-1.27	-3.23%	-1.16	-2.89%	-1.25
Country Neutral 52-week return	**0.30%**	3.08	**0.32%**	2.19	**0.15%**	0.76

TABLE 7-8: 52-week momentum returns (size-sorted portfolio)

12x6 months, Value-Weighted, 3 portfolios within each sub-sample, 1-month gap, US dollar, BHAR

	Small Size		Medium Size		Large Size	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	0.21%	0.38	-0.31%	-0.45	-0.42%	-0.45
Australia	-0.80%	-2.03	1.09%	5.42	0.49%	2.60
Austria	0.18%	0.46	0.56%	1.87	-0.08%	-0.22
Bangladesh	-0.04%	-0.05	1.77%	3.49	4.89%	2.00
Belgium	0.85%	3.42	1.12%	4.60	0.37%	2.29
Brazil	-2.44%	-1.36	0.04%	0.09	-0.33%	-0.46
Canada	-1.16%	-1.41	1.07%	4.11	0.79%	3.25
Chile	-0.01%	-0.01	0.32%	1.25	0.18%	0.64
China	0.18%	0.80	0.60%	2.56	0.84%	3.06
Colombia	12.35%	1.57	-0.09%	-0.22	0.17%	0.57
Cyprus	-1.97%	-2.17	-0.10%	-0.19	2.20%	5.33
Czech Republic	-0.38%	-0.74	0.80%	2.02	1.06%	2.42
Denmark	0.64%	1.63	1.16%	5.31	0.51%	2.19
Egypt	-2.01%	-3.47	-1.05%	-1.71	1.55%	2.49
Finland	1.27%	3.37	0.67%	1.80	1.08%	1.81
France	0.25%	0.85	0.73%	3.46	0.67%	3.37
Germany	0.57%	2.40	0.78%	3.84	0.44%	2.50
Greece	1.12%	1.51	0.72%	1.66	0.92%	2.33
Hong Kong	-0.25%	-0.51	0.37%	1.40	0.45%	2.37
Hungary	-1.64%	-1.42	0.22%	0.34	0.43%	0.94
India	-0.76%	-1.22	0.48%	1.20	0.88%	2.30
Indonesia	-2.18%	-2.39	-0.70%	-1.43	0.18%	0.39
Ireland	1.30%	2.03	1.00%	1.96	0.52%	1.09
Israel	-0.93%	-3.63	-0.49%	-2.01	-0.02%	-0.05
Italy	0.92%	4.70	0.77%	4.15	0.82%	2.95
Japan	0.03%	0.23	0.13%	0.82	0.05%	0.30
Kenya	0.69%	1.11	0.08%	0.11	0.46%	0.51
Lithuania	1.12%	0.61	0.65%	0.48	0.13%	0.19
Malaysia	-0.02%	-0.07	0.22%	0.93	0.16%	0.67
Mexico	0.02%	0.03	0.43%	1.15	0.91%	2.20
Morocco	0.29%	0.45	0.75%	1.37	1.18%	5.06
Netherlands	0.96%	3.86	0.92%	4.16	0.18%	0.83
New Zealand	0.92%	2.15	0.76%	3.21	0.55%	1.84
Norway	0.76%	1.49	0.36%	0.87	0.16%	0.54
Pakistan	-1.71%	-2.99	-0.61%	-1.78	0.43%	1.15
Peru	3.03%	0.73	0.64%	0.51	-0.89%	-1.44
Philippines	-2.22%	-3.31	-0.74%	-1.50	-0.66%	-1.82
Poland	0.64%	0.80	1.63%	5.31	1.15%	2.80
Portugal	-0.21%	-0.12	1.42%	2.50	-0.13%	-0.48
Romania	0.00%	0.00	-0.07%	-0.10	1.05%	1.10
Russian Federation	-0.86%	-0.57	-5.16%	-3.27	-0.95%	-1.08
Singapore	-0.13%	-0.39	0.41%	1.49	-0.28%	-0.96
South Africa	-0.25%	-0.65	0.88%	3.04	0.39%	1.52
South Korea	-0.16%	-0.29	-0.09%	-0.19	-0.19%	-0.43
Spain	0.16%	0.37	0.37%	1.35	0.13%	0.51
Sri Lanka	-1.27%	-1.95	-0.75%	-2.44	-0.39%	-1.58
Sweden	0.43%	0.77	0.90%	2.46	-0.23%	-0.64
Switzerland	0.84%	4.49	0.90%	4.48	0.53%	2.89
Taiwan	-0.15%	-0.37	0.09%	0.25	-0.14%	-0.41
Thailand	-0.95%	-1.80	0.29%	0.69	0.44%	0.95
Turkey	0.21%	0.37	-1.73%	-1.77	0.11%	0.12
UK	0.65%	3.34	1.17%	5.99	0.34%	2.06
US	0.17%	0.87	0.51%	2.88	0.18%	1.29
Venezuela	0.42%	0.48	-0.33%	-0.43	-2.08%	-1.20
Country Neutral 52-week return	**0.16%**	0.59	**0.29%**	2.08	**0.39%**	3.16

TABLE 7-10: 52-week momentum returns (return reversals)

