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The Profitability of Equity Trading Strategies

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Declaration

‘This thesis is the result of the author’s original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.’

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Abstract

Classification based on the attributes of firms' or stocks' performance is one of the commonly used methods in stock selection. This is known as style investing. This thesis examines three style investing techniques that classify stocks in different ways: (a) historical return based trading strategies, (b) value versus growth trading strategies, and (c) corporate solvency based trading strategies. In the context of these strategies this thesis aims to address two main research questions (a) can these trading strategies generate superior profits?, and (b) can risk, business cycles, and/or investors' sentiment explain the profitability of these strategies? The three-factor model by Fama and French (1993) is mainly used to control for risk. The investors' sentiment introduced by Baker and Wurgler (2006) and CLI index compiled by OECD are employed as the factors to investigate the role of investors' sentiment and business cycles, respectively.

Chapter 2 of the thesis deals with the historical return based trading strategies. Under this criteria portfolios are formed on the basis of trends in historical returns. The two commonly used trading strategies that involve analysis of historical return trends are momentum and contrarian trading. Going long (short) on winner stocks and short (long) on loser stocks is called momentum (contrarian) trading. Momentum profit is generated if the return from the strategy of going long on winner stocks and short on loser stocks is positive (i.e. returns from long position *minus* returns from short position are positive). The findings of this thesis, however, do not provide evidence of momentum profit when conventional methods of momentum trading strategies are applied. On the other hand, if the returns from the strategy of going long on loser stocks and short on winner stocks (i.e. contrarian) are positive, then contrarian profit exists. The finding of this thesis provides evidence of contrarian profit in the short-horizon and long-horizon when conventional contrarian trading strategies are applied. When the three-factor model is applied to control for risk, the intercept is statistically significant. This suggests contrarian profits are not explained by risk. Similar results are found after incorporating the investors' sentiment factor into the model. This suggests contrarian profit exists even when controlling for both risk and investors' sentiment – contrarian profit cannot be explained by risk and investors' sentiment. This thesis also employs the residual trading strategies, which form portfolios on the basis of residual returns. The residual contrarian profit, however, cannot be observed when portfolios are formed on the basis of residual returns.

In Chapter 3 this thesis examines whether strategies involving going long on value stocks and short on growth stocks generate superior returns. Value investors believe that value stocks are undervalued while growth stocks are overvalued but they should be correctly priced in the future, leading to excess returns. The value versus growth trading strategies are expected to generate profits, which are called value premiums. The findings of this thesis provide evidence that value premiums

are persistently observed for all holding periods. The observed value premium exists even after controlling for risk, suggesting that the value premium is not driven by risk. A positive and significant coefficient of business cycle factor is observed after the business cycle factor is incorporated into the three-factor model (i.e. after controlling for risk). This finding suggests that the value premium is positively driven by stages of the business cycle. The value premium, however, cannot be explained by investors' sentiment. At the industry level, the value premium of some industries (i.e. Consumer Durables, Manufacturing, Business Equipment, Shops, and Health) can be explained by stages of the business cycle. The relationship between value premium and investors' sentiment is consistent with the aggregate level, i.e. investors' sentiment is unable to explain the value premium of any of the industries.

Finally, in Chapter 4 this thesis investigates if strategy that takes a long position on high solvency stocks and a short position on low solvency stocks can generate abnormal returns. Solvency is the ability of firms to cover their financial obligations. The high solvency firms are those firms with sufficient cash flows (or balance) to cover their debt obligations while low solvency firms refer to firms that are unlikely to meet their debt obligations. The profitability of this strategy is called the solvency premium. The findings of this thesis show evidence of the solvency premium in the short-horizon but it reverts to solvency discount in the long-horizon. When the three-factor model is applied to control for risk, the solvency premium disappears. This suggests the solvency premium can be explained by risk. Further analysis, however, shows that after controlling for risk, the solvency premium exists in economic contraction and disappears during economic expansion. The solvency discount, inversely, is observed only during economic expansion. When the investors' sentiment factor is incorporated into the three-factor model, the positive and significant coefficient of investors' sentiment is observed. This suggests that investors' sentiment is also relevant in explaining solvency premium, i.e. high investors' sentiment leads to higher solvency premium.

This thesis shows that three styles of investing techniques can generate superior returns (i.e. conventional contrarian trading strategy, value versus growth trading strategies, and corporate solvency based trading strategy). However, momentum trading fails to generate any significant return. The findings benefit both individual and institutional investors to identify the stocks that are likely to generate superior returns and allocate their funds efficiently. These styles still exist until the market is more efficient relative to these styles and superior returns cannot be earned (Cao, 2011). These styles, then, disappear.

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LIST OF ABBREVIATIONS

AAII .... American Association of Individual Investors

AMEX ....The American Stock Exchange

APT ....Arbitrage Pricing Theory

BM... Book to Market Ratio

CAPM ....Capital Asset Pricing Model

CCAPM...Consumption-based Capital Asset Pricing Model

CCI .... Consumer Confidence Index

CFC ....Cash flow Coverage Ratio

CFD .... Cash flow to Debt Ratio

CLI ....Composite Leading Indicator

CP ....Cash-flow to Price Ratio

CRSP ....The Center for Research in Security Prices

DA .... Debt to Assets Ratio

DE .... Debt to Equity Ratio

DY ....Dividend Yield

EM .... Equity Multiplier

EP .... Earnings to Price Ratio

FCC ....Fixed Charge Coverage Ratio

HML ....High Minus Low

IC .... Interest Coverage Ratio

IPOs ....Initial Public Offering

LDA... Long-term Debt to Assets Ratio

NASDAQ ....National Association of Securities Dealers Automated Quotations

NBER ....National Bureau of Economic Research

NYSE ....The New York Stock Exchange

OECD .... Organization for Economic Co-operation and Development

SMB .... Small Minus Big

UK .... United Kingdom

US...United States of America

Chapter 1 – Introduction

Investing in stock markets is gaining investors' attention more than ever before. The number of investable assets in the financial markets is also ever increasing. The most difficult question for the investors is which asset is going to be the most profitable to invest in from the universe of the available ones. Identifying such assets from thousands of investable assets is not that simple. Instead of examining assets one by one, investors allocate cash to assets following certain criteria with the aim to make profits by going long in one type of assets and short in others. The key theme of this thesis is to examine if there are any patterns in firms' (or stocks') attributes that can be exploited in order to identify stocks suitable for long or short positions so that superior returns can be generated.

Classification is a mechanism of human thought that groups things into categories on the basis of their similarity (Roach and Lloyd, 1978). For example, investors are classified as individual investors and institutional investors on the basis of their ownership of investable funds. Firms are categorized into big firms and small firms based on their market capitalisation. Classification is one of the obvious mechanisms according to which objects or things are understood, recognized, and differentiated (Roach and Lloyd, 1978). Classifying things into groups is also beneficial to portfolio formation. In financial market, investors normally classify assets into various categories, for example, small-capitalisation stocks, value stocks, and growth stocks, before making a decision how to allocate their funds. Barberis and Shleifer (2003) claim that a popular approach in portfolio management is to categorize stocks into groups and allocate their funds among diverse asset groups. The diverse asset groups that investors employ are known as styles and the process to allocate funds across different styles is called style investing. The main purpose of this thesis is to examine the profitability of style investing.

According to Barberis and Shleifer (2003), assets in the same group, in other words same style, usually share similar characteristics. Some styles such as government bonds are relatively long lasting while other styles come and go. After poor long-term performance, styles disappear. In other words, a style disappears when the market is more efficient relative to that style (Cao, 2011). New investment styles arise due to two main reasons (a) a specific group of asset is observed to generate superior returns and (b) financial innovation. The empirical issues addressed in this thesis focuses on the first reason: whether particular styles can generate superior returns.

Style investing benefits both individual investors and institutional investors for many reasons. Mullainathan (2002) explain that classification simplifies the complication of choices and also allows large volume of information to be processed efficiently. Allocating funds among ten or twenty styles is easier than selecting assets from thousands of listed stocks. Sharpe (1992) also claims that classifying assets into categories facilitate investors to assess the performance of money managers as styles automatically generate peer groups who follow the same style.

Allocating stocks based on historical returns is one of the most popular style investing. Two of the most commonly used trading styles are momentum and contrarian strategy. The momentum and contrarian traders group assets on the basis of historical returns. The momentum investing strategy suggests that buying past winner stocks (high historical returns) and selling past loser stocks (low historical returns) can generate superior returns. Profits from momentum investing are documented during medium investment horizons (Jegadeesh and Titman 1993). The Contrarian invetsing strategy suggests taking long positions in past losers and short positions in past winners. The profitability of the contrarian strategy is recognised during short and long horizon investment periods (Conrad and Kaul 1998). Several studies confirms that momentum and contrarian style investing generate superior returns that are persistently observed from time to time (see e.g. Avramov and Chordia (2006), Fama and French (2012) and Blitz, Huij, Lansdorp, and Verbeek (2013)). The reason behind this superior return, however, is remain ambiguous.

Another style investing that is gaining attention for a long time is value investing. According to this strategy, buying value stocks and selling growth stocks can generate superior returns. This investing style is one of the oldest known investing styles (Graham and Dodd 1934). Evidence of profitability from value investing are documented in several studies throughout times (see e.g. Zhang (2005) and Fama and French (2012)). Almost all of these studies suggest that value investing is profitable but the reason behind this profitability remains unresolved. For example, some studies claim that value premium can be explained by risk (e.g. Fama and French (1992)) while some others (Lewellen and Nagel (2006)) do not share the same opinion.

The final style investing that is examined in this thesis is based on corporate solvency. High solvency firms are expected to generate higher returns than low solvency firms (George and Hwang 2010). However, in contrast to this belief, other studies such as Gomes and Schmid (2010) find that firms with low solvency are associated with high returns. Evidence of profitability from solvency investing remains ambiguous (see e.g. Griffin and Lemmon (2002) and Garlappi, Shu, and Yan

(2008)). The relation between the firms' solvency ratio and stock returns is not yet rigorously examined. This thesis aims to bridge this gap and introduce novel trading strategy based on corporate solvency.

1.1 Motivation

As mentioned in the previous section, investors tend to follow a certain pattern of asset allocation, which is called style investing. There are several styles to follow. This thesis studies three different investing styles: trading strategies based on historical returns, value versus growth trading strategies, and trading strategies based on corporate solvency. Although the profitability of the first two trading strategies is examined in several previous studies, there is limited work done with regard to the factors that can explain these profits. Earlier studies generally confirm the existence of momentum profits, contrarian profits, and value premium. However, the underlying reasons of these profits remain ambiguous. For example, some studies claim that these profits can be explained by risk (see e.g. Xing (2008)) but others support that risk is unable to explain such returns (see e.g. Avramov and Chordia (2006)). The trading strategy based on corporate solvency is introduced in this thesis. This section provides a brief summary of current understanding of these strategies and outlines the gaps that this thesis aims to bridge.

Historical Return and Trading Strategies: Can risk and investors' sentiment explain the observed profitability?

Random walk theory suggests that changes in the stock price should be unpredicted. Changes in stock prices should be independent to each other and trends or past movements cannot be used to predict future returns (Horne and Parker, 1967). Several studies such as Jegadeesh (1990), however, present evidence that historical trends in stock prices can be used to predict future trends. Similarly, technical analysis is associated with the belief that past movements such as a historical price trend is a superior indicator for future movements. Therefore, according to this view, trading strategies that are based on historical returns are expected to generate profits. Two of such commonly used strategies are the momentum and the contrarian trading strategy. Although both these strategies are based on historical returns, they are successful in generating extra returns. They differ though with regard to the investment horizons.

The momentum trading strategy suggests that investors should take long positions (buying) in past winners and short positions (selling) in past losers. As winner stocks are characterized stocks with high historical returns whereas loser stocks are those with low historical returns. The profit generated from this type of investing is called momentum profit. The momentum profit was first recognized by Levy (1967). The momentum profit is observed in a medium investment horizon, specifically more than a month and less than a year, (Jegadeesh and Titman 1993). Evidence of momentum profits is documented internationally (see e.g. Asness, Moskowitz, and Pedersen (2013)). In a more recent study, Blitz, Huij, and Martens (2011), claim that momentum trading strategies based on past residual returns can generate higher profits compared to the conventional momentum trading strategies. This thesis, therefore, also investigates residual momentum trading strategies to see whether forming portfolios on the basis of residual returns generates higher momentum profits. Previous studies provide both risk-based and behavioural-based explanations for momentum profits. Earlier studies generally agree that momentum profits cannot be explained by risk (see e.g. Avramov and Chordia (2006)). The evidence on the success of behavioural-based explanations is mixed. Some studies such as Cooper, Gutierrez, and Hameed (2004) document that momentum profit is driven by investor overconfidence while other studies such as Antoniou, Lam, and Paudyal (2007) claim that behavioural-based explanations cannot explain momentum profit.

In contrast, the contrarian investing strategy proposes that buying past losers and selling past winners can generate excess returns. Profits generated by this type of strategy which are called contrarian profits. Evidence of contrarian profits was first documented by Fama (1965). Contrarian profits are documented during either short investment horizons (one week to one month) or long ones (beyond a year) (see e.g. Fama and French (1988) and Lehmann (1990)) . Evidence of contrarian profits is documented internationally (see e.g. Kang, Liu, and Ni (2002)). Scholars generally agree that contrarian trading strategies are associated with such profits. De Bondt and Thaler (1985), (1987) assert that contrarian profits are due to investors' overreaction and cannot be explained by risk. Jegadeesh and Titman (1995) confirm that contrarian profits can be explained by investors' overreaction but they note that this is not the only explanation. Blitz, Huij, Lansdorp and Verbeek (2013) show that the short-term contrarian trading strategies based on past residual returns can earn higher returns compared to the conventional trading strategies providing empirical evidence of the superior performance of the residual contrarian trading strategies.

Regarding the above explanation though, there is no direct evidence whether residual momentum and residual contrarian profits can be explained by investor behaviour. The relation between (a) momentum and contrarian profits and (b) risk and investors' sentiment remain unclear. This study, thus, aims to fill this gap by providing evidence as to whether conventional momentum and contrarian profits as well as profits stemming from residual momentum and residual contrarian trading strategies can be explained by risk and/or investors' sentiment.

Business Cycles and the Profitability of Value vs. Growth Trading Strategies

The value versus growth trading strategies suggest investors should take long positions in value stocks (buying value stocks) and short positions in growth stocks (selling growth stocks). Value stocks are generally identified as firms with high book to market ratio whereas growth stocks are generally defined as those firms with low book to market ratio. Earlier studies suggest that the characterization of stocks as value or growth stocks can also be based on dividend yield (see e.g. Litzenberger and Ramaswamy (1979)), earnings to price (see e.g. Jagannathan and Wang (2007)), and cash-flow to price ratio (see e.g. Fama and French (1996)). The value versus growth trading strategy is first recognised by Graham and Dodd (1934). The profitability from buying value stocks and selling growth stocks is called value premium. Evidence of value premium is documented in several studies, for example, Chen, Petkova, and Zhang (2008) and Gulen, Xing, and Zhang (2011). The value premium is also observed globally (see e.g. Fama and French (1998) and Gharghori, Stryjkowski, and Veeraraghavan (2013)). Several studies provide evidence that value portfolio outperforms growth portfolio and there are also several attempts to identify the underlying reason of the observed value premium.

Difference in risk is one of the possible factors that can explain the value premium. Fama and French (1992) observed value premium post-1963 and claim that the observed value premium is due to risk. On the one hand, previous studies support Fama and French (1992) and assert that value premium can be explained by risk. Lettau and Ludvigson (2001) and Parker and Julliard (2005) used the book to market ratio as a measure of identifying value and growth stocks. They applied the Consumption Capital Asset Pricing Model (CCAPM) to examine whether CCAPM has the ability to explain the value premium. They found supportive evidence that the value premium can be explained by the CCAPM based measure of risk. Fama and French (1996) and Xing (2008) use the Fama and French (1993) three-factor model to examine whether the value premium can be explained by risk. They found that the three-factor model performs well in that case.

On the other hand, several studies found that the value premium cannot be attributed to risk. Reinganum (1981) found evidence of value premiums when earnings to price ratio is employed to identify value and growth stocks and concluded that the value premium cannot be explained by risk. Lewellen and Nagel (2006), Fama and French (2006), and Ang and Chen (2007) also agree that the value premium is not driven by risk. They employed book to market ratio to identify value and growth stocks. Both conventional and conditional CAPM are employed to investigate the relationship between value premium and risk. They show that the ability of the conditional CAPM to explain the value premium is almost as weak as that of the conventional CAPM. The debate regarding the relationship between value premium and risk is ongoing. This thesis, thus, attempts to challenge this point and answer the question whether the value premium can be explained by documented differences in risk.

Changes in economic conditions generally affect overall economy including stock markets. During different economic environments, firms bear different levels of risk that are, in turn, associated to different returns (Petkova and Zhang 2005). According to expectations, higher risk is documented during bad economic conditions (Zhang 2005). Different types of firms are also differently affected by risk. Petkova and Zhang (2005), Zhang (2005), and Chen, Petkova, and Zhang (2008) observe important relationships between value premium and business cycles. They define economic expansion and recession according to the National Bureau of Economic Research (NBER) and they find that higher value premium is observed during periods of economic recession than during expansion. They explain that value firms bear higher risk relative to growth firms during a bad economic environment. This higher level of risk is due to the lack of flexibility of such firms to cut their capital. Cutting capital in value firms is more costly than expanding capital in growth firms. Higher level of risk, thus, is associated with higher returns on value stocks during a recession. To the best of the author's knowledge, there are only a few studies to support this relationship between value premium and business cycles. Therefore, this thesis will also attempt to provide additional evidence with regard to the relationship between business cycles and value premium using a different methodology than previous studies. More specifically, business cycle factors will be defined based on the Organization for Economic Co-operation and Development Composite leading indicator (OECD CLI) index and the OECD business cycle turning point.

Earlier studies such as Lakonishok, Shleifer, and Vishny (1994) suggest that investor behaviour is another possible factor that can possibly explain value premiums. In particular, they argue that the value premium is mainly generated from cognitive biases in investors' behaviour. Xing (2008), however, claim that the value premium is inconsistent with investors' over or/and under reaction. Therefore, the relation between investor behaviour and value premium also remains ambiguous. This thesis, thus, aims to further examine the relationship between value premium and investors' sentiment both at aggregate and industry levels.

Corporate Solvency and Investment Profitability

Solvent firm are those firms with sufficient cash flows to pay their financial obligations. The term "solvent firms" can also refer to firms with good fundamentals, which make investors confidence to invest in. Solvency ratios indicate the ability of firms to pay their financial obligations. Higher solvency is associated with lower possibility of default on debt obligations. The solvency ratios can also be used to assess firms' financial risk. Earlier studies suggest that solvency ratios are generally used to indicate firms' credit rating (see e.g. Horrigan (1966)) and chance of bankruptcy (see e.g. Thomas Ng, Wong, and Zhang (2011)). The relation between firms' solvency ratios and stock returns, however, is not yet rigorously examined. This thesis, thus, aims to fill this gap.

As insolvent firms are characterized those firms with insufficient cash flows to pay their financial obligations. The insolvent firms are also known as distressed firms (Wruck 1990). Firms' solvency can be measured using financial ratios such as debt to equity ratio and debt to assets ratio, with a higher ratio indicating a lower solvency level (Geng, Bose and Chen, 2015). Similar ratios are also used to indicate firms' financial leverage. Leverage generally refers to the degree that firms use fixed-income securities as a source of finance relative to their equity. A higher level of debt financing leads to a higher level of financial leverage. Therefore, firms with high financial leverage are generally characterized as low solvency firms whereas high solvency firms generally carry low levels of debt (low leverage). This suggests that there is a link between leverage, financial distress, and firms' solvency. Specifically, firms with high financial leverage carry high level of debt that leads to low firms' solvency.

High level of financial leverage means high level of debt relative to equity amd can lead to an increase in the expected return due to the associated higher level of financial risk (Hall and Weiss, 1967). This positive relationship between leverage and stock return is also observed in several other studies. Baker (1973) found that financial leverage and return move in the same direction when financial leverage is measured using the inverse of equity to assets ratio. Bhandari (1988) confirmed that average stock returns are positively correlated with debt to equity ratio, suggesting a positive correlation between stock returns and financial leverage. This finding is also consistent with a number of more recent studies such as those of Gomes and Schmid (2010) and Gill and Obradovich (2012). The evidences from some earlier studies, however, show a different direction of this relation. Arditti (1967) investigated the relationship between return and financial leverage when the latter is measured by the debt to equity ratio. The results show that higher leverage is associated with lower returns. Hall and Weiss (1967) measured financial leverage using equity to assets ratio that is inversely relate to financial leverage. They also find a negative relationship between leverage and stock return. In other words, higher financial leverage leads to lower returns. This finding is also consistent with the work of Baxter (1967) and George and Hwang (2010). These studies suggest that a firm's solvency may have important implications for its stock returns. According to previous studies discussed in this section, the relation between financial leverage and stock returns remains ambiguous. Therefore, this relation re-examines this relation using alternative research methods.

Earlier studies find that lower financial leverage reduces the likelihood of financial distress. Wruck (1990) and Opler and Titman (1994) find that financial distress could be avoided by reducing financial leverage. However, there are studies that provide ambiguous evidence with regard to the relation between financial distress and stock returns. Griffin and Lemmon (2002) and Vassalou and Xing (2004) find that the proxies of financial distress are positively related to stock returns. In particular, they explain that higher returns experienced by distressed firms is a compensation to the investors for the higher level of risk they take. Other studies such as Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008), however, document a negative relationship between distressed firms and stock returns. One of the possible explanations they provided is related to unexpected developments that can occur during the sample period, such as an increase in the power of debt holders in the case of bankruptcy, which can have a negative impact on stock returns. They also claim that returns on distressed stocks cannot be considered as a reward for bearing with this higher risk.

The relations between (a) stocks returns and financial leverage and (b) financial leverage and financial distress remain ambiguous, which, in turn, leads to ambiguous findings regarding the relation between firm's solvency and stock returns. Therefore, this thesis aims to fill this gap in the literature by examining the relationship between firms' solvency and stock returns and introducing a novel investing style that generates superior returns. In addition, this thesis investigates whether risk, business cycle and investors' sentiment can explain solvency premiums.

1.2 Key Research Questions

This thesis aims to fill a number of gaps in the literature by examining the factors that can explain the profitability of the three trading strategies identified above. In order to do so, the thesis will answer two key research questions.

1) Can trading strategies based on historical return patterns, value versus growth trading strategies, and trading strategy based on corporate solvency generate abnormal profits?
2) If yes, can risk, business cycle and/or investors' sentiment explain the observed profits?

In other words, this thesis will examine whether past winners (losers), value stocks, and high solvent stocks outperform past losers (winners), growth stocks, and low solvent stocks respectively. Should there be sufficient evidence to support the latter, it will then be investigated whether the observed profits can be explained by risk, business cycle, and/or investors' sentiment.

1.3 Main Findings

Firstly, contrary to previous research findings, this thesis shows that momentum trading fails to generate excess returns in the medium term. Momentum profits cannot also be observed even when portfolios are formed on the basis of historical residual returns. This finding is inconsistent with Blitz et al. (2011). However, evidence of profits generated by contrarian trading strategy is similar to the evidence found in the literature. Contrarian profits are documented during either short (one month) or long horizons (36 and 60 months). The presence of contrarian profits during those holding periods is consistent with the findings of De Bondt and Thaler (1985) and Lehmann (1990). The highest contrarian profit of 0.67% (per month) is documented when the formation-period is 12 months and portfolios are held for 36 months. The 36 months holding period generally generates highest contrarian profits among all formation-periods. This result suggests that a decrease in stock returns will be followed by an increase in stock returns. The contrarian profits, however, disappear when portfolios are formed on the basis of historical residual returns. Therefore, the conventional contrarian trading strategy outperforms the residual contrarian trading strategy in terms of profitability. To investigate the relation between contrarian profits and risk, the three-factor model of Fama and French (1993) is employed. The findings of this thesis suggest that the three-factor model cannot explain the observed contrarian profits. In other words, contrarian profits are left unexplained by risk. The investors' sentiment factor, is then incorporated into the model to examine whether investors' sentiment as defined by Baker and Wurgler (2006) can explain contrarian profits. A statistically insignificant effect of investors' sentiment on contrarian profit is documented. Thus, risk and investors' sentiment cannot explain the superior returns stemming from historical patterns based strategies. More specifically, risk and investors' sentiment cannot explain contrarian profits.

Secondly, this thesis employs the four following criteria to classify stocks into value and growth stocks: dividend yield, book to market ratio, earnings to price ratio, and cash-flow to price ratio. The results confirm the existence of value premium apart from the case when dividend yield is used to classify stocks. The three-factor model of Fama and French (1993) is employed to investigate whether the documented value premium can be explained by risk. The findings are consistent with those of earlier studies such as Reinganum (1981) and Lewellen and Nagel (2006) that value premium cannot be explained by risk. In the next step of the empirical analysis, the business cycle factor is incorporated in the model to examine its relation with the value premium. The findings are consistent with those of Petkova and Zhang (2005) according to which there is an important relationship between the value premium and business cycle. However, although Petkova and Zhang (2005) report a negative relationship, this thesis finds a positive relationship between the value premium and stages of the business cycle. In other words, the value premium is positively related to the stages of the business cycle. The implication of this result is that during the economic expansion, investors are more optimistic and more confident to invest in risky assets (i.e. value stocks), which leads to a higher investment volume (or higher demand for stocks), increase in stock prices, and consequently, higher stock returns. This relation also is observed at industry level. Specifically, the stages of the business cycle is positively related to the value premium in Consumer Durables, Manufacturing, Business Equipment, Shops, and Health sectors while it fails to explain the value premium in some other sectors (i.e. Consumer Nondurables, Chemicals, and Energy). The impact of investors' sentiment on the value premium remains insignificant. This is consistent with the findings of Xing (2008). The relation between the value premium and investors' sentiment remains also insignificant at industry level.

Finally, this thesis introduces a trading strategy based on corporate solvency. This strategy suggests that investors should buy highly solvent stocks and sell low solvent stocks. The profitability of this strategy is called solvency premium. The solvency premium is documented during short-term holding periods while solvency discount is observed during long-term holding periods. The presence of solvency premium and solvency discount are consistent with earlier studies based on leverage such as George and Hwang (2010) and Gomes and Schmid (2010). The observed solvency premium can be partially explained by risk when the three-factor model of Fama and French (1993) is employed. The business cycle is another factor that can explain the solvency premium. Specifically, the solvency premium is documented during periods of economic contraction and reverses to solvency discount during periods of economic expansion even after adjusting for risk. Another factor that can explain the solvency premium is investors' sentiment. The positive and statistically significant coefficient of investors' sentiment suggests that the solvency premium is positively associated with investors' sentiment. In other words, a high solvency premium can be due to high confidence of investors in the stock market. When investors have more confidence in the market, they invest more in solvent stocks, which leads to higher returns in high solvency stocks.

According to the finding from each empirical chapter, findings of the first two empirical chapters provide some additional knowledge but it is not significantly different from the literature. The third empirical chapter, however, is difference from others. Only the third empirical chapter makes a novel contribution and sheds new light into the area of stock trading strategy introducing a novel trading strategy based on corporate solvency.

1.4 Thesis Structure

The profitability of trading strategies that are based on historical returns is presented in chapter 2. Chapter 3 investigates business cycles and the profitability of value versus growth trading strategies. The relation between corporate solvency and investment profitability is examined in chapter 4 and chapter 5 concludes.

Each empirical chapter has a stand-alone structure It begins with an introductory section, followed by a literature review, outline of the research questions and hypothesis development, presentation of methodology, sample data description, empirical results, and the conclusion. Some overlap is unavoidable between these three empirical chapters since similar methodologies are employed to investigate the research questions under consideration.

Chapter 2 - Historical Returns and Trading Strategies: Can risk and investors' sentiment explain the profit

2.1 Introduction

Extant literature shows that profitable trading strategies could be devised using historical trends in share prices. Two of such strategies are momentum and contrarian trading strategies. Momentum (contrarian) profit is generated when applying the momentum (contrarian) trading strategy. Momentum investing strategy suggests that investors take a long position on past winners and a short position on past losers. The basic idea of the momentum trading strategy is that when the trend of stock prices has been established, the future stock prices will tend to continue in the same direction, rather than move in the opposite direction. The purpose of this trading strategy is to capitalize on the continuation of trends in the stock market that already exist. Investors who employ the momentum trading strategy believe that an increase in stock prices will be followed by additional profits, while a decrease in stock prices will be followed by additional losses. The existence of momentum profit was first recognized by Levy (1967). Jegadeesh and Titman (1993) claimed that momentum profit is observed when portfolios are held for 3 to 12 months; they also observed a momentum profit of 1.31% in the US stock market. Morelli (2014) also found a momentum profit of 0.85% in the UK stock market. The momentum profit is internationally observed. Fama and French (2012) found a global momentum profit of 0.62% in four regions (Japan, Asia Pacific, Europe and North America).

Inversely, contrarian trading strategy suggests taking a long position on past losers and a short position on past winners (Jegadeesh, 1990). This trading strategy goes against the trend of the prevalent market by buying poor performance stocks and selling well-performing stocks. The contrarian trading strategy believes that the strong confidence among groups of investors can lead to mispricing in the stock market. The negative serial correlation of stock returns over the short-horizon has been documented by Fama (1965). The contrarian profit is also observed during long-term holding periods (see e.g. De Bondt and Thaler (1985) and Conrad and Kaul (1998)). The contrarian profit of 4.18% is observed by Conrad and Kaul (1998) when portfolios are held for 36 months. Lehmann (1990) observed contrarian profits of 0.11% after portfolios are held for 1 week. Blitz, Huij, Lansdorp and Verbeek (2013) also observed monthly short-term contrarian profits of 0.69%. The contrarian profit is normally observed in short-horizon (1 week to 1 month) and in long-horizon (36 to 60 months). The momentum profit generally exits when portfolios are held for 3 to 12 months (medium-horizon). Momentum profit and contrarian profit have gained attention from the many finance researchers. Generally the researchers agree on the profitability of momentum and contrarian trading strategies but the sources of profit from these strategies still remain elusive. Scholars have attempted to explain the existence of momentum profit and contrarian profit using (a) risk-based explanations and (b) behavioural-based explanations.

This chapter examines the abilities of both risk and behavioural explanations in explaining momentum and contrarian profits. To examine the successes of momentum and contrarian trading strategies in generating excess returns, portfolios are formed based on average historical returns. The formation periods applied are 3, 6, 9, and 12 months. The portfolios are then held for five different holding periods: 1, 3, 6, 36 and 60 months. Contrarian profit exists but momentum profit cannot be observed. The existence of contrarian profit suggests that an increase in stock prices will not be followed by additional profits but by decreasing stock returns, i.e. reversal in price trend.

Blitz, Huij and Martens (2011) and Blitz et al. (2013) suggest that residual momentum (contrarian) trading strategy, which forms portfolios based on residual returns, outperforms conventional momentum (contrarian) trading strategy to generate profit. They documented that the residual momentum (contrarian) trading strategy can reduce exposure to the three factors from the Fama and French (1993) model. The findings in this chapter, however, suggests that there is no evidence of momentum and contrarian profits when portfolios are formed based on historical residual returns. It also suggests that conventional contrarian trading strategy outperforms residual contrarian trading strategy to generate excess returns. The existence of contrarian profit leads to the next question: What are the underlying factors to explain the contrarian profit? Risk is one of the possible factors. The findings in this chapter, however, show that the statistical significance of intercept is found when three-factor model of Fama and French (1993) is applied. This suggests that these are excess returns, even after controlling for risk. Thus, risk is unable to explain contrarian profit. This result is consistent with De Bondt and Thaler (1987).

Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) also suggest that loser portfolios have a superior performance when compared to winner portfolios due to investor overreaction. The investors' sentiment, consequently, is employed in this chapter to investigate the relationship with contrarian profits. The investors' sentiment factor is incorporated in the three-factor model. The findings show the statistical significance of intercept but statistical insignificance of the coefficients of the investors' sentiment factor. This result leads to the conclusion that there is contrarian profit even after controlling for risk and the business cycle. In other words, contrarian profit cannot be explained by investors' sentiment. The contrarian profits are observed in this chapter when the portfolios are held for 1, 36 and 60 months. The observed contrarian profits, however, are left unexplainable by (a) risk-based explanations and (b) behavioural-based explanations in this chapter.

This chapter starts with the literature review in section 2.2, which is followed by a discussion of the research question and hypothesis in section 2.3. In section 2.4, the methodology and a sample description is provided. The results are explained in section 2.5, which is followed by the conclusion, in the last section, i.e. section 2.6.

2.2 Literature Review

2.2.1 Profitability of momentum trading strategies

Earlier studies have documented that average stock returns are associated with their performance in the past (Rouwenhorst, 1998). Stocks with high average returns over the past 3 to 12 months continue to outperform stocks with low average returns over the same period (Jegadeesh and Titman, 1993). The trading strategy that takes a long position on stocks with high past returns and a short position on stocks with low past returns is called the momentum trading strategy. Momentum investors believe in a continuation of gains and losses. Specifically, the momentum strategy sorts sample stocks into portfolios based on their past returns. A portfolio that contains stocks with the highest past returns is called a winner portfolio while a loser portfolio includes stocks with the lowest past returns. The momentum investors, thus, take a long position on winner stocks and a short position on loser stocks. The difference of the returns between a winner portfolio and a loser portfolio is called momentum profit.

The existence of momentum profit was first recognized by Levy (1967). Jegadeesh and Titman (1993) confirmed the existence of momentum profits in US stock markets such as NYSE and AMEX. They found that buying winner stocks and selling loser stocks significantly generates profits when these stocks have been held over periods of 3 to 12 months. The momentum profit of 1.31% is produced when (a) a portfolio's formation period is 12 months and (b) portfolios are held for 3 months. They also explained that systematic risk and the delay of the effects of the reaction to common factors on stock prices are not the causes that lead to these momentum profits. Their study, however, does not examine the behaviour explanation for momentum profits.

Not only does this phenomenon occur in US stock markets, evidence of the occurrence of momentum profit has also been provided internationally. Rouwenhorst (1998) has documented the occurrence of momentum profits in 12 European countries. Specifically, the international diversification portfolio (which includes 12 European stock markets: Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland and the UK) of past medium-term winners outperforms losers by approximately 1% per month, during the period from 1980-1995. This continuation of the momentum profits lasts for approximately 12 months. The momentum profits still exist, even after the returns are adjusted for risk, by using (a) the international firm size factor (the international SMB factor from Fama and French's three-factor model) and (b) the international market factor. There is evidence that this continuation of the returns is also negatively associated with firm size. Rouwenhorst (1999), then extended the study to cover emerging markets; the cross-sectional returns from the 20 emerging stock markets are driven by the same factors as the developed stock markets. There is evidence of momentum profits in these emerging markets. The existence of momentum profits has, thus, been confirmed both domestically and internationally.

In recent studies, however, the evidence for momentum profits has been different from the previous studies. Cakici, Fabozzi and Tan (2013) investigated the momentum profits in 18 emerging markets within three regions (Eastern Europe, Latin America and Asia) during the period from 1990-2011. They found strong evidence of momentum profits (0.93% in Asia and 0.96% in Latin America) but not in the emerging markets in Eastern Europe. Cakici, Tang and Yan (2016) also examined the momentum profits in 18 emerging markets during the period from 1990-2013. They documented the fact that the momentum trading strategy fails to generate profits in emerging stock markets.

Fama and French (2008) examined return anomalies such as momentum using cross-sectional regression. They estimated the return anomalies separately based on firm size: those with micro, small and large stocks. There is a strong relationship between momentum profits and average returns in firms of all these sizes. They suggested that momentum is the most robust market anomaly amongst other examined anomalies.

The previous studies attempted to explain the momentum anomaly using risk-based explanations and also behavioural explanations. The asset pricing models, such as the Capital Asset Pricing Model (CAPM), Consumption-based CAPM (CCAPM) and the three-factor model of Fama and French (1993), were used to identify a plausible explanation.

2.2.1.1 Momentum profits and risk-based explanations

<u>Single-factor models</u>

A single-factor model is a model of stock returns that employs only one factor to explain the returns; that factor is generally the returns of the market. The most well-known single-factor models are CAPM and CCAPM. Schwert (2003) explained that the market anomalies were mainly reversed or disappeared during their study. The momentum effect, however, cannot be explained by CAPM. Avramov and Chordia (2006) examined whether market anomalies such as the momentum effect are explained by asset pricing models. They found that both unconditional and conditional one-factor models such as CAPM and CCAPM cannot be used to explain the momentum anomaly, even after its beta is allowed to vary with (a) firms' value and size, (b) default spread, and (c) both (a) and (b).

Fama and French (2012) also agreed with the study of Schwert (2003) and Avramov and Chordia (2006) that momentum profits cannot be explained by CAPM. Fama and French (2012) examined value premium and momentum profit in four regions: Japan, Asia Pacific, Europe and North America. Momentum profit exists everywhere except for Japan and the global momentum profit for these four regions is 0.62%. They also documented the fact that the average momentum profit decreases when firms' size increases. The CAPM and the Fama and French (1993) three-factor model cannot capture any momentum patterns that occur in both global and local models.

Morelli (2014), however, found that time-varying systematic risk provides a partial explanation of momentum profits and also confirmed that including conditional information in CAPM provides a better explanation of momentum profits. The author applied the conditional version of CAPM to examine whether time-varying systematic risk drives momentum profits. The result clearly showed the existence of momentum profits in the UK stock market during the period 1980-2010. The author claimed that the highest amount of momentum profit is generated when the formation period is 12 months and the holding period is 6 months, which is 0.85%. The author found higher systematic risk in winner portfolios than in loser portfolios. This difference is statistically significant in some cases. The result suggested that momentum profit is partially explained by risk.

Other factors have been employed to explain the momentum profits. Johnson (2002) investigated the momentum anomaly using a simple partial-equilibrium model. The author found that the momentum profits are related to the expected growth rate that is correlated to risk. Specifically, Johnson (2002) found that past winner stocks seem to have a high expected growth rate, which is then exposed to high expected growth risk. If the expected growth risk is priced, the winner stocks outperform the loser stocks.

Sagi and Seasholes (2007) and Liu and Zhang (2008) have also investigated momentum profits using growth rates. Sagi and Seasholes (2007) examined whether momentum profit is driven by firm-specific factors. They found that the momentum strategy that employs firms with low costs, more growth options and high revenue volatility shows a better performance in generating momentum profit than the conventional momentum strategy. Specifically, they found that firms with low cost of goods sold generate higher momentum profits than firms with high cost of goods sold, from 2% to 9% per annum. Their momentum strategy outperforms the conventional strategy in both datasets: numerical simulated returns and CRSP/Compustat.

Liu and Zhang (2008) documented that winner stocks have temporarily larger expected growth rates than loser stocks. The differences in the expected growth rate roughly match the momentum profits. Their results suggested that the expected growth rate is a factor of price risk; once the expected growth increases, the expected growth risk increases. They also claimed that approximately 50% of the momentum profit is explained by the factor of macroeconomic risk. They then concluded that momentum profits could be explained by risk-based explanations; in other words, risk plays an important role in explaining momentum profits.

Multifactor models

A multifactor model is a model that includes multiple related factors to explain market phenomena, which in this case are momentum profits. Arbitrage pricing theory (APT) developed by Ross (1976) is one of the multifactor models. APT allows more than one generating factor to explain the stock returns (Roll and Ross, 1980). The most well-known multifactor model is the three-factor model of Fama and French (1993). Fama and French (1996) clarified the fact that momentum profit is the only market anomaly left unexplained by their three-factor model and this result is consistent when APT is employed. The study by Fama and French (2012) that has been mentioned in the previous section also falls within this area. They found that the three-factor model of Fama and French (1993) cannot be used to capture momentum patterns in both global and local models in four regions: Japan, Asia Pacific, Europe and North America. Fama and French (2012) again confirmed that the three-factor model of Fama and French (1993) fails to explain momentum profits.

Grundy and Martin (2001) observed average monthly momentum profits of 0.44%; they applied the Fama and French (1993) three-factor model to explain these momentum profits. The three-factor model can explain the variations of winner and loser returns; however, it cannot explain the average returns. Schwert (2003) explained that the market anomalies were mainly reversed or disappeared during his study. The momentum effect, however, cannot be explained by the three-factor model of Fama and French (1993); they documented the fact that momentum profit is larger when stock returns are adjusted for risk using their three-factor model.

Chordia and Shivakumar (2002) explained that irrational investors lead to time series patterns of returns and, hence, that abnormal profit occurs. Momentum profit is one of these time series patterns. They observed momentum profits of 0.83% during the period from 1951-1963 and 0.73% from 1963-1994. They showed that the set of lagged macroeconomic factors, which are correlated to a business cycle, could explain momentum profits. They documented the fact that there is a large momentum profit during expansions but that it does not exist during recessions. They also suggested that time-varying expected returns could be a reasonable explanation, which would clarify momentum profits. Specifically, momentum profits occur due to the differences of cross-sectional conditionally expected returns.

Griffin, Ji and Martin (2003) examined whether momentum profit can be explained by macroeconomic risks. They first found large momentum profits with a low co-movement amongst countries during periods of both expansion and contraction. Their study extended the study of Chordia and Shivakumar (2002) covering 16 international stock markets; however, they found different results. They observed the average monthly momentum profits in Africa, Americas (excluding US), and Europe, to be 1.63%, 0.78%, and 0.77%, respectively. They found that neither (a) an unconditional model based on the factors of Chen, Roll and Ross (1986) nor (b) a conditional estimation model based on lagged macroeconomic factors, provide any evidence that these momentum profits can be explained by macroeconomic risk. Cooper, Gutierrez and Hameed (2004) also followed the multifactor model of Chordia and Shivakumar (2002) and found that momentum profit is unexplained by macroeconomic factors. The studies of Griffin et al. (2003) and Cooper et al. (2004) followed the model of Chordia and Shivakumar (2002) but again discovered different results, i.e. that momentum profits are left unexplained by macroeconomic factors.

Wu (2002) documented that short-term past winners (losers) tend to be future winners (losers); the observed momentum profit is 1.48%. The pattern of returns, however, reverse when stocks are ranked based on longer performance (past 13-60 months). Wu (2002) agreed that the three-factor model of Fama and French (1993) cannot explain the momentum profit. The conditioning information is then incorporated into the model to explain the momentum profit. The author suggested that the conditional version of the Fama and French (1993) three-factor model does explain the momentum profit. Specifically, the momentum profit is explained by the asset pricing model that is conditioned on macroeconomic factors. The study of Avramov and Chordia (2006) also falls within this area. They too employed multifactor models, such as the three-factor model of Fama and French (1993), to test whether multifactor models could explain the momentum effect. They found that the momentum effect is left unexplained by both unconditional and conditional version of the Fama and French (1993) three-factor model. The momentum profit is captured by asset pricing misspecification that varies with macroeconomic factors. Two studies by Wu (2002) and Avramov and Chordia (2006) support the conclusion of the study of Chordia and Shivakumar (2002) that momentum profit is associated with business cycle factors.

The relationship between momentum profit and the business cycle is confirmed again in the study of Antoniou, Lam and Paudyal (2007). They document that momentum profits are 2.10%, 1.82%, and 1.44% in the UK, Germany, and France, respectively. They investigated whether risk-based explanations or behavioural-based explanations can explain the momentum profits. They examined whether business cycle factors can be used to explain momentum profits in European stock markets: i.e. the UK, France and Germany. The asset pricing model of Avramov and Chordia (2006) is employed in their study. They explained that even if the momentum profit is left unexplained by the conditional version of the asset pricing model, this result is due to asset mispricing that varies with international business conditions. They confirmed that the business cycle factor offers a better explanation for momentum profits.

The macroeconomic factors have also gained attention in recent studies. Cakici and Tan (2014) examined the momentum profits in 23 developed stock markets; they document the highest momentum profit in Canada at 1.35%. They found that momentum profits are small and negatively related to large market capitalization stocks; momentum profits are internationally related. They documented the fact that momentum profits exhibit low sensitivity to macroeconomic risks and market liquidity risks; they also showed that momentum profits are unaffected by funding liquidity risks.

Min and Kim (2016) also investigated whether time variation in momentum profits is associated with the business cycle. They document momentum profits of 0.76% (when portfolios are grouped following Jegadeesh and Titman (1993)) and 0.99% (when portfolios are set following Fama and French (1996)). They found that the winner stocks underperform the loser stocks once the margin of wealth value is highest, suggesting that a momentum trading strategy involves exposure to greater downside risk for investors. During recessions, when the expected market risk premium is high, the momentum strategy affects profits negatively; during expansions, however, the expected market risk premium is low and the momentum strategy generates profits. Their results are robust to (a) investors' sentiment, (b) the lagged nature of market returns, (c) the January effect, (d) out-of-sample estimation, and (e) expected market risk premium. The study of Cakici and Tan (2014) provided evidence that confirmed the relationship between momentum profits and macroeconomic factors, while Min and Kim (2016) provided significant results.

Avramov et al. (2007) investigated the relationship between credit rating and momentum profits. They found significantly large momentum profits among high credit risk firms (0.75% for BBB+[1] and 2.23% for BB) while momentum profits do not exist among firms with high credit quality (0.27% and statistically insignificant for A+). They documented that the momentum anomaly cannot be captured by (a) firms' size, (b) firms' age, (c) analyst estimation dispersion, (d) firms' leverage, (e) volatility of returns, or (f) volatility of cash flow. The existence of momentum

[1] This represents bond credit rating which is rated from D (lowest rate) to AAA (highest rate).

profits among low-grade firms suggests that momentum profits are larger during recessions, with which credit risk is mainly concerned. This result, however, is not consistent with the results obtained by Chordia and Shivakumar (2002) who mentioned that momentum profits are larger during expansions.

Asness, Moskowitz and Pedersen (2013) examined momentum profits and value premiums across eight stock markets (in four regions: the US, the UK, continental Europe and Japan) and across asset classes. They documented the annual momentum profit in the US, the UK, and continental Europe; the momentum profits are 5.4%, 6.0% and 8.1%, respectively. They found both value premiums and momentum profits in all asset classes. They also documented the strong co-movement of momentum profits across asset classes. Specifically, momentum profits are positively related to other momentum profits internationally, while momentum profits and value premiums are negatively related both within and throughout asset classes. They showed that international momentum profits across asset classes are captured by the three-factor model of Fama and French (1993) incorporating the global market index. The liquidity risk is also a partial cause of this co-movement and is related positively to momentum profits internationally across classes.

2.2.1.2 Momentum profits and behavioural explanations

The previous section has decribed those studies which have attempted to use risk-based explanation to clarify momentum profits. This section, however, describes earlier studies that attempted to explain momentum profits using behavioural-based explanations.

Daniel, Hirshleifer and Subrahmanyam (1998) improved a theory based on both investor overconfidence and biased self-attribution. They showed that investors overestimate their capability in several circumstances and that this overestimation might lead to forecasting errors. They specifically explained that investors generally overreact to private news while underreacting to public news. They showed that the continuation of this overreaction causes autocorrelation of positive returns which is then followed by a long-term correction. They concluded that short-term positive autocorrelation could be coherent with long-term negative autocorrelation.

Barberis, Shleifer and Vishny (1998) developed a model based on psychological biases. Their study mainly focused on overreaction and underreaction. There is evidence of underreaction during the short period of 1 to 12 months, during which stock prices underreact to information. The information, thus, is slowly incorporated into stock prices. This slow incorporation of information leads to positive autocorrelation during this period. The evidence of overreaction showed that stock prices overreact to the constant trend of information during the longer period of 3 to 5 years. Particularly, stocks with a good previous background for such a long time tend to turn into overpriced stocks and then they have low mean returns afterwards.

Hong and Stein (1999) also attempted to explain the momentum profits using behavioural-based explanations. They developed a unified behavioural model focusing mainly on two rational agents: new-watchers and momentum-traders. The new-watches traded based on their private news. If news spreads slowly among traders, the stock prices underreact to the news during short-term periods. The momentum-traders then generate profits by chasing trends during this underreaction period. Once momentum-traders start trend chasing, stock prices will unavoidably overreact in the long-term. The studies of Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) provided related explanations of momentum profits using a behavioural-based model. They also confirmed that momentum profits occur in short-term holding periods and then reverse to produce contrarian profits in longer holding periods.

Hong, Lim and Stein (2000) attempted to provide an explanation of momentum profits using the gradual-information-diffusion model proposed by Hong and Stein (1999). They found three main results: (a) momentum profits fall extremely when very small firms are excluded, (b) larger momentum profits occur among firms with small analyst coverage, and (c) the impact of analyst coverage is larger for firms which are past losers than for firms which are past winners. These three main findings are related to the firm-specific information hypothesis that the diffusion of bad news moves slowly across investors.

Jegadeesh and Titman (2001) evaluated several explanations for momentum profits. They found behavioural evidence that momentum profit is due to the delay of overreaction when a recent behavioural model is applied. Specifically, there is evidence of a negative post holding period return, which confirms the delay of overreaction that is finally reversed. Jegadeesh and Titman (2001) clarified their results from Jegadeesh and Titman (1993); they found momentum profits in the eight subsequent years after those analysed by Jegadeesh and Titman (1993). This finding explained that momentum profit is not completely a result of data snooping. Grundy and Martin (2001) also confirmed that momentum profit is not due to data mining.

They documented the existence of momentum profit during various sub-periods since 1926. Momentum profit exists even when returns are adjusted for risk.

The study of Cooper et al. (2004), mentioned in the previous section, also falls within this area. They documented the fact that the momentum profit depends on the market stage. Particularly, the momentum profit occurs only when followed by an up-market stage. The momentum profit rises once the lagged market return rises. They claimed that this result is due to the overconfidence of investors. In the long-term, however, the momentum reverses. This result is consistent with Jegadeesh and Titman (2001) who state that momentum profit is reversed during the long-term holding period due to the overreaction.

Huang (2006) extended the study of Cooper et al. (2004) to provide international evidence of momentum profits in the up-market by examining stock markets in 17 countries. The up-market is defined as a market that has non-negative market returns in the past 12, 24 and 36 months, and vice versa for the down-market. The momentum profits are then separated into up-market and down-market stages. The momentum profits largely arise in the up-market when the market stage is identified using the past 12 and 24 months. Huang (2006) provided international support to the study of Cooper et al. (2004). Both studies confirmed the existence of momentum profits in the up-market stage and this existence has been internationally confirmed.

As mentioned in the previous section, Antoniou et al. (2007) also investigated whether behavioural-based explanations explain the momentum profits. They extended the model of Avramov and Chordia (2006) by incorporating the behavioural factors; their findings suggested that the behavioural factors are less likely to relate to the business cycle factors and are unable to explain the momentum profit. The behavioural explanations, thus, could not be significantly used to explain the momentum profit.

Gutierrez and Prinsky (2007) explained the fact that an institution's momentum profit is independently contributed from (a) firm-specific abnormal returns and (b) relative-returns. They found that the momentum profit, which is due to firm-specific abnormal returns, continues for years, while the momentum profit, which is due to relative-returns, reverses after one year. They explained that the momentum profit that is due to firm-specific abnormal returns is consistent with underreaction, whereas the momentum profit that is due to relative-returns is consistent with overreaction.

As mentioned earlier, in Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999), the momentum could be the result of underreaction, for example, investors underreact to news. Agarwal and Taffler (2008) raised the argument that investors' underreaction to a firm's financial distress risk could lead to momentum profit. They examined whether momentum profit is driven by financial distress risk based on UK data. They claimed that market anomalies such as the momentum effect are driven by the underreaction of the market to financial distress risk. Particularly, they found that momentum is a proxy for distress risk. The momentum effect is mainly subsumed by the factor of distress risk. They also showed that there is no evidence that financial distress is linked to the effects of value or size in returns.

The underreaction of investors is also discussed by Asem (2009), who showed that momentum profit is lower among dividend-payout firms than among non-dividend-payout firms. The lower momentum profit is due to larger returns from loser of dividend-payout firms. The author argued that dividends might be used to explain momentum profits. In particular, this result is attributed to investor underreaction to announcements of dividends increasing or decreasing.

Blitz et al. (2011) introduced a residual momentum trading strategy, which involves sorting stocks based on residual returns instead of total raw returns. The residual returns are estimated using the three-factor model of Fama and French (1993). They found that risk-adjusted profits from the residual momentum strategy are approximately double conventional momentum profits. They explained that the conventional momentum strategy exhibits significant time-varying exposures towards the three factors from the Fama and French (1993) model and ranking stocks based on residual returns can reduce these exposures. In other words, the higher profits from the residual momentum strategy are mostly due to smaller variations of stock returns. They also claimed that the residual momentum strategy performs consistently through different economic environments. They concluded that the residual momentum trading strategy outperforms the conventional momentum one. They supported earlier studies, which held that conventional momentum profit is driven by the gradual-information-diffusion model used by Hong and Stein (1999). Their results contributed to explaining the momentum effect and support the assumption that the momentum effect is not related to risk-based explanations.

Antoniou, Doukas and Subrahmanyam (2013) examined whether there is a relationship between sentiment and momentum profits. They assumed that the diffusion of bad news is remarkably slow during periods of optimism. Their results indicated that momentum profits occur when investors are optimistic, or during periods of high sentiment. They also claimed that their results were robust among (a) size, (b) market stage, (c) analyst coverage, (d) risk adjustment, and (e) alternative sentiment. Antoniou et al. (2013) supported the study of Jegadeesh and Titman (2001) which claimed that long-term contrarians are experienced during periods of optimism.

According to previous studies, there is evidence that momentum profits do exist. Earlier studies have attempted to explain the momentum profits in several ways. The researchers mainly explained momentum profits based on two different explanations: (a) risk-based and (b) behavioural-based.

For the risk-based explanations, the well-known asset pricing models such as CAPM and the three-factor model of Fama and French (1993), are documented as failing to explain the momentum profits (see Fama and French (1996), Schwert (2003), and Avramov and Chordia (2006)). Incorporating macroeconomic factors, however, can capture these momentum profits. The studies of Chordia and Shivakumar (2002), Wu (2002), Avramov and Chordia (2006), Antoniou et al. (2007), and Min and Kim (2016) showed that there is a relationship between momentum profits and business cycle factors. The international evidence is confirmed by Cakici and Tan (2014). Some studies found that momentum profits are left unexplained by the macroeconomic factors (see Griffin et al. (2003) and Cooper et al. (2004)).

For the behavioural-based explanations, the studies of Daniel et al. (1998), Barberis et al. (1998), Hong and Stein (1999), and Hong et al. (2000) provide related explanations of momentum profits using behavioural-based models. According to their findings, the momentum profits are mainly due to investor overconfidence, slow diffusion of bad news and delay of overreaction. Jegadeesh and Titman (2001) also confirmed that momentum profit is due to the delay of overreaction correction. Cooper et al. (2004) specifically explained the fact that momentum profits exist in the up-market is due to investor overconfidence. The international evidence is confirmed by Huang (2006). Blitz et al. (2011) and Antoniou et al. (2013) agreed that momentum profit is driven by investor behavioural factors and is not associated with risk-based explanations.. However, Antoniou et al. (2007) claimed that behavioural-based explanations could not be significantly used to explain momentum profit.

2.2.2 Profitability of contrarian trading strategies

Contrarian profits are generated when applying a contrarian trading strategy, which suggests that investors should sell the past highest returns and buy the past lowest returns (Jegadeesh, 1990). This trading strategy goes against the trend of the prevalent market by selling well-performing assets and buying poorly performing assets. The contrarian trading strategy believes that the strong confidence of crowd behaviour among the group of investors can lead to mispricing in the stock market. The basic understanding of the contrarian trading strategy is that investors take a long position for past loser stocks and a short position for past winner stocks; this strategy is also known as a reversal trading strategy. The negative serial correlation of stock returns over the short-horizon has been documented by Fama (1965).

The stock prices should be unpredicted following the random walk model; however, the earlier studies showed evidence that stock prices are predictable. Fama and French (1988) observed the negative serial correlation in long-horizon returns beyond a year. Jegadeesh (1990) also examined the predictive power of monthly returns on individual stocks. The author formed 10 portfolios based on estimated returns. The predictive power on individual stock returns was investigated using different tests: (a) the out-of-sample predicted returns, (b) one-month lagged returns and (c) twelve-month lagged returns. The results showed a highly significant negative first-order serial correlation in monthly stock returns, while a significant positive serial correlation has been found in the longer lagged results. These results suggested that the stock prices do not follow the random walk model. The author also proposed that the predictability of returns on individual stocks could be attributed to (a) stock market inefficiency or (b) systematic changes in estimated returns.

The contrarian trading strategy has been considered by many groups of researchers because there is evidence that contrarian trading strategy earns significant profits. Lehmann (1990) examined whether there is a contrarian profit when weekly portfolio formation is applied. The author showed that the portfolio, which includes firms with negative returns in this week, tends to have positive returns in the next week (0.11%), whereas the portfolio, which includes firms with positive returns in this week, tends to have negative returns in the next week. These contrarian profits appear after both bid-ask spreads and transactions costs have been adjusted. Conrad, Gultekin and Kaul (1997) agreed with Lehmann (1990) and claimed that the contrarian strategy could generate positive profits because the winner stocks are likely to become future loser stocks, while the losers are likely to become future winners. Conrad and Kaul (1998) examined the return-based trading strategy, employing the short-term, medium-term, and long-term holding periods in their study. They documented that the momentum profit is observed when the medium-horizon (3-12 months) is employed, whereas contrarian profit is observed when portfolios are held longer: 0.76%, 1.18% and 4.18% when holding periods are 18, 24 and 36 months, respectively.

De Bondt and Thaler (1985) examined whether investor behaviour affects stock prices. They first explained that people are likely to overact to dramatic or unexpected information and provided evidence to support this overreaction hypothesis. They found that the loser portfolios outperform the winner portfolios in the next 36 months after the formation period. They suggested that loser portfolios have a superior performance due to investor overreaction. De Bondt and Thaler (1987) supported their previous study by providing additional evidence; they showed that (a) risk-based explanations from CAPM and (b) firm size cannot be used to explain the contrarian profits.

Lo and MacKinlay (1990) also confirmed the existence of contrarian profits and attempted to explain them. They explained that overreaction might not be the only explanation for contrarian profits. Specifically, there is evidence that lower than 50% of expected contrarian profits can be attributed to overreaction. They also showed that the contrarian profits are mainly due to a systematic lead-lag relation between returns of portfolios, which are formed on the basis of size. Jegadeesh and Titman (1995) also found that stock prices show an overreaction to firm-specific news; however, they have a delayed reaction to common factors. This delayed reaction created an increase of size-correlated lead-lag effects in asset returns. They then concluded that the contrarian profits were mainly due to the overreaction of the stock prices based on firm-specific news and a small part of the contrarian profits are a result of the lead-lag effect. Lo and MacKinlay (1990) and Jegadeesh and Titman

(1995) came to the same conclusion, i.e. that overreaction is not the only explanation of contrarian profits.

Several studies document the fact that contrarian profits, which are based on historical returns, mostly disappear when taking the transaction costs into account. Conrad et al. (1997) also used the strategy of selling winners and buying losers. They found that there were profits from the contrarian trading strategy in NASDAQ, NYSE and AMEX. These contrarian profits are mainly generated by a bid/ask bounce. These profits all disappear at the small level of transaction costs. Additionally, Avramov and Chordia (2006) claimed that even if the trading volume is controlled, there is a relationship between the contrarian profits and liquidity. The negative serial correlations increase due to the lower liquidity and higher turnover; the highest contrarian profits arise in firms with low liquidity and high turnover. These contrarian profits, however, are lower than transaction costs. In other words, when the transaction costs are taken into account, the profits of the contrarian trading strategy disappear. Avramov and Chordia (2006) and Conrad et al. (1997) confirmed that contrarian profits disappear when taking transaction costs into account.

The contrarian strategy exhibits dynamic exposures to the three factors from the Fama and French (1993) model. Chen and De Bondt (2004) claimed that these dynamic exposures increase momentum risks and negatively affect momentum profits. Blitz et al. (2013) also claimed that these dynamic exposures are both likely to affect contrarian profits negatively and contribute to the risk involved.

Blitz et al. (2013) then introduced a short-term residual contrarian strategy. They examined the performance of both (a) a short-term residual contrarian strategy and (b) a conventional short-term contrarian strategy, using the three-factor model from Fama and French (1993). When the short-term residual contrarian strategy is applied, stocks are ranked based on the past month's residual returns instead of the past month's total returns. They concluded that the dynamic factor exposures disappear when the residual contrarian strategy is used. Their result also shows that the residual contrarian strategy generates significantly higher and more stable profits than the conventional contrarian strategy; the conventional contrarian profit is 0.69% while the residual contrarian profit is 0.90%. In other words, the short-term residual contrarian strategy outperforms the conventional short-term contrarian strategy. The residual contrarian profits are statistically significant over time, even when they take transaction costs into account, unlike the conventional contrarian strategy in which contrarian profits disappear when adjusted for transaction costs (Avramov and Chordia (2006); Conrad et al. (1997)). Furthermore, they claimed that total returns provide less predictability on the future returns than residual returns. The study of Blitz et al. (2013), however, does not provide any direct evidence to support the behavioural explanation.

Contrarian profit is also observed internationally. The contrarian profits are observed in Germany (Schiereck, De Bondt and Weber, 1999). They found that the strategy that buys past losers and sells past winners for up to 5 years generates average accumulative profits of 21.7%. This result is similar to Sehgal and Balakrishnan (2002) who documented long-horizon contrarian profits in the Indian capital market. Additionally, Kang, Liu and Ni (2002) documented the short-term contrarian profit in China. The highest contrarian profit is found when portfolios are formed on basis of previous week return and held for one week.

According to earlier studies, the contrarian trading strategy that trades inversely to the momentum trading strategy does generate profits (see e.g. Conrad et al. (1997) and Lehmann (1990)). These researches attempted to explain the contrarian profits in several ways. The contrarian profit is observed in the short-horizon (e.g. Lehmann (1990)) and long-horizon (e.g. Fama and French (1988)). De Bondt and Thaler (1985, 1987) showed that contrarian profits were due to investor overreaction and also presented the view that risk could not be used to explain it. Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) then confirmed that contrarian profits can be explained by overreaction but that investor overreaction is not the only explanation for contrarian profits.

2.2.3 Investors' sentiment and returns

Sentiment generally refers to whether people individually feel extremely optimistic or excessively pessimistic about a specific situation. The current sentiment of people also affects their decisions in future situations. Generally people who have a positive sentiment decide to make an optimistic choice, while people who have a negative sentiment decide to make a pessimistic choice (Antoniou et al. 2013). Investors' sentiment, thus, refers to whether investors feel positive or negative about the stock market; their sentiment also leads to their decision whether or not to invest.

The earlier studies presented evidence that investors' sentiment does affect stock prices. Kumar and Lee (2006) examined the return co-movement for high levels of retail-concentration stocks (such as small stocks and value stocks). They found that the return co-movement could be explained by systematic retail trading. They also showed that macroeconomic information and analyst prediction could not be used to explain their results. They also claimed that investors' sentiment plays an important role in the returns' formation.

Han (2008) investigated the relationship between investors' sentiment and S&P 500 options prices. They found that changes in investors' sentiment could help to explain option prices. The author used (a) the difference between bullish investors and bearish investors from the American Association of Individual Investors (AAII) survey and (b) a study of valuation error by Sharpe (2002). The evidence also suggested that the effect of investors' sentiment becomes more powerful if there are more restrictions to arbitrage for the options. Additionally, Garcia (2013) showed that the content of news can be used to estimate the stock returns during an economic recession. In particular, the author used sections of negative and positive words from the financial news as a proxy for investors' sentiment. Kumar and Lee (2006), Han (2008), and Garcia (2013) came to the same conclusion, i.e. that investors' sentiment does affect stock prices. Nevertheless, the investors' sentiment proxies are different in each study and also they may lead to different conclusions.

Baker and Wurgler (2006) also provided evidence to support the effect of investors' sentiment on cross-sectional stock returns. They introduced the new investors' sentiment using the first principle component of six underlying sentiment proxies: (a) dividend premiums, (b) new issue equity shares, (c) mean returns on the first day of Initial Public Offering (IPOs), (d) the amount of IPOs, (e) NYSE shares turnover, and (f) closed end fund discounts, to form an investors' sentiment index. They found that high investors' sentiment in the beginning of a period leads to relatively low returns for (a) distressed stocks, (b) extreme growth stocks, (c) non-dividend paying stocks, (d) non-profit stocks, (e) high-volatility stocks, (f) young stocks, and (g) small stocks. Low investors' sentiment, however, leads to high returns among these types of stocks. They concluded that investors' sentiment has a substantial effect on cross-sectional stock returns.

Baker and Wurgler (2007) also agreed that investors' sentiment has an effect on stock return. Baker, Wurgler and Yuan (2012) provided evidence that a model of investors' sentiment based on Baker and Wurgler (2006) can be applied internationally. They constructed the local investors' sentiment indices for six stock markets and decomposed this into one international index. They found a negative relationship between the investors' sentiment and future returns. The evidence from earlier studies showed that the investors' sentiment constructed by Baker and Wurgler (2006) can be used to explain stock returns.

The investors' sentiment from Baker and Wurgler (2006) is widely used among the behavioural-based researchers. Stambaugh, Yu and Yuan (2012), for example, also used the model of investors' sentiment constructed by Baker and Wurgler (2006) for their study. They examined the role of investors' sentiment in financial market anomalies. Following high investors' sentiment, they found larger profits of the long-short strategy and from the short-leg strategy; however, there was no relationship between long-leg strategy and stock returns.

Additionally, Yu and Yuan (2011) used the investors' sentiment index constructed by Baker and Wurgler (2006) to measure the impact of investors' sentiment on the markets' average-variance trade-off. In a period of low investors' sentiment, the expected excess return of the stock market is positively correlated with variations in the markets' condition. During a period of high investors' sentiment, an unrelated result is found. McLean and Zhao (2014) also employed the investors' sentiment model from Baker and Wurgler (2006); they found that both employment and investment are more sensitive to firms' cash flow during the periods of low investors' sentiment and recession.

Antoniou et al. (2013), however, used the Consumer Confidence Index (CCI) as the basis for measuring investors' sentiment for their main analysis. The CCI is published by the Conference Board. The investors' sentiment model from Baker and Wurgler (2006) is also used for the robustness test. They found that the results are generally unchanged.

Huang et al. (2015), however, introduced the Investor Sentiment Aligned model. They claimed that the new investors' sentiment model outperformed the investor sentiment model from Baker and Wurgler (2006). They showed that their model of investors' sentiment provides more prediction power on stock returns than the model of investors' sentiment from Baker and Wurgler (2006).

According to the previous studies, investors' sentiment is one of the factors that can be used to estimate stock returns. The investors' sentiment model constructed by Baker and Wurgler (2006) is widely used in this research area; they also suggested that investors' sentiment should be incorporated into the asset pricing model for the purpose of providing greater explanation.

2.2.4 The gap in the literature

The literature almost unanimously shows that momentum and contrarian trading strategies can generate profit. The contrarian profit is observed in the short-horizon (see e.g. Lehmann (1990)) and long-horizon (see e.g. Fama and French (1988)). The momentum profit, however, is found when portfolios are held for 3 to

12 months (see e.g. Jegadeesh and Titman (1993)). More recently Blitz et al. (2011) and Blitz et al. (2013), show that the residual momentum and residual contrarian trading strategies can earn higher profits compared to conventional trading strategies. They showed that ranking stocks based on residuals earn significantly higher profits than conventional ones (see sections 2.2.1 and 2.2.2). The residual momentum and contrarian trading strategies are used in this chapter to form portfolios.

The earlier studies attempted to explain momentum profits. The researchers found that conventional momentum profit is explained by (a) risk-based explanations (see e.g. Chordia and Shivakumar (2002), Wu (2002), Avramov and Chordia (2006), Antoniou et al. (2007), and Min and Kim (2016)) or (b) behavioural-based explanations (see e.g. Daniel et al. (1998), Barberis et al. (1998), Hong and Stein (1999), and Hong et al. (2000)). In the study of Blitz et al. (2011), they mentioned that conventional momentum profit is not driven by risk-based explanations but can be captured by behavioural biases. There is, however, no direct evidence to support the idea that residual momentum profit can be explained by investor behaviour. Similarly to residual contrarian profit, Blitz et al. (2013) do not provide any direct evidence to support the behavioural explanation in their study. This study, thus, aims to fill this gap by providing evidence as to whether conventional momentum (contrarian) profit and residual profit from residual momentum and contrarian trading strategies are explained by investors' sentiment. This study also aims to examine (a) the profits from both conventional and residual momentum and contrarian trading strategies, and (b) the relationship between the profits from these strategies and investors' sentiment after controlling for risk.

2.3 The Research Questions and Hypotheses

The gap in the literature has been identified in Section 2.2.4. This chapter aims to fill the gap by empirical testing of the relationship between the returns from (a) the residual momentum trading strategy of Blitz et al. (2011), and (b) the residual contrarian trading strategy of Blitz et al. (2013) and investors' sentiment. The research questions and hypotheses of this chapter are as follows:

1) Can the momentum trading strategy of buying past winners and selling past losers generate profits?

To answer the first research question, momentum trading strategy suggests investors take a long position on past winners and a short position on past losers. The purpose of this trading strategy is to capitalize on the continuation of trends in the stock market that already exist. Blitz et al. (2011) claimed that forming portfolios on the basis of residual returns earns higher profits than conventional stock returns. This study anticipates finding empirical evidence of momentum profit when forming sample stocks based on the (a) conventional momentum strategy and (b) residual momentum strategy. The hypotheses that relate to the first research question are as follows:

$H_{2.1a}$: *The conventional momentum trading strategy that takes a long position in past winner stocks (highest raw returns) and a short position in past loser stocks (lowest raw returns) generates positive returns.*

$H_{2.1b}$: *The residual momentum trading strategy that takes a long position in past winner stocks (highest residual returns) and a short position in past loser stocks (lowest residual returns) generates positive returns.*

2) Can the contrarian trading strategy of buying past losers and selling past winners generate profits?

To answer the second research question, contrarian trading strategy suggests that investors should sell the past highest returns and buy the past lowest returns, which is called the contrarian trading strategy (Jegadeesh, 1990). This trading strategy goes against the trend of the prevalent market because this strategy believes that the strong confidence of crowd behaviour among the group of investors can lead to mispricing in the stock market. Blitz et al. (2013) claimed that forming portfolios on the basis of residual returns earns higher profits than conventional stock returns. This study attempts to find empirical evidence of contrarian profit when forming sample stocks based on the (a) conventional contrarian strategy and (b) residual contrarian strategy. The hypotheses that relates to the second research question are as follows:

$H_{2.2a}$: *The conventional contrarian trading strategy that takes a long position in past loser stocks (lowest raw returns) and a short position in past winner stocks (highest raw returns) generates positive returns.*

$H_{2.2b}$: *The residual contrarian trading strategy that takes a long position in past loser stocks (lowest residual returns) and a short position in past winner stocks (highest residual returns) generates positive returns.*

3) If momentum or contrarian profit is observed, do risk and/or investors' sentiment explain momentum and/or contrarian profits?

To answer the third research question, this study examines whether momentum or contrarian profit is driven by risk. The earlier studies, such as Chordia and Shivakumar (2002), claimed that risk is one of the possible factors to explain momentum profit. De Bondt and Thaler (1987) found that any risk-based explanation from CAPM fails to explain contrarian profits. This study, thus, employed the multifactor asset pricing model, which generally outperforms the single-factor asset pricing models to explain market anomalies. The hypotheses that relate to the third research question are as follows:

$H_{2.3a}$: *Conventional momentum and contrarian profits are explained by risk.*

$H_{2.3b}$: *Residual momentum and contrarian profits are explained by risk.*

To answer the same research question, this study examines the relationship between (a) momentum profits and contrarian profits and (b) investors' sentiment. Schwert (2003) claimed that momentum profits cannot be explained by the three-factor model itself. Baker and Wurgler (2006) then suggested that incorporating investors' sentiment into the asset pricing model should provide superior explanations. Following this suggestion, this study uses the three-factor model, incorporating an investors' sentiment factor to capture the relationship between (a) momentum profits and contrarian profits and (b) investors' sentiment. The hypotheses that relate to the third research question are as follows:

$H_{2.4a}$: *The conventional momentum and contrarian profits are explained by investors' sentiment.*

$H_{2.4b}$: *The residual momentum and contrarian profits are explained by investors' sentiment.*

2.4 The Methodology and Sample

2.4.1 The measurement of investors' sentiment

As mentioned in the literature review, the investors' sentiments, which have been used in the earlier studies, are measured differently. Han (2008), for example, used (a) the difference between bullish and bearish investors from the AAII survey and (b) valuation errors are used by Sharpe (2002) as the investors' sentiment factor. Garcia (2013), moreover, used sections of negative and positive words from the financial news as a factor for investors' sentiment. Antoniou et al. (2013) used the CCI as the factor for investors' sentiment.

According to the literature review, the factor for investors' sentiment that is most widely used in this research area is the investors' sentiment model constructed by Baker and Wurgler (2006) (see Yu and Yuan (2011), Stambaugh et al. (2012), and McLean and Zhao (2014)). The investors' sentiment model used by Baker and Wurgler (2006) is constructed using a first principle component of six underlying sentiment proxies; (a) dividend premiums, (b) new issue equity shares, (c) mean returns on the first day of IPOs, (d) amount of IPOs, (e) NYSE shares turnover, and (f) closed end fund discounts, to form an investors' sentiment index. This investors' sentiment index has been proved to provide predictability power on stock returns[2].

[2] The investors' sentiment model used by Baker and Wurgler (2006) is described below:
$Investor\ Sentiment_t = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P_t^{D-ND}$
where $\text{Investor Sentiment}_t$ is the investors' sentiment in month t, CEFD_t is the closed end fund discount in month t, TURN_{t-1} is the NYSE shares turnover in month t-1, NIPO_t is the total number of IPOS in month t, RIPO_{t-1} is the mean returns on the first day of IPOs in month t-1, S_t is the shares of equity issues in month t, and P_t^{D-ND} is the dividend premium in month t.

2.4.2 Methodology

To answer the research questions described in section 2.3, "Can the momentum (contrarian) trading strategy of buying (selling) past winners and selling (buying) past losers generate profits?" and "If momentum or contrarian profit is observed, do risk and/or investors' sentiment explain momentum and/or contrarian profits?", this section clarifies the methods of analysis.

<u>*The existence of momentum and contrarian profits*</u>

Conventional momentum and contrarian profits (Testing $H_{2.1a}$ and $H_{2.2a}$)

To test "$H_{2.1a}$: *The conventional momentum trading strategy that takes long position in past winner stocks (highest raw returns) and short position in past loser stocks (lowest raw returns) generate positive returns*", the momentum trading strategy is applied. This strategy requires taking a long position on winner stocks and a short position on loser stocks. Jegadeesh and Titman (1993) have documented the fact that stocks, which have earned higher returns than average in the past, will also earn higher returns again in the following period. The conventional momentum strategy in this study follows the common method used in many previous empirical studies (see e.g. Grundy and Martin (2001) and Gutierrez and Prinsky (2007)). The sample stocks are sorted into deciles on the basis of historical returns. The portfolio formation periods are 3, 6, 9, and 12 months. The average returns during the formation period are used to form the portfolios. After the average returns are calculated, the sample stocks are equally grouped into ten portfolios in ascending order. The two most extreme portfolios (portfolios 1 and 10) are considered. Winner portfolios include stocks with the highest average returns in each formation period (portfolio 10) while loser portfolios contain stocks with the lowest average returns in each formation period (portfolio 1). The conventional momentum trading strategy takes a long position on winner portfolios but a short position on loser portfolios. Inversely, to test "$H_{2.2a}$: *The conventional contrarian trading strategy that takes long position in past loser stocks (lowest raw returns) and short position in past winner stocks (highest raw returns) generate positive returns*", the conventional contrarian trading strategy is applied. This strategy takes a long position on loser portfolios but a short position on winner portfolios. The long and short positions are taken at the same time. After the long and short positions are taken, the portfolios are held for five holding periods. The holding periods are 1, 3, 6, 36 and 60 months. The profit from the momentum (contrarian) trading strategy is called momentum profit (contrarian profit).

To observe the momentum profits (in the medium-horizon) and contrarian profits (in the short-horizon and long-horizon), this chapter investigates 20 portfolio strategies. The portfolio strategies are indicated by formation period (F) and holding period (H), where portfolio strategy F-H is the portfolios that are formed on the average return of the past F months and are held for H months. The portfolio strategies for the 3-month formation period are 3-1, 3-3, 3-6, 3-36 and 3-60, for which the holding periods are 1, 3, 6, 36 and 60 months, respectively. The portfolio strategies for a 6-month formation period are 6-1, 6-3, 6-6, 6-36 and 6-60, for a 9-month formation period are 9-1, 9-3, 9-6, 9-36 and 9-60, and for a 12-month formation period are 12-1, 12-3, 12-6, 12-36 and 12-60.

After the winner and loser portfolios are formed and held for each holding period, the monthly average returns in winner and loser portfolios are calculated. The average return from winner portfolios *minus* average returns from loser portfolios is used to find the monthly momentum profits. In other words, the momentum profit is measured by the difference in returns between winner and loser portfolios. The two-tailed test is applied to investigate whether (a) return from winner portfolios, (b) return from loser portfolios and (c) the hedge portfolio returns (the returns in winner portfolio *minus* loser portfolio) are significantly different from zero. The test statistic is described below:

$$t = \frac{\bar{x}-\mu}{s/\sqrt{n}} \qquad (2.1)$$

where $\bar{x}$ is the portfolio average returns, μ is the hypothesized population mean, which is zero, s is the standard deviation, and n is the sample size, which is firm-month observations. This test provides the decision for the null hypothesis that average returns of portfolios equal zero. The statistical significance of the return is tested at the 5% level. If the p-value is lower than or equal to 0.05, there is evidence to reject the null hypothesis, suggesting that average portfolio returns are significantly different from zero.

If the result shows that the hedge portfolio returns (the returns in winner portfolio *minus* loser portfolio) are significantly different from zero, there is evidence of momentum profit. If the result shows that (a) the hedge portfolio returns are significantly different from zero and (b) the differences in returns between winner and loser portfolios are negative, there is evidence of contrarian profit, indicating that investors who take a long position in loser stocks and a short position in winning stocks can generate profit. This test is expected to have significant positive portfolio returns to confirm the existence of momentum profit, whereas significant negative returns confirm the existence of contrarian profit. To accept $H_{2.1a}$, this test is expected to generate statistically significant positive returns from hedge portfolios (the returns in winner portfolio *minus* loser portfolio) that are held for 3 and 6 months. To accept $H_{2.2a}$, this test is expected to generate statistically significant negative returns from hedge portfolios in 1, 36 and 60 months holding periods.

Residual momentum and residual contrarian profits (Testing $H_{2.1b}$ and $H_{2.2b}$)

To test "*$H_{2.1b}$: The residual momentum trading strategy that takes long position in past winner stocks (highest residual returns) and short position in past loser stocks (lowest residual returns) generate positive returns*" and "*$H_{2.2b}$: The residual contrarian trading strategy that takes long position in past loser stocks (lowest residual returns) and short position in past winner stocks (highest residual returns) generate positive returns*", this chapter follows the methodology of Blitz et al. (2011). They documented the fact that the conventional momentum and contrarian trading strategy exhibits significant time-varying exposures to the three factors from the Fama and French (1993) model and sorting stocks on the basis of residual returns can reduce these exposures. The residual momentum (contrarian) trading strategy, thus, aims to generate higher momentum (contrarian) profits.

The residual returns are estimated using the rolling window regression over 36 months (over the period from month_{t-36} to month_{t-1}). This analysis includes only stocks that have historical returns over 36 months. The residual returns are estimated using the three-factor model used by Fama and French (1993), as described below:

$$R_{i,t} = \alpha_i + \beta_i^{RmRf} RmRf_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \qquad (2.2)$$

where $R_{i,t}$ is the return of stock i in month t in excess of risk free rate, $RmRf_t$ represents the market factor, market excess return in month t, SMB_t represents the size factor in month t, and HML_t represents the value factor in month t.

$\alpha_i, \beta_i^{RmRf}, \beta_i^{SMB}$, and β_i^{HML} are parameters to be estimated. $\varepsilon_{i,t}$ is the residual return of stock i in month t. Following the studies of Gutierrez and Prinsky (2007) and Blitz et al. (2011), these residual returns are standardized by the standard deviation. The reason behind this is to avoid any noise from the estimation that might occur when the residual returns do not happen to be standardized. The residual returns, after having been standardized by the standard deviation, are used to form portfolios based on the residual momentum (contrarian) trading strategy. The returns from portfolios, which are grouped based on historical residual returns, are tested by using the statistical significance of the holding period hedge-portfolio return (long position *minus* short position) using the two-tailed test from equation (2.1). This test is expected to have positive (negative), significant results to confirm the existence of residual momentum profit (residual contrarian profit). Similarly to the previous section to accept $H_{2.1a}$, this test is expected to generate positive and statistically significant results for the returns in hedge portfolios during the 3 and 6 months holding periods. To accept $H_{2.2a}$, this test is expected to generate negative, statistically significant results of the returns in hedge portfolios in the 1, 36 and 60 month holding periods.

The momentum profits, contrarian profits and risk (Testing $H_{2.3a}$ and $H_{2.3b}$)

To test "$H_{2.3a}$*: The conventional momentum and contrarian profit are explained by risk*" and "$H_{2.3b}$*: The residual momentum and contrarian profits are explained by risk*", equation (2.3) is employed. Equation (2.3) is developed from Fama and French's (1993) three-factor model to test whether momentum and contrarian profits are explained by risk.

$$M_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \varepsilon_t \quad (2.3)$$

where M_t is the momentum profits at month t, which are (a) the momentum profits arising from the conventional momentum trading strategy and (b) the momentum profits arising from the residual momentum trading strategy, which are called residual momentum profits.

The momentum profits, contrarian profits and investors' sentiment (Testing $H_{2.4a}$ and $H_{2.4b}$)

To test "*$H_{2.4a}$: The conventional momentum and contrarian profit are explained by investors' sentiment*" and "*$H_{2.4b}$: The residual momentum and contrarian profits are explained by investors' sentiment*", equation (2.4) is employed. Equation (2.4) is used to test whether investors' sentiment factors explain momentum and contrarian profits. This model is developed from Fama and French (1993) three-factor model by incorporating the investors' sentiment factor. The model is described as below:

$$M_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{SENT} SENT_t + \varepsilon_t \quad (2.4)$$

where $SENT_t$ is the investors' sentiment from Baker and Wurgler (2006) at month t, and β_t^{SENT} is the parameter to be estimated. To confirm that momentum and contrarian profits are explained by investors' sentiment, this test is expected to have a statistically significant coefficient on the investors' sentiment factor.

2.4.3 Sample description

The sample includes stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ. The sample period is from July 1965 to September 2015, which covers 603 months with 2,019,237 firm-month observations. The study period covers from July 1965 to September 2015 due to the availability of investors' sentiment data at the time of data collection. The financial sector is excluded from the sample because it has a different structure of financing from other sectors. The common factors, i.e. market factor, size factor, and value factor, are collected from French's (2015) webpage[3]. The investors' sentiment data are collected from the Wurgler's (2015) webpage[4]. Stocks are required to have at least 36 months' data. The construction of the key variables is presented in Table 2.1.