12x6 months, Value-Weighted, 3 portfolios, US dollar, BHAR

	12 months gap		24 months gap	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.62%	-1.03	-0.53%	-0.93
Australia	-0.46%	-2.30	-0.45%	-1.92
Austria	-0.75%	-2.23	-0.33%	-0.92
Bangladesh	-1.01%	-1.33	-1.26%	-2.19
Belgium	0.07%	0.29	-0.18%	-0.98
Brazil	-0.65%	-0.94	0.36%	0.71
Canada	-0.19%	-0.78	-0.07%	-0.28
Chile	-0.99%	-2.07	0.42%	0.76
China	-0.22%	-0.77	-0.80%	-2.05
Colombia	-0.02%	-0.06	-0.86%	-3.05
Cyprus	1.62%	2.48	0.96%	1.23
Czech Republic	-0.03%	-0.07	-0.11%	-0.20
Denmark	0.25%	0.89	-0.68%	-3.12
Egypt	-0.91%	-1.51	-2.53%	-3.94
Finland	0.98%	1.43	-0.41%	-0.51
France	-0.35%	-1.73	-0.17%	-1.05
Germany	-0.18%	-1.02	-0.11%	-0.71
Greece	-1.11%	-1.79	-1.80%	-2.23
Hong Kong	-0.06%	-0.24	0.17%	0.69
Hungary	-0.31%	-0.72	1.39%	2.06
India	0.20%	0.61	-0.52%	-1.62
Indonesia	-0.05%	-0.09	-0.48%	-1.05
Ireland	-0.75%	-1.43	0.22%	0.43
Israel	0.36%	1.17	-0.35%	-1.01
Italy	0.04%	0.20	-0.24%	-1.20
Japan	-0.20%	-1.32	-0.04%	-0.29
Kenya	-0.04%	-0.08	-1.70%	-1.51
Lithuania	-2.15%	-2.32	0.26%	0.40
Malaysia	-0.68%	-1.95	-0.24%	-0.85
Mexico	0.53%	1.41	0.51%	1.61
Morocco	-0.30%	-0.81	-0.52%	-1.70
Netherlands	-0.44%	-1.77	-0.03%	-0.13
New Zealand	-0.13%	-0.53	-0.56%	-1.98
Norway	-0.45%	-1.50	-0.16%	-0.61
Pakistan	0.11%	0.26	0.05%	0.14
Peru	-0.22%	-0.48	-0.53%	-1.15
Philippines	-0.71%	-1.97	-0.20%	-0.63
Poland	-1.12%	-2.29	-0.45%	-1.46
Portugal	-0.47%	-1.82	-0.41%	-1.63
Romania	-1.82%	-2.30	-1.11%	-2.75
Russian Federation	-1.08%	-1.12	-1.62%	-5.41
Singapore	-0.17%	-0.66	-0.79%	-3.29
South Africa	-0.40%	-1.34	-0.45%	-1.54
South Korea	-0.25%	-0.64	0.11%	0.48
Spain	0.06%	0.24	-0.09%	-0.45
Sri Lanka	-0.59%	-1.74	-0.19%	-0.62
Sweden	-0.38%	-1.38	-0.44%	-1.82
Switzerland	-0.21%	-1.23	0.14%	0.88
Taiwan	-0.28%	-1.09	-0.34%	-1.24
Thailand	0.22%	0.58	-0.03%	-0.10
Turkey	-0.95%	-1.81	-0.40%	-0.92
UK	-0.38%	-2.46	-0.39%	-3.07
US	-0.36%	-2.35	-0.54%	-3.70
Venezuela	-3.66%	-2.24	4.46%	1.89
Country Neutral 52-week return	**-0.40%**	-3.94	**-0.26%**	-2.09

TABLE 7-12: 52-week momentum returns (local versus US dollar)

12x6 months, Value-Weighted, 1-month gap, 3 portfolios, BHAR

	Local currency		US currency	
Country	**W - L**	**t-stat**	**W - L**	**t-stat**
Argentina	-0.05%	-0.06	-0.09%	-0.12
Australia	0.76%	2.97	0.75%	3.05
Austria	-0.27%	-0.67	-0.09%	-0.25
Bangladesh	4.20%	2.13	4.39%	2.12
Belgium	0.41%	2.15	0.48%	2.51
Brazil	-0.95%	-1.53	-0.30%	-0.42
Canada	0.98%	7.43	0.94%	3.45
Chile	-0.54%	-0.72	0.05%	0.17
China	0.77%	2.91	0.83%	3.09
Colombia	-0.12%	-0.37	0.21%	0.81
Cyprus	0.97%	3.32	1.55%	2.81
Czech Republic	1.15%	3.30	1.23%	3.08
Denmark	0.60%	2.45	0.64%	2.75
Egypt	0.98%	1.69	1.28%	2.12
Finland	1.19%	2.11	1.25%	2.07
France	0.64%	3.51	0.69%	3.55
Germany	0.40%	2.33	0.46%	2.60
Greece	1.54%	3.43	1.29%	3.23
Hong Kong	0.45%	1.94	0.43%	1.90
Hungary	0.43%	0.81	0.29%	0.57
India	0.54%	1.02	0.71%	1.60
Indonesia	-0.16%	-0.25	-0.14%	-0.24
Ireland	0.11%	0.19	-0.12%	-0.18
Israel	-0.15%	-0.33	-0.04%	-0.10
Italy	0.79%	3.24	0.73%	3.00
Japan	0.20%	1.08	0.09%	0.49
Kenya	1.29%	2.10	0.90%	1.22
Lithuania	0.36%	0.47	0.05%	0.07
Malaysia	0.08%	0.26	0.21%	0.81
Mexico	0.68%	1.56	0.76%	1.84
Morocco	1.15%	4.94	1.07%	4.02
Netherlands	0.34%	1.54	0.30%	1.42
New Zealand	0.38%	1.23	0.44%	1.52
Norway	0.23%	0.75	0.18%	0.60
Pakistan	0.10%	0.25	0.10%	0.23
Peru	-1.21%	-2.22	-0.79%	-1.39
Philippines	-0.83%	-1.93	-0.93%	-2.31
Poland	0.92%	2.22	0.83%	2.06
Portugal	0.15%	0.56	0.23%	0.82
Romania	0.96%	1.02	0.44%	0.51
Russian Federation	-1.73%	-1.82	-1.73%	-1.82
Singapore	-0.27%	-0.89	-0.36%	-1.23
South Africa	0.73%	2.39	0.51%	1.78
South Korea	-0.12%	-0.26	-0.07%	-0.14
Spain	0.28%	1.15	0.22%	0.90
Sri Lanka	-0.63%	-2.05	-0.67%	-2.59
Sweden	-0.36%	-0.73	-0.33%	-0.73
Switzerland	0.56%	3.05	0.68%	3.55
Taiwan	-0.14%	-0.44	-0.13%	-0.38
Thailand	0.54%	1.16	0.36%	0.68
Turkey	-1.60%	-1.64	0.34%	0.38
UK	0.47%	2.43	0.47%	2.39
US	0.27%	1.81	0.27%	1.81
Venezuela	-0.32%	-0.38	-2.37%	-1.47
Country Neutral 52-week return	**0.38%**	3.06	**0.34%**	2.81

Chapter 8

FINDINGS: MOMENTUM RETURN OPTIMISATION

Analysis

The potential to improve momentum return using portfolio optimisation is investigated in this chapter. Various approaches to optimisation are discussed and tested. Portfolio optimisation cannot be tested in all 54 countries for which data are compiled for this study as the number of stocks within the Winner or Loser portfolios is not large enough to reduce idiosyncratic risk. Adoption of an arbitrary minimum number of 1,000 stocks for all the sample countries in any given month is set as a precondition for inclusion in the sample. The restriction of 1,000 stocks in any month ensures an adequate number of stocks in each portfolio for proper analysis and increased statistical reliability. For example, the Loser and Winner portfolio will contain around 100 stocks each if the whole sample is divided into 10 portfolios to calculate momentum returns. Similarly, the Loser and Winner portfolio will have at least 33 stocks each if the sample is divided into three sub-samples based on the market-capitalisation of each stock before forming Winner and Loser portfolios. The requirement is discussed further below. The number of stocks in the Winner and Loser portfolios are expected to decrease as a stock is only included in the Winner or Loser portfolio if 60-months of prior historical data are available.