[Table 2.1]

Panel A of Table 2.2 shows the statistical data of the key variables in portfolio sorting: raw returns and residual returns. There is evidence of positive skewness in the raw returns. The positive skewness is represented by the difference between the mean and the median. The residual returns, however, show negative skewness. When comparing the two sorting variables, raw returns have a lower standard deviation.

Panel B of Table 2.2 represents the data description for key variables in regression. There is evidence of positive skewness in the excess returns, the value factor (HML), and the investors' sentiment factor, while the negative skewness is shown in the market factor (Rm-Rf) and size factor (SMB). The market factor

[3] URL: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] URL: http://people.stern.nyu.edu/jwurgler/

provides the highest standard deviation whereas the lowest standard deviation is provided by the excess returns.

[Table 2.2]

The correlation matrix in the same table shows the positively correlated variables among the three variables: the excess returns, the market factor, and the size factor. The negative correlation is found in the value factor and the investors' sentiment factor. In other words, the excess returns, the market factor, and the size factor are positively correlated and these three factors are negatively correlated with the value factor and the investors' sentiment factor. Higher quantities of the market factor and the size factor lead to larger excess returns, while lower quantities of the value factor and the investors' sentiment factor lead to higher excess returns. Due to the statistically insignificant nature of the correlation coefficients among the variables for regression, these variables are expected to provide a different explanation.

2.5 Results

To examine the profit and loss arising from both the conventional and residual momentum trading strategies, this study forms portfolios on the basis of (a) average past returns and (b) average past residual returns that are estimated using equation (2.2). The formation periods for both trading strategies are 3, 6, 9 and 12 months. The sample stocks are grouped into deciles from the highest average past returns (residual returns) to the lowest past returns (residual returns). The two most extreme portfolios are called winner portfolios (the portfolios with the highest past average returns i.e. portfolio 1) and loser portfolios (the portfolios with the lowest past average returns i.e. portfolio 10). Following most of the earlier studies, equally weighted portfolio returns are used. A long position is taken on winner portfolios while a short position is taken on loser portfolios. After forming the portfolios, the sample portfolios have been held for five different holding periods: 1, 3, 6, 36 and 60 months. A significant positive hedge portfolio return (winner *minus* loser) will support the profitability of momentum trading strategies while a significant negative return will indicate the success of contrarian trading.

2.5.1 Conventional momentum and contrarian trading strategies

The two hypotheses tested in this section are: $H_{2.1a}$: *"The conventional momentum trading strategy that taken a long position in past winner stocks (highest raw returns) and a short position in past loser stocks (lowest raw returns) generates positive returns"* and $H_{2.2a}$: *"The conventional reversal trading strategy that taken a long position in past loser stocks (lowest raw returns) and a short position in past winner stocks (highest raw returns) generates positive returns"*. Earlier studies suggest that momentum profit is observed when portfolios are held for 3 to 12 months, whereas contrarian profit is observed in the short holding period (1 month) and long-term holding period (36 to 60 months).

2.5.1.1 Momentum and contrarian profits

Table 2.3 presents tests of the significance of returns from (a) winner portfolios, (b) loser portfolios and (c) the hedge portfolio returns (the returns in a winner *minus* loser portfolio) using equation (2.1). The average returns of the winner portfolio are presented in column W and the average returns of the loser portfolio in column L. The average of the returns from the hedge portfolio is presented in the W-L column.

When winner and loser portfolios are formed based on average returns in the past three months, both winner and loser portfolios show positive and statistically significant returns in all holding periods. The differences in returns between winner and loser portfolios that are represented in column W-L are negative in all holding periods. These returns from hedge portfolios, however, are statistically insignificant except for the 36 months holding period. This result suggests that contrarian profit can be earned when portfolios are held for 36 months. The contrarian profit is 0.55% per month. This result is consistent with De Bondt and Thaler (1985) who observed contrarian profits in the next 36 months after the formation period. The contrarian profits from this holding period mainly earn from the positive return of the loser portfolio, which is 1.64%.

[Table 2.3]

The results are shown to be positive and statistically significantly different from zero in both winner and loser portfolios when portfolios are formed on the basis of 6 months' historical returns. The differences in returns between winner and loser portfolios are negative and statistically significantly different from zero when 1, 36 and 60 months' holding periods are applied. This result suggests that contrarian profits are observed during these holding periods. The contrarian profits are 0.40%, 0.65% and 0.37%, respectively. This result is consistent with Lehmann (1990) who observed contrarian profits during short-horizons and Fama and French (1988) who observed contrarian profits during long-horizons. The contrarian profits from this holding period are mainly generated due to higher returns in loser portfolios than in winner portfolios. The returns from loser portfolios are 1.50%, 1.71% and 1.57%, respectively.

When the 9 months formation period is applied, the returns in winner and loser portfolios are positive and statistically significantly different from zero. The differences in returns between winner and loser portfolios are negative and statistically significant when portfolios are held for 36 and 60 months. This result leads to the conclusion that contrarian profits are observed during these holding periods. The contrarian profit is 0.61% when portfolios are held for 36 months and decreases to 0.41% when portfolios are held longer, to 60 months. This result is consistent with Fama and French (1988) who observed contrarian profits during long-term holding periods. The existence of contrarian profit is due to loser portfolios outperforming winner portfolios and earning significantly higher returns. The returns from loser portfolios are 1.69% and 1.63% while winner portfolios earn returns of 1.08% and 1.22% respectively.

The last formation period that is analysed is 12 months. The results again show positive and statistically significant differences from zero both in winner and loser portfolios. The returns from hedge portfolios (returns in winner *minus* loser portfolios) are statistically significantly different from zero and also negative when 36 and 60 months' holding periods are applied. This result suggests the existence of contrarian profits when portfolios are held for 36 and 60 months. The contrarian profits are 0.67% and 0.48%, respectively. This result is also consistent with Fama and French (1988) who observed contrarian profits during long-horizons. The contrarian profits exist due to the positive returns from loser portfolios, which are higher than winner portfolios. The returns from loser portfolios are 1.73% in both holding periods, whereas the returns from winner portfolios are 1.06% and 1.25% respectively.

The results in Table 2.3 show no evidence of momentum profit. The contrarian profits exist when portfolios are held for 1, 36 and 60 months. The highest contrarian profit is observed when portfolios are held for 36 months. Thus, the 36 months holding period should be the best strategy to earn the highest contrarian profit. The contrarian profit is due to the higher return in loser portfolios than winner portfolios. This result suggests that $H_{2.1a}$ is rejected whereas $H_{2.2a}$ is accepted. This result is also consistent with earlier studies such as Lehmann (1990) and Fama and French (1988) in which contrarian profit is observed when short-horizon or long-horizon is employed. After the contrarian profit is observed, the next question that needs to be answered is "What is the underlying factor to explain contrarian profits?" This question leads this chapter to the later section.

2.5.2 Residual momentum and contrarian trading strategies

Two hypotheses are tested in this section: *"$H_{2.1b}$: The residual momentum trading strategy that takes a long position in past winner stocks (highest residual returns) and a short position in past loser stocks (lowest residual returns) generates positive returns"* and *"$H_{2.2b}$: The residual contrarian trading strategy that takes a long position in past loser stocks (lowest residual returns) and a short position in past winner stocks (highest residual returns) generates positive returns"*.

2.5.2.1 Residual momentum and contrarian profits

Table 2.4 presents the test for the significant difference from zero of returns in (a) winner portfolios, (b) loser portfolios and (c) the hedge portfolio returns (the returns in the winner portfolio *minus* loser portfolio) using equation (2.1) when portfolios are formed on the basis of historical residual returns. The average returns of winner and loser portfolios are presented in columns W and L, respectively. The average of the returns from hedge portfolios is presented in column W-L. Similarly to the previous section, the formation periods are 3, 6, 9 and 12 months and the holding periods are 1, 3, 6, 36 and 60 months.

When winner and loser portfolios are formed based on average residual returns in the past 3 months, both winner and loser portfolios show a positive and statistically significant difference from zero in all holding periods. The differences in returns between winner and loser portfolios are negative except for the 6 months holding period. The returns from hedge portfolios, however, are statistically insignificant in all holding periods. This result suggests that there is no evidence of both momentum and contrarian profits when portfolios are formed on the basis of an average of 3 months' historical residual returns.

[Table 2.4]

Similarly to the 3 months formation period, the results show positive and statistically significant differences from zero in both winner and loser portfolios when portfolios are formed on the basis of an average of 6 months' historical residual returns. The returns from winner portfolios are 1.12%, 1.25%, 1.33%, 1.33% and 1.24% while loser portfolios earn returns of 1.41%, 1.23%, 1.25%, 1.40% and 1.78%. The differences in returns between winner and loser portfolios are negative except when 3 and 6 months holding periods are applied. The returns from hedge portfolios (returns in winner *minus* loser portfolios), however, are statistically insignificantly different from zero in all holding periods. This result leads to the conclusion that both momentum and contrarian profits cannot be observed during these given formation and holding periods.

Once the 9 months' formation period is analysed, the results show that returns in both winner and loser portfolios are positive and statistically significantly different from zero. The hedge portfolio's return is negative and statistically significant only for the 60 months holding period. This result suggests the existence of residual contrarian profits. This evidence, however, is relatively weak and does not seem to have any pattern. When other holding periods are applied, the statistically significant results cannot be observed. This result suggests that contrarian profits are observed only when a portfolio is held for 60 months. The contrarian profit is 0.62%.

The last formation period analysed in this section is 12 months. The results show statistically significant differences from zero both in winner and loser portfolios. The differences in return between winner and loser portfolios are positive for the 1 and 3 months' holding periods but negative for the 6, 36 and 60 months' holding periods. The hedge portfolios' returns, however, are statistically insignificantly different from zero. This result leads to the same conclusion as for the 3 and 6 months' formation periods. This result suggests that there is no evidence of both momentum and reversal profits when portfolios are formed on the basis of historical residual returns.

The results from Table 2.4 show no evidence of both residual momentum and residual contrarian profits except for the 9-60 strategy (9-month formation period with a 60-month holding period). This residual contrarian profit, however, does not seem to have any pattern and the evidence is relatively weak; it is not significantly different from the contrarian profits of conventional strategy (Table 2.3). This result, however, is not consistent with Blitz et al. (2011, 2013) who claimed that residual momentum and short-term contrarian strategies outperform the conventional ones to generate profits. The inconsistent result is due to the methodology and samples specific to the studies. Comparing this result with those in Table 2.3, conventional momentum (contrarian) strategies outperform residual momentum (contrarian) strategies to generate profits. In other words, contrarian profits disappear after returns in the formation period are adjusted for risk. The results in this section suggest that both $H_{2.1b}$ and $H_{2.2b}$ are rejected.

2.5.3 Momentum and contrarian profits and risk

Evidence in section 2.5.1 shows the profitability of contrarian trading strategies if portfolios are held for 1, 36 and 60 months. The next question to arise is "What is the underlying reason for the contrarian profits?" A risk difference in portfolios is one of the possible reasons. This section attempts to examine whether the observed contrarian profit can be explained by risk. The contrarian profit observed in section 2.5.1 is used in this section. To test *"$H_{2.3a}$: The conventional momentum and contrarian profit are explained by risk"*, the relationship between contrarian profit and risk is examined using equation (2.3).

Table 2.5 presents (a) the returns when the conventional momentum strategy is applied (the positive return is momentum profit while the negative return is contrarian profit), (b) alphas, (c) betas to the market factor (Rm-Rf), (d) betas to the size factor (SMB), (e) betas to the value factor (HML), and (f) the adjusted R-square. The portfolios are formed based on the average historical returns. The formation periods are 3, 6, 9 and 12 months. The portfolios are then held for five holding periods: 1, 3, 6, 36 and 60 months. The coefficients are estimated using equation (2.3).

The coefficients show the effects of (a) the market factor (Rm-Rf): the excess returns on market portfolios; (b) the size factor (SML): the difference in returns between portfolios of small stocks and large stocks; and (c) the value factor (HML): the difference in returns between portfolios of value stock and growth stock on momentum profits. When the 3 months formation period is analysed, the contrarian profit occurs only when a portfolio is held for 36 months and the contrarian profit is 0.55%. During this holding period, the intercept and coefficient of size factor are negative and statistically significant. The intercept is -0.49% and the coefficient on size factor is -23.34%. This result suggests that both intercept and size factor negatively affect momentum profit. In other words, both intercept and size factor positively affect contrarian profits. Specifically, when the contrarian trading strategy is used, investors take a long position on loser stocks and a short position on winner stocks, which is the inverse of momentum strategy. This result suggests that contrarian profit increases by 0.23% if the size factor is increased by 1%. The significance of intercept indicates that contrarian profits can be generated even after controlling for risk. This result suggests that these observed contrarian profits cannot be explained by risk.

[Table 2.5]

Once the 6 months formation period is applied, the contrarian profit occurs when a portfolio is held for 1, 36 and 60 months. The contrarian profits are 0.40%, 0.65%, and 0.37%, respectively. Only the coefficient of value factor is statistically significant for the 1-month holding period. The coefficient is -14%. This result suggests that contrarian profit increases by 14% if the value factor increases by 1%. The intercept during this holding period is not significant, which suggests that contrarian profit is partially explained by risk. The evidence, however, is relatively weak. The intercept and coefficient of the size factor are negative and statistically significant; the intercept is -0.66% and the coefficient of the size factor is -17%. This result suggests that both intercept and size factor positively affect contrarian profits. The contrarian profit during this holding period is mainly generated from intercept while size has only a small effect on this contrarian profit. The significance of intercept indicates that excess can be generated, even after adjusting for risk. This suggests that risk is unable to explain contrarian profit. Similar results also found that when portfolios are held for 60 months, contrarian profit cannot be explained by risk.

The formation periods of 9 and 12 months generate similar results. During these given formation periods, the contrarian profits are observed when portfolios are held for 36 and 60 months. The contrarian profits are 0.61% and 0.41%, respectively, for the 9 months formation period. When the formation period is 12 months, the contrarian profits are 0.67% and 0.48%, respectively. Only the intercept is statistically significant. This result shows that contrarian profit is mainly generated from intercept. The significance of intercept indicates that contrarian profits can be generated, even when controlling for risk, which suggests that risk is unable to explain contrarian profit.

The results from Table 2.5 show that the contrarian profits are generally unexplained by risk. During the formation periods of 3 and 6 months, contrarian profits are partially explained by risk. However, the majority of contrarian profits is generated from intercept. This leads to the conclusion that risk is unable to explain contrarian profits. The results in this section suggest that $H_{2.3a}$ is rejected. So far, the contrarian profits exist even after controlling for risk. The strategy that earns the highest contrarian profit is 12-16 (12-month formation period with a 36-month holding period). This result is consistent with that of De Bondt and Thaler (1987), that a risk-based explanation is unable to explain contrarian profits. De Bondt and Thaler (1985) suggested that loser portfolios have a superior performance due to investor overreaction; Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) also agree with De Bondt and Thaler (1985). This leads this chapter into the next section to investigate whether contrarian profit is explained by investors' sentiment.

2.5.4 Momentum and contrarian profits and investors' sentiment

The previous sub-section showed evidence of contrarian profit is unexplained by risk. De Bondt and Thaler (1985) suggested that contrarian profit is due to investor overreaction, i.e. investors take time to correct their earlier overreaction. This section, thus, attempts to examine whether contrarian profit can be explained by investors' sentiment. The contrarian profit that is observed in section 2.5.1 is used in this section. To test *"$H_{2.4a}$: The conventional momentum and contrarian profit are* *explained by investors' sentiment"*, the relationship between contrarian profit and investors' sentiment is examined using equation (2.4).

Table 2.6 presents (a) the returns when the momentum strategy is applied (the positive return is momentum profit while the negative return is contrarian profit), (b) alphas, (c) betas to the market factor (Rm-Rf), (d) betas to the size factor (SMB), (e) betas to the value factor (HML), (f) betas to investors' sentiment (constructed by Baker and Wurgler (2006)), and (g) the adjusted R-square. In Table 2.6, the coefficients are estimated using equation (2.4).

[Table 2.6]

When portfolios are formed on the basis of average returns in the past 3 months, the contrarian profit occurs only when a portfolio is held for 36 months and the contrarian profit is 0.55%. During this holding period, the coefficient on the investors' sentiment factor is positive but statistically insignificant. This result suggests that contrarian profit is unexplained by investors' sentiment.

When portfolios are formed on the basis of returns in the past 6 months, the contrarian profit occurs when a portfolio is held for 1, 36 and 60 months. The coefficients on investors' sentiment factors in these holding periods are statistically insignificant. This result leads to the same conclusion as for the 3-month formation period, i.e. contrarian profit is unexplained by investors' sentiment. Similar results are also found when 9 and 12 months' formation periods are employed. The coefficient of investors' sentiment factor is positive and statistically insignificant when portfolios are held for 36 months. When portfolios are held for 60 months, the coefficient on the investors' sentiment factor is negative and statistically insignificant. This result suggests that contrarian profit is unexplained by investors' sentiment.

The results from Table 2.6 show that the contrarian profits are left unexplained by investors' sentiment. Similarly to the previous section, the majority of contrarian profit is generated from intercept. This leads to the conclusion that investors' sentiment is unable to explain contrarian profits. The results in this section suggest that $H_{2.4a}$ is rejected, which is inconsistent with De Bondt and Thaler (1985). The contrarian profits exist even when controlling for both risk and investors' sentiment factors. The contrarian profits from hedge portfolios that are formed on the basis of average returns of the past 12 months and are held for 36 months earn highest excess returns. Investors, thus, should take a long position on loser stocks (lowest average returns of the past 12 months) and a short position on winner stocks (highest average returns of the past 12 months), then hold the portfolios for 36 months.

2.6 Conclusions

The momentum (contrarian) trading strategies involve going long (short) on winner stocks and going short (long) on loser stocks. Winner stocks are usually identified as stocks with high historical returns while loser stocks are generally indicated as stocks with low historical returns. The momentum profit is generated if returns from winner portfolios outperform loser portfolios. Inversely, the contrarian profit exists if returns from loser portfolios outperform winner portfolios. The momentum profit is observed during the medium-horizon (3 to 12 months holding periods) (see e.g. Jegadeesh and Titman (1993)) whereas contrarian profit is observed during (a) a short-term holding period (1week to 1 month) (see e.g. Lehmann (1990)) and (b) a long-term holding period (36 to 60 months) (see e.g. De Bondt and Thaler (1985)). This chapter, thus, forms portfolios based on 4 formation periods: 3, 6, 9 and 12 months. Then, portfolios are held for 1, 3, 6, 36 and 60 months to investigate the existence of momentum and contrarian profits. The results show that contrarian profit exists while momentum profit cannot be observed. Specifically, the holding period of 36 months generates the highest contrarian profits. The existence of contrarian profits is consistent with earlier studies such as that of De Bondt and Thaler (1985). This result suggests that an increase in stock prices will not be followed by additional profits but by decreasing stock returns. In other words, the strong confidence of crowd behaviour among the group of investors can lead to mispricing in the stock market.

Blitz et al. (2011, 2013) documented that forming portfolios on the basis of past residual returns earn higher profits than when forming portfolios on the basis of historical raw returns. The residual momentum (contrarian) trading strategy, thus, aims to generate higher momentum (contrarian) profits. This study, however, does not observe both momentum and contrarian profits from the residual trading strategy. In other words, the observed contrarian profits disappear when portfolios are formed on the basis of residual returns. The inconsistent results should be due to the methodology and the sample specificity of the studies. This chapter suggests that conventional contrarian trading strategy outperforms residual contrarian trading strategy to generate contrarian profit.

The existence of contrarian profit leads to the next question: "Do risk and/or investors' sentiment explain contrarian profits?" Risk difference in portfolios is one of the possible reasons. The statistical significance of intercept is observed when the relationship between risk and contrarian profit is examined. The significance of intercept suggests that there are excess returns from this trading strategy, even after controlling for risk. In other words, contrarian profits cannot be explained by risk. This result is consistent with De Bondt and Thaler (1987), that a risk-based explanation is unable to explain contrarian profits. De Bondt and Thaler (1985) also suggest that loser portfolios have a superior performance due to investor overreaction. This chapter, thus, examines whether contrarian profit is explained by investors' sentiment; the investors' sentiment constructed by Baker and Wurgler (2006) is employed in this chapter. The statistically insignificant results of the coefficient of the investors' sentiment factor are found in all formation and holding periods. This suggests that contrarian profit is unexplained by investors' sentiment. The statistical significance of intercept is mainly observed. The significance of intercept suggests that there is contrarian profit, even when adjusting for both risk and investors' sentiment. The results from this chapter suggest that contrarian profit is left unexplainable by both risk and investors' sentiment.

In conclusion, contrarian profit exists both in the short-term and long-term holding periods. To earn the highest profit, investors should take a long position on loser stocks and a short position on winner stocks, and then hold the portfolios for 36 months. The observed contrarian profits are unable to be explained by risk and investors' sentiment. The key implication in this chapter is the observed contrarian profit can be evidence against the weak form of efficient market hypothesis (EMH). The contrarian trading strategy outperforms the market and generates superior returns. This study, however, does not take transaction cost into account, which is an acknowledged limitation. Earlier studies, such as Conrad et al. (1997), found that when transaction cost is taken into account the contrarian profit disappears. Further study is recommended to incorporate transaction cost in order to fill this gap.

Table 2.1 Construction of key variables

A: Construction of key variables in portfolio sorting

Key variables	Construction
Average of past raw returns	The portfolios are formed using four formation periods: 3, 6, 9 and 12 months. The average raw returns of the previous 3, 6, 9 and 12 months are employed to form portfolios. The monthly returns are collected from the CRSP database. The sample stocks are listed in three main US stock markets: NYSE, AMEX and NASDAQ. The sample period is from July 1965 to September 2015.
Average of past residual returns	The portfolios are formed using three formation periods: 3, 6, 9 and 12 months. The average residual returns of the previous 3, 6, 9 and 12 months are employed to form portfolios. The monthly residual stock returns are estimated using rolling window regression over 36 months (over the period of $month_{t-36}$ to $month_{t-1}$) – equation (2.2). Following the studies of Gutierrez and Prinsky (2007) and Blitz et al. (2011), these residual returns are standardized by their standard deviation.

B: Construction of key variables in regression

Key variables	Construction
Excess Return	The stock returns that exceed the risk free rate. The monthly returns are collected from the CRSP database. The holding periods of monthly returns are from month-end to month-end. The risk-free return is the one-month treasury bill rate[5].

[5] The one-month Treasury bill rate data from Ibbotson Associates is collected from the Fama and French data library.

Table 2.1 Construction of key variables (cont.)

Key variables	Construction
R_m-R_f	The market excess return is a factor from the Fama-French three-factor model. The market return is constructed by Fama and French using value-weighted returns from US firms listed on three main stock markets: NYSE, AMEX and NASDAQ, available via CRSP. The risk-free return is the one-month treasury bill rate.
SMB	Small minus Big is one factor from the Fama-French three-factor model. SMB is the difference between average return on (a) three small portfolios and (b) three big portfolios, as constructed by Fama-French[6].
HML	High minus low is the last factor from the Fama-French three-factor model. HML is the difference between the average return of (a) two value portfolios and (b) two growth portfolios, as constructed by Fama-French.
Investors' Sentiment constructed by Baker and Wurgler (2006)	The investors' sentiment is constructed using the first principle component of six underlying sentiment proxies: (a) dividend premium, (b) new issue equity shares, (c) mean returns on first day of IPOs, (d) amount of IPOs, (e) NYSE shares turnover, and (f) closed end fund discount, to form an investors' sentiment index.

6 Available from the Fama and French data library.

Table 2.2 Sample data descriptions

A: Data description for Key variables in portfolio sorting

Key variables in portfolio sorting	Mean	Median	Standard deviation
Raw Return	1.32%	0%	0.1785
Residual Return	7.14%	8.82%	2.1905

B: Data description for Key variables in regression

Key variables in regression	Mean	Median	Standard deviation
Excess Return	-0.39%	-0.40%	0.3237
Rm-Rf	0.52%	0.92%	4.5513
SMB	0%	0.01%	3.2425
HML	0.46%	0.35%	3.0281
Investors' Sentiment	0.0762	0.0001	0.9235

Correlation

	Excess Return	Rm-Rf	SMB	HML	Investor Sentiment
Excess Return	1.0000	0.2180	0.1556	-0.1004	-0.1569
Rm-Rf		1.0000	0.2356	-0.3279	-0.0707
SMB			1.0000	-0.2812	-0.1117
HML				1.0000	0.1374
Investors' Sentiment					1.0000

Table 2.3: Profits from conventional momentum trading strategy

Table 2.3 presents portfolios' average returns when sample stocks are sorted based on average past returns; 3, 6, 9 and 12 months and are held for 1, 3, 6, 36 and 60 months. The winner portfolios' average return is presented in column W. The loser portfolios' average return is presented in column L. The momentum profit is represented in column W-L. The negative return from the same column represents the contrarian profit. The sample stocks include stocks that are listed in three main US stock markets: NYSE, AMEX and NASDAQ from July 1965 to September 2015, covering 603 months but excluding the financial sector. The t-stat indicates the significance level of the two-tail t-test. * and ** denote the statistical significance levels of 5% and 1% respectively.

Formation periods (months)	**Returns**	**Holding Periods (months)**				
		1	**3**	**6**	**36**	**60**
3	**W**	1.08%	1.15%	1.12%	1.09%	1.26%
	L	1.21%	1.23%	1.21%	1.64%	1.46%
	W-L	-0.13%	-0.08%	-0.09%	-0.55%	-0.20%
	(T-stat)	(-0.8247)	(-0.4561)	(-0.4741)	(3.6155**)	(-1.0295)
6	**W**	1.10%	1.05%	1.23%	1.06%	1.20%
	L	1.50%	1.25%	1.18%	1.71%	1.57%
	W-L	-0.40%	-0.20%	0.05%	-0.65%	-0.37%
	(T-stat)	(-2.3667**)	(-1.1285)	(0.2567)	(-3.2014**)	(-2.0355*)
9	**W**	1.14%	1.20%	1.24%	1.08%	1.22%
	L	1.40%	1.26%	1.46%	1.69%	1.63%
	W-L	-0.26%	-0.06%	-0.22%	-0.61%	-0.41%
	(T-stat)	(-1.3408)	(-0.3176)	(-1.2390)	(5.3736**)	(-2.2867*)
12	**W**	1.24%	1.20%	1.22%	1.06%	1.25%
	L	1.37%	1.37%	1.30%	1.73%	1.73%
	W-L	-0.13%	-0.17%	-0.08%	-0.67%	-0.48%
	(T-stat)	(-0.6389)	(-0.8659)	(-0.4072)	(-3.2536**)	(-2.7257**)

Table 2.4: Profits from residual momentum trading strategy

Table 2.4 presents portfolios' average returns when sample stocks are sorted based on average past returns; 3, 6, 9 and 12 months and are held for 1 3, 6, 36 and 60 months. The residual return is estimated using equation (2.2) with the rolling window regression over 36 months (over the period of month t-36 to month t-1). Following the studies of Gutierrez and Prinsky (2007) and Blitz et al. (2011), these residual returns are standardized by their standard deviation over the same period. The winner portfolios' average return is presented in column W. The loser portfolios' average return is presented in column L. The momentum profit is represented in column W-L. The negative return from the same column represents the contrarian profit. The sample stocks include stocks that are listed in three main US stock markets: NYSE, AMEX and NASDAQ from July 1965 to September 2015 covering 603 months, but excluding the financial sector. The t-stat indicates the significance level of the two-tail t-test. * and ** denote the statistical significance levels of 5% and 1% respectively.

Formation periods (months)	Returns	Holding Periods (months)				
		1	3	6	36	60
3	W	1.13%	1.15%	1.25%	1.31%	1.30%
	L	1.43%	1.42%	1.21%	1.41%	1.70%
	W-L	-0.30%	-0.27%	0.04%	-0.10%	-0.40%
	(T-stat)	(-1.2592)	(-1.1727)	(0.1835)	(-0.3266)	(-1.4637)
6	W	1.12%	1.25%	1.33%	1.33%	1.24%
	L	1.41%	1.23%	1.25%	1.40%	1.78%
	W-L	-0.29%	0.02%	0.08%	-0.07%	-0.54%
	(T-stat)	(-1.2070)	(0.0725)	(0.3194)	(-0.2173)	(-1.8812)
9	W	1.25%	1.31%	1.34%	1.31%	1.30%
	L	1.32%	1.21%	1.21%	1.51%	1.92%
	W-L	-0.07%	0.10%	0.13%	-0.20%	-0.62%
	(T-stat)	(-0.2782)	(0.4280)	(0.5368)	(-0.5953)	(-2.0378*)
12	W	1.33%	1.34%	1.30%	1.32%	1.40%
	L	1.29%	1.23%	1.33%	1.49%	1.96%
	W-L	0.04%	0.11%	-0.03%	-0.17%	-0.56%
	(T-stat)	(0.1445)	(0.4645)	(-0.1212)	(-0.5190)	(-1.8207)

Table 2.5: Momentum and contrarian profits and risk

Table 2.5 presents momentum profits, alphas, and betas to three factors from Fama and French (1993): market factor (Rm-Rf); size factor (SMB); value factor (HML), and adjusted R-square from conventional momentum trading strategy. The momentum profit is defined as the difference between two extreme portfolios: winner and loser. The portfolios are ranked into deciles based on their average past returns; 3, 6, 9 and 12 months. Portfolios are then held for 1, 3, 6, 36 and 60 months. In the return column, the positive return represents the momentum profit, while the negative return is represented the contrarian profit. The alphas and betas are estimated using equation (2.3). The sample stocks include stocks that are listed in three main US stock markets: NYSE, AMEX and NASDAQ from July 1965 to September 2015 covering 603 months but excluding the financial sector. The t-stat indicates the significance level of the regression. * and ** denote the statistical significance levels of 5% and 1% respectively.

Formation periods	**Holding periods**	**Return**	**α (T-stat)**	**Rm-Rf (T-stat)**	**SMB (T-stat)**	**HML (T-stat)**	**Adj.RSQ**
3	1	-0.13%	-0.01%	-6.47%	-12.91%	-16.29%	2%
			(-0.0391)	(-1.8102)	(-2.5141*)	(-2.9570**)	
	3	-0.08%	-0.03%	0.38%	-1.83%	-9.25%	0%
			(-0.1407)	(0.0927)	(-0.3090)	(-1.4597)	
	6	-0.09%	-0.02%	-4.44%	-2.84%	-12.50%	0%
			(-0.1005)	(-1.0527)	(-0.4686)	(-1.9293)	
	36	-0.55%	-0.49%	1.43%	-23.34%	-12.97%	2%
			(-2.2990*)	(0.2918)	(-3.3400**)	(-1.7369)	
	60	-0.20%	-0.20%	2.15%	-0.17%	-0.12%	0%
			(-1.0317)	(0.4819)	(-0.0258)	(-0.0177)	

Table 2.5: Momentum, contrarian profits and risk (cont.)

Formation periods	Holding periods	Return	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	Adj.RSQ
6	1	-0.40%	-0.32%	-0.39%	-8.46%	-14.29%	1%
			(-1.8505)	(-0.0984)	(-1.4941)	(-2.3559*)	
	3	-0.20%	-0.12%	-0.95%	-2.86%	-15.55%	1%
			(-0.6686)	(-0.2270)	(-0.4768)	(-2.4188*)	
	6	0.05%	0.06%	3.27%	-3.45%	-7.91%	0%
			(0.3337)	(0.7797)	(-0.5744)	(-1.2292)	
	36	-0.65%	-0.66%	6.39%	-17.38%	-5.80%	1%
			(-3.1445**)	(1.3290)	(-2.5343*)	(-0.7921)	
	60	-0.37%	-0.39%	3.00%	-3.22%	0.51%	0%
			(-2.0554*)	(0.7026)	(-0.5213)	(0.0775)	
9	1	-0.26%	-0.21%	3.64%	-6.28%	-15.26%	1%
			(-1.0442)	(0.8072)	(-0.9690)	(-2.2007*)	
	3	-0.06%	-0.03%	4.13%	-2.55%	-10.61%	0%
			(-0.1564)	(0.9397)	(-0.4046)	(-1.5731)	
	6	-0.22%	-0.22%	1.06%	-2.08%	-0.92%	0%
			(-1.2057)	(0.2492)	(-0.3412)	(-0.1404)	
	36	-0.61%	-0.60%	4.37%	-4.43%	-8.31%	0%
			(-3.2577**)	(1.0331)	(-0.7311)	(-1.2864)	
	60	-0.41%	-0.39%	1.58%	-2.12%	-4.39%	0%
			(-2.1055*)	(0.3766)	(-0.3442)	(-0.6798)	

Table 2.5: Momentum, contrarian profits and risk (cont.)

Formation periods	Holding periods	Return	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	Adj.RSQ
12	1	-0.13%	-0.12%	5.34%	-5.04%	-8.14%	0%
			(-0.5707)	(1.0899)	(-0.7184)	(-1.0856)	
	3	-0.17%	-0.15%	3.60%	-3.80%	-7.42%	0%
			(-0.7563)	(0.8019)	(-0.5913)	(-1.0761)	
	6	-0.08%	-0.07%	6.12%	-6.54%	-7.03%	0%
			(-0.3735)	(1.4084)	(-1.0500)	(-1.0503)	
	36	-0.67%	-0.68%	9.37%	-4.80%	-9.27%	1%
			(-3.2404**)	(1.9539)	(-0.6987)	(-1.2625)	
	60	-0.48%	-0.45%	2.32%	-2.56%	-7.04%	0%
			(-2.4933*)	(0.5645)	(-0.4262)	(-1.1175)	

Table 2.6: Momentum, contrarian profits and investors' sentiment

Table 2.6 presents momentum profits, alphas, and betas to three factors from Fama and French (1993): market factor (Rm-Rf); size factor (SMB); value factor (HML), betas to investors' sentiment from Baker and Wurgler (2006), and adjusted R-square from conventional momentum trading strategy. The momentum profit is defined as the difference between two extreme portfolios: winner and loser. The portfolios are ranked into deciles based on their average past returns; 3, 6, 9 and 12 months. Portfolios are then held for 1, 3, 6, 36 and 60 months. In the return column, the positive return represents the momentum profit while the negative return represents the contrarian profit. The alphas and betas are estimated using equation (2.4) that incorporates the investors' sentiment factor. The sample stocks include stocks that are listed in three main US stock markets: NYSE, AMEX and NASDAQ from July 1965 to September 2015 covering 603 months, but excluding the financial sector. The t-stat indicates the significance level of the regression. * and ** denote the statistical significance levels of 5% and 1% respectively.

Formation periods	Holding periods	Return	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	SENT (T-stat)	Adj.RSQ
3	1	-0.13%	-0.02%	-6.32%	-12.43%	-16.75%	0.19%	2%
			(-0.1084)	(-1.7661)	(-2.4147*)	(-3.0342**)	(1.1982)	
	3	-0.08%	-0.02%	0.33%	-2.03%	-9.07%	-0.07%	0%
			(-0.1197)	(0.0790)	(-0.3416)	(-1.4264)	(-0.4031)	
	6	-0.09%	-0.02%	-4.43%	-2.79%	-12.55%	0.02%	0%
			(-0.1044)	(-1.0482)	(-0.4588)	(-1.9296)	(0.0975)	
	36	-0.55%	-0.49%	1.43%	-23.33%	-12.99%	0.01%	2%
			(-2.2930*)	(0.2914)	(-3.3258**)	(-1.7296)	(0.0343)	
	60	-0.20%	-0.20%	2.15%	-0.09%	-0.22%	0.03%	0%
			(-1.0285)	(0.4812)	(-0.0139)	(-0.0325)	(0.1466)	

Table 2.6: Momentum, contrarian profits and Investors' sentiment (cont.)

Formation periods	Holding periods	Return	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	SENT (T-stat)	Adj.RSQ
6	1	-0.40%	-0.32%	-0.30%	-8.15%	-14.57%	0.11%	1%
			(-1.8790)	(-0.0766)	(-1.4331)	(-2.3947*)	(0.6540)	
	3	-0.20%	-0.12%	-0.97%	-2.93%	-15.48%	-0.03%	0%
			(-0.6616)	(-0.2316)	(-0.4863)	(-2.4001*)	(-0.1416)	
	6	0.05%	0.06%	3.21%	-3.68%	-7.64%	-0.10%	0%
			(0.3472)	(0.7660)	(-0.6101)	(-1.1830)	(-0.5179)	
	36	-0.65%	-0.66%	6.39%	-17.59%	-5.50%	-0.10%	1%
			(-3.1557**)	(1.3284)	(-2.5553*)	(-0.7465)	(-0.4091)	
	60	-0.37%	-0.39%	2.99%	-3.33%	0.64%	-0.04%	0%
			(-2.0541*)	(0.7008)	(-0.5365)	(0.0976)	(-0.1913)	
9	1	-0.26%	-0.22%	3.84%	-5.59%	-15.93%	0.27%	1%
			(-1.0939)	(0.8504)	(-0.8613)	(-2.2933*)	(1.3241)	
	3	-0.06%	-0.03%	4.03%	-2.96%	-10.12%	-0.18%	0%
			(-0.1326)	(0.9169)	(-0.4688)	(-1.4959)	(-0.8977)	
	6	-0.22%	-0.22%	0.99%	-2.64%	-0.10%	-0.25%	0%
			(-1.1972)	(0.2318)	(-0.4325)	(-0.0150)	(-1.2707)	
	36	-0.61%	-0.60%	4.36%	-4.08%	-8.83%	0.16%	0%
			(-3.2255**)	(1.0317)	(-0.6723)	(-1.3597)	(0.8058)	
	60	-0.41%	-0.39%	1.57%	-2.19%	-4.28%	-0.03%	0%
			(-2.1028*)	(0.3749)	(-0.3544)	(-0.6583)	(-0.1430)	

Table 2.6: Momentum, contrarian profits and Investors' sentiment (cont.)

Formation periods	Holding periods	Return	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	SENT (T-stat)	Adj.RSQ
12	1	-0.13%	-0.12%	5.27%	-5.41%	-7.68%	-0.17%	0%
			(-0.5546)	(1.0756)	(-0.7695)	(-1.0194)	(-0.7579)	
	3	-0.17%	-0.15%	3.54%	-4.28%	-6.72%	-0.21%	0%
			(-0.7488)	(0.7876)	(-0.6649)	(-0.9691)	(-1.0363)	
	6	-0.08%	-0.07%	6.08%	-7.12%	-5.89%	-0.29%	0%
			(-0.3935)	(1.4004)	(-1.1422)	(-0.8748)	(-1.3938)	
	36	-0.67%	-0.68%	9.36%	-4.43%	-9.80%	0.18%	1%
			(-3.2130**)	(1.9528)	(-0.6425)	(-1.3291)	(0.7559)	
	60	-0.48%	-0.45%	2.29%	-2.71%	-6.85%	-0.06%	0%
			(-2.4853*)	(0.5576)	(-0.4485)	(-1.0790)	(-0.2824)	

Chapter 3 - Business Cycles and the Profitability of and Value vs. Growth Trading Strategies

3.1 Introduction

The value versus growth trading strategies is one of the oldest trading strategies formally documented by Graham and Dodd (1934). In this strategy, investors take long positions in value stocks and short positions in growth stocks. Investors believe that value stocks are undervalued while growth stocks are overvalued and their prices will be corrected in due course. The investors also believe that stock markets overreact to both bad and good news. This overreaction leads to the movement of stock prices that is inconsistent with the long-term fundamentals of firms. This irrational price movement, thus, allows investors to earn excess returns when the market corrects for earlier overreaction. Such excess return is known as the value premium, which is defined as the return on a value portfolio *minus* the return on a growth portfolio. To earn excess returns from value versus growth trading strategies, investors must understand what causes the profit. This chapter, thus, attempts to provide the answer to this question.

Generally, stocks with high book value to market value ratio are defined as value stocks, while stocks with low book value to market value ratio are called growth stocks. The book value to market value ratio is not the only method to identify the value and growth stocks. Litzenberger and Ramaswamy (1979) and Fama and French (1996, 1998) suggest that dividend yield, earnings-to-price ratio and cash-flow-to-price ratio could also be used to classify the stocks into value and growth stocks. Irrespective of their definitions, the value versus growth trading strategy involves going long in value stocks (buying) and going short (selling) in growth stocks. This is based on the view that as the price correction takes place in the near future value firms generate higher returns when compared to growth firms. Studies on value versus growth trading strategies provide strong evidence of profitability, and have an impact on professional investors' investment decisions that are generally adopted in the stock market (Chan and Lakonishok 2004).

Earlier studies, for example Jagannathan and Wang (1996) and Fama and French (2012), confirm the existence of the value premium. There is a question, however, that needs to be answered: What is the underlying reason for such a premium? Fama and French (1992) claim that risk is a possible reason to explain the value premium. Santos and Veronesi (2006) agree with Fama and French (1992) and find that the value premium can indeed be explained by risk differentials. Others studies (e.g. Lewellen and Nagel (2006)) disagree with the suggestion of Fama and French (1992) as they find that the risk differential is unable to explain the value premium. The argument between value premium and risk thus needs to be examined further.

In an earlier study, Zhang (2005) finds that the value premium can be explained by the stages of business cycles. Earlier studies (Petkova and Zhang, 2005; Zhang, 2005;) measure the business cycle using the National Bureau of Economic Research (NBER) business cycle turning point. This chapter, however, employs the Organization for Economic Co-operation and Development Composite leading indicator (OECD CLI) index and OECD business cycle turning point to define the business cycle. According to Brockman, Liebenberg and Schutte (2010), to study the relationship between the business cycle and stock returns, the growth cycle approach outperforms the classic cycle approach. The NBER defines the business cycle using the classical cycle approach while OECD defines it using the growth cycle approach. The OECD CLI index and OECD business cycle turning point, thus, are applied in this chapter to investigate whether the business cycle is able to explain the value premium. To the best of our knowledge, the OECD CLI index has never been used in the study of value versus growth trading strategies.

Another possible factor to explain the value premium is investors' sentiment. Lakonishok, Shleifer and Vishny (1994) suggest that the value premium can be explained by investor behaviour. The relationship between value premium and investors' sentiment thus, is also examined in this thesis. By examining the possible implications of all three factors (risk, business cycles, and investors' sentiment) in a nested form allows us to identify the factor responsible more accurately.

The results of this chapter confirm the existence of the value premium when book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio are employed to classify the stocks into value and growth portfolios. This leads to the next question: What are the underlying reasons behind the observed value premium? Risk is the first factor that this chapter controls for. This chapter finds that the value premium exists even after controlling for risk. This finding is consistent with Lewellen and Nagel (2006), who state that the value premium is left unexplained by risk. The business cycle factor is, then, employed. The positive and statistical significance of the coefficient of the business cycle factor is found. This result suggests the positive effect of the stage of business cycle on value premium. In other words, the value premium increases during economic expansion. When examining if investors' sentiment is able to explain the value premium, the statistical insignificance of the coefficient of the investors' sentiment factor is observed. There is no evidence that the value premium is explained by investors' sentiment.

This chapter also investigates the relationship between business cycle, investors' sentiment and value premium at the industry level. Following Fama and

French (1997), the sample stocks are categorised into nine industry groups. The value premium varies by industry sector and at different stages of economic conditions. The value premium is partially explained by the business cycle in Consumer Durables, Manufacturing, Business Equipment, Shops, and Health. However, the business cycle is unable to explain the value premium in Consumer Nondurables, Chemicals, and Energy industries.

The value premium is persistently observed in this chapter. The observed value premium is partially explained by business cycle factor but unable to explain by risk and investor's sentiment. Specifically, value premium is high during economic expansion but low during economic contraction. The similar result is also found in industries level. The implication of the overall finding is that investors should take a long position on value stocks (buying value stocks) and a short position on growth stocks (selling growth stocks), especially during economic expansion, in order to earn the highest value premium.

This chapter starts with a review of the literature on value vs. growth trading strategies in section 3.2, followed by research questions and hypotheses in section 3.3. In section 3.4, the methodology and sample description are provided. The results are explained in section 3.5 followed by conclusions in the last section, section 3.6.

3.2 Literature Review

3.2.1 Value versus growth trading strategies

The value premium was first documented by Graham and Dodd (1934) and has been confirmed by several subsequent studies. Basu (1977) showed that returns of stocks with high earnings-to-price ratio (value stocks) tend to be higher when compared to returns of stocks with low earnings-to-price ratio (growth stocks); he suggests that value stocks outperform growth stocks. Jaffe, Keim and Westerfield (1989) also employed the earnings-to-price ratio to identify value and growth stocks. Their test concerns the January effect, evading data bias selection, and lengthening the sample period. Over the period 1951 to 1986, the results show that the value premium is significant in both January and eleven-month periods. This finding suggests consistency with value versus growth trading strategies. The value stocks with high earnings-to-price ratio generate higher returns than growth stocks with low earnings-to-price ratio.

Dividend yield is also used to indicate value and growth stocks. Litzenberger and Ramaswamy (1979) used dividend yield to indicate value stocks and growth stocks. The value stocks generally pay higher dividends while growth stocks normally do not pay or else pay lower dividends. They incorporated wealth and income to extend the CAPM after tax version. The results showed that there is evidence of a significantly positive relationship between (a) the before-tax expected stock returns in the NYSE and (b) dividend yield; before-tax expected returns of stock with high dividend yield (value stocks) are larger when compared to before-tax expected returns of stock with low dividend yield (growth stocks). The relationship between before-tax expected stock returns and dividend yield is linear. Chen, Petkova and Zhang (2008) also use dividend yield as a criteria for indicating value stocks and growth stocks. They apply value versus growth trading strategies that involve taking a long position in value stocks (stocks with high dividend yield) and taking a short position in growth stocks (stocks with low dividend yield); they observed the value premium.

The book value to market value ratio is widely used to classify the stocks into value and growth. Rosenberg, Reid and Lanstein (1985) attempted to find the value premium using book value to market value ratio to identify value stocks and growth stocks. Their study employed value versus growth trading strategies that take a long position in stocks with high book value to market value ratio (value stocks), and a short position in stocks with low book value to market value ratio (growth stocks). As expected, positive abnormal returns (i.e. evidence of the value premium) was observed during the sample period. Earlier academic studies of market anomalies build on the study of Fama and French (1992). They capture the variation of cross-sectional average stock returns using book value to market value ratio. The book value to market value ratio gains more attention from academic studies because of this work. They find that stocks with high book value to market value ratio (value stocks) earn higher returns than stocks with low book value to market value ratio (growth stocks) in the US stock market after 1963. Fama and French (1992) suggest the higher returns from value trading strategy are due to a higher level of their risk.

Loughran (1997) then extends the study of Fama and French (1992). He explains that the results from Fama and French (1992) are due to two factors: (a) the January seasonal component that appears in the book-to-market effect, and (b) extraordinarily low returns from small, young and growth stocks. He sorts sample stocks into portfolios based on the book-to-market ratio during the post 1963 period in US stock markets. He finds that the cross-sectional returns could not be explained by book-to-market ratio in the largest firms. This result suggests that book-to-market ratio and size should not play an important role in the decision of asset allocation. Davis, Fama and French (2000) also used the book-to-market ratio as a method of indicating value and growth stocks; they also document the value premium during the sample period.

Cash flow to price ratio is another to be employed in indicating value and growth stocks. Chan, Hamao and Lakonishok (1991) used the book value to market value ratio, earnings to price ratio, and cash flow to price ratio to indicate value and growth stocks. Evidence of the value premium was observed. They also discovered that investment based on value versus growth trading strategies generates larger abnormal returns compared to size-based strategy in the Japanese stock market. Kothari, Shanken and Sloan (1995) then explained that the returns from value trading strategy are affected by a data-selection bias. In the same year, however, Chan, Jegadeesh and Lakonishok (1995) showed that the high returns from value versus growth trading strategy cannot be explained by this data-selection bias.

Evidence of the value premium is observed globally. Fama and French (1998) attempted to provide international evidence of the value premium both in developed and emerging stock markets. They employ dividend-to-price, book-to-market, earnings-to-price, and cash-flow-to-price ratios to indicate value stocks and growth stocks. As expected, value stocks outperform growth stocks in 12 major stock markets and in emerging stock markets. Fama and French (2012) also examine international value premium. Their method of identifying value stocks and growth stocks is book value to market value ratio. As expected, the value premium was observed in three regions: Asia Pacific, Europe and North America. Fama and French (1998, 2012) confirm that the value premium is observed internationally.

Based on the overall studies, investing in value stock outperforms growth stock investment. However, the question about what the underlying reasons for these higher returns are needs to be investigated.

3.2.2 Value premium and risk

Risk is one of the possible reasons to explain why investing in value stocks outperforms investing in growth stocks. Fama and French (1992) observed the value premium post-1963. They found evidence that value versus growth trading strategies that hold a long position on value stocks and a short position on growth stocks generate abnormal returns. They claim that such abnormal returns are due to risk. Risk can be measured in several ways using an asset pricing model such as the Capital Asset Pricing Model (CAPM), Consumption-based CAPM (CCAPM), conditional CAPM, and the Fama and French (1993) three-factor model. Reinganum (1981), however, claims that the value premium is left unexplained by risk. The argument of the value premium and risk has interested financial researchers.

<u>*Value premium cannot be explained by risk*</u>

Evidence from single-market based studies:

Previous studies claim that the value premium is unexplained by risk. Reinganum (1981) discovered the value premiums when using the earnings-to-price ratio as a method of identifying value stocks and growth stocks. He also employed CAPM to adjust stock returns for risks. His study suggests that either (a) CAPM is misspecified or (b) stock markets are inefficient. He further documented that the earnings-to-price effect disappears when stocks' returns were controlled for size effect[7]. This size effect mainly subsumes the earnings-to-price effect.

Lewellen and Nagel (2006) employed the conditional CAPM to explain market anomalies such as the value premium. They formed portfolios based on the book value to market value ratio. During the period from 1964-2001, they estimated both conditional alphas and betas for book-to-market effect using the short-window regression. Their results suggested that betas vary noticeably over time. The large pricing errors, however, could not be explained by this beta variation. The conditional CAPM could not be held because the result reported large and significant conditional alphas. The performance of conditional CAPM from this test is almost as inefficient as the conventional CAPM and cannot explain the value premium.

Fama and French (2006) extended the study of Fama and French (1992). They grouped sample stocks into portfolios based on book-to-market ratio, size and beta and separated the sample period into two: (a) 1926-1963 and (b) 1963-2004. Their results suggest that the conditional CAPM can explain value premium during the period from 1926-1963 but cannot explain the value premium from 1963-2004. Moreover, Ang and Chen (2007) attempt to find the value premium using the book value to market value ratio to identify value and growth stocks. They agree that the value premium is one of CAPM anomalies in US stock markets, especially the period post-1963. They argue that the value premium might be explained by time-varying betas, and extended their study by incorporating time-varying betas and market risk premiums to examine the longer period. Their results show that the value premium

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[7] Banz (1981) provided evidence that stock returns from small firms outperform stock returns from large firms.

can be explained by the conditional CAPM only during the period from 1926-1963 but this model is unable to explain the value premium during the post-1963 period.

Furthermore, Avramov and Chordia (2006) applied seven different asset-pricing models to study whether they have abilities to explain the following market anomalies: value effect, size effect, and momentum effect. In their first step, the conventional CAPM was employed. The effect of past returns, turnover, book-to-market ratio, and size, which are market anomalies, cannot be explained by this conventional CAPM with constant beta. They then applied the conditional CAPM that allows market betas to vary with (a) size and book-to-market ratio, (b) default spread, and (c) default spread and firm-level factors. They find similar results to Fama and French (2006) that conditional CAPM cannot capture any effect on book-to-market ratio and size. Avramov and Chordia (2006) also examine whether both the unconditional CCAPM and the conditional CCAPM can capture market anomalies such as the value premium. They sort sample stocks into portfolios based on book value to market value ratio. The conditional CCAPM allows consumption betas to vary with (a) size and book-to-market ratio, (b) default spread, and (c) default spread and firm-level factors. Their evidence showed that both the unconditional and conditional CCAPMs are unable to explain any of the market anomalies.

Evidence from multiple market based studies:

The international evidence that the value premium is left unexplained by risk is observed by Fama and French (1998). They present international evidence on value and growth trading strategies. They studied stock returns on value and growth portfolios in 13 major stock markets[8]. Not only the major stock markets but also emerging stock markets were examined. The stocks in these 13 major stock markets have been sorted by (a) dividend-to-price ratio, (b) book-to-market ratio, (c) earnings-to-price ratio, and (d) cash-flow-to-price ratio. The returns on value stocks are higher than the returns on growth stocks in 12 major markets. The average returns on international portfolios of high book-to-market stocks are higher than the average returns of low book-to-market stocks, at 7.68% during the period 1975-1995. The portfolios of value stocks outperform the portfolios of growth stocks in 12 major stock markets. They also found evidence of the value premium in emerging stock markets during the period from 1987-1995. They define the CAPM with global market portfolio as international CAPM, and then explain that the value premium from global returns, however, cannot be explained by an international CAPM. However, a global two-factor (ICAPM by Merton (1973) and APT by Ross (1976)) model can capture the value premium from global returns.

Value premium can be explained by risk

Evidence from single-market based studies:

Fama and French (1995) agree with Fama and French (1992) that the value premium is driven by risk. They looked for additional explanations on whether the earning behaviour has an effect on stock price. Portfolios are formed on basis of book-to-market ratio and size. Their results confirm that (a) the stock price and book-to-market ratio are affected by a short-term time variation in profitability and (b) the differences of profitability in the long-term are associated with the book-to-market

[8] The 13 major stock markets consist of United States (NYSE, AMEX, and Nasdaq) and 12 major EAFE countries (Europe, Australia, and the Far East)

ratio. Firms with low book-to-market tend to provide strong profitability whereas firms with high book-to-market tend to be consistently distressed. They also argued that stock with low book-to-market ratio indicates high earning while stock with high book-to-market ratio indicates the opposite. After stocks are sorted based on book-to-market ratio and size, stock prices predict the reversion of earning growth. So, the stocks with low book-to-market ratio have higher prices and lower returns, whereas stocks with high book-to-market ratio generate lower prices and higher returns. Fama and French (1995) also explained that the value premium is driven by risk factor if financial distress is priced as a risk factor.

Lettau and Ludvigson (2001) used the book value to market value ratio to identify value and growth stocks. They applied the CCAPM to examine whether CCAPM has the ability to explain the cross-sectional average stock returns. They conditioned the CCAPM using log consumption-to-wealth ratio to allow a time-varying risk premium and also claimed that the performances of conditional models are much better than the performance of unconditional models. The results when conditional CCAPM were applied showed that growth stocks have lower average returns than value stocks. They explained that this result is due to the high correlation between average value stock returns and consumption growth during the contraction period when the risk premium was high. This result supported the point of view that value stock is riskier than growth stock. The value premium attributes to the higher risk of portfolios with high book-to-market stocks. Thus, the value premium based on the book value to market value ratio can be explained by the conditional CCAPM-based measure of risk.

Furthermore, Parker and Julliard (2005) also used the book value to market value ratio to indicate value and growth stocks. They explained that stock returns are determined by consumption risk. They measured the consumption risk using the covariance between consumption growth and stock return instead of contemporaneous covariance between consumption growth and stock return. This measuring of consumption risk provides the best explanation at a three years' horizon. Their study, then, confirmed that the value premium could be explained by the CCAPM based measure of risk. Additionally, Jagannathan and Wang (2007) use not only the book value to market value ratio but also the earnings-to-price ratio and cash-flow-to-price ratio to identify value and growth stocks. They aim to examine the explanation ability of the CCAPM when 25 portfolios formed by Fama and French (1993) are employed. Their consumption beta was measured using yearly consumption growth at the fourth quarter. They confirmed that the CCAPM-based measure of risk performs as well as Fama and French's (1993) three-factor model-based measure of risk to explain cross-sectional stock returns.

Some studies such as Fama and French (1996) and Avramov and Chordia (2006) use the Fama and French (1993) three-factor model-based measure of risk to examine whether the value premium can be explained by risk. Fama and French (1996) attempted to explain the market anomalies that are associated with firm characteristics, such as book-to-market ratio, earnings-to-price ratio, and cash flow-to-price ratio. They found that the three-factor model performs well to explain the portfolios' returns that are sorted based on the book-to-market ratio and size. They also discovered evidence to support a strong explanatory ability of this model on average returns when portfolios are sorted based on sales growth, cash-flow-to-price ratio, and earnings-to-price ratio. They conclude that the three-factor model performs well to explain different market anomalies definitions, namely book-to-market ratio, size, sales growth, cash-flow-to-price ratio, long-term reversal trading strategy, and earnings-to-price ratio.

After the failure of Avramov and Chordia (2006), argued earlier, they applied the multifactor model instead of the one-factor model. The three-factor model was employed to answer the question whether both the unconditional and conditional three-factor model by Fama and French (1993) has the ability to explain market anomalies. The result shows that the unconditional Fama and French (1993) three-factor model, which is constant in both expected stock returns and risk, is unable to explain the effect of (a) past returns, (b) turnover, (c) book-to-market ratio, and (d) size. The conditional three-factor model with time-varying risk, however, can capture market anomalies. This conditional model does explain the effect of book-to-market ratio and size on the cross-sectional stock returns. Avramov and Chordia (2006) conclude that the conditional three-factor model outperforms both CAPM and CCAPM in explaining the effect of book-to-market ratio and size.

Evidence from multiple market based studies:

Moreover, international evidence that the value premium is explained by risk is found internationally. Drew and Veeraraghavan (2002) attempted to explain the value premium by employing the book-to-market ratio to identify value and growth stocks. They apply Fama and French's (1993) three-factor model to examine (a) whether size and value premium appear outside the US and (b) whether this model can capture the cross-sectional average returns in the Malaysian stock market. They found 17.70% is generated from small-minus-big portfolios and 17.69% is created from high-minus-low portfolios. The market, however, generates a 1.92% return. This result supports the earlier studies that Fama and French's (1993) three-factor model explains the cross-sectional average return.

Furthermore, Spyrou and Kassimatis (2009) examined the value premium in 12 European stock markets. The book-to-market ratio is employed to identify value and growth stocks. In some years, the value premium is driven when the portfolio of stocks with a high book-to-market ratio significantly outperforms the portfolio of stocks with low book-to-market ratio. This result suggests that time has an effect on the value premium. Significant evidence that past betas of both the value portfolio and growth portfolio vary over different economic environments was also found during the sample period. They argued that the conventional CAPM cannot capture the value premium but the conditional CAPM with time-varying component does. The value premium, thus, could be explained by the conditional CAPM-based measure of risk.

In addition, Fama and French (2012) examined (a) whether the pattern of momentum trading strategies and value versus growth trading strategies in international portfolios' returns can be explained by asset pricing models and (b) whether asset pricing across four regions; Asia Pacific, Japan, Europe, and North America, appears to be united. Book value to market value ratio is employed. The results do not show any strong support when the asset pricing is integrated across the four regions. The local model, however, provides acceptable explanations of local average stock returns sorted based on size and book value to market value ratio.

Previous studies show ambiguous evidence of the relationship between value premium and risk. Some studies claimed that value premium is explained by risk (see e.g. Fama and French (1992) and Fama and French (2012)). Others found that risk is unable to explain value premium (see e.g. Reinganum (1981) and Jagannathan and Wang (1996)). Additional evidence of the relationship between risk and the value premium needs to be examined.

3.2.3 Value premium and stages of the business cycles

This section reviews the literature on the role of business cycles in generating the value premium. During different economic environments, firms bear a different level of risk that can lead to a different level of returns (Petkova and Zhang 2005). Zhang (2005) argues that different types of firms are differently affected by risk. Value firms are expected to bear higher risk than growth firms due to sceptical attitudes towards value firms. This higher risk is compensated by higher returns. Thus, value stocks are expected to outperform growth stocks and the value premium is expected to be observed, especially during economic contraction.

Studies such as Petkova and Zhang (2005) examine the value premium during different economic stages. They employed book-to-market ratio to identify value stocks and growth stocks. They measured beta based on market risk premium, which is more accurate; the beta is built by business cycle relative factors. They studied average returns of value stocks and growth stocks in both economic environments: expansion and contraction. They found a positive relationship between value portfolio betas and estimated market risk premium but a negative relationship between betas of growth portfolio and estimated market risk premium was observed. They also documented that value stocks carry a higher a level of risk than growth stocks during bad times (high estimated market risk premium period), inversely, growth stock can carry a higher level of risk than value stocks during good times (low estimated market risk premium period). A higher level of risk during the contraction period leads to a return in value stocks. The result of Petkova and Zhang (2005) is similar to Zhang (2005), that value stocks outperform growth stocks during economic contraction and observe the value premium.

Zhang (2005) examined the value premium during different stages of the business cycle, not only at the aggregate level but also at the industry level[9]. During contraction, value firms (firm with high book-to-market ratio) are loaded with additional unproductive capital. This unproductive capital is more difficult to cut when compared to growth firms (firms with low book-to-market ratio). Hence, both returns and dividends from value firms will co-vary with economic contraction. During expansion, growth firms increase the level of investment to take advantage of economic booms. This larger investment leads to higher costs of adjustment. For value firms, however, it is not urgent to expand their capital because their previous unproductive capital becomes more productive now. Expanding capital is less difficult than cutting it. The returns and dividends from growth, thus, do not co-vary with economic expansion. The net impact of risk dispersion in value versus growth trading strategy is high during contraction and low (or negative) during expansion. This result confirms that value firms are riskier than growth firms, with inflexibility to cut capital, particularly during contraction. Therefore, firms with low growth of investment have larger expected returns.

Chen *et al.* (2008) use dividend yield as a method of indicating value and growth stocks. They observe relationships between the value premium and business

[9] Zhang (2005) formed industries' portfolios following Fama and French (1997).

cycle. They define contraction according to the National Bureau of Economic Research (NBER) and this contraction is a countercyclical variable; the value premium is positively correlated to the countercyclical variable (economic contraction). They provide an additional explanation, related to Zhang (2005), that value firms bear higher risk than growth firms during a bad economic environment. Higher level of risk is due to the inflexibility of value firms to cut their capital. Cutting capital in value firms is more costly than expanding capital in growth firms. Higher level of risk, thus, leads to higher returns in value stocks during a contraction. This result is similar to Petkova and Zhang (2005), and Zhang (2005) who reveal value premium peaks during contraction, and that the relationship between value premium and business cycle is explained by risk in different economic stages.

There are few studies to support the relationship between the value premium and business cycles. Previous studies suggest that the value premium is positively correlated with economic contraction. In other words, a higher value premium is observed during contraction than during expansion.

3.2.4 Value premium and investors' sentiment

This section reviews the literature on the role of investors' sentiment in generating value premium. Lakonishok *et al.* (1994) provide evidence that higher returns from a value versus growth trading strategy have been generated mainly from cognitive biases based on investor behaviour. Their work also claims that the high returns of this trading strategy are not being generated by risk. Du (2011) also agrees with Lakonishok *et al.* (1994). He clarifies that researches attempt to explain the value premium using (a) risk and (b) investors' sentiment; so, he tests risk and investors’ sentiment together to explain the value premium. The correlation between value premium and investors’ sentiment is observed in his study but risk is not seen as being able to explain the value premium.

The finding of Xing (2008), however, is different from the others. He also attempts to provide an explanation for the value premium and uses book-to-market ratio as a method of identifying value and growth stocks. Xing (2008) compares the explanatory performance of Fama and French's (1993) three-factor model with the standard Q-theory. He claims that the high-minus-low factor three-factor model performs well to explain the value premium, similarly to the investment growth factor from the standard Q-theory. Xing (2008) confirms that the value premium is not consistent with (a) investors’ overreaction or underreaction and (b) mispricing by investors.

There are few studies of the role of investors’ sentiment in generating value premium. The findings of previous studies are mixed requiring further analysis to confirm the relationship between the value premium and investors’ sentiment.

3.2.5 The gap in the literature

The literature shows that the value premium exists internationally. Several studies attempt to explain the sources of the value premium, and one possible source is risk (Lettau and Ludvigson 2001). However, the evidence is mixed, requiring further analysis. Earlier studies mainly focus on the relationship between the value premium and risk (see section 3.2.2), when the different asset pricing models are employed to investigate the relationship between other factors. Earlier studies show that Fama and French's (1993) three-factor model outperforms other models to explain the value premium. This model, thus, is used in this chapter.

The literature appears to have very few empirical studies on the relationship between the value premium and the stages of business cycles. The earlier studies employed the NBER business cycle turning point to the identify business cycle (see e.g. Chen *et al.* (2008)). This chapter introduces the OECD CLI index to identify the business cycle factor[10]. None of the existing studies uses the OECD CLI index to study the relationship with the value premium. Moreover, this chapter not only investigates the relationship of the value premium at the aggregate level but also examines it at an industry level. Additionally, the earlier studies such as Zhang (2005) mainly investigated the relationship between the value premium, risk, and business cycle but do not incorporate the investors' sentiment factor. Lakonishok *et al.* (1994) suggested that the value premium can be explained by investor behaviour. Xing (2008), however, claimed that the value premium is not consistent with investors' behaviour. The findings of the relationship between the value premium and investors' sentiment remain ambiguous and require further analysis. This chapter aims to fill this gap by investigating the relationship between the value premium and investors' sentiment.

[10] Three reasons led to the adoption of the OECD CLI index. The first is that the OECD business cycle turning point fills the gap in the NBER business cycle turning point, claimed by Beveridge and Nelson (1981). The OECD business cycle turning point is decided based on monthly data. Lustig and Verdelhan (2012) also claim that the OECD is sensitive and any change in economic situation quickly affects decisions on business cycle indicators. The second reason is, according to Brockman *et al.* (2010), that OECD is the method of choice to define the business cycle, especially when compared to the NBER, arguing that a business cycle that is measured based on the growth cycle approach suits the study of the relationship between the business cycle and stock returns. The third reason is that the OECD CLI index is available monthly. This thesis uses monthly data that suit the OECD CLI index well.

3.3 The Research Questions and Hypotheses

The gap in the literature is identified in section 3.2.4. This chapter aims to investigate whether the value premium is explained by (a) risk, (b) the stages of business cycles, and (c) investors' sentiment. In an attempt to fill the above void in the literature, the following research questions are addressed:

1) Do portfolios of value stocks outperform the portfolios of growth stocks?

To answer the first research question, the sample stocks are grouped into value and growth stocks on the basis of (a) dividend yield, (b) book-to-market ratio, (c) earnings-to-price ratio, and (d) cash-flow-to-price ratio. The first research question leads to the first testable hypothesis that:

$H_{3.1a}$: The value versus growth trading strategies that take long positions in value stocks and short positions in growth stocks generate positive returns.

2) Do the observed value premium (if any), risk, business cycle, and/or investors' sentiment explain the value premium?

It is possible that the observed value premium is simply a compensation for risk. If so, there should be a significant relationship between the value premium and time-varying risk. In other words, there should be no value premium after adjusting for risk premium. The literature on asset pricing suggests that the multifactor asset pricing model is superior to a single factor asset pricing model such as CAPM. Several studies confirm that Fama and French's (1993) three-factor model performs well to capture the value premium (see e.g. Fama and French (1996)). Therefore, this chapter uses the three-factor model to control for risk and examines the relationship between the value premium and risk. The value stocks are expected not to generate significantly higher returns, after controlling for risk, than growth stocks. This leads to a second hypothesis that:

$H_{3.2a}$: The observed value premium can be explained by time varying risk.

Earlier studies found that the value premium cannot be explained by time varying risk. Some studies show that returns of some stocks are more influenced by the business cycle condition than others. It is possible that the value premium is explained by the business cycle. Thus, this chapter empirically examines if the value premium can be explained by the business cycle. According to Brockman *et al.* (2010), the business cycle turning point, which measures based on the growth cycle approach, is preferred when studying the business cycle and stock returns. The OECD CLI index, which is measured based on the growth cycle approach, is the method of choice to define the business cycle. The OECD CLI index, thus, is used as the business cycle variable in this chapter. The value stocks are expected not to generate higher returns than growth stocks after controlling for the business cycle. This leads to the third hypothesis that:

$H_{3.3a}$: The stages of business cycles can explain the value premium.

Risk and the business cycle might not fully explain the value premium. Lakonishok *et al.* (1994) suggest that the value premium can be explained by investor behaviour. Therefore, this chapter empirically examines if the value premium can be explained by investors' sentiment. Similarly to Chapter 2, the investors' sentiment that is constructed by Baker and Wurgler (2006) is employed. The value stocks are expected not to generate significantly higher returns, after controlling for the investors' sentiment factor, than growth stocks. This leads to the fourth hypothesis that:

$H_{3.4a}$: The investors' sentiment can explain the value premium.

Not only at the aggregate level, this chapter also examines the value premium at the industry level. Studies suggest that some stock returns are influenced differently, depending on their business types. Therefore, this chapter empirically examines if the value premium varies by industry. The sample stocks are grouped into industries based on the studies of Fama and French (1997). The value stocks are expected to generate significantly higher returns, after controlling for risk, business cycle, and investors' sentiment factors, than growth stocks. This leads to the fifth hypothesis that:

$H_{3.5a}$: The value premium varies by industry sector.

3.4 The Methodology and Sample

3.4.1 The measurement of key variables

3.4.1.1 Defining value and growth stocks

The definition of value stocks and growth stocks has already been clarified. Stocks can be classified into value and growth stocks based on their fundamentals such as sales, dividends, and earnings relative to their market value. Stocks, which are traded at a lower price when compared to their fundamentals, are called the value stocks. The basic characteristics of these value stocks consist of high dividend yield, high book-to-market ratios, and high earnings-to-price ratios. Inversely, common characteristics of growth stocks include zero or low dividend yield, low book-to-market ratios, and low earnings-to-price ratios. The growth stocks are a group of high quality firms. The future earnings of these growth stocks are anticipated to increase above average when compared to the market. Typically, growth stocks do not pay dividend because firms tend to reinvest instead of paying dividends. Investors who believe in value versus growth trading strategies perceive the growth stocks as being overvalued and that their price should decline in the future.

The book-to-market ratio is widely used in earlier studies to form the portfolios of value and growth stocks (see section 3.2.1). Other ratios, such as earnings-to-price, cash flow to price, and dividend yield, can also be used to form the value and growth portfolios (see e.g. Litzenberger and Ramaswamy (1979) and Fama and French (1996, 1998)). In this chapter the sample stocks are sorted into four ratios; dividend yield (DY), book-to-market (BM), earnings-to-price (EP), and cash-flow-to-price (CP); these four ratios are employed to ensure that the findings are robust with respect to the classification of stocks into value and growth. The construction of key variables is presented in Table 3.1.

[Table 3.1]

<u>Dividend yield (DY)</u>

Dividend yield is a financial ratio indicating the total cash dividends relative to a firm's share price. The firms with high dividend yield are called value firms while growth firms are those with low dividend yield (Fama and French, 1998). The growth firm pays a low or zero dividend because growth firms tend to reinvest instead. This chapter calculates dividend yield as follows:

$$Dividend\ yield = \frac{Dividend\ per\ share}{Share\ price}$$

Book to market ratio (BM)

Book-to-market ratio is a financial ratio indicating a firm's value by comparing its book value to the market value. Value firms are those with high book-to-market ratio while firms with low book-to-market ratio are considered as growth firms (Loughran, 1997). This chapter calculates the book-to-market ratio as follows:

$$Book\ to\ market\ ratio = \frac{Book\ value}{Market\ Value}$$

Book value is a net asset value that is calculated by total assets less intangible assets and total liability. Market value is market capitalisation, which is calculated by shares outstanding multiplied by share price.

Earnings to price ratio (EP)

Earnings-to-price is a financial ratio indicating the firm's earning per share relative to its share price. The earnings-to-price ratio is the inverse of price-to-earnings ratio. The ratio indicates the amount that investors receive when they invest one pound sterling (or US dollar). Firms with a high earnings-to-price ratio are considered value firms, whereas a low earnings-to-price ratio indicates growth firms (Basu, 1977). This chapter calculates the earnings-to-price ratio as follows:

$$Earnings\ to\ price\ ratio = \frac{Earning\ per\ share}{Share\ price}$$

Earnings per share is calculated as follows:

$$Earning\ per\ share = \frac{net\ income - preferred\ dividends}{share\ outstanding}$$

Cash-flow to price ratio (CP)

Cash-flow-to-price is a financial ratio of cash flow per share relative to its share price. The cash-flow-to-price indicates stock value and mainly considers the operating cash flow. Value firms are those with high cash-flow-to-price, whereas those with low cash-flow-to-price are called growth firms (Fama and French 1996). This chapter calculates cash-flow-to-price ratio as follows:

$$Cash\ flow\ to\ price\ ratio = \frac{operating\ cash\ flow\ per\ share}{share\ price}$$

3.4.1.2 Stages of the business cycles

This chapter examines the role of the stages of business cycles on the value premium. There are two key measurements of business cycle: (a) the classic cycle approach and (b) the growth cycle approach. The classic cycle approach classifies absolute troughs and peaks in the real GDP. The NBER business cycle turning point is a well-known business cycle factor that is measured by the classic cycle approach. The growth cycle approach classifies comparative troughs and peaks in the real GDP growth comparative to long-term trends. The OECD business cycle turning point is a well-known business cycle factor that is measured by the growth cycle approach.

Earlier studies, for example, Chen *et al.* (2008) use the NBER business cycle turning point as the means of identifying economic expansion and economic contraction. Beveridge and Nelson (1981), however, argue that the contraction period, which is identified by the NBER business cycle turning point, is too short relative to economic expansion. The OECD business cycle turning point fills this void; it is decided based on monthly data. In addition, Brockman *et al.* (2010) claim that the growth cycle approach is more suitable than the classic cycle approach to study the relationship between the business cycle and stock returns. The OECD business cycle turning point is decided following the composite leading indicator (CLI) that is available monthly. The expansion starts immediately after the CLI reaches a trough of economic activity and ends when the CLI reaches its peak. CLI data are available monthly, similarly to other data in this chapter based on monthly data. The OECD CLI index, thus, is the method of choice to define the business cycle, especially when compared to the NBER.

The OECD CLI is used in other trading strategies studies, for example, by Lustig and Verdelhan (2012). They examine feasible trading strategies and use the OECD business cycle turning point as the method of identifying economic expansion and economic contraction. The author of this thesis believes that, the OECD CLI index has never been used in the study of value versus growth trading strategies. This chapter, therefore, sheds new light on the value premium and business cycle.

The OECD CLI provides the business cycle based on the growth cycle approach The OECD CLI offers an early sign of a business cycle turning point and shows instability of economic activity. Up to April 2012, the main component, the Industrial Production Index (IP), was the same for all OECD countries, while after April 2012 the GDP is used only to identify the turning point from the growth cycle as a reference. The IP covers all industry sectors, excluding construction. The component of CLI is different among countries examined and for the US the CLI index consists of (a) permits issued for dwellings, (b) the net of new durable goods orders, (c) share price, (d) consumer sentiment index, (e) weekly working hours, (f) industrial confidence index, and (g) interest rate spread. These series of components is chosen based on several conditions, such as cyclical behaviour and economic significance. The OECD business cycle turning point and CLI index are used in this chapter as the business cycle factor.

3.4.2 Methodology

To answer the research questions (in section 3.3) "Do portfolios of value stocks outperform the portfolios of growth stocks?" and "Do the observed value premium (if any), risk, business cycle, and/or investors' sentiment explain the value premium?" This section clarifies methodologies to answer these two main research questions.

The value premium (Test $H_{3.1a}$)

The value and growth portfolios are formed using the definitions specified earlier. A value premium that is significantly greater than zero would support the hypothesis. To test *"$H_{3.1a}$: The value versus growth trading strategies that take long positions in value stocks and short positions in growth stocks generate positive returns"*, portfolios of value and growth stocks are formed on the basis of four financial ratios namely, dividend yields, book-to-market ratio, earnings-to-price ratio, and cash-flow-to-price ratio. The ratios are measured three months after a firm's fiscal year end. The three months' gap[11] (between fiscal year-end and the beginning of the holding period) ensures that all data needed to calculate ratios are available for the investors. The three-month-lag of data from a financial report with current prices and market capitalization is used to measure the ratios. After the ratios are calculated, the sample stocks are equally grouped into ten portfolios in ascending order. Portfolio 1 is considered as the growth portfolio while portfolio 10 is considered as the value portfolio. The value portfolio includes stocks with high dividend yields, book-to-market ratio, earnings-to-price ratio, and cash-flow-to-price ratio, and the growth portfolio includes stocks with low dividend yields, book-to-

[11] According to the U.S. Securities and Exchange Commission, annual reports from US domestic firms should be released within 90 days.

market ratio, earnings-to-price ratio, and cash-flow-to-price ratio. The long position on value portfolios and short position on growth portfolios are taken at the same time. After the long and short positions are taken, portfolios are held for four different holding periods: 3, 6, 12 and 24 months.

After the portfolios are formed and held for each holding period, the returns in value and growth portfolios are calculated. The average return from the value portfolio *minus* the average return from the growth portfolio is used to find the value premium. The two-tailed test is applied to investigate whether (a) return from value portfolios, (b) return from growth portfolios and (c) the hedge portfolio returns (the returns in value portfolio *minus* growth portfolio) are significantly different from zero. The test statistic is described below:

$$t = \frac{\bar{x}-\mu}{s/\sqrt{n}} \qquad (3.1)$$

where $\bar{x}$ is the portfolio average returns, μ is the hypothesized population mean, which is zero, s is standard deviation, and n is sample size, which is firm-month observations. This test provides the decision for the null hypothesis that average returns of portfolios equal zero. If the result shows that (a) the hedge portfolio returns (the returns in value portfolio *minus* growth portfolio) are significantly different from zero and (b) differences in returns between value and growth portfolio are positive, there is evidence of value premium. This test is expected to have positive and significant results to confirm the existence of the value premium.

Value premium and risk (Test $H_{3.2a}$)

Theoretically, higher risk is compensated by higher returns. Value stocks are generally expected to bear a higher risk than growth stocks due to the sceptical attitude towards the characteristics of value stocks. The value portfolio, thus, is expected to outperform the growth portfolio due to the higher level of risk (Petkova and Zhang, 2005). The three-factor model of Fama and French (1993) is used to estimate risk-adjusted stock returns and to test *"$H_{3.2a}$: The observed value premium can be explained by time varying risk"*. According to the literature, the one-factor asset pricing model fails to explain the market anomalies such as value premium (see e.g. Fama and French (1992, 1993)). The multifactor model, specifically the three-factor model, does have the ability to capture the value premium (see e.g. Fama and French (1995, 2012)). The three-factor model of Fama and French (1993) is described as:

$$R_{i,t} = \alpha_i + \beta_i^{RmRf} RmRf_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \quad (3.2)$$

where $R_{i,t}$ is return of stock i in month t excess of risk free rate, $RmRf_t$ represents market factor, market excess return in month t, SMB_t represents size factor in month t, and HML_t represents value factor in month t. $\alpha_i, \beta_i^{RmRf}, \beta_i^{SMB}$, and β_i^{HML} are parameters to be estimated. $\varepsilon_{i,t}$ is the residual return of stock i in month t. The difference between stock return and estimated stock return from equation (3.2) is used as the risk-adjusted return to find if the value premium is driven by risk.

To test $H_{3.2a}$, the risk-adjusted returns are employed to test the statistical significance of hedge-portfolio return (return from long position *minus* short position portfolios) using the two-tailed test from equation (3.1). If the result shows that average risk-adjusted returns in hedge portfolios are statistically insignificantly different from zero, there is no evidence of a risk-adjusted value premium. The statistically insignificant result implies that returns, after being adjusted for risk, cannot generate a value premium. In other words, a statistically insignificant result suggests that the value premium is driven by risk. Inversely, the statistically significant result suggests that the value premium cannot be explained by risk.

Value premium and stages of business cycle (Test $H_{3.3a}$)

Zhang (2005) suggested that the business cycle is a possible factor to explain the value premium, thus, it is applied in this section to test *"$H_{3.3a}$: The stages of business cycles can explain the value premium"*. To examine the relationship between the value premium and stages of business cycle, Equation (3.3) is applied. Equation (3.3) is used to test whether market factor, size factor, value factor, and business cycle factors explain the value premium; the business cycle variable is added as noted in equation (3.3):

$$V_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{BUS} BUS_t + \varepsilon_t \quad (3.3)$$

where V_t is the value premium in month t, BUS_t is the CLI index that represents the business cycle factor in month t, and β_t^{BUS} is the parameter to be estimated. To confirm that the value premium is explained by the business cycle, this test is expected to have a statistically significant coefficient of the business cycle variable (CLI).

Value premium and investors' sentiment (Test $H_{3.4a}$)

Lakonishok *et al,* (1994) suggest that the value premium can be explained by investors' behaviour. In this section *"$H_{3.4a}$: The investors' sentiment can explain the value premium"* is tested. Equation (3.4) is used to test whether investors' sentiment factors explain the value premium; the investors' sentiment variable[12] is incorporated as noted in equation (3.4):

$$V_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{BUS} BUS_t + \beta_t^{SENT} SENT_t + \varepsilon_t \qquad (3.4)$$

where V_t is the value premium in month t, $SENT_t$ is investors' sentiment from Baker and Wurgler (2006) in month t, and β_t^{SENT} is the parameter to be estimated. To confirm that the value premium is explained by investors' sentiment, this test is expected to have a significant coefficient of the investors' sentiment variable.

Value premium by industry sectors (Test $H_{3.5a}$)

To test *"$H_{3.5a}$: The value premium varies by industry sector"*, the value premium of industry is examined. Earlier studies suggest that returns of some stocks are influenced differently, depending on their business type. The sample stocks are grouped into nine industries[13] based on the studies of Fama and French (1997); the value premium is calculated from each industry. The value premium of each industry is employed in equation (3.4). If the result shows the statistical significance of intercept, the value premium of industry is observed even after controlling for risk, business cycle, and investors' sentiment. To confirm that the value premium varies by industry sector, this test is expected to have a positive significance of intercept.

[12] The measurement of investors' sentiment is explained in chapter 2.
[13] The 9 industries are grouped using the CRSP SIC code. Data for each industry are reported in the Sample and data description section.

3.4.3 Sample description

The sample includes stocks that are listed in three main US stock markets: NYSE, AMEX, and NASDAQ from the CRSP database. The sample period starts from July 1972 to December 2015 and covers 522 months with 2,314,841 firm-month observations including 14,945 firms. The study period starts in July 1972 because of the availability of data to measure financial ratios. The financial and utilities sectors are excluded from this sample. The stocks from the financial sector are excluded because their asset structure is different from other non-financial stocks. The stocks from the utilities sector are excluded because there is a high level of strictly regulated investment when compared with other sectors. To stay in the sample, stocks are required to have at least 36 months' returns data. After financial ratios are calculated, all the negative ratios are excluded from the sample. The data on three factors for Fama and French's (1993) model: market factor (Rm-Rf), size factor (SMB), and value factor (HML) are sourced from the webpage[14] of French (2015). The OECD Composite Leading Indicator (CLI) index is sourced from the webpage of OECD (2016a)[15] and the OECD business cycle turning points[16] are from the OECD's (2016b) webpage[17]. The investors' sentiment data are collected from Wurgler's (2015) webpage[18].