Of the 54 countries only seven meet this condition of 1,000 stocks. These markets are Australia, Canada, China, India, Japan, UK and the United States. Due to the restriction of a minimum of 1,000 stocks in any given month, the sample range also decreases for Australia, Canada, China, India and Japan. The sample range for UK and US markets did not change as the number of stocks listed from the beginning of January 1973 through to July 2007 exceeded 1,000.

The new sample starting dates are:

(i) Australia- March 2000 to July 2007,

(ii) Canada- October 1988 to July 2007,

(iii) China- October 2000 to July2007,

(iv) India- June 1993 to July 2007,

(v) Japan- August 1987 to July 2007,

(vi) UK- January 1973 to July 2007, and

(vii) US- January 1973 to July 2007.

The inclusion of 60 months of data, as a restriction, leads to the exclusion of the Australian and Chinese markets from the analysis as the time period for both (2000-2007) is not long enough to test this strategy. Consequentially, momentum optimisation techniques are tested on Canada, India, Japan, UK and US.

Unlike the previous analysis of momentum returns where 5 portfolios were selected, the following analysis uses 10 portfolios to compute optimised momentum returns. A primary consideration supporting this decision is the high computation time needed to optimise the Winner and Loser portfolio in each month. The computation time increases exponentially as the number of stocks within the Loser and Winner portfolio rise. Also dividing the sample into 10 portfolios is not unusual, e.g., Jegadeesh and Titman (1993) use 10 portfolios. Further, the restriction of a minimum of 1000 stocks in any month leaves an adequate number of stocks in each portfolio to allow for diversification of idiosyncratic risk.

The momentum returns are calculated for Canada, India, Japan, UK and the US markets using equal-weighted and value-weighted approaches. These two methods are favoured in prior research for calculating momentum return. The calculation of a normal momentum return also faces the same estimation period restriction as the momentum returns computed using various optimisation techniques. Each stock within the sample will only be included in the momentum return calculations when the previous 60 months of data prior to the starting of the formation period are available. This measure leads to consistency of results when comparing the momentum returns calculated with different optimisation techniques.

Table 8-1: Momentum returns under equal- and value-weighted approach

Country		Loser(L)	t-stat	Winner(W)	t-stat	W-L	t-stat
Canada	Equal-weighted	3.35%	4.04	3.27%	5.18	-0.09%	-0.15
	Value-weighted	0.17%	0.21	1.31%	4.31	1.14%	1.49
India	Equal-weighted	1.04%	1.10	1.66%	2.55	0.63%	0.84
	Value-weighted	0.30%	0.52	0.91%	1.53	0.62%	1.10
Japan	Equal-weighted	0.80%	2.27	0.26%	1.00	-0.53%	-1.71
	Value-weighted	0.21%	0.66	0.34%	1.61	0.14%	0.39
UK	Equal-weighted	0.13%	0.45	1.08%	3.47	0.95%	3.47
	Value-weighted	-0.59%	-1.92	0.61%	5.29	1.20%	3.57
US	Equal-weighted	1.81%	5.33	1.85%	7.33	0.04%	0.13
	Value-weighted	0.33%	1.32	0.69%	4.20	0.36%	1.39

The findings presented in Table 8-1 show strikingly different results when the portfolio weighting changes from an equal-weighted approach to value-weighted approach, indicating that the momentum return increases under the value-weighted approach. A further segmentation of momentum return into Loser and Winner portfolios indicates that the return difference primarily arises in the Loser portfolio. The Loser portfolio under the equal-weighted approach exhibits positive returns and these positive returns are greater than the Loser portfolio returns calculated under the value-weighted approach.

These findings demonstrate that the small-size Loser portfolio stocks under the equal-weighted approach do not maintain momentum and rather show a reversal pattern during the holding period. The value-weighted returns in the Loser portfolios are positive except in the UK, but not as high as those from the equal-weighted approach. The underlying reason is that the large allocation of weight to the large-size stock in the Loser portfolio reduces the contribution of the small-size stocks towards the momentum return. Therefore, the initial inspection of results from Table 8-1 indicates that the small-size Loser portfolio stocks do not maintain the same momentum, whereas large-size stocks within the Loser portfolio show some momentum. A further breakdown of the momentum return into size-sorted portfolios may clarify the picture further.

At the beginning of each formation month, the stocks are ranked according to their market value from lowest to highest. Next, the whole sample is subdivided into three sub-samples based on the ranking. The small-size sample will include only those stocks that fall into the bottom one-third of the ranking and similarly the large-size sample will include only those stocks that are present in the top one-third of the ranking. The medium-size portfolio includes the rest of the companies. The momentum return for each size-sorted portfolio is calculated with the same restriction as previously mentioned.

The size-sorted momentum returns are calculated for the equal-weighted approach and reported in Table 8-2 and for the value-weighted approach are presented in Table 8-3. The size-sorted momentum returns under the equal- and value-weighted approaches will indicate whether or not the momentum returns still differ substantially after dividing the whole sample into size-sorted sub-samples.

Table 8-2: Size-sorted momentum returns using equal-weighted approach

Country		Loser(L)	t-stat	Winner(W)	t-stat	W-L	t-stat
Canada	Small	4.64%	4.62	2.95%	5.77	-1.69%	-2.33
	Medium	1.01%	0.90	1.26%	2.87	0.25%	0.28
	Large	-1.19%	-2.84	1.03%	3.84	2.22%	5.11
India	Small	9.62%	4.23	4.71%	3.45	-4.91%	-2.99
	Medium	2.92%	2.55	3.02%	3.60	0.10%	0.10
	Large	-0.12%	-0.21	0.92%	2.12	1.04%	1.95
Japan	Small	0.96%	1.98	-0.16%	-0.43	-1.12%	-4.74
	Medium	0.24%	0.61	0.02%	0.09	-0.22%	-0.83
	Large	0.18%	0.58	0.41%	1.89	0.23%	0.60
UK	Small	1.11%	2.25	1.37%	4.25	0.26%	0.76
	Medium	-0.55%	-1.79	1.12%	5.19	1.67%	7.61
	Large	-0.72%	-2.78	0.70%	6.52	1.42%	5.75
US	Small	6.42%	2.89	2.66%	7.21	-3.77%	-1.74
	Medium	0.45%	1.14	1.15%	5.65	0.71%	2.02
	Large	-0.06%	-0.31	0.67%	5.14	0.73%	3.52

The results presented in Table 8-2 suggest that small-size momentum return is negative for all countries except the UK. The momentum return changes to positive when the large-size sample is taken into consideration. Further, the small-size Loser portfolio return is positive in all five markets but these change to negative in four markets for the large-size sample. These results clearly point to the difference in momentum return for small-size and large-size samples, which is mainly driven by the variation within the Loser portfolio return. Within the large-size sample, all markets show a statistically significant positive return for both equal- and value-weighted approaches, except Japan, as presented in Table 8-3.

Table 8-3: Size-sorted momentum returns using value-weighted approach

Country		Loser(L)	t-stat	Winner(W)	t-stat	W-L	t-stat
Canada	Small	2.22%	2.86	1.85%	3.34	-0.37%	-0.56
	Medium	-0.26%	-0.37	1.34%	3.09	1.60%	2.80
	Large	-1.20%	-2.95	0.79%	3.63	1.99%	4.42
India	Small	5.86%	3.97	3.98%	3.64	-1.88%	-1.29
	Medium	2.71%	2.43	3.02%	3.92	0.31%	0.30
	Large	-0.74%	-1.57	0.72%	2.02	1.46%	2.32
Japan	Small	0.76%	1.65	-0.29%	-0.74	-1.05%	-4.47
	Medium	0.23%	0.61	0.03%	0.13	-0.19%	-0.72
	Large	0.16%	0.61	0.44%	2.04	0.29%	0.76
UK	Small	0.16%	0.37	1.24%	4.05	1.08%	3.64
	Medium	-0.68%	-2.30	1.16%	5.69	1.84%	8.17
	Large	-0.61%	-2.96	0.45%	5.14	1.06%	4.19
US	Small	1.43%	3.33	1.79%	5.44	0.36%	1.14
	Medium	-0.05%	-0.17	1.00%	5.05	1.04%	4.70
	Large	-0.21%	-1.44	0.47%	3.47	0.67%	2.92

The results presented in Table 8-3 confirm the same picture as the results reported in Table 8-2. Momentum return changes from negative to positive when the market-capitalisation size of the sample increases. The underlying reason for the change in the momentum return can be traced again to the Loser portfolio return. However, the momentum return in the large-size sample does not vary significantly if the weighting approach is changed from equal-weighted to value-weighted, suggesting the size of the company is not very different in the large-cap sample. Since a significant variation in returns is noticed in the small-size sample, it is appropriate that the optimisation technique is deployed only for the large-size sample and results compared for the traditional equal- and value-weighted large-cap momentum returns. The selection of only large-cap stocks also avoids problems noted in the small-size stocks which have particularly high volatility and transaction cost, suffer from inaccurate data collection and various other problems as noted in the literature.

All results reported below are average-monthly momentum returns using a 6-month formation period, 1-month gap, 6-month holding period and computed using 10 portfolios. The stock prices are converted into US dollars and all the momentum strategies place a restriction on availability for 60 months of prior data before the start of the formation period. The equal- and value-weighted Winner-Loser momentum return is presented in each table for ease of comparison, with the momentum return arising from various optimisation techniques. The equal- and value-weighted momentum return reported is computed only on the large-cap.

8.1. Markowitz approach

The momentum return under the Markowitz approach are reported in Table 8-4. The momentum return under the equal- and value-weighted methods, using the same restriction of 60 months, are reported on the right side of the table. An initial inspection of results indicates the superiority of optimising momentum return using the Markowitz approach, except for Canada. The momentum return for all countries outperforms the momentum return computed under the equal- or value-weighted approaches. The most remarkable improvement in return is seen in the Japanese stock market where the average-monthly momentum return tripled from 0.23% (under equal-weighted) to 0.76% (under Markowitz approach). The momentum return for the Japanese stock market is, however, not statistically significant. An increase of about 0.20% over equal-weighted and 0.60% over value-weighted method is also observed in the UK market. The least benefit from employing optimisation techniques is seen in the Canadian stock market where the average-monthly momentum return remains the same for the Markowitz and equal-weighted process.

Table 8-4: Momentum optimisation: Markowitz approach

	Using Markowitz approach						Equal-	Value-
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W-L**	**t-stat**	weighted	weighted
Canada	-1.33%	-3.45	0.89%	3.96	2.22%	5.42	2.22%	1.99%
India	-0.68%	-1.25	0.86%	2.20	1.54%	2.70	1.04%	1.46%
Japan	-0.19%	-0.75	0.56%	1.65	0.76%	1.54	0.23%	0.29%
UK	-0.83%	-3.54	0.78%	6.00	1.60%	6.62	1.42%	1.06%
US	-0.28%	-1.59	0.66%	4.01	0.94%	4.23	0.73%	0.67%

One of the important reasons for using the Markowitz approach, as well as other approaches outlined later in this study, is the surety that the Winner and Loser portfolios are well diversified. This is due to the constraint of placing a maximum 5% allocation in any one stock. This is in contrast with the value-weighted approach where there is a high possibility that stocks with high market capitalisation will be allocated a major weight and the rest of the stocks will be allocated a very small weight. The equal-weighted approach follows naïve diversification where 1/n weight is allocated to each stock of the portfolio.

8.2. Markowitz approach after excluding extreme 5%

In this approach, the momentum return is calculated after excluding the extreme 5% of the stocks from within the Winner and Loser portfolios. The exclusion of extreme stock returns decreases the variability of returns within each portfolio. This action is considered in the literature where it is noted that the Markowitz method has a high sensitivity to various inputs and that a small change in input can lead to a big change in the allocating of weight to a stock.