[Table 3.2]

Summary statistics in Table 3.2 show evidence of positive skewness in dividend yield, earnings-to-price ratio, and cash-flow-to-price ratio while evidence of negative skewness is found in book-to-market ratios. The positive skewness of

[14] URL: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[15] URL: https://data.oecd.org/leadind/composite-leading-indicator-cli.htm#indicator-chart
[16] See Appendix A for OECD business cycle turning point.
[17] URL: http://www.oecd.org/std/leading-indicators/CLI-components-and-turning-points.pdf.
[18] URL: http://people.stern.nyu.edu/jwurgler/.

dividend yield, earnings-to-price ratio, and cash-flow-to-price ratio is represented by the difference between mean and median, and also high standard deviation. The difference between mean and median of the book-to-market ratio is statistically insignificant, suggesting normal distribution of the book-to-market ratio. The cash flow to price ratio has the highest standard deviation while the book-to-market ratio has the lowest. The firm-month observations exclude the negative ratios. The correlation matrix in the table shows positive correlation among three sorting variables: dividend yields, book-to-market ratio, and earnings-to-price ratio. The cash-flow-to-price ratio is negatively correlated with (a) book-to-market ratio and (b) earnings-to-price ratio while positively correlated with dividend yields. The correlation coefficients among sorting variables are statistically insignificant, indicating these variables provide different economic insights.

[Figure 3.1]

Figure 3.1 presents the movement of CLI, which shows the fluctuation in economic activities over time. The highest peak of CLI is in May 1973, followed by September 1985 and October 2007 respectively. The peak indicates the last month of economic boom and then economic expansion turns into economic contraction after the peak month. Inversely, the trough indicates the last month of economic contraction and turns into economic expansion immediately after the trough month. The lowest trough is in May 2009 followed by April 1975 and November 1982 respectively. CLI also provides an early sign of a business cycle turning point.

[Figure 3.2]

Figure 3.2 presents returns in each of the 10 portfolios when sample stocks are sorted into deciles on the basis of four ratios: dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio. Portfolios are held for four holding periods: 3, 6, 12 and 24 months. Portfolio 1 represents growth portfolio (portfolio of stocks with low dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio) whereas portfolio 10 represents value portfolio (portfolio of stocks with high dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio). The X-axis represents the portfolio number and the Y-axis represents an average of portfolios' returns. In Figure 3.2a, sample stocks are grouped into portfolios on the basis of dividend yields. The graph shows that returns tend to decrease with higher dividend payment. In other words, growth portfolios generate higher returns than value portfolios.

In Figure 3.2b, sample stocks are grouped into portfolios on the basis of book value to market value ratio. The graph shows that returns tend to increase when portfolios include stocks with a high book-to-market ratio (value portfolio). In other words, value portfolios outperform growth portfolios to generate returns. Similar results are also found in Figures 3.2c and 3.2d.

[Figure 3.3]

Figure 3.3 presents risk-adjusted returns (equation (3.2)) in each of the 10 portfolios. Similarly to Figure 3.2, portfolio 1 represents the growth portfolio while portfolio 10 represents the value portfolio. In Figure 3.3a, sample stocks are grouped into portfolios on the basis of dividend yield. The graph shows that the value portfolio (portfolio 10) outperforms the growth portfolio (portfolio 1) to generate risk-adjusted returns. In Figure 3.3b, sample stocks are grouped into portfolios on the basis of book-to-market ratio. The returns tend to increase with a high book-to-market ratio (value portfolio). This suggests that value portfolios outperform growth portfolios even after controlling for risk. Similar results are also found in Figures 3.3c and 3.3d.

[Table 3.3]

Following Fama and French (1997), sample stocks are grouped based on the SIC code from the CRSP database into nine industries consisting of Consumer Nondurables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telecommunication, Shops, and Health. Table 3.3 presents summary statistics of the nine industries. The value premium is observed in all industries except Telecommunication. The Health sector generates the highest value premium of 1.89%, whereas the lowest value premium of 0.77% is generated from Consumer Durables.

3.5 Results

To examine gains/losses from value versus growth trading strategies, this chapter forms portfolios on the basis of four financial ratios; dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio. The sample stocks are grouped into deciles in ascending order. The portfolios of stocks with the highest dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio are value portfolios, and the portfolios of stocks with the lowest dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio are growth portfolios. The returns for each portfolio are calculated. The sample portfolios are held for different lengths of time: 3, 6, 12 and 24 months.

3.5.1 The value premium

To examine the first hypothesis, *"$H_{3.1a}$: The value versus growth trading strategies that take long positions in value stocks and short positions in growth stocks generate positive returns",* the statistical significance of average hedge portfolio returns (i.e. returns from value portfolios *minus* returns from growth portfolios) is tested using the t-test in equation (3.1). Table 3.4 presents the value premium.

[Table 3.4]

The first measure of value and growth stocks is dividend yields. The results show that the difference in returns between value and growth portfolios is negative and statistically insignificant in all holding periods. This result suggests that there is no evidence of value premium when portfolios are formed on the basis of dividend yield. The next measure used in classifying the stocks into value and growth is book-to-market ratio. The results show that returns from hedge portfolios (returns in value portfolio *minus* growth portfolio) are positive and statistically significantly different from zero. In other words, there is evidence of the value premium. Specifically, the value premium is 0.94%, 0.80%, 0.97% and 0.74% when holding portfolios for 3, 6, 12 and 24 months, respectively. The value premium is mainly generated from the positive return of value portfolios, which are higher than growth portfolio. The returns from value portfolios are 1.87%, 1.73%, 1.74%, and 1.61%, respectively. The holding period that generates the highest value premium is 12 months. The existence of the value premium when the book-to-market ratio is used to identify value and growth stocks is consistent with the findings of Chan *et al.* (1991).

The third measure used to group the stocks is earnings-to-price ratio. Similarly to the book-to-market ratio, returns from hedge portfolios are positive and statistically significantly different from zero. This result suggests that a value premium exists. The value premiums are 0.38%, 0.48%, 0.59% and 0.43%, respectively. The value premiums are relatively low when compared, once the book-to-market ratio is used. The lower value premium is due to high returns from growth portfolios. The highest value premium is observed when portfolios are held for 12 months. The existence of the value premium, when the earnings-to-price ratio is used, indicates that value and growth stocks are consistent with Reinganum (1981).

The final measure used to classify the stocks into value and growth is cash-flow-to-price ratio. The results show positively and statistically significant returns from hedge portfolios. This suggests evidence of the value premium. The value premiums are 0.81%, 1.01%, 0.80% and 0.52%, respectively. The six-months holding period generates the highest value premium. The value premiums mostly earn from positive returns in value portfolios. The existence of a value premium when cash-flow-to-price ratio is employed to classify value and growth stocks, is consistent with Jagannathan and Wang (2007).

The value premium can be generated when book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio are used to group the sample stocks into value and growth categories. The existence of the value premium is consistent with the earlier studies, such as Fama and French (2012). The holding period that generates the highest value premium is 12 months. The holding period of six months generates the highest value premium when value and growth stocks are identified using the cash-flow-to-price ratio. To earn the highest value premium, cash-flow-to-price ratio should be employed to indicate value and growth stocks, and portfolios should be held for six months. This should be the best strategy according to the results. Investors, however, cannot earn a value premium if they use dividend yields to form the portfolio of value and growth stocks.

The results show that the value portfolios mainly outperform the growth portfolios. The returns from hedge portfolios (returns from value portfolio *minus* growth portfolio) are positive and statistically significantly different from zero. These results suggest that $H_{3.1a}$ is accepted. Given the findings discussed above, investors can earn the value premium. However, the next question is: What can explain the value premium? Previous studies such as Fama and French (1996) argue that risk can explain the value premium. Lewellen and Nagel (2006), however, claim that risk differential cannot explain the value premium. Given the mixed evidence, the question remains unanswered. This issue is addressed in the next section.

3.5.2 The value premium and risk

This section examines the second hypothesis $H_{3.2a}$: that: *"The observed value premium can be explained by time varying risk"*. To examine this, risk-adjusted returns are estimated using equation (3.2). To examine whether the observed value premium is driven by risk, the statistical significance of the difference in the risk-adjusted returns of value and growth portfolios is tested using the t-test in equation (3.1).

[Table 3.5]

Table 3.5 presents the risk-adjusted value premium when sample stocks are grouped into portfolios on the basis of dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio. The first measure for identifying value and growth stocks is dividend yields. The results show the positive and statistical significance of risk-adjusted returns from hedge portfolios (risk-adjusted returns in value portfolio *minus* growth portfolio). This suggests the existence of a risk-adjusted value premium. Compared to the estimates reported in Table 3.4 the value premium exists when the returns are adjusted for risk. This result suggests that the value premium is not driven by risk when portfolios are grouped on the basis of dividend yields.

The second measure for identifying value and growth stocks is the book-to-market ratio. The results show that risk-adjusted returns from hedge portfolios are positive and statistically significantly different from zero. This result confirms the evidence of risk-adjusted value premium. The risk-adjusted value premiums are 3.70%, 3.35%, 3.04% and 1.74% given the holding periods are 3, 6, 12 and 24 months, respectively. The highest risk-adjusted value premium is 3.70% when portfolios are held for three months. The risk-adjusted value premiums tend to decrease with the longer holding period. Compared to the estimates reported in Table 3.4, the value premiums increase even after controlling for risk. The results suggest that the value premium is left unexplained by risk when portfolios are grouped on the basis of book-to-market ratio.

The third measure for identifying value and growth stocks is the earnings-to-price. The results show a positive and statistical significance of the difference in the risk-adjusted returns of value and growth portfolios, which suggests the existence of a risk-adjusted value premium. Specifically, the risk-adjusted value premiums are 1.63%, 1.45%, 1.32% and 0.93%, respectively, during the given holding periods.

Holding portfolios longer leads to a lower risk-adjusted value premium. Compared to the estimates reported in Table 3.4 value premiums exist and even increase after controlling for risk, which suggests that the value premium is unable to be explained by risk when portfolios are grouped on the basis of earnings-to-price ratio.

The last measure for identifying value and growth stocks is the cash-flow-to-price ratio. The positive and statistically significant results of hedge portfolios' returns are observed, which confirms the existence of a risk-adjusted value premium. Similarly to when book-to-market ratio and earnings-to-price ratio are employed, the value premiums tend to decrease after holding portfolios longer. The value premiums are 2.83%, 2.70%, 1.84% and 0.80%, respectively. Compared to the estimates reported in Table 3.4, the value premiums increase after adjusting for risk. The results suggest that the value premium is not driven by risk when portfolios are grouped on the basis of cash-flow-to-price ratio.

The evidence above suggests that a risk-adjusted value premium exists when (a) dividend yields, book-to-market ratio, earnings-to-price ratio, and cash-flow-to-price ratio are used to group the stocks into value and growth, and (b) portfolios are held for 3, 6, 12 and 24 months. The value premium cannot be explained by risk differentials between value and growth stocks. Comparing the overall results in Table 3.5 with those in Table 3.4, a higher value premium is generated after returns are adjusted for risk. Consequently, the risk is unable to explain the premium. These results reject hypothesis $H_{3.2a}$. This result is consistent with earlier studies such as Reinganum (1981) and Ang and Chen (2007).

3.5.3 The value premium, risk and stages of the business cycle

The results in the previous section (section 3.5.2) show that risk is unable to explain the value premium. Earlier studies such as Petkova and Zhang (2005) suggest that the value premium can be explained by stages of the business cycle. This section examines the role of business cycle on value premium: $H_{3.3a}$ *"The stages of business cycles can explain the value premium"*. To investigate whether the observed value premium is driven by stages of the business cycle, the statistical significance of the coefficient of the business cycle factor is tested using equation (3.3).

[Table 3.6]

Table 3.6 presents the results from the regression in equation (3.3). When dividend yields are used as measures for indicating value and growth stocks, the results are statistically insignificant for the coefficient of the business cycle factor after controlling for risk. The value premium, however, cannot be observed when dividend yields are employed (section 3.5.1). This result suggests that stages of business cycles have no effect on hedge portfolios' return. When the book-to-market ratio is employed as a measure of identifying value and growth stocks, the statistical significance of the coefficient of the business cycle factor after controlling for risk is observed. This result suggests that the value premium is partially driven by the stages of the business cycle. Specifically, the estimated coefficients are positive and these positive coefficients suggest that stages of the business cycle positively explain the value premium. Similar results are also found when the earnings-to-price ratio and cash-flow-to-price ratio are used as the measures for identifying value and growth stocks. The evidence that the value premium is positively explained by stages of the business cycle is relatively strong among all holding periods and all definitions of value and growth stocks, except dividend yields.

Economic expansion leads investors to be more optimistic, whereas during economic contraction investors are more pessimistic. The investors have more confidence in the stock market and intend to invest more on risky assets (i.e. value stocks) to earn higher returns during an economic boom than during an economic contraction. Higher demands for value stocks lead to higher prices, consequently, higher returns during an economic boom. The results confirm that the value premium is positively explained by stages of the business cycle and suggest that $H_{3.3a}$ is accepted.

3.5.4 The value premium, risk, stages of the business cycle and investors' sentiment

The results in the previous section (section 3.5.3) suggest that the value premium is partially explained by stages of the business cycle. There should be other factors to explain the value premium. Lakonishok *et al.* (1994) suggest that the value premium can be explained by investors' behaviour. Therefore, this section examines the role of investors' sentiment on the value premium: $H_{3.4a}$ *"The investors' sentiment can explain the value premium"*. To investigate whether the observed value premium is explained by investors' sentiment, the statistical significance of the coefficient of investors' sentiment factor is tested using equation (3.4).

[Table 3.7]

Table 3.7 presents the results from the regression in equation (3.4). When the book-to-market ratio is employed to indicate value and growth stocks, the statistical insignificance of the coefficient of investors' sentiment factor, after controlling for risk and the business cycle, is observed. This result suggests that the value premium is unexplained by the investors' sentiment factor. The statistical insignificance of the coefficient of investors' sentiment factor is found when earnings-to-price ratio and cash-flow-to-price ratio are used as the measures for identifying value and growth stocks. The results show the statistical insignificance of the coefficient of investors' sentiment factor among all holding periods and definitions of value and growth stocks, except dividend yields. When dividend yields are used as measure of indicating value and growth stocks, the results are statistically significant for the coefficient of investors' sentiment factor. The value premium, however, cannot be observed when dividend yields are employed (section 3.5.1). This result cannot suggest that investors' sentiment has an effect on the value premium because the value premium does not exist when dividend yields are employed.

The results generally suggest that investors' sentiment is not the underlying factor to explain the value premium. This result is consistent with Xing (2008). The results confirm that the value premium is unexplained by investors' sentiment and suggest that $H_{3.4a}$ is rejected.

3.5.5 The value premium by industry sectors, stages of the business cycle and investor sentiment

Each industry produces different products, which are expected to be affected differently when economic conditions and investors' sentiment change. This section, thus, aims to examine the roles of the business cycle and investor sentiment on the value premium of industry. To investigate $H_{3.5a}$: *"The value premium varies by industry sector"*, equation (3.4) is applied. The results from the previous section are consistently observed among all holding periods and the definitions of value and growth stocks. In this section, the book-to-market ratio[19] is employed as the measure to identify value and growth stocks, and portfolios are held for 12 months[20].

[Table 3.8]

Table 3.8 presents the results from equation (3.4) when the value premium of industry is employed. The industries that generate the value premium are considered. The statistical insignificance of the coefficient of the investors' sentiment factor after controlling for risk and the business cycle is observed in all industries. This insignificant result suggests that the value premium is unable to be explained by investors' sentiment. This result is consistent with the aggregate level (section 3.5.4) that the value premium is left unexplained by investors' sentiment, and is also consistent with Xing (2008).

The statistical insignificance of the coefficient of the business cycle factor after controlling for risk and investors' sentiment is observed in the Consumer Nondurables, Chemicals, and Energy sectors. The insignificant result suggests that the value premiums of these industries are not explained by the stages of the business cycle. Consumer Nondurables (i.e. food and apparel), Chemicals, and Energy (i.e. oil and gas) industries produce goods the level of need for which is not considerably different during economic boom and bust periods. So, as the demand for the product of these industries is not considerably different, this leads to an insignificant difference in both the performance and return of these industries during different economic stages. This should be the reason why the business cycle is unable to explain the value premium in these three industries. In the same industries,

[19] Book to market ratio is the most widely used measure to indicate value and growth stocks.
[20] The 12 months holding period generates the highest returns when the book to market ratio is employed (see section 3.5.1).

statistically significant results on intercept are also observed. This suggests that the value premium is not driven by stages of the business cycle and is also unexplained by risk.

The statistical significance of the coefficient of the business cycle factor, after controlling for risk and investors' sentiment, is observed in Consumer Durables, Manufacturing, Business Equipment, Shops, and Health. In the same industries, statistically significant results on intercept are also found. This suggests that the value premium is partially explained by the stages of the business cycle. The coefficients of the business cycle factor are positive. These positive and significant results suggest that the value premium is positively explained by the stages of the business cycle – in other words, a higher value premium due to economic boom. This is similar to the results for the aggregate level. The positive effect of the stages of the business cycle on the value premium is found in Consumer Durables (i.e. cars and furniture), Manufacturing (i.e. machinery and trucks), Business Equipment (i.e. software and computers), and Shops (retail and services), which produce non-essential goods. These types of industries tend to earn higher profits during economic expansion. During economic contraction, the need for the product from these industries can be postponed. Thus, different economic stages lead to different performances of these industries. During economic contraction people tend to use government healthcare (i.e. public hospitals) because they may be unable to afford the high cost of private hospitals. During economic expansion, however, people have more ability to afford the high costs of private hospitals, for a higher service quality. Health (i.e. medical equipment and healthcare), thus, earns higher profits during an economic boom. This should be the reason why the stages of the business cycle positively affect the value premium of the Health industry.

The value premiums of Consumer Durables, Manufacturing, Business Equipment, Shops, and Health are partially explained by the business cycle but not for the Consumer Nondurables, Chemicals, and Energy industries. The value premium is driven by different factors due to the type of industry. To the best of the author's knowledge, this finding provides a new conclusion regarding the value premium and stages of the business cycle. These results suggest that $H_{3.5a}$ is accepted.

3.5.6 Robustness tests

3.5.6.1 Risk-adjusted value premium during expansion and contraction

This section examines the role of risk on the value premium during economic expansion and contraction. To examine this, risk-adjusted returns are estimated using equation (3.2). To do this, the sample period is divided into two different stages of economy: expansion and contraction[21]. Next, the significance of the risk-adjusted value premium (i.e. return from value portfolio *minus* return from growth portfolio) is tested using the two-tailed test (equation (3.1)).

[Table 3.9]

Table 3.9 shows the results of the risk-adjusted value premium during economic expansion and contraction. During economic contraction, returns from hedge portfolios (returns in value portfolios *minus* returns in growth portfolios) are positive and statistically significant different from zero, except when (a) dividend

[21] The periods of expansion and contraction are decided by the OECD business cycle turning point. Economic expansion begins immediately after an economy reaches its trough and ends when reaching the peak. Economic contraction is the period between its peak and trough.

yields and cash-flow-to-price ratio are used to classify value and growth stocks and (b) portfolios are held for 24 months. This significant result suggests that a risk-adjusted value premium exists. The existence of a risk-adjusted value premium confirms that the value premium during economic contraction exists even after controlling for risk. This result leads to the conclusion that the value premium is not driven by risk during economic contraction. This result supports the finding in section 3.5.2 and is also consistent with previous studies, which claim that risk is unable to explain the value premium, such as Reinganum (1981).

A similar result is also observed during economic expansion. During economic boom, returns from hedge portfolios are positive and statistically significantly different from zero, except when (a) dividend yields are employed to identify value and growth stocks and (b) portfolios are held for 24 months. Overall, the results suggest the presence of a risk-adjusted value premium during economic expansion too. This result leads to the conclusion that the value premium is not driven by risk during economic expansion. These results reject the prediction of hypothesis $H_{3.2a}$ and suggest that the value premium is not explained by risk in all economic conditions.

3.5.6.2 The value premium and business cycle interaction variables

To ensure the findings of the previous sub-section (3.5.3), an alternative method of testing the role of the business cycle on the value premium is applied. More specifically, equation (3.5) is employed to test whether the interaction between (a) business cycle and (b) market factor, size factor, and value factor, affect the value premium. The interaction between the business cycle condition and the three factors is employed because the three factors can be explained as fundamental proxies of economic risk. This model is developed from Fama and French's (1993) three-factor model by incorporating the interaction variables and business cycle factor as described below:

$$V_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{RmRf\_BUS} RmRf\_BUS_t + \beta_t^{SMB\_BUS} SMB\_BUS_t + \beta_t^{HML\_BUS} HML\_BUS_t + \beta_t^{BUS} BUS_t + \varepsilon_t \quad (3.5)$$

where $RmRf\_BUS_t$, SMB_BUS_t, and HML_BUS_t are interaction variables between the business cycle and market factors, size factors and value factors, respectively, and $\beta_t^{RmRf\_BUS}$, $\beta_t^{SMB\_BUS}$, and $\beta_t^{HML\_BUS}$, are the parameters to be estimated. This test is expected to have a statistically significant coefficient of the business cycle factor. Additionally, interaction variables are also expected to generate significant coefficients if the interaction between (a) business cycle and (b) market factor, size factor and value factor affect the value premium.

[Table 3.10]

Table 3.10 presents the results from the regression in equation (3.5). The statistical and economic insignificance of coefficients of interaction variables (i.e. Rm-RF_BUS, SMB_BUS, and HML_BUS) are generally observed when dividend yields and earnings-to-price ratio are used as criteria to indicate value and growth stocks. This result suggests that the value premium is unexplained by interaction variables. When the book-to-market ratio is employed, the interaction variable (i.e. HML_BUS) generates statistically significant results, except for the 12 months holding period. The significance level, however, is lower than the significance level of HML itself. This suggests that the business cycle decreases the ability of HML to explain the value premium. The statistical significance of the coefficient of

SMB_BUS is also observed, but the evidence is relatively weak and does not seem to have any pattern.

When the cash-flow-to-price ratio is used to classify value and growth stocks, the coefficient of HML_BUS is statistically significant but the significance level is smaller than the significance level of HML itself. Thus, the business cycle decreases the ability of HML to explain the value premium. The statistical significance of the coefficients of Rm-RF_BUS and SMB_BUS are also observed but the evidence does not seem to have any pattern. The positive and statistical significance of the coefficient of the business cycle factor is observed in all holding periods and definitions of value and growth stocks, except when dividend yields are employed. This result suggests that the value premium is positively explained by stages of the business cycle and this is consistent with the findings in section 3.5.3. The results confirm that the value premium is positively driven by stages of the business cycle. These results suggest that $H_{3.3a}$ is accepted.

3.6 Conclusions

Value versus growth trading strategies involves going long in value stocks (buying) and going short (selling) on growth stocks. Value stocks are usually identified as stocks with a high book value to market value ratio while growth stocks are generally indicated as stocks with a low book value to market value ratio. Book value to market value ratio, however, is not the only measure for identifying value and growth stocks. The dividend yields, earnings-to-price ratio and cash-flow-to-price ratio can also be employed (Fama and French 1996, 1998). The value premium is profit that is earned from value versus growth trading strategies. Earlier studies such as Graham and Dodd (1934) and Basu (1977) confirm the existence of the value premium.

This chapter attempts to provide evidence of the value premium. Portfolios are grouped using four different definitions of value and growth stocks, namely dividend yields, book value to market value ratio, earning to price ratio and cash flow to price ratio. The two extreme portfolios are called the value portfolio (the portfolio with the highest dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio) and the growth portfolio (the portfolio with the lowest dividend yields, book-to-market ratio, earnings-to-price ratio and cash-flow-to-price ratio). Portfolios are held for four lengths of time: 3, 6, 12 and 24 months. The returns from the hedge portfolios (returns from value portfolio *minus* returns from growth portfolio) are positive and statistically significant. This result confirms the existence of the value premium.

The existence of the value premium leads to the next question; which factor explains the value premium? Fama and French (1992) claimed that risk is able to explain the value premium. On the one hand, several studies agree with Fama and French (1992) (see e.g. Fama and French (1996)). On the other hand, some studies show evidence that the value premium is not driven by risk (see e.g. Lewellen and Nagel (2006)). The argument regarding the value premium and risk is still ongoing. This chapter, then, attempts to answer whether the value premium is driven by risk. The results show that the risk-adjusted returns from hedge portfolios are positive and statistically significant. This suggests that a risk-adjusted value premium exists. In other words, a value premium exists even after controlling for risk. The implication of this result is that the value premium is not driven by risk. This conclusion is consistent with several studies such as Ang and Chen (2007).

Previous studies such as Zhang (2005) claimed that the business cycle is able to explain the value premium. Their finding leads this chapter to the next question, whether the value premium is explained by stages of the business cycle. The evidence of a positive relationship of the business cycle on the value premium can be found when equations (3.3), (3.4), and (3.5) are applied. Specifically, the positive significance of the coefficient of the business cycle factor is observed. This leads to the conclusion that the value premium is positively driven by stages of the business cycle. The positive relationship between the value premium and stages of the business cycle is due to optimistic investors. Investors have more confidence to invest in risky stocks (i.e. value stocks) during an economic boom, leading to higher investment volume (or higher demand), higher price, consequently, higher returns. This conclusion, however, is inconsistent with earlier studies such as Petkova and Zhang (2005). One possible reason to explain this is the measurement of the business cycle factor. The business cycle employed for this is the OECD CLI index that measures based on the growth cycle approach, which outperforms the classic cycle approach that is employed to measure the NEBR business cycle turning point, as used in Petkova and Zhang (2005).

The results from previous section suggest that the value premium is partially explained by stages of the business cycle. Thus there must be another factor to explain the value premium. Lakonishok *et al.* (1994) suggest that the value premium can be explained by investor behaviour. Therefore, the role of investors' sentiment on the value premium is examined. The results, however, show the statistical insignificance of the coefficient of the investors' sentiment factor. This leads to the conclusion that the value premium is left unexplained by investors' sentiment and this is consistent with Xing (2008). This result leads us to the next question, if the value premium is explained differently at the industry level.

The sample stocks are grouped into nine industries following Fama and French (1997). The value premium is observed in Consumer Nondurables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Shops, and Health but not in Telecommunication. After the value premiums of industries are observed, whether the observed value premium of industries is explained by the business cycle and/or investors' sentiment needs to be answered. The statistical insignificance of the coefficient of investors' sentiment factor is observed. This leads to the same conclusion as the aggregate level, i.e. that the value premium is unexplained by investors' sentiment. The positive and statistical significance of the coefficient of the business cycle factor is observed in Consumer Durables, Manufacturing, Business Equipment, Shops, and Health sectors. This suggests that stages of the business cycle positively explain the value premium in these industries.

The positive effect of the business cycle on the value premium is mostly found in the industries that produce non-essential goods (i.e. excluding the Health industry) in that the need for these products can be postponed during an economic bust. These types of industries tend to earn higher profits during economic expansion. Thus, different economic stages lead to different performances of these industries. For the Health industry, people tend to use government healthcare (i.e. public hospitals) during economic contraction, whereas they are able to afford private healthcare during economic expansion. The health industry, thus, earns higher profits during an economic boom. The implication of this finding is that the value premium is explained differently depending on the type of industry. The business cycle, however, is unable to explain the value premium in Consumer Nondurables, Chemicals, and Energy industries. These industries produce goods for which the level of need is not considerably different during times of economic boom and bust. So, the demand for the product of these industries not being considerably different leads to an insignificant difference in both the performance and return of these industries during different economic stages.

The implication of key empirical finding is the observed value premium can be evidence against the weak form of efficient market hypothesis (EMH). The value portfolios generally outperform growth portfolios and generate the value premium in both aggregate and industry levels. The value versus growth trading strategies outperforms the market. In other words, the abnormal return is generated when this trading strategy is employed. In the aggregate level, the observed value premium is left unexplained by risk and investors' sentiment, while the stages of the business cycle are able to explain the value premium. At the industry level, factors that explain the value premium are different depending on the type of industry. The limitation of this chapter is the transaction cost, which is not taken into account in this chapter. Further study is recommended to take transaction cost into account to fill this gap.

Table 3.1 Construction of key variables

A: Construction of key variables in portfolio sorting

Key variables	Construction
Dividend yield	Dividend per share scaled by dividend-common (DVC-COMPUSTAT) divided by common share outstanding (CSHO- COMPUSTAT). Share price scaled by price at end of period (PRC-CRSP)
Book to market ratio	Book value scaled by total asset (AT- COMPUSTAT) minus (a) intangible asset (INTAN- COMPUSTAT) and (b) total liabilities (LT- COMPUSTAT). Market value scaled by market capitalisation at end of period (TCAP-CRSP).
Earnings to price ratio	Earnings per share scaled by basic earnings per share including extraordinary items (ESPI- COMPUSTAT). Share price scaled by price at end of period (PRC-CRSP)
Cash-flow to price ratio	Cash flow per share scaled by operating activity net cash flow (OANCF-COMPUSTAT) divided by common share outstanding (CSHO- COMPUSTAT). Share price scaled by price at end of period (PRC-CRSP)

B: Construction of key variables in regression

Key variables	Construction
Excess Return	The stock returns that exceed the risk free rate. The monthly returns are collected from the CRSP database. The holding period of monthly returns is from month-end to month-end. The risk-free return is the one-month Treasury bill rate[22].

[22] The one-month Treasury bill rate data from Ibbotson Associates are collected from the Fama and French data library.

Table 3.1 Construction of key variables (cont.)

Key variables	Construction
R_m-R_f	The market excess return is a factor from Fama and French's (1993) three-factor model. The market return is constructed by Fama and French using value-weighted return from US firms, listed on three main stock markets: NYSE, AMEX, and NASDAQ available via CRSP. The risk-free return is the one-month Treasury bill rate.
SMB	Small minus Big is one factor from Fama and French's (1993) three-factor model. SML is the difference between average return on (a) three small portfolios and (b) three big portfolios constructed by Fama and French.
HML	High minus low is the last factor from Fama and French's (1993) three-factor model. HML is the difference between average return of (a) two value portfolios and (b) two growth portfolios constructed by Fama and French.
Business cycle constructed by The OECD	The composite leading indicator is constructed by the OECD using (a) permits issued for dwellings, (b) the net of new durable goods orders, (c) share price, (d) consumer sentiment index, (e) weekly working hours, (f) industrial confidence index, and (g) interest rate spread.

Table 3.2: Sample data descriptions

Data description for key variables in portfolio sorting

Key variables in portfolio sorting	Min	Max	Mean	Median	S.D.	Firm-month Observations
Dividend yield (DY)	0	5128.20	0.0346	0.0000	8.47	1,603,595
Book-to-market ratio (BM)	0	32.83	0.0036	0.0005	0.10	1,387,267
Earnings-to-price ratio (EP)	0	1010.23	0.1423	0.0645	1.80	1,103,215
Cash-flow-to-price ratio (CP)	0	21274.79	0.3418	0.0959	47.67	872,217

Correlation

	DY	*BM*	*EP*	*CP*
DY	1.0000	0.0006	0.0012	0.0201
BM		1.0000	0.0171	-0.0119
EP			1.0000	-0.0314
CP				1.0000

Figure 3.1: Composite Leading Indicator (CLI)

Figure 3.1 presents the movement of the OECD CLI index, which vary from July 1972 to December 2015. The CLI index is measured based on (a) permits issued for dwellings, (b) the net of new durable goods orders, (c) share price, (d) consumer sentiment index, (e) weekly working hours, (f) industrial confidence index, and (g) interest rate spread. These components are chosen based on several conditions such as cyclical behaviour and economic significance. The CLI provides the early signs of the business cycle.

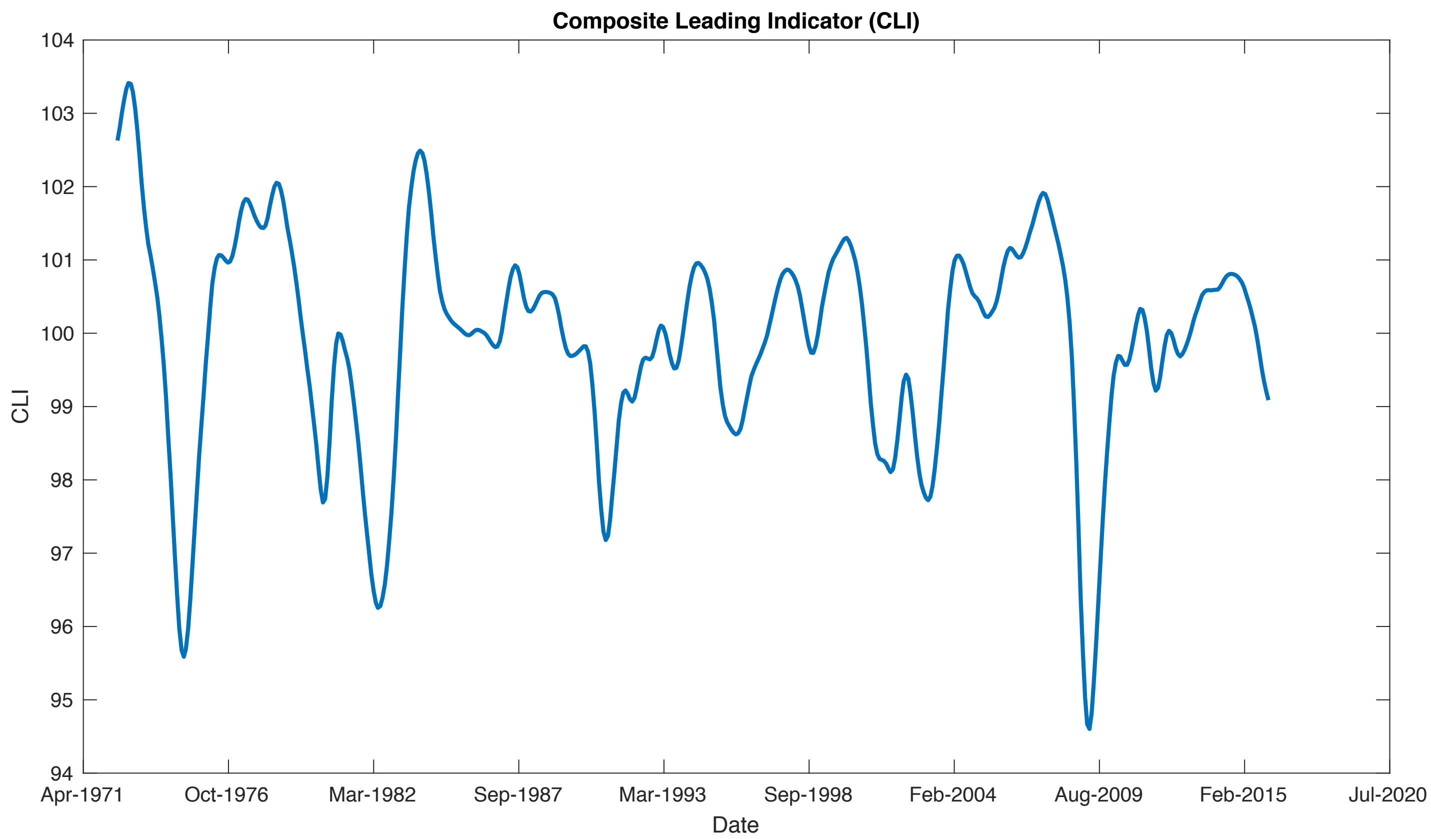

Figure 3.2: Portfolios' returns

Figure 3.2 presents the portfolios' average returns from portfolio 1 to portfolio 10 when portfolios are formed on the basis of (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio and (d) cash-flow to price ratio. Portfolios are held for 3, 6, 12 and 24 months. The first portfolio represents growth portfolio, including stocks with low (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio, and (d) cash-flow to price ratio. The value portfolio is represented by the tenth portfolio, including stocks with high (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio and (d) cash-flow to price ratio. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors.

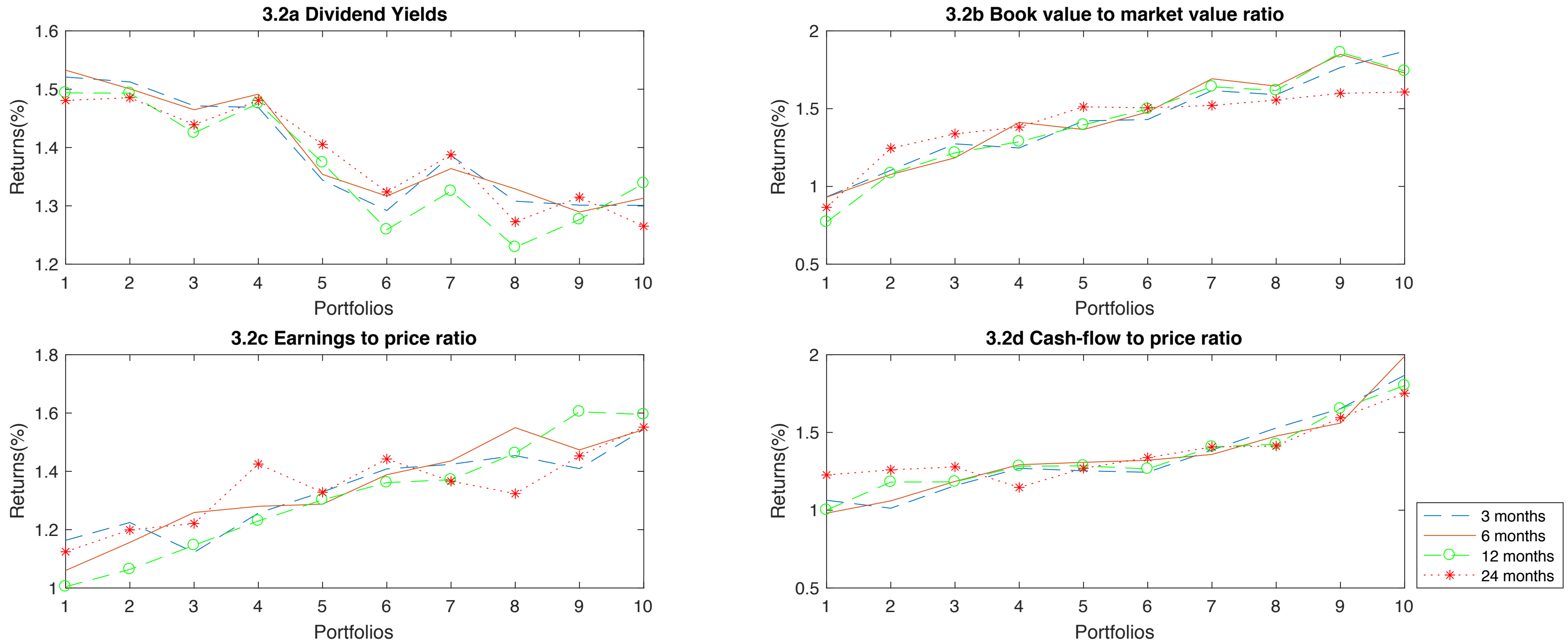

Figure 3.3 Risk-adjusted portfolios' return

Figure 3.3 presents the portfolios' average risk-adjusted returns from portfolio 1 to portfolio 10 when portfolios are formed on the basis of (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio and (d) cash-flow to price ratio. Portfolios are held for 3, 6, 12 and 24 months. The risk-adjusted return is estimated using equation (3.2). The first portfolio represents growth portfolio, including stocks with low (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio and (d) cash-flow to price ratio. The value portfolio is represented by the tenth portfolio, including stocks with high (a) dividend yields, (b) book to market ratio, (c) earnings to price ratio and (d) cash-flow to price ratio. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors.

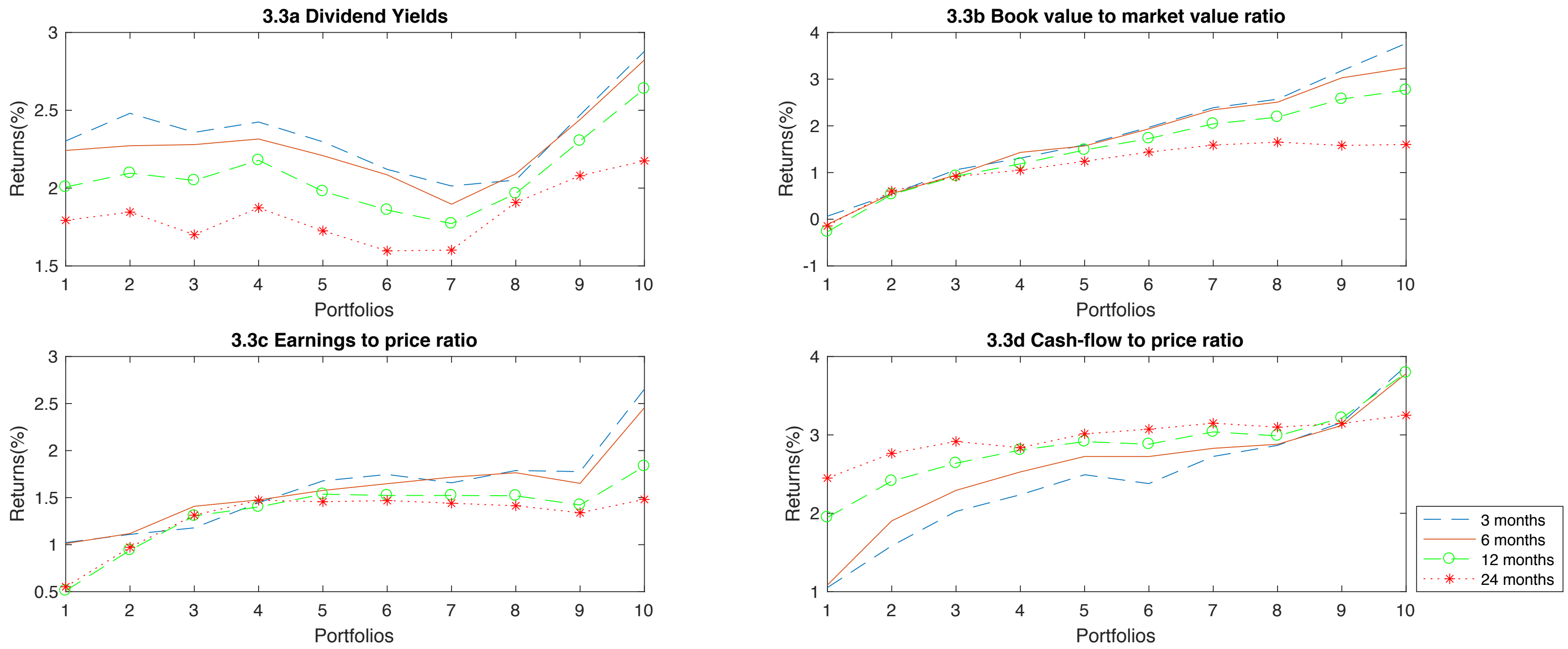

Table 3.3: Description and summary statistics of industries

Table 3.3 presents the summary statistics of 9 industries. Following Fama and French (1997), the 10 industries are grouped based on the SIC code from the CRSP database. This table reports (a) value premium of industry, (b) number of stocks in each industry, (c) industries' minimum returns, (d) industries' maximum returns, (e) industries' average returns, (f) standard deviation of industries' returns, (g) industries' average book-to-market ratio, and (h) standard deviation of industries' book to market ratio. The sample stocks from each industry include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months. * and ** denote the statistical significance levels of 5% and 1% respectively when equation (3.1) is employed to test the value premium of the industries.

Industries	**Value Premium**	**No. of stocks**	**Min**	**Max**	**Average return**	**S.D. of return**	**Average BM**	**S.D. of BM**
Consumer Nondurables	0.97%**	1,015	-0.8949	9.4000	0.0128	0.1548	0.0049	0.0677
Consumer Durables	0.74%**	465	-0.8129	5.2500	0.0119	0.1634	0.0107	0.1379
Manufacturing	1.12%**	1,880	-0.9527	6.0769	0.0133	0.1563	0.0032	0.0342
Energy	1.15%**	1,001	-0.9375	14.0000	0.0100	0.1900	0.0036	0.0630
Chemicals	1.38%**	357	-0.7333	4.0230	0.0122	0.1464	0.0079	0.0762
Business Equipment	1.66%**	3,090	-0.9737	11.8000	0.0149	0.2182	0.0022	0.0559
Telecommunication	0.40%	529	-0.8714	9.5644	0.0132	0.1861	0.0283	0.8001
Shops	1.31%**	1,814	-0.9813	9.3736	0.0124	0.1720	0.0041	0.1884
Health	1.89%**	1,604	-0.9641	13.4951	0.0150	0.2172	0.0009	0.0139

Table 3.4: Value premiums

Table 3.4 presents the value premium when dividend yields (DY), book to market ratio (BM), earnings to price ratio (EP), and cash-flow to price ratio (CP) are used as definitions of value and growth stocks. Value represents the average returns from value portfolios and Growth represents the average returns from growth portfolios. The value premium is measured by average returns in value portfolio *minus* growth portfolio, which is represented in V-G. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tailed test (equation (3.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Definition of Value and Growth stocks			
		DY	BM	EP	CP
3	Value	1.30%	1.87%	1.54%	1.87%
	Growth	1.52%	0.93%	1.16%	1.06%
	V-G	-0.22%	0.94%	0.38%	0.81%
	(T-stat)	(-1.3288)	(4.2970**)	(2.2501**)	(2.6323**)
6	Value	1.31%	1.73%	1.54%	1.99%
	Growth	1.53%	0.93%	1.06%	0.98%
	V-G	-0.22%	0.80%	0.48%	1.01%
	(T-stat)	(-1.3166)	(3.9926**)	(3.0491**)	(3.6174**)
12	Value	1.34%	1.74%	1.59%	1.80%
	Growth	1.49%	0.77%	1.00%	1.00%
	V-G	-0.15%	0.97%	0.59%	0.80%
	(T-stat)	(-0.8983)	(5.1238**)	(3.6134**)	(3.0326**)
24	Value	1.27%	1.61%	1.55%	1.75%
	Growth	1.48%	0.87%	1.12%	1.23%
	V-G	-0.21%	0.74%	0.43%	0.52%
	(T-stat)	(-1.1962)	(4.4323**)	(2.6640**)	(2.2891*)

Table 3.5: Risk-adjusted value premiums

Table 3.5 presents the risk-adjusted value premium when dividend yields (DY), book to market ratio (BM), earnings to price ratio (EP), and cash-flow to price ratio (CP) are used as definitions of value and growth stocks. Equation (3.2) is employed to estimate the risk-adjusted return. Value represents the average risk-adjusted returns from value portfolios and Growth represents the average risk-adjusted returns from growth portfolios. The risk-adjusted value premium is measured by average risk-adjusted returns in value portfolio *minus* growth portfolio, which is represented in V-G. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tailed test (equation (3.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Definition of Value and Growth stocks			
		DY	BM	EP	CP
3	Value	2.88%	3.77%	2.65%	3.88%
	Growth	2.30%	0.07%	1.02%	1.05%
	V-G	0.58%	3.70%	1.63%	2.83%
	(T-stat)	(3.6564**)	(15.9537**)	(8.9081**)	(9.6366**)
6	Value	2.82%	3.24%	2.46%	3.78%
	Growth	2.24%	-0.11%	1.01%	1.08%
	V-G	0.58%	3.35%	1.45%	2.70%
	(T-stat)	(3.7425**)	(19.0207**)	(8.9081**)	(11.3408**)
12	Value	2.64%	2.77%	1.83%	3.79%
	Growth	2.01%	-0.27%	0.51%	1.95%
	V-G	0.63%	3.04%	1.32%	1.84%
	(T-stat)	(4.0626**)	(19.1244**)	(8.4537**)	(7.8149**)
24	Value	2.18%	1.60%	1.48%	3.25%
	Growth	1.79%	-0.14%	0.55%	2.45%
	V-G	0.39%	1.74%	0.93%	0.80%
	(T-stat)	(2.3105*)	(11.9108**)	(6.2476**)	(4.0536**)

Table 3.6: Value premiums and stages of the business cycle

Table 3.6 presents the value premium, alphas, and betas to three factors from Fama and French (1993); market factor (Rm-Rf); size factor (SMB); value factor (HML), betas to business cycle factor (BUS), which is the OECD CLI index and adjusted R-square from equation (3.3). The value premium is defined as the difference in average returns between value and growth portfolios. The criteria for identifying value and growth stocks are dividend yields (DY), book to market ratio (BM), earnings to price ratio (EP), and cash-flow to price ratio (CP). The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Sorting Variables	Holding Periods	Value Premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	Adj.RSQ
DY	3	-0.22%	-0.16%	-5.32%	-63.23%	37.61%	-0.94%	49%
			(-1.3237)	(-1.7298)	(-14.9030**)	(8.4431**)	(-1.5190)	
	6	-0.22%	-0.15%	-4.48%	-61.16%	41.79%	-0.86%	50%
			(-1.2644)	(-1.4648)	(-14.5900**)	(9.3675**)	(-1.3986)	
	12	-0.15%	-0.12%	-3.29%	-57.39%	44.24%	-0.95%	50%
			(-1.0004)	(-1.0926)	(-13.8220**)	(10.0290**)	(-1.5738)	
	24	-0.21%	-0.18%	-2.63%	-56.81%	44.72%	-1.07%	48%
			(-1.4384)	(-0.8282)	(-12.9670**)	(9.6244**)	(-1.6811)	
BM	3	0.94%	0.83%	-14.32%	-12.22%	80.53%	4.36%	34%
			(4.5509**)	(-3.1498**)	(-1.9479)	(12.2290**)	(4.7688**)	
	6	0.80%	0.72%	-20.92%	-8.24%	78.31%	4.38%	43%
			(4.6246**)	(-5.3625**)	(-1.5415)	(13.7750**)	(5.6045**)	
	12	0.97%	0.97%	-25.77%	-6.98%	70.84%	4.42%	45%
			(6.6801**)	(-7.118**)	(-1.3989)	(13.3550**)	(6.0787**)	
	24	0.74%	0.79%	-22.76%	-9.63%	52.66%	3.88%	39%
			(5.9214**)	(-6.8483**)	(-2.1012*)	(10.8290**)	(5.8398**)	

Table 3.6: Value premiums and stages of the business cycle (Cont.)

Sorting Variables	Holding Periods	Value Premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	Adj.RSQ
EP	3	0.38%	0.29%	-9.74%	2.19%	53.40%	2.27%	22%
			(1.8734)	(-2.5576*)	(0.41751)	(9.6775**)	(2.9702**)	
	6	0.48%	0.41%	-14.39%	7.71%	53.54%	2.44%	27%
			(2.9331**)	(-4.1148**)	(1.6085)	(10.5010**)	(3.4820**)	
	12	0.59%	0.49%	-11.20%	8.98%	57.66%	2.67%	28%
			(3.4551**)	(-3.1527**)	(1.8340)	(11.0810**)	(3.7381**)	
	24	0.43%	0.38%	-11.44%	11.46%	43.15%	2.41%	18%
			(2.5694**)	(-3.0919**)	(2.2453*)	(7.9685**)	(3.2586**)	
CP	3	0.81%	0.60%	7.96%	13.07%	105.70%	4.09%	33%
			(2.3302*)	(1.1921)	(1.5477)	(11.5340**)	(3.0250**)	
	6	1.01%	0.82%	1.59%	20.66%	105.92%	4.64%	42%
			(3.7285**)	(0.2802)	(2.8768**)	(13.5950**)	(4.0346**)	
	12	0.80%	0.65%	0.06%	17.37%	93.09%	4.20%	38%
			(3.0426**)	(0.0103)	(2.5080*)	(12.4010**)	(3.7926**)	
	24	0.52%	0.35%	5.36%	10.42%	74.51%	3.66%	35%
			(1.8565)	(1.1126)	(1.7172)	(11.4030**)	(3.7892**)	

Table 3.7: Value premiums, stages of the business cycle and investors' sentiment

Table 3.7 presents the value premium, alphas, and betas to three factors from Fama and French (1993); market factor (Rm-Rf); size factor (SMB); value factor (HML), betas to business cycle factor (BUS), which is the OECD CLI index, betas to investors' sentiment factor (SENT), which is constructed by Baker and Wurgler (2006), and adjusted R-square from equation (3.4). The value premium is defined as the difference in average returns between value and growth portfolios. The criteria for identifying value and growth stocks are: dividend yields (DY), book to market ratio (BM), earnings to price ratio (EP), and cash-flow to price ratio (CP). The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to September[23] 2015 covers 519 months but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Sorting Variables	Holding Periods	Value Premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	SENT (T-stat)	Adj.RSQ
DY	3	-0.22%	-0.18%	-5.79%	-63.13%	35.56%	-0.70%	0.40%	50%
			(-1.4660)	(-1.8901)	(-14.956**)	(7.9872**)	(-1.1324)	(2.6981**)	
	6	-0.22%	-0.17%	-4.85%	-61.18%	39.86%	-0.70%	0.33%	51%
			(-1.3865)	(-1.5832)	(-14.607**)	(8.8750**)	(-1.1418)	(2.2301*)	
	12	-0.15%	-0.15%	-3.59%	-57.51%	42.15%	-0.81%	0.35%	51%
			(-1.2069)	(-1.1928)	(-13.872**)	(9.4762**)	(-1.3366)	(2.3282*)	
	24	-0.21%	-0.21%	-2.51%	-57.03%	43.10%	-1.04%	0.25%	48%
			(-1.5727)	(-0.7867)	(-12.9900**)	(9.1168**)	(-1.6261)	(1.4890)	

[23] The period of study is due to the availability of investors' sentiment data until the collection time.

Table 3.7: Value premiums, stages of the business cycle and investors' sentiment (cont.)

Sorting Variables	Holding periods	Value premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	SENT (T-stat)	Adj.RSQ
BM	3	0.94%	0.85% (4.6155**)	-14.84% (-3.2534**)	-11.50% (-1.8302)	79.95% (12.059**)	4.35% (4.7136**)	0.03% (0.1363)	34%
	6	0.80%	0.73% (4.6962**)	-21.12% (-5.4213**)	-7.32% (-1.3728)	77.59% (13.5790**)	4.35% (5.5514**)	0.10% (0.5528)	43%
	12	0.97%	0.94% (6.4731**)	-26.26% (-7.2695**)	-5.81% (-1.1682)	69.26% (12.9790**)	4.52% (6.2229**)	0.31% (1.7351)	45%
	24	0.74%	0.77% (5.6411**)	-22.74% (-6.8169**)	-8.87% (-1.9308)	52.15% (10.5400**)	3.89% (5.8256**)	0.14% (0.7984)	39%
EP	3	0.38%	0.32% (2.0598*)	-10.67% (-2.8068**)	2.46% (0.4692)	52.96% (9.5822**)	2.25% (2.9219**)	-0.11% (-0.5739)	22%
	6	0.48%	0.43% (3.0402**)	-15.23% (-4.3573**)	8.04% (1.6814)	52.64% (10.2700**)	2.48% (3.5247**)	0.03% (0.1807)	27%
	12	0.59%	0.51% (3.5280**)	-11.63% (-3.2617**)	9.32% (1.8976)	57.21% (10.8600**)	2.65% (3.6941**)	0.00% (-0.0235)	28%
	24	0.43%	0.34% (2.2585*)	-11.98% (-3.2385**)	12.57% (2.4666*)	41.88% (7.6330**)	2.52% (3.3947**)	0.25% (1.2842)	19%

Table 3.7: Value premiums, stages of the business cycle and investors' sentiment (cont.)

Sorting Variables	Holding Periods	Value Premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	SENT (T-stat)	Adj.RSQ
CP	3	0.81%	0.68%	6.61%	14.47%	107.03%	3.82%	-0.49%	33%
			(2.6412**)	(0.9870)	(1.7072)	(11.4160**)	(2.7887**)	(-1.1363)	
	6	1.01%	0.92%	0.52%	22.39%	108.15%	4.23%	-0.64%	42%
			(4.1870**)	(0.0910)	(3.1238**)	(13.6500**)	(3.6611**)	(-1.7609)	
	12	0.80%	0.70%	-0.93%	18.02%	92.82%	4.11%	-0.13%	38%
			(3.2519**)	(-0.1685**)	(2.5907*)	(12.0770**)	(3.6681**)	(-0.3785)	
	24	0.52%	0.40%	4.90%	11.12%	75.81%	3.47%	-0.32%	35%
			(2.0712*)	(1.0039)	(1.8102)	(11.228**)	(3.5141**)	(-1.0305)	

Table 3.8: Value premiums of industries, stages of the business cycle and investors' sentiment

Table 3.8 presents the value premium of industries, alphas, and betas to three factors from Fama and French (1993); market factor (Rm-Rf); size factor (SMB); value factor (HML), betas to business cycle factor (CLI), which is the OECD CLI index, betas to investors' sentiment factor (SENT), which is constructed by Baker and Wurgler (2006), and adjusted R-square from equation (3.4). Following Fama and French (1997), the industries are grouped based on SIC code from CRSP database. The value premium is defined as the difference in average returns between the value and growth portfolios. A criterion for identifying value and growth stocks is the book to market ratio. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to September 2015 covering 519 months but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Industries	**Value Premium**	**α (T-stat)**	**Rm-Rf (T-stat)**	**SMB (T-stat)**	**HML (T-stat)**	**BUS (T-stat)**	**SENT (T-stat)**	**Adj.RSQ**
Consumer Nondurables	0.97%	0.93%	-13.60%	7.58%	9.86%	1.74%	-0.15%	1%
		(3.8221**)	(-2.2489*)	(0.9092)	(1.1221)	(1.4269)	(-0.5117)	
Consumer Durables	0.74%	1.05%	-33.55%	-25.98%	1.53%	4.06%	0.01%	5%
		(3.1157**)	(-4.0295**)	(-2.2642*)	(0.1266)	(2.4096*)	(0.0158)	
Manufacturing	1.12%	1.10%	-17.15%	-7.44%	24.36%	2.59%	0.28%	8%
		(5.3388**)	(-3.3584**)	(-1.0566)	(3.2815**)	(2.5134*)	(1.1301)	
Energy	1.15%	1.12%	-14.42%	-16.33%	19.88%	-0.34%	0.73%	3%
		(3.2636**)	(-1.6931)	(-1.3910)	(1.6056)	(-0.1994)	(1.7681)	
Chemicals	1.38%	1.13%	6.49%	4.76%	56.84%	0.09%	0.27%	3%
		(2.8541**)	(0.6599)	(0.3512)	(3.9774**)	(0.0447)	(0.5701)	
Business Equipment	1.66%	1.53%	-29.65%	8.01%	93.93%	3.54%	0.02%	31%
		(6.5153**)	(-5.0965**)	(0.9994)	(11.1060**)	(3.0058**)	(0.0699)	
Shops	1.31%	1.24%	-36.43%	34.39%	48.40%	5.78%	0.41%	16%
		(4.7459**)	(-5.6188**)	(3.8481**)	(5.1350**)	(4.4103**)	(1.2943)	
Health	1.89%	2.00%	-31.28%	7.59%	48.08%	4.37%	-0.37%	10%
		(6.7530**)	(-4.26810**)	(0.7511)	(4.5122**)	(2.9460**)	(-1.0514)	

Table 3.9: Risk-adjusted value premiums during expansion and contraction

Table 3.9 presents the risk-adjusted value premium during economic expansion and contraction when dividend yields (DY), book to market ratio (BM), earnings to price ratio (EP), and cash-flow to price ratio (CP) are used as definitions of value and growth stocks. The business cycle turning point is defined using the OECD business cycle turning point. Equation (3.2) is employed to estimate the risk-adjusted return. Value represents the average risk-adjusted returns from value portfolios and Growth represents the average risk-adjusted returns from growth portfolios. The risk-adjusted value premium is measured by average risk-adjusted returns in value portfolio *minus* growth portfolio, which is represented in V-G. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tailed test (equation (3.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Definitions of Value and Growth stocks							
		Economic contraction				Economic expansion			
		DY	BM	EP	CP	DY	BM	EP	CP
3	Value	0.69%	1.85%	1.65%	6.19%	3.71%	5.14%	3.75%	2.61%
	Growth	0.21%	-1.48%	-0.63%	2.84%	3.08%	1.22%	2.50%	0.06%
	V-G	0.48%	3.33%	2.28%	3.35%	0.63%	3.92%	1.25%	2.55%
	(T-stat)	(1.9937*)	(9.5602**)	(7.3999**)	(5.8732**)	(3.0629**)	(12.8097**)	(5.5541**)	(7.6770**)
6	Value	0.68%	1.51%	1.39%	5.97%	3.71%	4.79%	3.62%	2.63%
	Growth	0.20%	-1.34%	-0.60%	3.18%	3.07%	1.15%	2.49%	-0.03%
	V-G	0.48%	2.85%	1.99%	2.79%	0.64%	3.64%	1.13%	2.66%
	(T-stat)	(1.9986*)	(9.0633**)	(7.1217**)	(5.5190**)	(3.1660**)	(17.5354**)	(6.4041**)	(10.6059**)

Table 3.9: Risk-adjusted value premiums during expansion and contraction (cont.)

Holding Periods	Return	Definitions of Value and Growth stocks							
		Economic contraction				Economic expansion			
		DY	**BM**	**EP**	**CP**	**DY**	**BM**	**EP**	**CP**
12	**Value**	0.63%	1.23%	1.18%	5.43%	3.52%	4.36%	3.23%	2.25%
	Growth	0.15%	-1.36%	-0.69%	3.39%	2.80%	1.05%	2.25%	0.53%
	V-G	0.48%	2.59%	1.87%	2.04%	0.72%	3.31%	0.98%	1.72%
	(T-stat)	(2.0535*)	(9.6864**)	(6.0637**)	(4.7894**)	(3.5159**)	(16.9140**)	(5.9964**)	(6.1684**)
24	**Value**	0.44%	0.75%	0.60%	5.61%	2.95%	3.27%	2.82%	2.49%
	Growth	0.09%	-0.94%	-0.67%	4.89%	2.54%	1.51%	2.11%	1.64%
	V-G	0.35%	1.69%	1.27%	0.72%	0.41%	1.76%	0.71%	0.85%
	(T-stat)	(1.3758)	(6.7210**)	(5.2405**)	(1.7200)	(1.8534)	(9.9581**)	(3.7993**)	(4.0445**)

Table 3.10: Value premiums and business cycle interaction variables

Table 3.10 presents the value premium, alphas, and betas to three factors from Fama and French (1993); market factor (Rm-Rf); size factor (SMB); value factor (HML), betas to interaction variables between the business cycle and three factors from Fama and French (1993); market factor (Rm-Rf_BUS); size factor (SMB_BUS); value factor (HML_BUS), betas to the business cycle factor (BUS), which is the OECD CLI index, and adjusted R-square from equation (3.5). The value premium is defined as the difference in average returns between value and growth. The criteria for identifying value and growth stocks are (a) dividend yield (DY), (b) book to market ratio (BM), (c) earnings to price ratio (EP), and (d) cash-flow to price ratio (CP). The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from July 1972 to December 2015 covering 522 months but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding periods	Value premium (Adj.RSQ)	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	Rm-Rf _BUS (T-stat)	SMB_BUS (T-stat)	HML_BUS (T-stat)	BUS (T-stat)
				Dividend yield					
3	-0.22%	-0.20%	-4.10%	-63.24%	37.06%	23.36%	-33.25%	-22.14%	-0.71%
	(49%)	(-1.5464)	(-1.2820)	(-14.9380**)	(8.2382**)	(2.0670*)	(-1.4736)	(-1.3820)	(-1.1275)
6	-0.22%	-0.25%	-1.82%	-60.87%	41.95%	34.95%	-23.12%	-18.95%	-0.71%
	(51%)	(-1.9560)	(-0.5708)	(-14.6110**)	(9.2644**)	(3.1138**)	(-1.0394)	(-1.1789)	(-1.1262)
12	-0.15%	-0.18%	-1.57%	-57.35%	43.63%	21.92%	-12.60%	-22.59%	-0.87%
	(50%)	(-1.4387)	(-0.4975)	(-13.8040**)	(9.6556**)	(1.9685)	(-0.5638)	(-1.4090)	(-1.4080)
24	-0.21%	-0.28%	-0.30%	-56.58%	44.19%	21.79%	5.87%	-24.42%	-1.13%
	(48%)	(-2.0467*)	(-0.0901)	(-12.9150**)	(9.2805**)	(1.8608)	(0.2502)	(-1.4509)	(-1.7297)

Table 3.10: Value premiums and business cycle interaction variables (cont.)

Holding periods	Value premium (Adj.RSQ)	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	Rm-Rf _BUS (T-stat)	SMB_BUS (T-stat)	HML_BUS (T-stat)	BUS (T-stat)
					Book-to-market ratio				
3	0.94%	0.63%	-10.70%	-11.42%	84.50%	18.90%	83.15%	74.44%	3.75%
	(37%)	(3.3490**)	(-2.3099*)	(-1.8612)	(12.956**)	(1.1533)	(2.5418*)	(3.2043**)	(4.0795**)
6	0.80%	0.55%	-16.92%	-7.09%	83.24%	23.86%	51.10%	62.66%	4.01%
	(45%)	(3.3861**)	(-4.1974**)	(-1.3492)	(14.582**)	(1.6850)	(1.8221)	(3.0926**)	(5.0675**)
12	0.97%	0.85%	-23.06%	-5.82%	72.96%	10.69%	54.38%	16.12%	4.05%
	(45%)	(5.5681**)	(-6.0802**)	(-1.1682)	(13.471**)	(0.80112)	(2.0303*)	(0.8388)	(5.4345**)
24	0.74%	0.83%	-23.64%	-9.66%	55.74%	-0.13%	-31.63%	56.80%	4.10%
	(40%)	(5.9585**)	(-6.8102**)	(-2.1224*)	(11.263**)	(-0.0105)	(-1.2979)	(3.2471**)	(6.0613**)
					Earnings-to-price ratio				
3	0.38%	0.23%	-8.77%	2.32%	55.13%	9.85%	8.37%	33.58%	2.19%
	(22%)	(1.4390)	(-2.2120*)	(0.4416)	(9.8756**)	(0.7021)	(0.2990)	(1.6890*)	(2.7860**)
6	0.48%	0.32%	-12.03%	8.14%	55.43%	25.23%	-4.21%	16.09%	2.46%
	(28%)	(2.1628*)	(-3.2753**)	(1.6993)	(10.6510**)	(1.9539)	(-0.1647)	(0.8708)	(3.4100**)
12	0.59%	0.47%	-10.71%	9.04%	57.50%	4.67%	1.52%	-6.22%	2.65%
	(27%)	(3.1390**)	(-2.8538**)	(1.8355)	(10.7280**)	(0.3537)	(0.0572)	(-0.3273)	(3.6018**)
24	0.43%	0.41%	-11.84%	11.07%	43.85%	7.50%	-38.70%	15.22%	2.67%
	(18%)	(2.5931**)	(-3.0283**)	(2.1585*)	(7.8703**)	(0.5474)	(-1.4108)	(0.7728)	(3.5029**)

Table 3.10: Value premiums and business cycle interaction variables (cont.)

Holding periods	Value premium (Adj.RSQ)	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	Rm-Rf _BUS (T-stat)	SMB_BUS (T-stat)	HML_BUS (T-stat)	BUS (T-stat)
					Cash-flow-to-price ratio				
3	0.81%	0.42%	11.48%	13.74%	115.92%	31.36%	-11.13%	114.81%	4.14%
	(36%)	(1.5872)	(1.6753)	(1.6504)	(12.266**)	(1.3737)	(-0.2414)	(3.4006**)	(3.4006**)
6	1.01%	0.59%	6.13%	21.37%	115.93%	39.60%	0.63%	112.68%	4.76%
	(46%)	(2.6845**)	(1.0670)	(3.0645**)	(14.6470**)	(2.0724*)	(0.0162)	(3.9865**)	(4.1875**)
12	0.80%	0.46%	3.36%	18.68%	100.94%	22.02%	38.53%	90.65%	4.13%
	(41%)	(2.0986*)	(0.5986)	(2.7449**)	(13.0800**)	(1.1823**)	(1.0256**)	(3.2929**)	(3.7341**)
24	0.52%	0.33%	5.71%	10.32%	80.04%	8.54%	-44.39%	59.35%	3.68%
	(36%)	(1.6879)	(1.1402)	(1.7034)	(11.7220**)	(0.5197)	(-1.3411)	(2.4505*)	(3.7497**)

Chapter 4 - Corporate Solvency and Investment Profitability

4.1 Introduction

Solvency is the ability of firms to cover their financial obligations. 'Solvent firms' refers to firms with sufficient cash flows to pay their debt obligations. The solvency ratio indicates if firms have sufficient cash flow to cover their liabilities. The solvency ratio is generally used to predict corporate bankruptcy (Geng, Bose, and Chen 2015). Higher solvency leads to lower possibility to default on their debt obligations. The solvency ratio can also be used to access firms' financial risk. The insolvent firms identify firms with insufficient cash flows to pay their total financial obligations, which is distressed firms in stock-basis (Wruck, 1990). Firms with good fundamentals (i.e. high solvency) tend to attract investors to invest in their stock, which leads to higher stock returns. The relationship between solvency ratio and stock returns, however, has not yet been rigorously examined in earlier studies.

Earlier studies investigate the link between firms' solvency and (a) credit rating (Horrigan, 1966) and (b) bankruptcy (Ng, Wong and Zhang, 2011) but not stock returns. The financial ratios, such as debt to equity ratio and debt to assets ratio, are used to indicate the solvency level of firms, suggesting the higher the ratios, the lower the solvency level (Geng et al., 2015). Financial leverage is also measured using these financial ratios, implying a link between leverage and solvency level. According to the information above, there is relationship between financial leverage, financial distress, and firms' solvency.

Financial distress is a situation when the firm does not have sufficient cash flow to meet existing financial obligations (Wruck, 1990), and is associated with financial leverage. Financial leverage commonly refers to the degree of fixed-income securities that firms use. Higher levels of fixed-income securities that a firm uses lead to higher levels of a firm's financial leverage. George and Hwang (2010) explained that leverage negatively relates to the expected stock returns. Gomes and Schmid (2010), however, claimed that they found a positive relationship between financial leverage and returns. Earlier studies mentioned that financial distress could be avoided by reducing financial leverage (see e.g. Wruck (1990) and Opler and Titman (1994)). Previous studies, for example Griffin and Lemmon (2002), found a positive relationship between financial distress and its stock return. Other previous studies such as Garlappi, Shu and Yan (2008) and Avramov et al. (2009), however, found a negative relationship between distressed firms and their stock returns. The studies above examine the relation between stock returns and (a) financial leverage and (b) financial distress. The results remain ambiguous and require further analysis.

Earlier studies such as Arditti (1967), Bhandari (1988) and Geng et al. (2015) use financial ratios to indicate solvency of stock. This chapter uses the same ratios, which are: debt to assets, long-term debt to assets, debt to equity, equity multiplier, interest coverage, fixed charge coverage, cash flow coverage, and cash flow to debt. To examine premium and discount from solvency trading strategies, this chapter groups sample stocks into ten portfolios on the basis of these eight financial ratios. The two extreme portfolios are high solvency and low solvency. Solvency based trading strategies take a long position in highly solvent stocks and a short position in low solvent stocks. The hedge portfolio return is calculated as the return from a long position less the return from a short position. If the hedge return is positive (negative), this is known as solvency premium (solvency discount).

The results show solvency premium in the short-term holding period and solvency discount in the long-term holding period. Thus, different holding periods lead to different results in the relationship between a firm's solvency and its return. The existence of solvency premium and solvency discount leads to the next question: "What is the underlying reason to explain solvency premium and solvency discount?" This chapter examines the role of three possible factors to explain solvency premium and discount: risk, business cycle, and investors' sentiment. Some earlier studies support the solvency discount as being due to the compensation for risk (low solvency portfolios outperform high solvency portfolios). This study found that solvency premium is partially explained by risk. So, there must be other factors to explain solvency premium and discount.

The different stages of the economy might generate different performances of trading strategies, for example, value premiums increase during economic contraction (see e.g. Petkova and Zhang (2005)). The business cycle factor might possibly explain the observed solvency premium and discount. The sample stocks are, then, grouped into economic expansion and economic contraction, based on the OECD business cycle turning point. There is evidence that solvency premium exists in economic contraction, even after controlling for risk, and reverses to solvency discount in economic expansion. This result suggests that poor economic conditions lead to higher solvency premium. During economic contraction, investors tend to invest in stocks with good fundamentals (i.e. solvent stocks) to avoid uncertain situations that might happen during unstable economic conditions. The solvency discount is observed in economic expansion, which suggests that good economic conditions lead to higher solvency discount. The reason behind this result could be optimistic investing or overconfidence of investors. During economic expansion, investors are more optimistic and have more confidence to invest in low solvent stock (high risk) to earn higher returns.

The explanation above leads to the next question, which is whether solvency premium and solvency discount can be explained by investors' sentiment as this could be another underlying factor in explaining the observed solvency premium and discount. This chapter observes a positive coefficient of the investors' sentiment factor. In other words, investors' sentiment is positively explained by solvency premium. This result suggests that when investors have more confidence in stock markets it leads to higher solvency premium during periods of high investors' sentiment.

Investors generally trade stocks by following a certain trading strategy such as momentum, contrarian, and value versus growth. This chapter introduces a novel trading strategy "corporate solvency based trading strategy" that takes long and short positions based on firms' solvency ratios. Understanding the new trading strategies creates alternative ways to trade stocks and earn profits.

This chapter starts with the literature review in section 4.2. In section 4.3, the research questions and hypotheses are provided, followed by the methodology and sample description in section 4.4. The results of all estimations are explained in section 4.5, followed by the conclusion in section 4.6.

4.2 Literature Review

4.2.1 Leverage

The solvency of firms can be measured in many ways. Firms' leverage is one of the ways to indicate solvent firms. Leverage generally refers to the degree to which firms use fixed-income securities relative to their equity. Higher levels of debt financing that firms use leads to higher levels of firms' financial leverage. The higher level of leverage causes higher interest payments that negatively affect a firm's earnings per share. Increases in fixed-income securities, such as debt and preferred equities, lead to increasing the financial risk for shareholders. The high level of leverage can be implied by a low level of solvency. This next section shows the link between leverage and stock returns.

4.2.1.1 Financial leverage and stock returns

Financial leverage commonly refers to the degree to which a firm uses debt to obtain more assets. A high level of financial leverage refers to a high level of debt when compared to equity, which leads to an increase in returns due to the high level of financial risk (Hall and Weiss, 1967). Financial leverage is measured using, for example, the inverse of equity to assets ratio (Hall and Weiss, 1967). High equity to assets ratio identifies a low proportion of debt, which leads to low financial leverage. The relationship between equity to assets ratio and stock return is expected to vary inversely. A lower equity to assets ratio associates with riskier stocks, implying higher returns.

Previous studies found mixed evidence of the relationship between financial leverage and stock returns: (a) negative relationship, (b) positive relationship, and (c) financial leverage are not related to stock returns. On the one hand, several studies observe the negative relationship between financial leverage and stock returns; the negative relationship suggests that high financial leverage leads to low stock returns. Hall and Weiss (1967) found a negative relationship between financial leverage and stock returns, which is different from their expectation. They measured financial leverage using the equity to assets ratio that inversely relates to financial leverage. They found that the relationship between equity to assets ratio and return on equity is significantly positive, suggesting lower leverage leads to higher returns. Arditti (1967) also investigated the relationship between returns and financial leverage. Instead of equity to assets ratio, they used debt to equity ratio to indicate firms' financial leverage. The negative sign had been found in all regressions, suggesting that higher debt to equity ratio, which implies higher financial leverage, leads to lower returns. Baxter (1967) argued that risk, related to financial leverage, leads to increasing firms' cost of capital. A higher level of leverage raises the bankruptcy probability and thus raises overall risk. All other things being equal, higher financial leverage leads to lower returns.

Penman, Richardson and Tuna (2007) found (a) a positive association between expected stock returns and book to market ratio and (b) a negative association between expected stock returns and leverage, component of the book to price ratio. The stock returns can also be explained by leverage, using Fama and French (1993). George and Hwang (2010) found that the endogenous choices of leverage and the model of ratio asset pricing indicate a negatively significant relationship between leverage and expected stock returns. They explained that although firms with high costs select low leverage in order to avoid distress, these firms retain a systematic risk exposure. Their results show that the premiums of average stock return to low leverage are statistically significant in both raw returns and risk-adjusted returns. Johnson et al. (2011) agree with the study of George and Hwang (2010). They investigated whether the endogenous choice of leverage indicate negatively the relationship between leverage and estimated stock returns. They employed a standard parameterization of cross section heterogeneity in profitability and risk, suggesting (a) a negative relationship between estimated stock returns and leverage and (b) a positive relationship between estimated stock returns and book to market ratio.

The relationship between stock return and leverage is also explained through financial constraints. Lamont, Polk and Saaá-Requejo (2001) investigated whether financial constraints have an effect on stock returns. The portfolios were formed based on firms' characteristics that relate to financial constraints. They then tested common variations in stock returns. The constrained firms normally have low earning, low dividend, and high leverage; these firms' characteristics are recognised as being related to firms with high returns. Their study, however, found that these firms with high financial constraints generate lower stock returns than other firms.

On the other hand, the positive relationship between financial leverage and stock returns is observed in several studies. The positive relationship suggests that high financial leverage leads to higher return. Baker (1973) found that financial leverage does affect return on equity but in a different way from the previous studies. Instead of an inverse relationship between financial leverage and return, this study found that financial leverage and returns move in the same direction. The financial leverage is measured using the inverse of equity to assets ratio; a lower equity to assets ratio implies higher financial leverage. Baker's study also found a significantly negative relationship between equity to assets ratio and returns on equity, using the simultaneous equation approach, suggesting that higher financial leverage leads to higher returns. This study also suggested that higher returns are due to more financial leverage, implying larger risks.

Christie (1982) also examined the relationship between the variation of stock returns and several descriptive variables including financial leverage. His study found a significant positive relationship between (a) the variations of equity return and (b) both financial leverage and interest rate. Specifically, he explained that the variation of equity returns increase with financial leverage but at a declining rate. In addition, Bhandari (1988) used the model, which controls for beta and size both including and excluding January, to investigate whether average stock returns relate to debt to equity ratio. The results confirmed that average stock returns positively correlate with debt to equity ratio, suggesting a positive correlation between stock returns and financial leverage. This positive relationship is much larger in January and insensitive to market proxy variations. Bhandari (1988) also suggested that the premium that related to financial leverage is not a risk premium.

In addition, Gomes and Schmid (2010) reconsidered the theoretical relationship between financial leverage and returns. They found that the link between financial leverage and returns is more complex, depending on firms' opportunities to invest. There is a significant correlation between financial leverage and investment; firms with higher financial leverage are mature firms that have high book assets and low growth opportunity. They also found that the results support Fama and French (1992), in that higher market leverage leads to higher stock returns while higher book leverage leads to low stock returns. The quantitative model that incorporates an economic mechanism was used in their study. This quantitative model is successful in duplicating the empirical relationship between financial leverage and stock returns even when both size and book to market ratios are controlled.

Livdan, Sapriza and Zhang (2009) examined the relationship between stock return and leverage through financial constraints. They explained the hypothesis of standard leverage as a high level of market leverage implies a high stock beta when the asset beta is fixed, meaning higher average stock returns. The inflexibility mechanism is the cause that increases asset beta with higher leverage. Firms with higher leverage are loaded with high levels of debt that need to be repaid before financing the next investment. Firms with high levels of leverage, thus, seem to be constrained, inflexible and risker. Their results proposed that the inflexibility mechanism estimates a convex relationship between leverage and expected returns. They also suggested that the inflexibility mechanism, based on the positive relationship of financial constraint and average returns, provides a new explanation for the effect of leverage on risk and returns.

Some earlier studies found an unrelated relationship between leverage and firms' returns. Hurdle (1974) found unrelated relationship between levels of leverage and return. He attempted to investigate the relationships between leverage, risk and return. He found that the level of leverage does not affect a firm's return. He also mentioned that (a) level of leverage has an independent effect on a firm's return and (b) the leverage cannot be used to measure industry risk. Obreja (2013) used the dynamic model to explain the relationship between leverage and (a) value premium and (b) book leverage premium in the stock returns. His study explained that firms with high levels of financial and operating leverage have higher risk premiums. The firms with high leverage maintain lower book leverage ratios. Specifically, the difference in expected returns is explained by the book to market ratio; firms with low productivity have high leverage. The book leverage ratio, however, is less helpful to explain the difference between expected returns; firms with both high and low book leverage ratios can have higher risk premiums. Grauer and Hakansson (1985) claimed that the investing performance is substantially improved by rebalancing amongst the major assets class. The leverage, however, does not improve the performance of portfolios while growth optimal strategy with leverage does.

4.2.1.2 Financial leverage and future growth

Earlier studies found that the relationship between financial leverage and returns is explained through firms' future growth. Firms with low growth opportunity due to high financial leverage leads to higher stock returns (Gomes and Schmid 2010). The previous studies focus not only on the relationship between leverage and stock returns but also the relationship between leverage and firms' future growth. Lang, Ofek and Stulz (1996) examined the relationship between future growth and leverage over 20 years. They found a negative relationship between these two considered variables at both (a) firm level and (b) business segment level, suggesting that firms with high leverage could not benefit from the growth opportunity advantages. Only firms with low Tobin's q ratio provided the negative relationship between leverage and future growth, not firms with high Tobin's q ratio. They also explained that the leverage does not decrease the growth of firms that already have good opportunities to invest but does affect growth of firms that (a) do not have sufficient value to overcome the impact of surplus debt and (b) the capital market does not recognise.

The study of Livdan et al. (2009) also falls into this section. They explained that firms with a high level of leverage are loaded with high debt that needs to be repaid before financing the next investment. This might lead to a decrease in new investment opportunities, implying a decrease in future growth opportunities. In addition, Hennessy (2004) used the dynamic capital accumulation model incorporating the debt factor. He found the debt overhang is statistically significant, and debt affects firms' investment negatively. Specifically, the debt overhang, which refers to high leverage, generates larger associative bias in contradiction of long-lived assets when compared to short-lived assets. He also explained that because of agency cost, firms with high opportunities of growth options tend to issues lower levels of debt; firms with better growth options, together with lower leverage, leads to more investment opportunities.

According to earlier studies, high leverage leads to low opportunity to invest and thus inversely affects future growth. Gomes and Schmid (2010) found that firms' opportunity to invest is able to explain the relationship between financial leverage and stock returns. They explain that firms with higher financial leverage are mature firms that have high book assets and low growth opportunities. They also found that higher market leverage leads to higher stock returns. This finding suggests that firms with low growth opportunities due to high financial leverage leads to higher stock returns.

Although, Chen and Zhao (2006) found different results, they investigated whether market to book ratio negatively relates to leverage ratio. They found that lower borrowing costs are provided for firms with a high market to book ratio, thus, those firms employ more debt. The firms with high market to book ratio are known as growth firms, which normally have the capability to increase their revenue more than the average industry. The results for the majority of firms show a significantly positive relationship between market to book ratio and leverage, suggesting a positive relationship between growth firms and leverage. The earlier studies, for example Jagannathan and Wang (1996), suggest that growth firms with high market to book ratio earn lower return than firms with low market to book ratio. This finding concludes that firms with high future growth employ more debt, which leads to high leverage, earning low returns. This conclusion leads to ambiguous results for the relationship between growth, leverage and stock returns.

4.2.1.3 Operating leverage

Operating leverage generally refers to the degree of a firm's fixed cost against its total cost. High operating leverage refers to a larger proportion of firms' fixed cost while low operating leverage refers to a larger proportion of firms' variable cost. Peterson (1994) explained that, given the imperfect financial market, firms might reduce their risk by decreasing the financial leverage of operating leverage, suggesting a relationship between operating leverage and firms' risk. Higher levels of risk are compensated with higher returns.