The results presented in Table 8-5 indicate a decrease in momentum return compared to the Markowitz approach without excluding any stocks. This decrease in momentum return is primarily due to a lower Loser portfolio return compared to the Loser portfolio return of the Markowitz method without excluding any stocks. However, the Winner portfolio return is no different when compared to the Winner portfolio return under the Markowitz approach without excluding any stock. The momentum return for all countries, except Canada and India, shows an improvement of return over the equal- and value-weighted approach.

Table 8-5: Momentum optimisation: Markowitz approach excluding extreme 5%

	Using Markowitz approach excluding extreme 5%						Equal-	Value-
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W-L**	**t-stat**	weighted	weighted
Canada	-1.23%	-3.01	0.88%	3.78	2.11%	4.89	2.22%	1.99%
India	-0.55%	-1.00	0.85%	2.18	1.40%	2.45	1.04%	1.46%
Japan	0.01%	0.05	0.56%	1.69	0.55%	1.13	0.23%	0.29%
UK	-0.84%	-3.85	0.72%	5.99	1.56%	6.91	1.42%	1.06%
US	-0.31%	-1.86	0.59%	3.81	0.91%	4.30	0.73%	0.67%

8.3. Single Index Model

The previous two tests show that the Markowitz optimising method, without excluding extreme stocks, generates impressive returns when compared to the equal- and value-weighted approaches. However, the computational burden is high for the Markowitz model and a large number of inputs are required. Further, as the previous literature postulates some estimates, e.g., covariance among stocks, may not be very important in terms of optimising results. A Single Index model is next tested to establish whether this model, with fewer inputs, can outperform the Markowitz method.

The momentum returns presented in Table 8-6 offer mixed results, with Canada, UK and US each generating a higher return under the Single Index model and a decline in the momentum return for India and Japan when compared to the Markowitz method. The momentum returns for all countries except India, however, outperform both an equal- and value-weighted momentum return. The momentum return for the Japanese stock market shows the most promising improvement but remains not statistically significant under all approaches. The average-monthly momentum return in the US market also stood at 1.05%, an impressive increase of about 0.32% over the equal-weighted approach, and 0.38% over the value-weighted approach.

Table 8-6: Momentum optimisation: Single Index Model

	Using Single Index Model						Equal-	Value-
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W-L**	**t-stat**	weighted	weighted
Canada	-1.32%	-3.36	1.00%	4.24	2.32%	5.48	2.22%	1.99%
India	-0.55%	-0.93	0.87%	2.03	1.42%	2.33	1.04%	1.46%
Japan	-0.11%	-0.42	0.60%	1.65	0.71%	1.37	0.23%	0.29%
UK	-0.85%	-3.32	0.79%	5.94	1.64%	6.37	1.42%	1.06%
US	-0.31%	-1.75	0.74%	4.03	1.05%	4.41	0.73%	0.67%

8.4. Single Index Model with adjusted beta

The momentum returns under the Single Index model with adjusted betas show the best results when compared to other optimisation methods and the traditional equal- and value-weighted approaches. The results presented in Table 8-7 show that the momentum return can be increased over the traditional value-weighted approach from an average-monthly 0.08% (India: over value-weighted) to as much as average-monthly 0.59% (UK: over value-weighted). Similarly, when the momentum return is compared to the equal-weighted approach, the minimal increase is 0.09% (Canada: over equal-weighted) and the highest increase is 0.56% (Japan: over equal-weighted).

The highest average-monthly momentum return is seen in the Canadian stock market at 2.31%, which is statistically significant, and the lowest is in the Japanese stock market with an average-monthly return of 0.79%, which is not statistically significant. The momentum return in the US stock market increases under this method but the increase in returns is very small (an average-monthly 0.01%) when compared to the Single Index model without adjusted beta.

Table 8-7: Momentum optimisation: Single Index Model with adjusted beta

	Using Single Index Model with adjusted beta						Equal-	Value-
Country	**Loser(L)**	**t-stat**	**Winner(W)**	**t-stat**	**W-L**	**t-stat**	weighted	weighted
Canada	-1.33%	-3.33	0.99%	4.23	2.31%	5.44	2.22%	1.99%
India	-0.64%	-1.07	0.91%	2.12	1.54%	2.55	1.04%	1.46%
Japan	-0.17%	-0.63	0.62%	1.78	0.79%	1.59	0.23%	0.29%
UK	-0.86%	-3.33	0.79%	5.69	1.65%	6.37	1.42%	1.06%
US	-0.30%	-1.69	0.76%	3.97	1.06%	4.51	0.73%	0.67%

These increases in return also outperform the previous best results of the Markowitz approach without excluding extreme stocks, as well as the shrinkage method results discussed next. The analysis of results does confirm that the optimisation techniques can generate higher returns when an appropriate model is selected and constraints are imposed correctly.

8.5. Shrinkage method

Four shrinkage methods are presented together in Table 8-8. The 25% to global mean suggests that the expected return of each stock consists of 25% of the stock mean + 75% of the global mean (in this case market return). The same logic applies to 50% and 75% to global mean. The results of zero-expected returns are also included in the same table, as all expected returns are set to zero and therefore, in a sense, all individual stock means are converged to a grand mean (zero in this case).

Table 8-8: Momentum optimisation: Shrinkage method

Weighting approach		Canada	India	Japan	UK	US
Equal-weighted	Winner-Loser	2.22%	1.04%	0.23%	1.42%	0.73%
	t-stat	5.11	1.95	0.60	5.75	3.52
Value-weighted	Winner-Loser	1.99%	1.46%	0.29%	1.06%	0.67%
	t-stat	4.42	2.32	0.76	4.19	2.92
25% to global mean	Winner-Loser	2.24%	1.49%	0.76%	1.58%	0.90%
	t-stat	5.48	2.67	1.56	6.54	4.13
50% to global mean	Winner-Loser	2.23%	1.46%	0.61%	1.55%	0.87%
	t-stat	5.51	2.63	1.37	6.50	4.01
75% to global mean	Winner-Loser	2.19%	1.33%	0.40%	1.52%	0.82%
	t-stat	5.35	2.49	1.00	6.20	4.16
Zero-expected return	Winner-Loser	2.27%	0.75%	0.47%	1.44%	0.65%
	t-stat	5.03	1.28	1.20	5.06	2.42

These findings point to momentum returns continuing to decline as the shrinkage to global mean increases. Of the four shrinkage methods the 25% to global mean generates the best momentum returns. However, the optimised momentum return under various shrinkage methods fails to outperform the momentum return calculated using a Single Index model with adjusted beta as shown in Table 8-7. This implies that converging individual means to a grand mean may not be a good idea when the technique is applied in the context of momentum return.