Guthrie (2011) also suggested that larger operating leverage raises systematic risk and also leads to greater expected stock returns. He found a non-monotonic relationship between the expected stock returns and operating leverage due to the abandonment option. The higher operating leverage leads to smaller expected stock return when the abandonment option is valuable; the expected stock return is an incremental function when the abandonment option is invaluable.

Taussig and Akron (2016) agreed with the earlier study that operating leverage affects expected returns positively. They then investigated operating leverage's predictive power on expected returns through industry return to scale. They explained that revenues have more variation than cost due to high elasticity output. Operating profits, thus, are sensitive when systematic risk increases. They also found operating leverage affects positively the expected cross-sectional stock returns, given the high returns to scale industries.

According to the previous studies, the relationship between leverage and stock return has gained interest from academic researchers for a long time. The context of the relationship between leverage and stock return is examined in many ways. Some studies explain the relationship between leverage and stock returns through risk. Earlier studies suggested that operating leverage is positively related to risk, which leads to higher expected returns to compensate for this risk (see Guthrie (2011), and Taussig and Akron (2016)). Some studies explain the relationship between leverage and stock returns through future growth. The relationship between financial leverage and future growth is expected to be negative. The earlier studies do confirm the relationship between financial leverage and future growth in different ways. The study of Gomes and Schmid (2010) found a negative relationship. The low growth firms due to high financial leverage are expected to generate high stock returns. Chen and Zhao (2006), however, claimed that financial leverage is positively related to future growth and these two are negatively related to returns. Several studies have directly examined the relationship between leverage and stock returns; however, the studies of the relationship between financial leverage and returns are also unclear. On the one hand, some found that leverage negatively relates to stock returns (see e.g. Arditti (1967), Hall and Weiss (1967), and George and Hwang (2010)). On the other hand, previous studies, for example Bhandari (1988), Fama and French (1992), and Gomes and Schmid (2010), found a positive relationship between financial leverage and stock returns. Other studies found unrelated relationships between these two considered variables (see e.g. Obreja (2013)). The question of the relationship between financial leverage and stock returns remains ambiguous and needs to be answered.

4.2.2 Financial distress

Financial distress occurs if firms' cash flow is insufficient to meet existing financial obligations (Wruck, 1990). Firms with a high cost of financial leverage find it difficult to pay off their financial obligation to their creditors, generally due to (a) high level of fixed-cost, and (b) sensitivity of revenue or illiquidity asset during economic contraction. The firms with high and long-term cost of financial distress usually become bankrupt.

4.2.2.1 Financial distress and returns

The earlier studies suggested that firms with high distress risk leads to larger expected stock returns. Theoretically, the firm that carries high risk is compensated by high returns. The distressed firm with higher risk, thus, should positively relate to the expected stock returns. Griffin and Lemmon (2002) investigated the relationship between book to market, distress risk and stock returns. Among distressed firms, which contain firms with high distress risk measured by Ohlson's O-score, the difference in returns between high book to market stock and low book to market stock is double, relative to other firms. They claimed that the Fama-French three-factor model or the differences of economic fundamentals could not be used to explain this higher return. They found that both size and value effects are related to distress risk. Consistently with the argument of mispricing, distressed firms generate the highest returns during the earning announcement. Vassalou and Xing (2004) provided a risk-based explanation for both value effect and size effect using the option-pricing model of Merton (1974) to measure default risk. Their study also found that size and value effects are related to financial distress. The value stocks generate higher stock returns relative to growth stocks when the default risk is high. They also claimed that firms with a high default risk gain larger stock returns than firms carrying a low default risk, only for small firms with high book to market ratio. Da and Gao (2010), however, showed that the default risk premium documented by Vassalou and Xing (2004) is driven by short-term reversal instead of default risk. They explained that the abnormal return (a) appears only in the first month after portfolios' formation period and (b) occurs mainly in a small subsection of stocks with high default risk that are currently experiencing high negative returns. In the second month after portfolios' formation period, the premium from default risk disappears and the factor of aggregate default risk is insignificant, suggesting that the abnormal return during the first month after portfolios' formation period is not a compensation for high default risk.

Some previous studies, on the other hand, found a negative relationship between financial distress and return. Dichev (1998) used bankruptcy risk as firm distress. The results showed that higher bankruptcy risk does not lead to higher returns. The distressed firms with high levels of bankruptcy risk, unfortunately, earn lower than average stock returns. The relationship between book to market effect and bankruptcy risk is non-monotonic; distressed firms usually carry a large book to market ratio but the majority of distressed firms carry a smaller book to market ratio. Consequently, the risk-based interpretation cannot completely explain the book to market effect.

Garlappi and Yan (2011) explained that financial distress is a contributory factor in understanding the cross-section of stock returns. They claimed that Fama and French (1992) also confirmed the association of (a) the value premium and other financial market anomalies and (b) financial distress risk. They incorporated financial leverage in the standard model of equity valuation. This model is employed to examine how potential shareholders recovering from financial distress affect the relationship between a firm's possibility to default and its expected stock returns. They found that potential shareholders recovering from financial distress affects the equity risk structure and leads to a hump-shaped equity beta and its expected returns in default possibility, suggesting a non-monotonic relationship.

Campbell, Hilscher and Szilagyi (2008) sorted stocks based on the estimation of failure risk. They measured portfolios' risk and returns from 1981 to 2003. They found distressed firms with a high failure risk generate anomalies low returns. Specifically, a portfolio that contains distressed firms generates low returns, but high market betas, standard deviations, and loading on small-capitalization and value risk from Fama and French (1993). This distressed portfolio tends to perform poorly when market volatility increases, suggesting negative alphas. This result is different from the previous study in which the size and value effect leads to a financial distress premium. They explained one of the possible explanations for this low return is that unexpected development during the sample period, such as increased power of the debt holder in bankruptcy, can decrease the distress stocks' returns. In addition, Garlappi et al. (2008) obtained a default risk to indicate a firm's financial distress. This documented that greater default risk is not related to larger expected returns. Their results indicated that the relationship between default risk and average stock return is (a) positive for firms with low shareholder advantage and (b) negative for high shareholder advantage firms, implying distressed firms with high shareholder advantage earn lower cross-sectional expected stock returns.

Additionally, Avramov et al. (2009) explained that if distress risk is systematic, firms with high credit risk earn similar stock returns to those with low credit risk. They used high levels of credit risk to explain distressed firms. Their empirical results, however, suggested that firms with lower credit risk earn larger stock returns, implying the negative relationship between credit risk and expected stock returns. Hilscher, Campbell and Szilagyi (2011) presented a corporate failure model incorporating market-based measures to forecast the future financial distress during the period from 1981-2008. They found that distressed stock tends to underperform the safe stock. The returns from distressed stock are not being rewarded for bearing this high risk. The distressed stock generates low returns in all value and size quintiles.

Avramov et al. (2013) examined the interpretation of financial distress for the abnormal returns of anomalies-based trading strategies: earning momentum, price momentum, idiosyncratic volatility, credit risk, capital investment, and dispersion earn profitability for the investor from selling high credit risk stock that are experiencing worsening credit conditions. The value strategy, however, earns profitability from buying stock with a high credit risk that survives the financial distress and realises high returns. The accruals anomaly is robust amongst firms with high and low credit risk and in all different credit conditions.

The studies of the relationship between financially distressed firms and stock returns have also gained interest from many researchers. The previous studies mainly suggested that there is a relationship between financial distress and stock returns. The earlier studies, however, found different signs of this relationship. Griffin and Lemmon (2002) and Vassalou and Xing (2004) found that the proxies of financial distress positively relate to stock returns. Other studies found different results; using bankruptcy risk, failure risk, default risk, and credit risk as proxies of financial distress, they found negative relationships between distressed firms and their stock returns (see Dichev (1998), Campbell et al. (2008), Garlappi et al. (2008), Avramov et al. (2009), and Hilscher et al. (2011)). Some studies such as Garlappi and Yan (2011) suggested that the relationship between financial distress and stock returns is non-monotonic. Avramov et al. (2013) suggested that financial distress is mainly unrelated to profitable or anomalies-based trading strategies. It is clear that lower financial leverage leads to lower chances of financial distress. Nevertheless, the earlier studies suggested ambiguous results for the relationship between financial distress and stock return.

4.2.3 The gap in the literature

The solvency firms refer to firms with sufficient cash flows to pay their total obligations. The solvency firm, thus, can be indicated using a financial ratio such as debt to equity ratio and debt to assets ratio; the higher the ratios, the lower the solvency level (Geng et al., 2015). These financial ratios are also employed to indicate financial leverage, suggesting the link between leverage and solvency level. Earlier studies found that lower financial leverage reduces the chance of firms' financial distress (see e.g. Wruck (1990) and Opler and Titman (1994)). This suggests the association between financial leverage, financial distress, and solvency.

According to previous studies, the relationship between financial leverage and stock returns are ambiguous. Some studies found a positive relationship (see e.g. Fama and French (1992), and Gomes and Schmid (2010)), while others found a negative relationship (see e.g. Hall and Weiss (1967), and George and Hwang (2010)). The later studies, for example Obreja (2013), found that financial leverage and stock return are not related. Not only the relationship between financial leverage and stock returns is confusing, the relationship between financial distress and stock returns is also unclear. Griffin and Lemmon (2002) and Vassalou and Xing (2004) suggested a positive relationship, while Dichev (1998), Campbell et al. (2008), Garlappi et al. (2008), Avramov et al. (2009), and Hilscher et al. (2011) found the negative relation. Other studies such as Avramov et al. (2013) claimed that there is an unrelated relationship. The relationship between (a) financial leverage and returns and (b) financial distress and returns, remains ambiguous, which leads to the ambiguous result regarding the relationship between a firm's solvency and stock returns.

This chapter aims to provide the empirical evidence to fill this gap in the literature by investigating the relationship between solvency and returns. Eight financial ratios, thus, are employed to investigate whether the solvency ratio is related to portfolio returns, and firms with different solvency levels leads to different levels of returns. This study formed portfolios based on solvency ratios in ascending order. It is different from other studies by using two main types of financial ratios to indicate solvency stocks: component percentage solvency ratio that inversely relates to solvency stock, and coverage solvency ratio that positively relates to solvency stock.

4.3 The Research Questions and Hypotheses

The gap in literature is identified in Section 4.2.3. This chapter aims to fill the gap in the literature review by the empirical testing of whether forming portfolios based on solvency ratios generates abnormal portfolio returns. This section aims to form the research questions and develop the hypotheses for empirical testing. The research questions that aim to be addressed in this chapter are as follows:

1) Do trading strategies of buying high solvent stocks and selling low solvent stocks generate excess returns?

To answer this first research question, this study anticipates finding empirical evidence of the presence of solvency premiums when forming portfolios based on the component percentage solvency ratio and coverage solvency ratio in ascending order. The hypothesis that relates to the first research question is as follows:

$H_{4.1a}$: The trading strategies that take a long position on high solvency stocks and a short position on low solvency stocks generate positive returns.

2) If the solvency premium is observed, do risk, business cycle, and/or investors' sentiment explain the solvency premium?

To answer the second research question, this study expects to find empirical evidence of a relationship between the solvency premium and time-varying risk.

According to the previous chapter, this study applies Fama and French's (1993) three-factor model to capture the relationship between solvency premium and risk. The hypothesis that relates to the second research question is as follows:

$H_{4.2a}$: The solvency premium is explained by time-varying risk.

The business cycle is one of the possible factors to explain market anomalies. During economic contraction, investors are expected to invest in stocks with low levels of risk to avoid uncertain circumstances in the unstable economic environment. Thus, the solvency premium is expected to be high during economic contraction. In the economic expansion, investors have more confidence, which leads to riskier investing. During this period, the solvency premium is expected to be low or turn into solvency discount. To answer the second research question, this study attempts to find empirical evidence of a relationship between the solvency premium and stages of the business cycle. The OECD CIL index and OECD business cycle turning point, which have been used in Chapter 3, are employed in this chapter to investigate whether the solvency premium is explained by the business cycle. The hypothesis that relates to the second research question is as follows:

$H_{4.3a}$: The solvency premium is explained by the stages of the business cycle.

Investors' sentiment indicates investors' attitude toward the market. Investors tend to invest more during periods of high investors' sentiment than during periods of low investors' sentiment. Thus, the solvency premium is expected to be high during the period of high investors' sentiment. To answer the second research question, this study attempts to investigate whether the solvency premium is explained by investors' sentiment. The investors' sentiment from Baker and Wurgler (2006), which has been used in Chapter 2, is employed in this chapter. The hypothesis that relates to the second research question is as follows:

$H_{4.4a}$: The solvency premium is explained by investors' sentiment.

4.4 The Methodology and Sample

4.4.1 The measurement of key variables

This study focuses on whether excess returns can be generated by forming portfolios based on solvency ratios. The earlier studies, such as Arditti (1967), Bhandari (1988), and Geng et al. (2015), use financial ratios to indicate solvent firms. The financial ratios that are employed as methods of identifying solvent firms are grouped into two main types of solvency ratios: component percentage solvency and coverage solvency ratios. Both of these can be used to measure the solvency of stocks. The construction of key variables is presented in Table 4.1.

[Table 4.1]

4.4.1.1 Component percentage solvency ratios

The component percentage solvency ratios contain those ratios that are used to compare the components in firms' capital structure, including debt to assets ratio (DA), long-term debt to assets ratio (LDA), debt to equity ratio (DE), and equity multiplier (EM), and inversely relate to firms' solvency level. Firms with high component percentage solvency ratios are classified as low solvency firms, whereas firms with low component percentage solvency ratios are classified as high solvency firms. According to earlier studies, the relationship between firms' solvency and returns remains ambiguous. Some studies such as Gomes and Schmid (2010) claimed that low solvency firms (high leverage firms) generate high returns. Other studies such as George and Hwang (2010) claimed that low solvency firms (high leverage) generate low returns. This chapter examines the relationship between solvency and returns using the trading strategies that go long in stock with low component percentage solvency ratios and short in stocks with high component percentage solvency ratios. In this chapter, the high solvent group is expected to generate higher returns than the low solvent group. The superior returns of high solvent stock are due to the good performance of the firm, which attracts investors to invest in that stock. The positive return from this strategy is called the solvency premium.

Debt to assets ratio (DA)

The debt to assets ratio is also known as the leverage ratio. This ratio defines total debt (short-term plus long-term debt) relative to total assets. Specifically, it describes the percentage of firms' total assets that are financed by debt. A higher ratio implies a higher level of debt, consequently, higher leverage. Thus, a high debt to assets ratio indicates low solvency firms, while a low debt to assets ratio indicates high solvency firms. This study calculates the debt to assets ratio as follows:

$$Debt\ to\ assets\ ratio = \frac{Total\ debt}{Total\ assets}$$

Long-term debt to assets ratio (LDA)

The long-term debt to assets ratio is also known as the leverage ratio. This ratio defines long-term debt relative to total assets. Specifically, it describes the percentage of firms' total assets that are financed by loan or other financial debt that matures over more than a year. Thus, the long-term debt to assets ratio is considered here to focus on the financial debt that matures over more than a year. A higher long-term debt to assets ratio leads to a higher level of leverage, and consequently low solvency. A lower long-term debt to assets ratio leads to a lower level of leverage, and consequently high solvency. This study calculates the long-term debt to assets ratio as follows:

$$Long - term\ debt\ to\ assets\ ratio = \frac{Long - term\ debt}{Total\ assets}$$

Debt to equity ratio (DE)

The debt to equity ratio measures firms' financial leverage. It indicates the level of debt that firms use to finance their total assets relative to shareholders' equity. A higher ratio implies a higher level of debt, and higher leverage. Thus, a high debt to equity ratio indicates low solvency firms, while low debt to equity ratio indicates high solvency firms. This study calculates the debt to equity ratio as follows:

$$Debt\ to\ equity\ ratio = \frac{Total\ debt}{Total\ shareholders'equity}$$

Equity multiplier (EM)

The equity multiplier is also known as the financial leverage ratio. A high equity multiplier indicates a high proportion of a firm's total asset is attributed to debt. A higher equity multiplier leads to a higher level of leverage, and subsequently, low solvency. A lower equity multiplier leads to low level of leverage, subsequently, high solvency. This study calculates the equity multiplier as follows:

$$Equity\ multiplyer = \frac{Total\ asset}{Total\ shareholders'equity}$$

4.4.1.2 Coverage solvency ratios

The coverage solvency ratios comprise the ratios that are used to measure firms' ability to pay their interest and also other fixed-financing commitments. The coverage solvency ratios, including interest coverage ratio (IC), fixed charge coverage ratio (FCC), cash flow coverage ratio (CFC), and cash flow to debt ratio (CFD), are positively related to firms' solvency level. Firms with high coverage solvency ratios are indicated as high solvent firms, whereas firms with low coverage solvency ratios are indicated as low solvent firms. These ratios are also used in previous studies, such as Geng et al. (2015). According to the literature, the relationship between solvency and returns is ambiguous. This chapter, thus, investigates the relationship between solvency and returns based on trading strategies such as holding stocks with high coverage solvency ratios and selling stocks with low coverage solvency ratios. Similarly to the previous section, high solvency firms are expected to generate higher returns than low solvency firms. The positive return from this strategy is called the solvency premium.

<u>Interest coverage ratio (IC)</u>

The interest coverage ratio measures the ability of firms to pay interest on their outstanding debt. The interest coverage ratio is normally calculated by dividing firms' earnings before interest and taxes (EBIT) by firms' interest payment. A high interest coverage ratio also defines how easily firms pay interest on their outstanding debt. A higher interest coverage ratio, suggesting higher solvency, leads to lower firms' default risk. This study calculates the interest coverage ratio as follows:

$$Interest\ coverage\ ratio = \frac{EBIT^{24}}{Interest\ payments}$$

[24] Earning before interest and taxes

Fixed charge coverage ratio (FCC)

The fixed charge coverage ratio measures the ability of firms to pay fixed charges, such as lease and interest payments. The fixed charge coverage ratio is usually calculated by dividing both firms' earnings before interest and taxes (EBIT) and lease payments together by firms' lease and interest payment[25]. A higher fixed charge coverage ratio, suggesting higher ability to pay firms' fixed charge, leads to lower firms' default risk. A higher fixed charge coverage ratio also implies higher solvency. This study calculates the fixed charge coverage ratio as follows:

$$Fixed\ charge\ coverage\ ratio = \frac{EBIT + lease\ payment}{Interest\ payments + lease\ payment}$$

Cash flow coverage ratio (CFC)

The cash flow coverage ratio measures the ability of firms to satisfy interest payments with their cash flow[26]. The cash flow coverage ratio is calculated by dividing the total of operating cash flow, interest payment, and tax payment by firms' interest payment. A higher cash flow coverage ratio, suggesting higher ability of firms to pay their interest with their cash flows, leads to lower firms' default risk. This study calculates the cash flow coverage ratio as follows:

$$Cash\ flow\ coverage\ ratio = \frac{Operating\ cash\ flow + interest\ payment + tax\ payment}{Interest\ payments}$$

Cash flow to debt ratio (CFD)

The cash flow to debt ratio measures the ability of firms to pay their total debt using their yearly operating cash flow. The cash flow to debt ratio is calculated by dividing operating cash flow during the period by total debt for the same period.

[25] In some cases this ratio and interest coverage ratio will be the same because not all firms have lease payments.
[26] Cash flow is measured based on a cash basis while EBTT is measured based on an accrual basis.

A higher cash flow to debt ratio indicates firms' greater ability to carry more debt, which leads to lower firms' default risk. The reciprocal of cash flow to debt ratio also implies how long firms need to pay their total debt with their cash flows. The cash flow coverage ratio is calculated as follows:

$$Cash\ flow\ to\ debt\ ratio = \frac{Operating\ cash\ flow}{Total\ debt}$$

4.4.2 Methodology

To answer the research questions (in section 4.3); "Do trading strategies of buying high solvent stocks and selling low solvent stocks generate excess returns?" and "If the solvency premium is observed, do risk, business cycle, and/or investors' sentiment explain the solvency premium?" This section clarifies the methodologies used to answer these research questions.

The existence of a solvency premium

To test "$H_{4.1a}$: *The trading strategies that take a long position on high solvency stocks and a short position on low solvency stocks generate positive returns*", this methodology is employed to form portfolios and test the significance of returns in portfolios. This analysis is expected to have (a) positive and statistically significant differences from zero in returns from high solvency portfolios (long portfolios), (b) negative and statistically significant differences from zero in returns from low solvency portfolios (short portfolios), and (c) positive and statistically significant differences from zero in returns from hedge portfolios (long *minus* short portfolios).

Component percentage solvency ratios (Test $H_{4.1a}$)

The solvency portfolios are formed on the basis of four financial ratios: debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier, in ascending order. The ratios are measured 3 months after firms' fiscal year end to ensure the statements are available to investors[27]. The three-month-lag of data from financial reports is used to measure the ratios. After the ratios are calculated, they are used as criteria to indicate solvent stocks. This study separates firms into 12 different months of fiscal year-ends[28] before forming portfolios. For each fiscal year-end, the sample stocks are grouped into ten portfolios in ascending order of the solvency ratios. The solvency level of a firm is inversely related to the component percentage solvency ratio, suggesting that a higher component percentage solvency ratio leads to lower solvency and a lower component percentage solvency ratio leads to higher solvency. To find the solvency premium, the long position on stocks with a low component percentage solvency ratio (high solvent stock) and a short position on stocks with a high component percentage solvency ratio (low solvent stock) are taken. After the long and short positions are taken, portfolios are held for four different holding periods: 3, 6, 12 and 24 months. At the end of the holding period, all 12 different year-ends are merged to calculate portfolios' returns.

After the portfolios are formed and held for each holding period, the returns in high solvency and low solvency portfolios are calculated. The average returns from a high solvency portfolio *minus* the average returns from a low solvency portfolio are used to find the solvency premium. In other words, the solvency profit

[27] According to U.S. Securities and Exchange Commission, the annual report from U.S. domestic firms should be released within 90 days.
[28] Number of firms in each fiscal year-end is presented in Appendix A.

is measured by the difference in returns between high solvency and low solvency portfolios. The two-tailed test is applied to investigate whether (a) returns from high solvency portfolios, (b) returns from low solvency portfolios and (c) the hedge portfolio returns (the returns in high solvency portfolios *minus* low solvency portfolios) are significantly different from zero. The test statistic is described below:

$$t = \frac{\bar{x}-\mu}{s/\sqrt{n}} \qquad (4.1)$$

where $\bar{x}$ is the portfolio average returns, μ is the hypothesized population mean, which is zero, s is the standard deviation, and n is the sample size, which is firm-month observations. This test provides the decision for the null hypothesis that average returns of portfolios equal zero. The result from this test is at a 5% significance level. If the results show that (a) the hedge portfolio returns (the returns in high solvency portfolio *minus* low solvency portfolio) are significantly different from zero and (b) the differences in returns between high solvency and low solvency portfolios are positive, there is evidence of a solvency premium. If the results show that (a) the hedge portfolio returns (the returns in the high solvency portfolio *minus* low solvency portfolio) are significantly different from zero and (b) differences in returns between high solvency portfolio and low solvency portfolio are negative, there is evidence of solvency discount. This test is expected to have positive and significant results to confirm the existence of a solvency premium. To accept $H_{4.1a}$, this test is expected to generate positive, statistically significant results from the two-tailed test.

Coverage solvency ratios (Test $H_{4.1a}$)

The solvency portfolios are also formed on the basis of four financial ratios: interest coverage, fixed charge coverage, cash flow coverage, and cash flow to debt ratios. To find the solvency premium, the long position on stocks with high coverage solvency ratio (high solvent stock) and the short position on stocks with low coverage solvency ratio (low solvent stock) are taken. The solvency premium is measured by the difference in returns between high solvent and low solvent portfolios. After stocks are sorted into portfolios, the average portfolio returns are calculated. The average returns from high solvency portfolios (portfolio 10) *minus* average returns from low solvency portfolios (portfolio 1) each year are used to calculate the solvency premium. Similarly to the previous section, the two-tailed test in equation (4.1) is then applied.

Solvency premium and risk (Test $H_{4.2a}$)

According to the second chapter of this thesis, the multifactor model outperforms the one-factor asset-pricing model to explain the market anomalies. To test "*$H_{4.2a}$: The solvency premium is explained by time-varying risk*", the three-factor model of Fama and French (1993) with 36 months' window regression is applied in this study to estimate risk-adjusted stock returns. This three-factor model is described below:

$$R_{i,t} = \alpha_i + \beta_i^{RmRf} RmRf_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \quad (4.2)$$

where $R_{i,t}$ is return of stock i in month t excess of risk free rate, $RmRf_t$ represents the market factor, market excess return in month t, SMB_t represents size factor in month t, and HML_t represents the value factor in month t. $\alpha_i, \beta_i^{RmRf}, \beta_i^{SMB}$, and

β_i^{HML} are the parameters to be estimated. $\varepsilon_{i,t}$ is the residual return of stock i in month t. The difference between stock returns and estimated stock returns from equation (4.2) are used as risk-adjusted returns to find if the solvency premium is driven by risk.

To test $H_{4.2a}$, the risk-adjusted returns are employed to test the statistical significance of hedge-portfolio returns (returns from long position *minus* short position portfolios) using the two-tailed test from equation (4.1). If the result shows that average risk-adjusted returns in hedge portfolios (the returns in high solvency portfolio *minus* low solvency portfolio) are statistically, insignificantly different from zero, there is no evidence of a risk-adjusted solvency premium. The statistically insignificant result implies that returns after being adjusted for risk cannot generate a solvency premium. In other words, a statistically insignificant result suggests that a solvency premium is driven by risk. Inversely, the statistically significant result suggests that a solvency premium cannot be explained by risk. To accept $H_{4.2a}$, this test is expected to have statistically insignificant results.

Solvency premium and stages of the business cycle (Test $H_{4.3a}$)

The business cycle is one of the possible factors to explain market anomalies i.e. solvency premium. To examine "$H_{4.3a}$*: The solvency premium is explained by the stages of the business cycle*", sample stocks are grouped into two economic stages on the basis of the OECD business cycle turning point[29]. The two economic stages[30] are

[29] The OECD business cycle turning point is explained in Chapter 3.

[30] The economic contraction starts immediately after the economy reaches a peak of economic activity and ends at its trough. Inversely, the economic expansion starts immediately after the economy reaches its trough and ends at the peak. The peak and trough are decided by OECD business cycle turning point based on CLI index.

expansion and contraction. After the sample period is divided into two economic stages, the risk-adjusted returns are employed to examine whether the risk-adjusted solvency premium varies in different economic conditions. If the result shows that the risk-adjusted return in hedge portfolios (the risk-adjusted returns in high solvency portfolio *minus* low solvency portfolio) is positive and statistically significantly different from zero, there is evidence of a risk-adjusted solvency premium. If the result shows that the risk-adjusted return in hedge portfolios (the returns in high solvency portfolio *minus* low solvency portfolio) is negative and statistically significantly different from zero, there is evidence of a risk-adjusted solvency discount. To confirm that the solvency premium (solvency discount) is explained by business cycle, this test is expected to have a positive (negative) significant result in different economic stages. To accept $H_{4.3a}$, this test is expected to have statistically significant results.

Equation (4.3) is also used to test whether business cycle factors explain the solvency premium. This model is developed from the three-factor model by incorporating the business cycle factor. The model is described below:

$$S_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{BUS} BUS_t + \varepsilon_t \quad (4.3)$$

where S_t is the solvency premium in year t, BUS_t is the CLI index that represents the business cycle factor in year t, and β_i^{BUS} is the parameter to be estimated. To confirm that the solvency premium is explained by the business cycle, this test is expected to have a significant coefficient of the business cycle variable.

Solvency premium and investors' sentiment (Test $H_{4.4a}$)

Another factor to explain the solvency premium should be investors' sentiment. Investors' sentiment indicates the view of investors in the market; thus, different investors' sentiments lead to differences in stock returns. Equation (4.4) is used to test "*$H_{4.4a}$: The solvency premium is explained by investors' sentiment*". This model is developed from Fama and French's (1993) three-factor model by incorporating the investors' sentiment factor constructed by Baker and Wurgler (2006)[31]. The model is described as below:

$$S_t = \alpha_t + \beta_t^{RmRf} RmRf_t + \beta_t^{SMB} SMB_t + \beta_t^{HML} HML_t + \beta_t^{BUS} BUS_t + \beta_t^{SENT} SENT_t + \varepsilon_t \qquad (4.4)$$

where S_t is the solvency premium in year t, $SENT_t$ is the investors' sentiment from Baker and Wurgler's (2006) year t, and β_t^{SENT} is the parameter to be estimated. To confirm that the solvency premium is explained by investors' sentiment, this test is expected to have a significant coefficient of the investors' sentiment variable.

4.4.3 Sample description

The sample includes all listed stocks on the three main US stock markets: NYSE, AMEX and NASDAQ. The sample period runs from January 1973 to December 2015 and covers 516 months with 2,303,104 firm-month observations. The study period starts in January 1973 due to the accessibility of data to measure solvency ratios. The financial sector and utilities sector are excluded from this sample. According to Fama and French (1992), the meaning of high leverage in financial and non-financial firms is different, thus, excluding the financial sector

[31] The investors' sentiment factor constructed by Baker and Wurgler (2006) is explained in Chapter 2.

from the sample data. There is a higher level of strictly regulated investment in the utilities sector and, as a result, the stocks from the utilities sector are also excluded. The common factors, e.g. market, size, and value factors are collected from the French's (2015) webpage[32]. The investors' sentiment data are collected from the Wurgler's (2015) webpage[33]. The OECD Composite leading indicator (CLI) index is available at the OECD's (2016a) webpage[34] and the OECD business cycle turning point[35] is available at the OECD's 2016b)'s webpage[36]. At least 36 months are required for all stocks. The negative financial ratios are excluded to avoid data mining.

In Table 4.2, there is evidence that the mean of measures of solvency variables is higher than its median, except in the case of long-term debt to assets ratio. The difference between mean and median represents positive skewness. The negative skewness is found in the long-term debt to assets ratio. The cash flow coverage ratio has the highest standard deviation while the asset ratio has the lowest.

[Table 4.2]

From the correlation section in the same table, the correlation matrix shows as being positively correlated among measures of solvency variables in the same type. The positive correlation is shown among the component percentage solvency ratios: debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier, also among the coverage solvency ratios: interest coverage, fixed charge coverage, cash flow coverage, and cash flow to debt ratios. The negative correlation, however, occurs between component percentage solvency ratios and

[32] URL: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[33] URL: http://people.stern.nyu.edu/jwurgler/
[34] URL: https://data.oecd.org/leadind/composite-leading-indicator-cli.htm#indicator-chart
[35] See Appendix A for OECD business cycle turning point.
[36] URL: http://www.oecd.org/std/leading-indicators/CLI-components-and-turning-points.pdf

coverage solvency ratios. This negative relationship is due to the way of calculating these ratios. High component percentage solvency ratios indicate low solvency firms, while high coverage solvency ratios indicate high solvency firms, as mentioned in the previous section. The correlation between DE and EM is 0.9959, which is the highest correlation. The correlation coefficients among sorting variables, however, are statistically insignificant. Thus, these variables provide a different explanation.

4.5 Results

To examine gains and losses from trading strategies based on firms' solvency, the first methodology is employed. The firms' solvency is indicated on the basis of (a) component percentage solvency ratios: debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier and (b) coverage solvency ratios: interest coverage, fixed charge coverage, cash flow coverage, and cash flow to debt ratios.

4.5.1 Portfolios' returns

Component percentage solvency ratio

Figure 4.1 presents returns in each of the 10 portfolios. In Figure 4.1a, sample stocks are grouped into portfolios on the basis of debt to assets ratio. Portfolio 1 includes stocks with low debt to assets ratio (high solvency) while portfolio 10 includes stocks with high debt to assets ratio (low solvency). The graph shows a decreasing trend during 3 and 6 months' holding periods and an increasing trend during 12 and 24 months' holding periods. The graph suggests that portfolios of high solvency stocks generate higher average returns than portfolios of low solvency stocks in 3 and 6 months' holding periods and vice versa in 12 and 24 months' holding periods. Similar results are also observed in Figure 4.1b, c, and d.

[Figure 4.1]

Figure 4.1 reveals that portfolios of stocks with low debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (high solvency) generate higher average returns than portfolios of stocks with high debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (low solvency) during 3 and 6 months' holding periods. Inversely, portfolios that include stocks with low debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (high solvency) generate lower average returns than portfolios that include stocks with high debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (low solvency) during 12 and 24 months' holding periods.

Coverage solvency ratio

In Figure 4.2a, sample stocks are grouped into portfolios on the basis of interest coverage ratio. Portfolio 1 includes stocks with low interest coverage ratio (low solvency) while portfolio 10 includes stocks with high interest coverage ratio (high solvency). The graph shows that portfolios' average returns slightly increase when stocks have high interest coverage ratio when 3 and 6 months' holding periods are applied. During the 12 and 24 months' holding periods, the returns tend to decrease with high interest coverage ratio stocks. The graph suggests that portfolios with high solvency stocks generate higher average returns than portfolios with low solvency stocks in given holding periods during short-term holding periods and vice versa during long-term holding periods. A similar result is also presented in Figures 4.2b, c, and d.

[Figure 4.2]

Figure 4.2 reveals that portfolios of stocks with high interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (high solvency) generate higher average returns than portfolios of stocks with low interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (low solvency) during 3 and 6 months' holding periods. Inversely, portfolios that include stocks with high interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (high solvency) generate lower average returns than portfolios that include stocks with low interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (low solvency) during 12 and 24 months' holding periods.

4.5.2 Solvency premium

Table 4.3 presents the solvency premium. To answer the first research questions, *"$H_{4.1a}$: The trading strategies that take a long position on high solvency stocks and a short position on low solvency stocks generate positive returns"* is tested. To find the solvency premium, portfolios are sorted based on solvency ratios into deciles. The solvency premium is measured using the difference in returns between high solvency and low solvency portfolios. After stocks are sorted into portfolios, the portfolios' returns are calculated. This study, then, uses average returns from high solvency portfolios *minus* average returns from low solvency portfolios each year to find the solvency premium. The two-tailed test (equation

(4.1)) is employed to test whether returns from hedge portfolios (returns from high solvency *minus* low solvency portfolios) are statistically significantly different from zero, given the holding periods are 3, 6, 12 and 24 months.

[Table 4.3]

Table 4.3 shows the results when portfolios are sorted based on component percentage solvency ratios and interest coverage ratios. The first criterion for identifying solvency stocks is the debt to assets ratio. The difference in returns between high solvency and low solvency portfolios are positive during the 3 and 6 months holding periods and negative during the 12 and 24 months holding periods. The statistically significant results are found among all holding periods. The results suggest that there is evidence of solvency premiums. When a 3 months holding period is applied, the solvency premium is 0.91%. This solvency premium is mainly generated from positive returns in high solvency portfolios. The solvency premium is 0.86% when a 6 months holding period is applied. The solvency premium from this holding period is mainly generated from the negative returns in the low solvency portfolio. The solvency premium tends to decrease when holding portfolios for longer. The solvency premium reverts to solvency discount when portfolios are held for 12 and 24 months. The solvency discounts are 0.74% and 0.92%, respectively. The solvency discounts are mainly generated from low solvency portfolios.

The second criterion for indicating solvent stocks is the long-term debt to assets ratio. The difference in returns between high solvency and low solvency portfolios is negative and statistically significantly different from zero only when portfolios are held for 24 months. This result suggests the existence of solvency discount, which is 0.80%. The low solvency portfolio generates 2.06% whereas the high solvency portfolio generates 1.26%. The solvency discount exists due to higher returns in low solvency portfolios than in high solvency portfolios.

The third criterion for identifying solvency stocks is the debt to equity ratio. The results show that returns in hedge portfolios (the differences in returns between high solvency and low solvency portfolios) are statistically significantly different from zero except for the 3 months holding period. The differences in returns between high solvency and low solvency portfolios are positive when a 6 months holding period is applied but negative when 12 and 24 months holding periods are applied. Hence, there is evidence of solvency premium when a 6 months holding period is employed. The solvency premium is 0.90%. The solvency premium mainly comes from negative returns in the low solvency portfolio. There is also evidence of solvency discounts when portfolios are held for 12 and 24 months. The solvency discounts are 1.21% and 0.80%, respectively. These solvency discounts exist due to higher returns in short portfolios (low solvency portfolios) than long portfolios (high solvency portfolios). Thus, to generate the highest solvency premium, portfolios should not be held for longer than 6 months. The solvency premium tends to decrease after portfolios have been held longer than 6 months and reverse to solvency discount.

When the equity multiplier is used as criterion of identifying solvent stocks, a similar result to the debt to equity ratio is found. The solvency premium is observed when portfolios are held for 6 months while solvency discount exists when portfolios are held for 12 and 24 months. The solvency premium is 0.87%, which is mostly generated from the negative return of low solvency portfolio (-0.66%). The solvency discounts are 0.0118 (12 months) and 0.0083 (24 months). When the interest coverage ratio is employed as a method of identifying solvency stocks, both solvency premium and discount cannot be observed. A fixed charge coverage ratio is then employed as the next criterion for identifying solvency stocks. The solvency discount is observed when portfolios are held for 24 months, which is 0.56%. The solvency discount exists due to the positive returns in the low solvency portfolio (2.23%), which is higher than the high solvency portfolio (1.67%). Only the solvency premium is observed when the cash flow coverage ratio is employed as a method of indicating solvency stocks when portfolios are held for 3 months. The solvency premium is 0.96%. This solvency premium comes from positive returns in long portfolios (0.56%) and negative returns in short portfolios (-0.40%). The last method for identifying solvency stocks is the cash flow to debt ratio. Similarly to the cash flow coverage ratio, the solvency premium is observed when portfolios are held for 3 months. The solvency premium is 0.81%. This solvency premium is mainly generated from the positive return in high solvency portfolios (long portfolios), which is 0.65%.

In Table 4.3, there is evidence that high solvency portfolios outperform low solvency portfolios and generate solvency premiums during the 3 and 6 months holding periods. However, evidence of solvency premium in the short-run is relatively weak. The results also show that low solvency portfolios outperform high solvency portfolios and generate solvency discounts during the 12 and 24 months holding periods. The evidence of solvency discount is relatively strong in the long-run. This result suggests that $H_{4.1a}$ is accepted.

[Figure 4.3]

Figures 4.3 and 4.4 present the solvency premium during the study period. In Figure 4.3, debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier are used as the methods of indicating solvency stocks. Similar results are presented in the four subfigures. The solvency premium fluctuates when the holding periods are changed. The holding periods of 3 and 6 months generally generate a higher solvency premium than 12 and 24 months holding periods. In other words, solvency premium is generally observed during the short-term holding period while solvency discount is generally observed during the long-term holding period.

[Figure 4.4]

In Figure 4.4, interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio are used to identify solvency stocks. Similar results are found to Figure 4.3; the solvency premium is larger during the short-term holding period than during the long-term holding period. The results from Figures 4.3 and 4.4 are consistent with the results in Table 4.3, i.e. solvency premium is generally observed in 3 and 6 months holding periods while solvency discount is observed during 12 and 24 months holding periods.

The solvency premium is observed during the short-term holding period while solvency discount is observed during the long-term holding period. The existence of solvency premium is confirmed by earlier studies (see e.g. Arditti (1967), George and Hwang (2010), and Johnson et al. (2011)). These earlier studies explained that low financial leverage or high solvency firms lead to higher returns. The solvency premium during the short-term holding period in Table 4.3 may be due to overreaction. De Bondt and Thaler (1985) suggest that the market tends to overreact to new information, such as earnings announcements. This overreaction leads to a solvency premium during the short-term holding period. After the market realisation, the stock price returns to its real value and then the solvency discount occurs. Generally high solvency stocks are the stocks with low financial leverage, and vice versa. Earlier studies such as Baker (1973) found that the financial leverage and stock returns move in the same direction. A high level of financial leverage refers to a high level of debt when compared to equity, which leads to an increase of returns to compensate for the high level of financial risk (Hall and Weiss, 1967). In other words, financial leverage positively relates to stock returns. This explanation leads this chapter to the next section which attempts to provide evidence for whether solvency premium is explained by risk.

4.5.3 Solvency premium and risk

The previous section (4.5.2) observed solvency premium during short-term holding periods and solvency discount during long-term holding periods. This section attempts to provide an explanation for the observed solvency premium and solvency discount. Following Baker (1973), risk seems to be a possible factor to explain solvency premium and discount. This section aims to answer the second research question, and *"$H_{4.2a}$: The solvency premium is explained by time-varying risk"* is tested. The risk-adjusted returns are estimated using equation (4.2). The risk-adjusted returns are employed to test the statistical significance of hedge-portfolio returns (long position *minus* short position) using the two-tailed test in equation (4.1). If the difference in average risk-adjusted return in high solvency and low solvency portfolios are statistically insignificantly different from zero, there is evidence that solvency premium and solvency discount are driven by risk, and vice versa.

4.5.3.1 Risk-adjusted portfolios' returns

Before the risk-adjusted solvency premium is examined to answer the second research question, this section aims to present the results of risk-adjusted portfolio returns in each portfolio.

Component percentage solvency ratio

In Figure 4.5a, sample stocks are grouped into portfolios on the basis of debt to assets ratio. During the holding periods of 3 months and 6 months, the graph shows that the risk-adjusted return fluctuates slightly when the debt to assets ratio increases (solvency decreases). The risk-adjusted return from the high solvency portfolio (portfolio 1) generates slightly larger risk-adjusted returns than the low solvency portfolio (portfolio 10). During the long-term holding period, the average risk-adjusted return tends to increase when the debt to assets ratio increases (solvency decreases). The graph suggests that portfolios with high solvency stocks generate lower average risk-adjusted returns than portfolios with low solvency stocks during long-term holding periods and generate slightly difference in risk-adjusted return during short-term holding periods. Similar results are also presented in Figures 4.5b, c, and d.