8.6. Momentum returns comparison under different approaches

The momentum return under all approaches is summarised in Table 8-9. The momentum return optimised using the Single Index model with adjusted beta clearly outperforms momentum return calculated using the traditional equal- and value-weighted approaches, as well as other optimisation methods considered in this study. This observation is important as momentum return can be further be increased by simply changing weights allocated to each stock of the portfolio. Therefore, the results suggest that the optimisation techniques may be an important factor in generating higher returns and the benefits of allocating weight to each stock of the portfolio cannot be ignored. The optimised momentum returns also guarantee that the portfolio is well diversified.

Table 8-9: Momentum returns comparison

	Canada	India	Japan	UK	US
Equal-weighted	2.22%	1.04%	0.23%	1.42%	0.73%
t-stat	5.11	1.95	0.60	5.75	3.52
Value-weighted	1.99%	1.46%	0.29%	1.06%	0.67%
t-stat	4.42	2.32	0.76	4.19	2.92
Markowitz method	2.22%	1.54%	0.76%	1.60%	0.94%
t-stat	5.42	2.70	1.54	6.62	4.23
Markowitz method excluding extreme 5%	2.11%	1.40%	0.55%	1.56%	0.91%
t-stat	4.89	2.45	1.13	6.91	4.30
Single Index Model without adjusted beta	2.32%	1.42%	0.71%	1.64%	1.05%
t-stat	5.48	2.33	1.37	6.37	4.41
Single Index Model with adjusted beta	**2.31%**	**1.54%**	**0.79%**	**1.65%**	**1.06%**
t-stat	5.44	2.55	1.59	6.37	4.51
25% to global mean	2.24%	1.49%	0.76%	1.58%	0.90%
t-stat	5.48	2.67	1.56	6.54	4.13
50% to global mean	2.23%	1.46%	0.61%	1.55%	0.87%
t-stat	5.51	2.63	1.37	6.50	4.01
75% to global mean	2.19%	1.33%	0.40%	1.52%	0.82%
t-stat	5.35	2.49	1.00	6.20	4.16
Zero-expected return	2.27%	0.75%	0.47%	1.44%	0.65%
t-stat	5.03	1.28	1.20	5.06	2.42

8.7. Momentum returns with a short-period restriction

In the previous analysis, the optimised momentum return is calculated using historical 60-month data prior to the start of the formation month. In this section, the study proposes to cut down the estimation period to 18 months. The momentum return estimated with a shorter restriction period will indicate whether the optimised momentum return can sustain the same returns as seen in Table 8-9.

There is one more important difference between the optimisation methods considered in this section and those methods documented above. As 18 months is a relatively a short period, the mean return for all Winner and Loser portfolio stocks are set to zero. Four alternative methods of optimisation are presented in Table 8-10. The shrinking of 25%, 50% and 75% individual mean to global mean is not used in this section as all returns are already set to zero, i.e., same grand mean for all stocks.

Table 8-10: Momentum returns with a restriction of 18 months and setting all expected return to zero

	Canada	**India**	**Japan**	**UK**	**US**
Equal-weighted	1.71%	1.87%	0.08%	1.04%	0.87%
t-stat	4.34	4.01	0.23	3.72	4.56
Value-weighted	1.96%	2.21%	0.19%	1.09%	0.76%
t-stat	3.63	4.41	0.53	3.36	3.53
Markowitz method	1.65%	1.97%	0.24%	1.09%	0.83%
t-stat	3.60	3.88	0.61	3.60	3.57
Markowitz method excluding extreme 5%	1.84%	2.03%	0.24%	1.04%	0.69%
t-stat	4.42	4.09	0.64	3.61	3.05
Single Index Model without adjusted beta	1.56%	1.95%	0.07%	0.24%	0.65%
t-stat	3.28	3.89	0.17	1.02	2.95
Single Index Model with adjusted beta	1.60%	2.08%	0.16%	1.07%	0.62%
t-stat	3.40	4.16	0.43	3.54	2.70

The results presented in Table 8-10 suggest that optimising momentum return, with a shorter estimation period, does not outperform momentum return when compared to equal- or value-weighted approaches. Equal- or value-weighted methods dominate all other optimisation techniques except for Japan. The results presented in Table 8-10 may be influenced by setting all the returns to zero as noted previously in Table 8-9, that optimisation techniques generate fewer momentum returns when the percentage of shrinkage to the global mean increases. Therefore, it seems that shrinkage method does not work very well when this technique is applied in the context of momentum returns.

Chapter 9

CONCLUSION

This research investigated four main issues relating to momentum returns. First, the impact on momentum returns when alternative computation metrics are used, different time-periods are considered, different countries and markets are involved and different currencies are used. Secondly, the impact on alternative approaches to calculating momentum returns e.g., conventional, 52-week high, etc., when differing methods are used to generate country-neutral returns is considered. Thirdly, the likelihood that data-snooping is the primary explanation for abnormal returns from industrial and 52-week high momentum returns is investigated. Finally, the impact of various optimisation techniques applied to momentum portfolios in terms of their consequential impact on returns is analysed.

In summary, the results suggest that momentum returns are not due to data-snooping processes and by-and-large remain statistically significant and positive when calculated using different methods. The country-neutral positive momentum return, involving 54 countries, suggests that this anomaly is not restricted to a particular set of countries but rather appears in all major markets.

The industrial momentum and 52-week high momentum returns also remain statistically significant when applied in different markets and when computed by a number of methods. However, the claim that industrial momentum and 52-week high momentum returns generate superior returns compared to the conventional momentum strategy is not established.

The most important finding of this research lies in documenting the power of optimisation methods to generate extra momentum returns. This issue has not been considered previously in the context of momentum returns which makes these results important from the perspectives of researchers and practitioners, showing how an anomaly can be further exploited by wisely allocating money to each stock in the portfolio.

The results are, however, not very encouraging when normal momentum, industrial momentum, 52-week high momentum and optimisation techniques are applied to small-cap stocks. A significant variation in momentum returns, especially in small developing markets, is noticed when the momentum returns are calculated using a number of methods. The most likely explanations for these variations range from high bid/ask spread, incorrect data recording and being subject to high illiquidity.

9.1. Momentum results and portfolio structure

The various empirical analyses of momentum returns reported in Chapter 5 suggest that changes in portfolio structure can significantly alter momentum returns. The results of CAR versus BHAR calculations indicate that country-neutral momentum returns are generally higher under the CAR method than the BHAR method. The difference, although not large, of average monthly momentum returns under the CAR method is 0.67% against 0.64% under the BHAR method. Momentum returns for the Austrian market change from a positive average monthly return of 0.36% under the BHAR method to a negative -0.16% under the CAR method. The statistical significance of momentum returns in the Indonesian stock market change from remaining statistically significant under the CAR method to not statistically significant under the BHAR method.

The results for equal- versus value-weighed portfolios indicate that momentum returns can significantly change, especially for those countries where stock return volatility is high and/or a large number of stocks come from the small-cap category. The average monthly momentum returns for Brazil and Russia drastically reduce from an unrealistic -136.39% and -82.38% under equal-weight to a more realistic -0.03% and -0.58% respectively under the value-weighted approach. The country-neutral momentum returns (excluding Brazil and Russia) indicate that the Loser portfolio, using the equal-weighted method, does not exhibit momentum movement as the returns are positive. However, loser portfolio returns are negative under the value-weighted method. These results suggest that those stocks with small market capitalisation within the Loser portfolio do not continue to generate the same magnitude of negative returns during the holding period. The average monthly momentum return under the value-weighted method is more than double those computed using the equal-weighted method. The returns are statistically significant under value-weighted and not statistically significant under the equal-weighted method. This suggests that momentum returns may almost double, or the statistical significance of results may change markedly, when the portfolio weighting method is altered.

The importance of the number of portfolios to be considered when calculating momentum returns suggests that when excluding countries with small markets the country-neutral momentum returns are generally positive for 2 to 20 portfolios. The returns continue to increase as the number of portfolios increase, i.e., momentum return increases with fewer stocks in the Loser and Winner portfolios. The breakdown of momentum return into Winner and Loser portfolios shows that the extreme positive return stocks in the Winner portfolio offer the most promising returns over the next 6 months. The Loser portfolio stocks with the most negative returns over the last months, however, do not continue to decline with the same momentum over the next six months. The results also show that country-neutral (excluding Venezuela and Russia) average monthly returns can almost double from 0.45% (2 portfolios) to 0.80% (5 portfolios).

An analysis of the impact of size-effect on momentum return indicates that value-weighted country-neutral average monthly momentum returns increase from -0.29% (small-cap sample) to 0.55% (large-cap sample). The negative momentum return in small-cap stocks is primarily due to positive returns from the Loser portfolio, suggesting that small-cap Loser stocks have a tendency toward low momentum or reversal. A significant amount of volatility is also noted in the small-cap momentum sub-sample.

The choice of log return instead of simple return on momentum profitability suggests higher momentum return than using simple returns. The primary reason for higher momentum log return is attributed to greater negative return for the country-neutral Loser portfolio. One-month and zero-month skip between formation and holding period results indicate that country-neutral momentum return will be lower when a one-month gap is not allowed between the formation and holding periods. The low return for the zero-month gap calculation may be due to possible reversal in the first month of the holding period. These reversals are noticed in both Winner and Loser portfolios in the first month of the holding period. The importance of excluding the top and bottom 5% of extreme return stocks from Winner and Loser portfolios respectively receives no empirical support.

9.2. Industrial momentum

The study investigates the industrial momentum anomaly by implementing this strategy across seven markets (Australia, Canada, China, Japan, India, UK and US) with additional tests. The contribution of this investigation, vis-à-vis previous studies, is that the comparison across markets uses individual stock returns. The overall results from this study are mixed. There are significant and positive industry momentum returns in all but the Japanese stock market. The results for industry momentum return profitability in the Canadian, Chinese, Indian and UK markets exhibit statistically significant and positive momentum returns. This suggests that the strategy does not arise from a data-snooping process as the returns are statistically significant in both developed and developing stock markets. The absence of an industry momentum return in the Japanese stock market is not surprising and is consistent with cited prior studies noting the absence of individual momentum return profitability in the Japanese stock market.

The data used in this study, however, differ from previous studies of industry momentum return. The expansive seven country data set coupled with Datastream based industry classification is used to test the robustness of the industry momentum factors in the seven markets. The results are not dissimilar to some earlier studies as discussed above. Industry momentum returns calculated from Datastream maintained indices also show statistically significant, positive returns. These findings suggest that the industry momentum returns are not restricted to a particular database.

Industry momentum return is not seen to be present within a particular time period. Moskowitz and Grinblatt (1999) test industry momentum returns in the US stock market for the time period July 1963 to July 1995. Some studies suggest that a new anomaly (e.g. January effect) disappears when the same anomaly is tested in the next period. For example, if an industry momentum return is published in 1999 and if the market has accepted this anomaly, then the returns should disappear subsequently after this period. However, two samples used in this study: Australia (sample period: March-00 to July-07) and China (sample period: October-00 to July-07) still show high and statistically significant momentum returns.

The dominance of industry momentum return over individual momentum return and the power of industry factors in explaining individual momentum returns is, however, not consistent with the findings of Moskowitz and Grinblatt (1999). Industry-return adjusted and industry-neutral momentum return, in this study, show positive and statistically significant profit, suggesting that the Winner and Loser stocks are not drawn from the same industry. Thus, the industry factor may not be as important in explaining individual momentum return as advocated by Moskowitz and Grinblatt (1999). Further, the return generated from an industry momentum strategy fails to outperform the return earned by implementing an individual momentum strategy. The difference in results between this study and that of Moskowitz and Grinblatt (1999) on US stock is attributable to the use of several countries' data in the analysis. Nevertheless, when this studies' analysis of US data is compared with Moskowitz and Grinblatt (1999), the results differ. Given that the method used is the same, the explanation lies in the period covered and the industry classification scheme followed.

The recent debate on the importance of a one-month gap between the formation and holding period is also considered in relation to industry momentum. The results suggest that a one-month gap is not an important factor in the industry momentum return and the returns are almost the same irrespective of whether a gap of one-month is allowed between the formation and holding period.

One of the important contributions of this study is the extension of 52-week high momentum returns to industry 52-week high momentum returns. A 52-week high momentum return is a recently documented anomaly and the inclusion of industry factors will show whether or not the returns outperform individual, industry, or 52-week high momentum returns. The results reveal a statistically significant positive industry 52-week high momentum return for all countries except Japan and US. However, the returns generated from this strategy are not the most profitable when compared to other momentum strategies available.

The presence of an industry momentum return in markets other than the US, in different dataset, time period and with different computational methods, enhances the robustness of this strategy. However, the dominance of industry momentum return over the individual momentum return is not revealed in this study. Individual momentum return continues to generate higher return during the same holding period when compared to industry momentum return.

9.3. 52-week high momentum return

The results from this study suggest that a 52-week high momentum strategy is profitable on a country-neutral global basis with an average monthly return of 0.34% over market. The results, however, do not support the superiority of 52-week high momentum return over country-neutral normal momentum return. The findings do not suggest the reversal of momentum return after first 12 months of holding period. The results from this study show that returns start to decline after a 12 month holding period, suggesting that the reversal of momentum returns is prevalent in a 52-week high momentum strategy.

To further test whether the 52-week high momentum strategy is a product of data mining bias, different formation and holding periods are applied. The results indicate that the 52-week high momentum yields a negative return with formation and holding period combinations of 24 and 36 months.

Various computational approaches indicate that BHAR and CAR method do not appear to be present statistically significant different results. Similarly, the returns are computed under the equal- or value-weighted portfolio approaches. These show no statistically significant return under equal-weighted approach, whereas they are statistically significant under a value-weighted approach. The lack of statistical significance in returns under the equal-weighted approach most likely arises from the small-cap stocks. When the 52-week high momentum sample is divided into three sub-samples based on market capitalisation, the results reveal low momentum returns in the small-cap sample with increasing returns as the sample size increases. These results suggest that small-cap stocks do not exhibit 52-week high momentum properties.

An alternative explanation arises from low coverage of small-cap stocks. Since a 52-week high momentum strategy is primarily based on an anchoring-and-adjust behavioural concept and there is readily available information in the media about the stocks' trading at 52-week high and low prices, it is unlikely that small-cap stocks will be given the same coverage as large-cap stocks. Therefore, small-cap stocks may not exhibit momentum properties due to the lack of necessary information in the market.

In summary, the results suggest that the 52-week high momentum return is not due to data-snooping as the strategy results in a positive and statistically significant return on a global basis. The results, however, are not robust when this strategy is applied to small-cap stocks. The results also fail to find a superior 52-

week high momentum return when compared to normal momentum return. Further, the results show reversals in the 52-week high momentum return.

9.4. Momentum return optimisation

The results from this study suggest that optimisation techniques can be important tools to generate extra momentum return. The Single Index model with adjusted beta is seen as the best optimising tool in terms of generating superior momentum return compared to the equal- or value-weighted momentum approaches. The momentum return in the Japanese stock market jumped from an average-monthly 0.23% using an equal-weighted approach to 0.79% applying a Single Index model with adjusted beta, although it is not statistically significant. Similarly, the momentum returns in the UK stock market increased substantially from an average-monthly 1.06% under value-weighted to 1.65% under a Single Index model with adjusted beta. This increase was achieved by using the same momentum strategy with the same set of Winner and Loser portfolio stocks but with different weights allocated to each stock in the portfolio.

The conventional Markowitz method and Single Index model without adjusted beta also show promising results with both optimising methods outperforming equal- and value-weighted approaches in almost all countries under investigation. The momentum return is also seen to decrease under the Markowitz method after excluding extreme return stocks from the Winner and Loser portfolios and this decrease is potentially due to fewer returns from the Loser portfolio. This suggests that excluding extreme return stocks, i.e., excluding stocks that have high sensitivity to Markowitz input estimates, may not lead to superior results when compared to the Markowitz method without excluding any stocks. The likely reason can be traced to the constraint of a 5% maximum allocation to each stock included in the portfolio.

The shrinkage methods do not generate impressive momentum returns when compared to other optimisation techniques tested. Further, it is noticed that the momentum return falls when the percentage of shrinking individual mean to grand mean increases. For example, the average-monthly momentum return for the Indian stock market falls from 1.49% (25% individual mean shrinkage to grand mean) to 1.33% (75% individual mean shrinkage to global mean). The same drop in return can be observed in other countries. These results suggest that the shrinkage method may not be the best optimising approach when applied in the context of momentum return. Setting all expected returns to zero, as suggested by Chopra et al. (1993), does not yield any better results.

An added benefit of using optimisation processes in generating higher momentum returns is the guarantee that the portfolio is well diversified. Since, a constraint of 5% is placed on the maximum allocation to each stock and a minimum allocation of 0.1% to each stock, the portfolio is well diversified. This diversification may not be achieved under a value-weighted approach, especially when a number of stocks within the portfolio have a high market-capitalisation relative to other stocks in the portfolio.

The robust testing of different methods of calculating momentum return profitability is summarized in this research. This in turn adds empirical evidence for a number of markets where momentum return has not been previously tested.

The results of this study are also robust across all the countries, covering 52,593 stocks from 54 countries and therefore presents a grand picture of momentum return profitability under different methods.

One of the most important findings of this research relates to the utilisation of optimisation techniques to increase momentum returns. The Single Index model with adjusted beta is found to have the potential to increase returns by more than 50% for some countries. This is important for researchers and practitioners. Researchers may avail themselves of optimisation techniques to test whether or not the same opportunity exists in other anomalies, i.e., can optimisation techniques increase return in other anomalies? E.g., contrarian strategy. Similarly, practitioners can take advantage of generating extra returns by simply allocating money to each stock in the Winner and Loser portfolio in a sophisticated way.

Practitioners may also note various approaches to calculating momentum returns for several countries under multiple methods. Momentum returns for 54 countries are presented in this single study and the returns are calculated in local and US dollars. The ability to readily determine a method of calculating momentum return is important in a global scale setting. These alternative methods substantially change momentum return when applied in a particular country. The magnitude is now greatly clarified through this current study, promoting informed choice through detailed and expansive empirical results.

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