[Figure 4.5]

Figure 4.5 reveals that portfolios of stocks with low debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (high solvency) generate higher average risk-adjusted returns than portfolios of stocks with high debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (low solvency) during short-term holding periods. Inversely, portfolios that include stocks with low debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (high solvency) generate lower average risk-adjusted returns than portfolios that include stocks with high debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier (low solvency) during long-term holding periods.

[Figure 4.6]

Coverage solvency ratio

In Figure 4.6, the graph shows that portfolios' average risk-adjusted return tends to decrease when stocks have a higher interest coverage ratio during short-term holding periods. The graph suggests that portfolios with high solvency stocks generate lower average risk-adjusted returns than portfolios of low solvency stocks in short-term holding periods. During the long-term holding periods, the risk-adjusted return fluctuates when the interest coverage ratio increases. Similar results are also found in the other subfigures, where sample stocks are grouped into portfolios on the basis of fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio. Figure 4.6 reveals that portfolios of stocks with high interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (high solvency) generate lower average risk-adjusted returns than portfolios of stocks with low interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio (low solvency).

4.5.3.2 Risk-Adjusted solvency premium

In Table 4.4, debt to assets ratio is used as the first criterion for identifying solvency stocks. The differences in risk-adjusted returns between high solvency and low solvency portfolios are statistically insignificant among all holding periods. This result suggests that the risk-adjusted solvency premium and discount do not exist. Both solvency premium and discount disappear when returns are adjusted for risk. In other words, both solvency premium and solvency discount are explained by risk.

[Table 4.4]

When the long-term debt to assets ratio is used as the criterion for indicating solvent stocks, the statistically insignificant result is also found in the 3 and 6 months holding periods. The solvency premium disappears when returns are adjusted for risk. This insignificant result suggests that the solvency premium is driven by risk. During the 12 and 24 months holding periods, the results show that the difference in risk-adjusted returns between the high solvency and low solvency portfolios is negative and statistically significantly different from zero. This result suggests the existence of a risk-adjusted solvency discount. The risk-adjusted solvency discounts are 0.65% and 0.72%, respectively. The risk-adjusted solvency discount is mainly generated from short portfolios (low solvency portfolios). Comparing this result with the results in Table 4.3, the solvency discount increases after returns are adjusted for risk when portfolios are held for 12 months. This result suggests that solvency discount is not driven by risk during the holding period of 12 months. During the 24 months holding period, the risk-adjusted solvency discount is also observed, but it decreases when compared to the solvency discount in Table 4.3. This result suggests that solvency discount decreases after returns are adjusted for risk. In other words, solvency discount is partially explained by risk. Similar results are also found when debt to equity ratio and equity multiplier are used as criteria for identifying solvency stocks. The risk-adjusted solvency discounts are largest when portfolios are held for 12 months, which are 1.31% (when debt to equity ratio is used) and 1.28% (when equity multiplier is used). The risk-adjusted solvency discounts are mainly due to positive risk-adjusted returns from low solvency portfolios, which are 1.80% and 1.78%.

When the interest coverage ratio is used as a criterion for identifying solvency stocks during the 3 and 6 months holding periods, the differences in risk-adjusted returns between high solvency and low solvency portfolios are negative and statistically significant different from zero. This result suggests that instead of solvency premium, a solvency discount is observed after returns are adjusted for risk. The risk-adjusted solvency discounts are 0.90% and 1.16%, respectively. The risk-adjusted solvency discounts mostly come from positive risk-adjusted returns in low solvency portfolios, which are 2.00% and 1.99%. This solvency discount implies that stocks with a low interest coverage ratio outperform stocks with a high interest coverage ratio. This outperformance is due to utilising cash. Firms with too high cash are not utilising their cash, which leads to lower returns, while firms with low cash seem to be more efficient to utilising their cash. During long-term holding periods, the differences in risk-adjusted returns are also negative but statistically insignificant different from zero. Comparing this result with the results in Table 4.3, the solvency discount decreases when returns are adjusted for risk. This result suggests that solvency discount is explained by risk during the 12 and 24 months holding periods.

After the fixed charge coverage ratio is used as a criterion for identifying solvency stocks, risk-adjusted solvency discounts are observed when portfolios are held for 3, 6, and 12 months. This result is also due to cash utilisation. The statistically insignificant difference in risk-adjusted returns is found when portfolios are held for 24 months, suggesting that solvency discount is explained by risk during this holding period. The next criterion for indicating solvency stocks is the cash flow coverage ratio. The risk-adjusted return in high solvency *minus* low solvency portfolios (hedge portfolios) are negative and insignificantly different from zero during the short-term holding period. This result suggests that the observed solvency premium (from Table 4.3) is explained by risk. When portfolios are held longer, i.e. for 12 months, negative and significant differences in risk-adjusted return are observed. The risk-adjusted solvency discount is 1.17%, which is mainly due to higher risk-adjusted returns in short portfolios (low solvency portfolios) than in long portfolios (high solvency portfolios). This result suggests that solvency discount during this period is not explained by risk but by cash utilisation. The negative and insignificant result is observed when portfolios are held for 24 months. This result suggests that solvency discount during this period is explained by risk. A similar result is also found when cash flow to debt ratio is used as a criterion for identifying solvency stocks. The risk-adjusted solvency discount is observed only when portfolios are held for 12 months, which is 0.74%. This risk-adjusted solvency discount is mainly due to higher risk-adjusted returns in low solvency portfolios than in high solvency portfolios.

In Table 4.4, the solvency premium is generally explained by risk, while solvency discount mostly is not fully explained by risk. This result suggests that $H_{4.2a}$

is accepted. The solvency discount that cannot be explained by risk might be explained by tax inefficiency. The solvency discount occurs due to low solvency portfolios outperforming high solvency portfolios. In other words, low solvency portfolios generate higher returns than high solvency portfolios. The low solvency stocks are indicated as using long-term debt to assets ratio, debt to equity ratio, and equity multiplier. The stocks with high long-term debt to assets ratio, debt to equity ratio, and equity multiplier are identified as low solvency stocks, while the stocks with low long-term debt to assets ratio, debt to equity ratio, and equity multiplier are identified as high solvency stocks. The high solvent stocks have too low a debt when compared to equity, which leads to tax inefficiency. In other words, high solvency firms are not utilising tax efficiently while low solvency firms do. This tax inefficiency leads to lower returns in high solvency stocks than in low solvency stocks. The results in Table 4.4 generally suggest that solvency premium is partially explained by risk, which could be another factor to explain solvency premium and discount. This leads this study into the next section to study the relationship between solvency premium and business cycle.

4.5.4 Solvency premium and stages of the business cycle

The previous section (4.5.3) attempts to explain solvency premium using risk. The results show that risk partially explains solvency premium. It could be another underlying factor to explain the observed solvency premium. Generally stock returns and market anomalies such as value premium are explained by the business cycle (see e.g. Petkova and Zhang (2005)). The stages of the business cycle might be possible to explain the observed solvency premium. This section aims to answer the second research question, and *"$H_{4.3a}$: The solvency premium is explained by the stages of the business cycle"* is tested. In this section, debt to assets ratio, debt to equity ratio, fixed charge coverage ratio, and cash flow to debt ratio are employed[37].

4.5.4.1 Solvency premium during economic expansion and contraction

To test $H_{4.3a}$, the sample period is divided into two different economic stages: economic expansion and economic contraction. If a different result in economic expansion and economic contraction is observed, there is evidence that solvency premium is explained by the stages of the business cycle, and vice versa.

[Table 4.5]

During the expansion period, in Table 4.5, the results show that the differences in average risk-adjusted returns between high solvency and low solvency portfolios (risk-adjusted return in hedge portfolios) are negative and statistically significantly different from zero when debt to equity ratio, fixed charge coverage ratio, and cash flow to debt ratio are used as criteria for identifying solvent stocks and the holding period is 3 months. The risk-adjusted solvency discounts are 0.96%, 2.14%, and 0.93%. The risk-adjusted solvency discounts are also observed when (a) portfolios are held for 6 and 12 months and (b) the fixed charge coverage ratio is used. The risk-adjusted solvency discounts are 1.01% and 0.64%, respectively. This result suggests the existence of solvency discount even after returns are adjusted for risk during economic expansion. In other words, risk does not fully explain solvency discount.

[37] The debt to assets ratio and debt to equity ratio are employed because these two measurements of solvency generate significant solvency premium and discount that persistency strong when compare to others in component percentage solvency ratio. Similar reason is also applied to fixed charge coverage ratio and cash flow to debt ratio when interest coverage ratios are considered.

During the contraction period, in Table 4.5, the results show that the risk-adjusted returns from hedge portfolios are positive and statistically significantly different from zero when portfolios are held for 3 months. This result suggests the existence of a risk-adjusted solvency premium during this holding period. The risk-adjusted solvency premiums are 1.23% and 1.33% when debt to assets ratio and debt to equity ratio are used to identify solvent stocks. This result suggests that a risk-adjusted solvency premium exists even when returns are adjusted for risk. The solvency premium, however, disappears in other holding periods. The risk-adjusted solvency discounts are also observed during economic contraction; however, they do not seem to have any pattern.

According to the overall results, there is evidence that solvency premium exists after controlling for risk during economic contraction and reverts to solvency discount during economic expansion when the 3 months holding period is applied. This result suggests that solvency premium is explained by the stages of the business cycle during short-term holding periods. Specifically, stages of the business cycle negatively affect the solvency premium. In other words, bad economic conditions lead to a higher solvency premium while good economic conditions lead to a higher solvency discount. During economic contraction, investors tend to invest in solvent stocks to avoid uncertain situations that might happen during unstable economic conditions. During economic expansion, investors have an optimistic attitude and are more confident to invest in low solvent stock (high risk) in order to earn higher returns. The different economic stages lead to different results of solvency premium and solvency discount. This result suggests that the stages of the business cycle is another factor to explain solvency premium, thus $H_{4.3a}$ is accepted.

4.5.4.2 Solvency premium and business cycle (CLI index)

The previous section (4.5.4.1) clarifies the solvency premium during economic expansion and contraction; the results show that solvency premium is explained by the stages of the business cycle. This section attempts to provide evidence to support the relationship between solvency premium and the stages of the business cycle. In this section, the observed solvency premium is used to test against the business cycle factor by using equation (4.3). The CLI index is used to indicate the business cycle. If a significant coefficient of the business cycle factor is observed, then the solvency premium is driven by the stages of the business cycle, and vice versa. To accept $H_{4.3a}$, this test is expected to have a statistically significant result on the coefficient of the business cycle factor. Only the holding periods of 3 and 24 months are examined in this section; they have been selected due to the relatively strong evidence observed during these holding period.

[Table 4.6]

In Table 4.6, the negative and statistical significance of the business cycle factor after controlling for risk is mainly observed when debt to assets ratio, debt to equity ratio, and cash flow to debt ratio are used to identify solvent stocks. This result suggests that solvency premium is negatively driven by the stages of the business cycle when portfolios are held for 3 months. This negative relationship of the stages of the business cycle with solvency premium is consistent with the result in section 4.5.4.1 that solvency premium is negatively explained by the stages of the business cycle; in other words, solvency discount is positively explained by the stages of the business cycle. This result therefore leads to the same conclusion as in section 4.5.4.1. During economic contraction, the solvency premium exists due to the avoidance of uncertain situations. The investor, thus, tends to invest in stocks with good fundamentals (i.e. solvent stocks). However, a period of economic expansion leads investors to become more optimistic and overconfident. The investors, thus, tend to invest in riskier assets (low solvent stocks) to earn higher returns. The results confirm that both solvency premium and solvency discount are explained by the stages of the business cycle. These results suggest that $H_{4.3a}$ is accepted.

4.5.5 Solvency premium and investors' sentiment

The previous section (4.5.3) attempts to explain solvency premium using the business cycle. The results show that there is a relationship between solvency premium and stages of the business cycle (Tables 4.5 and 4.6). During economic expansion, investors are overconfident and tend to invest in riskier assets (low solvent stocks) while they tend to avoid risky assets and invest in high solvent stocks during economic contraction. Thus, the investors' sentiment could be another underlying factor to explain the observed solvency premium. This section aims to answer the second research question, and *"$H_{4.4a}$: The solvency premium is explained by investors' sentiment"* is tested.

The observed solvency premium is used to test against the investors' sentiment factor using equation (4.4). The investors' sentiment by Baker and Wurgler (2006) is used to indicate the investors' sentiment factor. If a significant coefficient of the investors' sentiment factor is observed, then the solvency premium is driven by the investors' sentiment, and vice versa. To accept $H_{4.4a}$, this test is expected to have a statistically significant result on the investors' sentiment factor.

Similarly to section 4.5.3.2, this test investigates the holding periods of 3 and 24 months.

[Table 4.7]

Table 4.7 presents the results from the regression in equation (4.4). When debt to assets ratio and cash flow to debt ratio are used as the criteria for identifying solvent stocks, the coefficients of the investors' sentiment are positive and statistically significant after controlling for risk and business cycle during the 24 months holding period while an insignificant result is observed in the 3 months holding period. This result suggests that investors' sentiment positively explains solvency premium in the long-run. In other words, solvency premium increases when investors are optimist about the stock market. The insignificant results of the coefficient of the business cycle factor are found when debt to equity and fixed charge coverage ratios are used to indicate solvent stocks. This result suggests that solvency premium is unexplained by investors' sentiment when debt to equity and fixed charge coverage ratios are employed. Comparing this with the results in Table 4.6, the significance level of the business cycle increases when the investors' sentiment factor is incorporated into the model. The adjusted R-squared also increases. The model that incorporates both business cycle and investors' sentiment factors outperforms the model that incorporates only the business cycle factor to explain solvency premium.

According to the overall results in Table 4.7, the positive and statistical significance of the investors' sentiment factor is observed when (a) debt to assets ratio and cash flow to debt ratio are used as the method for identifying solvent stocks and (b) portfolios are held for 24 months. The positive and significant results also suggest that solvency discount is negatively explained by investors' sentiment. In the long-term holding period, solvency premium decreases and reverses to solvency discount (Table 4.3). The solvency discount should, due to the decrease in investors' sentiment after market realisation and stock price, return to its real value. Thus, solvency premium is positively explained by investors' sentiment. In other words, solvency discount is negatively explained by investors' sentiment. These results suggest that $H_{4.3a}$ is accepted.

4.6 Conclusions

The trading strategies based on solvency ratios involve going long (buying) on high solvency stocks and going short (selling) on low solvency stocks. High solvency stocks are usually identified as stocks with low financial leverage while low solvency stocks are generally indicated as stocks with high financial leverage.

Solvency premium is the profit that is earned from the trading strategies based on solvency ratios. This chapter attempts to provide evidence that solvency premium exists. Portfolios are grouped using eight different definitions of solvent stocks, namely debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, equity multiplier, interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio. The two extreme portfolios are called the high solvency portfolio (the portfolio with the highest interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio and the lowest debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, and equity multiplier) and the low solvency portfolio (the portfolio with the opposite). Portfolios are held for four holding periods: 3, 6, 12 and 24 months.

The results show that the returns in hedge portfolios (difference in average returns between high and low solvency portfolios) are positive and statistically significantly different from zero during the short-term holding period. This result suggests that there is evidence of solvency premium in the short-run. The existence of solvency premium is consistent with earlier studies, such as George and Hwang (2010). This solvency premium may be due to investors' overreaction. De Bondt and Thaler (1985) suggest that the market tends to overreact to new information such as earnings announcements. The negative and statistically significant result, however, is observed when portfolios are held for longer. This suggests that solvency discount exists in the long-run. The existence of solvency discount is consistent with earlier studies such as Gomes and Schmid (2010). Normally high solvency stocks are the stocks with low financial leverage. A high level of financial leverage refers to a high level of risk, and leads to an increase in returns to compensate for the high level of financial risk (Hall and Weiss, 1967). After market realisation, the stock price returns to its real value and then the solvency discount occurs.

The existence of solvency premium and solvency discount leads to the next question; "What is the underlying factor to explain solvency premium and solvency discount?" The solvency discount may be due to the compensation for risk. Thus, risk could be the possible factor to explain solvency premium and solvency discount. This chapter, then, attempts to answer whether solvency premium and solvency discount are driven by risk. The results show that the solvency premium is partially explained by risk. This result leads this chapter to find other factors to explain solvency premium.

The previous studies suggest that generally stock returns and market anomalies such as value premium are explained by the business cycle (see Petkova and Zhang (2005)). The stages of the business cycle might be possible to explain the observed solvency premium. After the relationship between solvency premium and the stages of the business cycle is examined, there is evidence that solvency premium exists in economic contraction and reverts to solvency discount in economic expansion. This result suggests that a business cycle negatively affects the solvency premium. In other words, bad economic conditions lead to a higher solvency premium. During economic contraction, investors tend to invest in solvent stocks to avoid uncertain circumstances that might happen during unstable economic conditions. The solvency discount, however, is observed in economic expansion. This result suggests that the business cycle positively affects the solvency discount. In other words, good economic conditions lead to a higher solvency discount. The reason behind this result should be optimistic investing or investors' overconfidence. During economic expansion, investors have an optimistic attitude and are more confident to invest in risky assets (low solvent stocks) in order to earn higher returns. This explanation leads to the next question regarding whether solvency premium and solvency discount are explained by investors' sentiment.

After the relationship between solvency premium and investors' sentiment is examined, the positive coefficients of investors' sentiment factor are observed. These coefficients, however, are statistically significant only when (a) debt to assets ratio and cash-flow to debt ratio are used as the method of identifying solvent stocks and (b) during the long-term holding period. This result suggests a positive relationship between solvency premium and investors' sentiment. During a period of high investors' sentiment, investors tend to invest more in the stock market. Firms with good fundamentals such as high solvency firms must be of interest. This leads investors to invest more in high solvent stocks, consequently, a higher solvency premium. Thus, solvency premium is positively explained by investors' sentiment.

In conclusion, solvency premium exists in short-term holding periods due to investors' overreaction to firms' fundamentals. The solvency premium, however, reverses to solvency discount in long-term holding periods due to the correction of investors' overreaction. Solvency premium is partially explained by risk. The stages of the business cycle is another factor to explain solvency premium and solvency discount. Solvency premium is observed during economic contraction whereas solvency discount is observed during economic expansion. The last underlying factor to explain solvency premium is investors' sentiment. High investors' sentiment seems to generate higher solvency premium while low investors' sentiment seems to generate higher solvency discount. This chapter supports the existence of solvency premium during the short-term holding period and solvency discount during the long-term holding period; this existence is explained by time-varying risk, business cycle and investors' sentiment. The finding in this chapter suggests short-term investor to take a long position on high solvent stocks and short position on low solvent stocks especially during economic contraction. Inversely, the long-term investor is suggested to take a long position on low solvent stocks and take a short position on high solvent stocks particularly during economic expansion. This study, however, does not take transaction cost into account, which is an acknowledged limitation. Another limitation of the chapter is that short selling is not always feasible. Further study is recommended to incorporate the transaction cost to fill this gap.

Table 4.1 Construction of key variables

A: Construction of key variables in portfolio sorting

Key variables	Construction
Debt to assets ratio	Total debt scaled by total liabilities (LT-COMPUSTAT) that represent the sum of total current liabilities, deferred taxes and investment tax credit, other liabilities, total long-term debt, and minority interest. Total assets scaled by total assets (AT-COMPUSTAT) that represent the sum of current assets, net property, plant, equipment, and other non-current assets.
Long-term debt to assets ratio	Long-term debt scaled by total long-term debt (DLTT-COMPUSTAT) that represents the debt obligations, which are due longer than one year from the balance sheet of firms. The same total assets that are used to calculate the debt to assets ratio are also employed in this calculation.
Debt to equity ratio	Total equity scaled by total stockholders' equity (SEQ-COMPUSTAT) that represents the sum of total common equity and carrying value of preferred stock. The same total debt that is used to calculate debt to assets ratio is also employed in this calculation.
Equity multiplier	The same total assets that are used to calculate debt to assets ratio are also employed in the calculation of equity multiplier. The total equity of equity multiplier is also scaled the same as the calculation of debt to equity ratio.
Interest coverage ratio	The earning before interest and taxes (EBIT) scaled by pre-tax income (PI-COMPUSTAT) plus interest expense (XINT-COMPUSTAT) and subtract interest capitalized (INTC-COMPUSTAT). The interest expense is the same interest expense that is used to scale the EBIT.

Table 4.1 Construction of key variables (cont.)

Key variables	Construction
Fixed charge coverage ratio	This calculation uses the same EBIT and interest payment. The lease payment scaled by lease obligation (DCLO-COMPUSTAT) that represents the firms' debt obligation suffers when capitalizing leases.
Cash flow coverage ratio	Operating cash flow scaled by net cash flow of operating activities (OANCF-COMPUSTAT) that represents change in cash of all items categorized in operating activities on statement of cash flows. Tax payment scaled by total income tax (TXT) that represents all income taxes charged by federal, state, and also foreign governments. The same interest payment for calculating interest coverage ratio is also used in this calculation.
Cash flow to debt ratio	The same operating cash flow for calculating cash flow coverage ratio and the same total debt that is used to calculate debt to assets ratio is also employed in this calculation for cash flow to debt ratio.

B: Construction of key variables in regression

Key variables	Construction
Excess Return	The stock returns that exceed the risk free rate. The monthly returns are collected from the CRSP database. The holding periods of monthly returns are from month-end to month-end. The risk-free return is the one-month treasury bill rate[38].
R_m-R_f	The market excess return is a factor from the Fama-French three-factor model. The market return is constructed by Fama and French using value-weighted returns from the US firms, listed on three main stock

[38] The one-month Treasury bill rate data from Ibbotson Associates is collected from the Fama and French data library.

Table 4.1 Construction of key variables (cont.)

Key variables	Construction
R_m-R_f (cont.)	markets: NYSE, AMEX, and NASDAQ available via CRSP. The risk-free return is the one-month treasury bill rate.
SMB	Small minus Big is one factor from the Fama-French three-factor model. SML is the difference between average returns on (a) three small portfolios and (b) three big portfolios constructed by Fama-French[39].
HML	High minus low is the last factor from the Fama-French three-factor model. HML is the difference between average returns of (a) two value portfolios and (b) two growth portfolios constructed by Fama-French.

[39] Available from the Fama and French data library.

Table 4.2 Sample data descriptions

Data description for Key variables in portfolio sorting

Key variables in measure of solvency	Min	Max	Mean	Median	Standard deviation
Debt to assets ratio (DA)	0	247.10	0.52	0.50	1.04
Long-term debt to assets ratio (LDA)	0	39.59	0.18	1.14	0.22
Debt to equity ratio (DE)	0	87701.5	3.15	0.97	236.91
Equity multiplier (EM)	0	87702.5	4.19	1.98	236.97
Interest coverage ratio (IC)	0	119846	77.12	5.48	1158.58
Fixed charge coverage ratio (FCC)	0	119846	70.91	4.28	1132.25
Cash flow coverage ratio (CFC)	0	179910	118.86	7.77	1587.32
Cash flow to debt ratio (CFD)	0	464.45	0.34	0.20	0.98

Correlation

	DA	*LDA*	*DE*	*EM*	*IC*	*FCC*	*CFC*	*CFD*
DA	1.0000	0.2782	0.0014	0.0014	-0.0082	-0.0080	-0.0121	-0.0119
LAD		1.0000	0.0021	0.0022	-0.0128	-0.0137	-0.0326	0.0005
DE			1.0000	0.9959	-0.0003	-0.0004	-0.0006	-0.0003
EM				1.0000	-0.0003	-0.0004	-0.0007	-0.0003
IC					1.0000	0.9583	0.8420	0.0983
FCC						1.0000	0.8067	0.0918
CFC							1.0000	0.1009
CFD								1.0000

Figure 4.1: Portfolios' returns (component percentage solvency ratios)

Figure 4.1 presents the portfolios' average returns when sample stocks are sorted on the basis of component percentage solvency ratios: (a) debt to assets ratio (DA), (b) long-term debt to assets ratio (LDA), (c) debt to equity ratio (DE), and (d) equity multiplier (EM). The portfolios are sorted in ascending order. The first portfolio represents the high solvency portfolio including stocks with low DA, LDA, DE, and EM. The low solvency portfolio is represented by the tenth portfolio including stocks with high DA, LDA, DE, and EM. Portfolios are held for 3, 6, 12 and 24 months. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

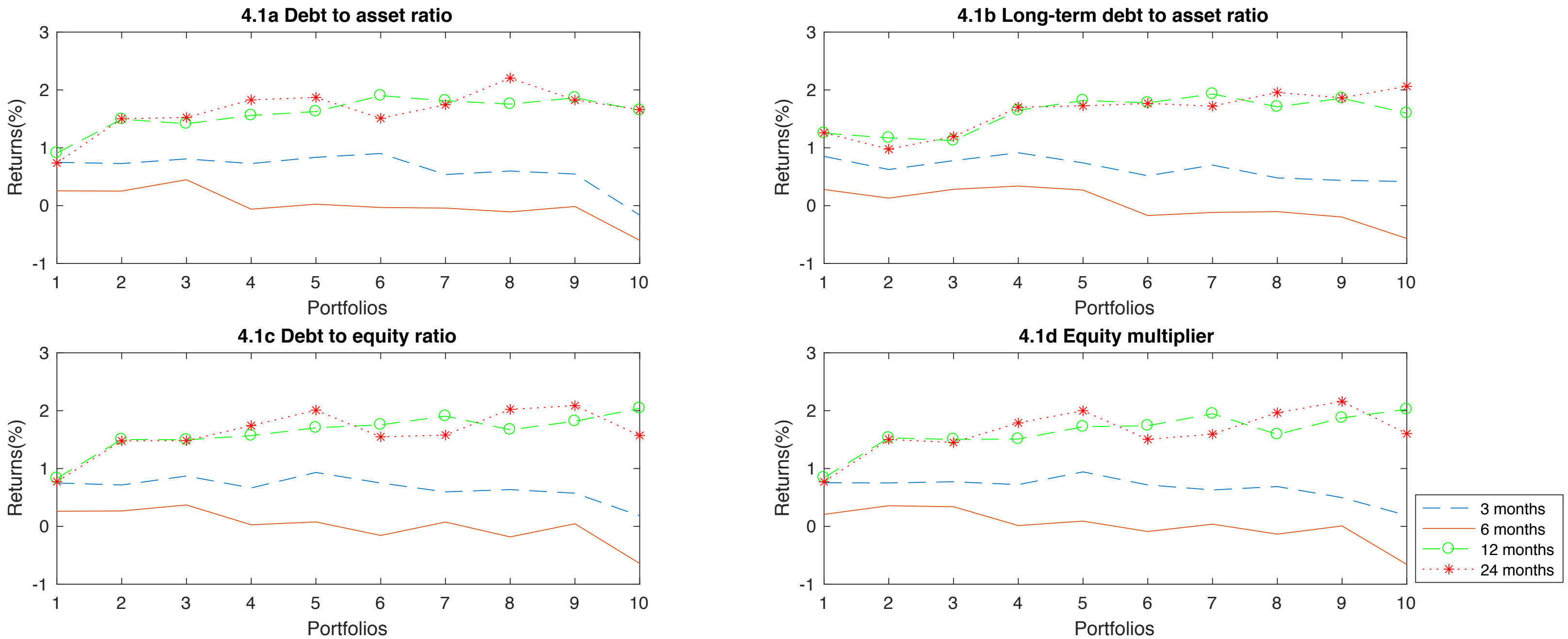

Figure 4.2: Portfolios' returns (coverage solvency ratios)

Figure 4.2 presents the portfolios' average returns when sample stocks are sorted based on coverage solvency ratios: (a) interest coverage ratio (IC), (b) fixed charge coverage ratio (FCC), (c) cash flow coverage ratio (CFC), and (d) cash flow to debt ratio (CFD). The portfolios are sorted in ascending order. The first portfolio represents the low solvency portfolio including stocks with low IC, FCC, CFC, and CFD. The high solvency portfolio is represented by the tenth portfolio including stocks with high IC, FCC, CFC, and CFD. Portfolios are held for 3, 6, 12 and 24 months. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

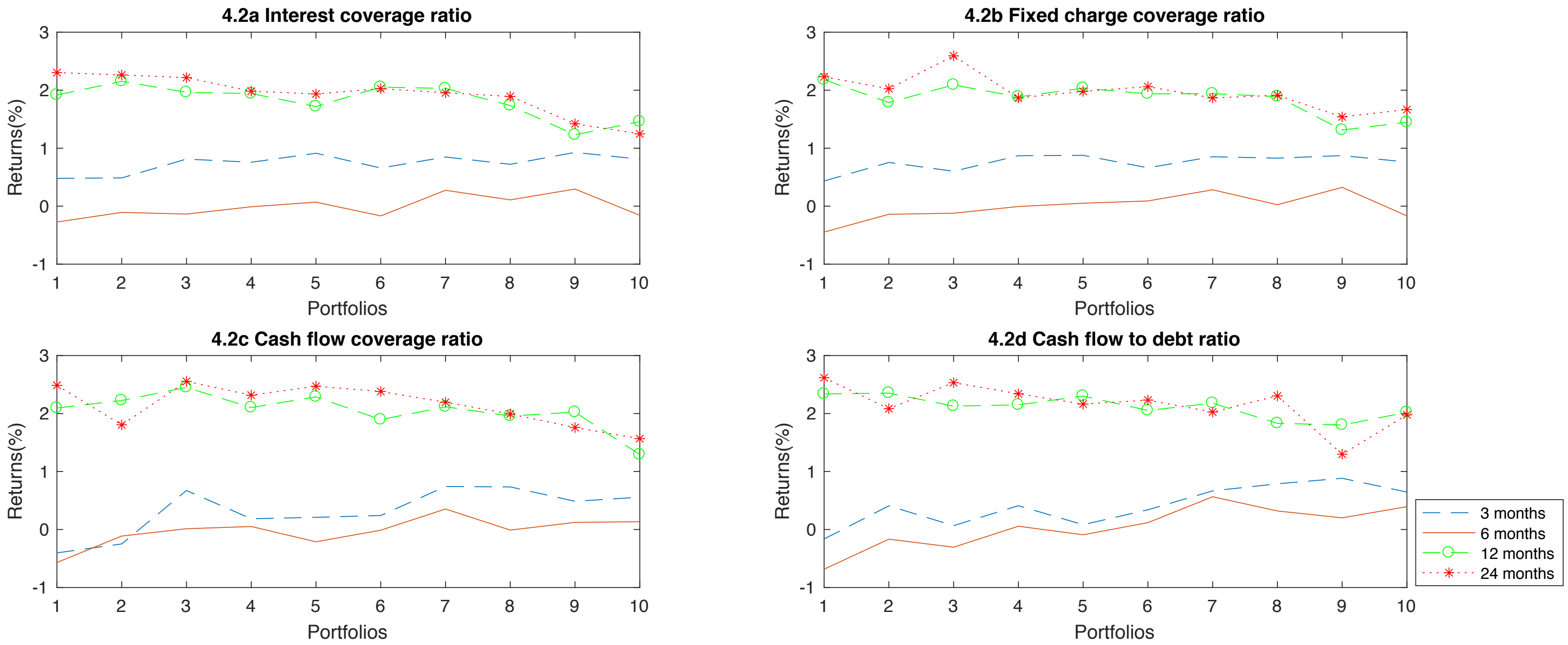

Table 4.3: Solvency premiums

Table 4.3 presents the solvency premiums when sorting portfolios on the basis of the solvency ratios: debt to assets ratio (DA), long-term debt to assets ratio (LDA), debt to equity ratio (DE), equity multiplier (EM), interest coverage ratio (IC), fixed charge coverage ratio (FCC), cash flow coverage ratio (CFC), and cash flow to debt ratio (CFD). H represents the average return from high solvency portfolios and L represents the average return from low solvency portfolios. The solvency premium is measured by the difference in returns between high and low solvency portfolios that is represented in H-L. Sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tail test (equation (4.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Measure of Solvency							
		Component percentage solvency ratio				Interest coverage ratio			
		DA	**LDA**	**DE**	**EM**	**IC**	**FCC**	**CFC**	**CFD**
3	**H**	0.75%	0.85%	0.75%	0.75%	0.81%	0.76%	0.56%	0.65%
	L	-0.16%	0.42%	0.18%	0.19%	0.48%	0.43%	-0.40%	-0.16%
	H-L	0.91%	0.44%	0.57%	0.57%	0.33%	0.33%	0.96%	0.81%
	(T-stat)	(2.3828*)	(1.4118)	(1.5339)	(1.4736)	(1.1573)	(0.9817)	(2.3209*)	(2.3953*)
6	**H**	0.26%	0.28%	0.26%	0.21%	-0.16%	-0.17%	0.13%	0.39%
	L	-0.60%	-0.57%	-0.64%	-0.66%	-0.27%	-0.45%	-0.57%	-0.68%
	H-L	0.86%	0.85%	0.90%	0.87%	0.12%	0.28%	0.70%	1.08%
	(T-stat)	(2.0299*)	(1.9143)	(2.5427*)	(2.3919*)	(0.9090)	(1.5551)	(1.1368)	(1.9564)

Table 4.3: Solvency premiums (cont.)

Holding Periods	Return	Measure of Solvency							
		Component percentage solvency ratio				Interest coverage ratio			
		DA	**LDA**	**DE**	**EM**	**IC**	**FCC**	**CFC**	**CFD**
12	**H**	0.91%	1.25%	0.83%	0.84%	1.46%	1.45%	1.29%	2.02%
	L	1.65%	1.60%	2.04%	2.02%	1.92%	2.18%	2.09%	2.34%
	H-L	-0.74%	-0.34%	-1.21%	-1.18%	-0.46%	-0.73%	-0.80%	-0.32%
	(T-stat)	(-2.2786*)	(-1.1846)	(-3.8579**)	(-3.9503**)	(-0.8945)	(-1.4921)	(-0.6019)	(-1.2089)
24	**H**	0.74%	1.26%	0.77%	0.77%	1.25%	1.67%	1.57%	1.98%
	L	1.66%	2.06%	1.57%	1.60%	2.30%	2.23%	2.49%	2.62%
	H-L	-0.92%	-0.80%	-0.80%	-0.83%	-1.06%	-0.56%	-0.92%	-0.64%
	(T-stat)	(-3.7197**)	(-2.7098*)	(-3.8554**)	(-4.2600**)	(-1.4189)	(-2.0808*)	(-0.4971)	(-0.9137)

Figure 4.3: Solvency premiums (component percentage solvency ratios)

Figure 4.3 presents the movement of solvency premiums when sorting portfolios on the basis of the component percentage solvency ratios: (a) debt to assets ratio (DA), (b) long-term debt to assets ratio (LDA), (c) debt to equity ratio (DE), and (d) equity multiplier (EM) during the study period. The solvency premium is measured by the difference in returns between high and low solvency portfolios from the first methodology. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

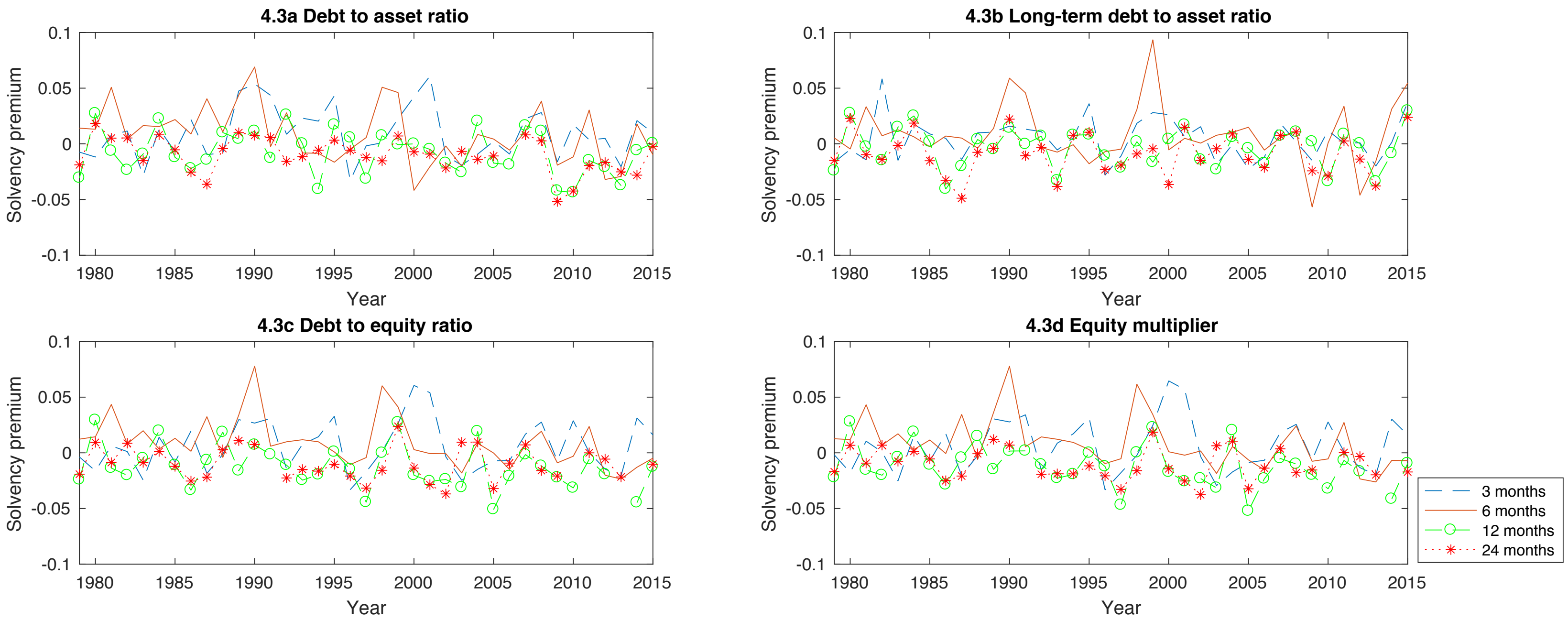

Figure 4.4: Solvency premiums (coverage solvency ratios)

Figure 4.4 presents the movement of solvency premiums when sorting portfolios on the basis of the coverage solvency ratios: (a) interest coverage ratio (IC), (b) fixed charge coverage ratio (FCC), (c) cash flow coverage ratio (CFC), and (d) cash flow to debt ratio (CFD) during the study period. The solvency premium is measured by the difference in returns between high and low solvency portfolios from the first methodology. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

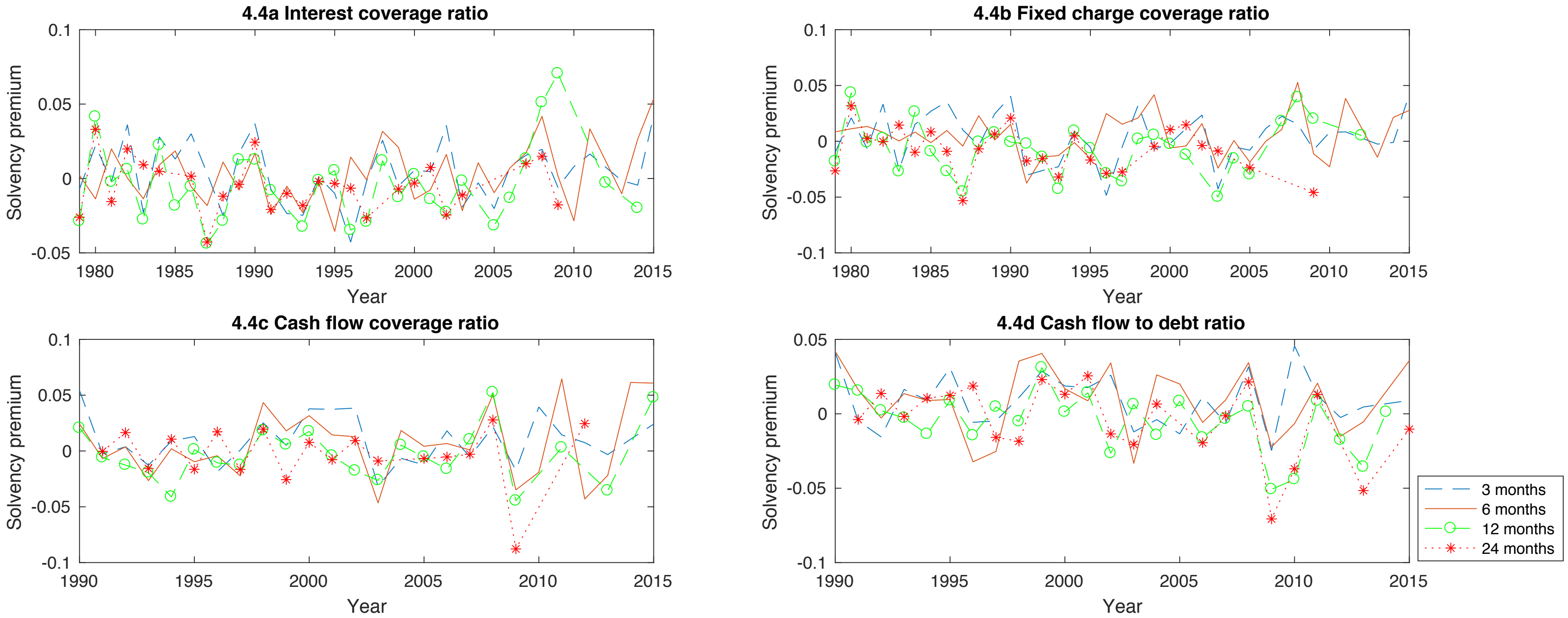

Figure 4.5: Risk-adjusted portfolios' returns (component percentage solvency ratios)

Figure 4.5 presents portfolios' average risk-adjusted returns from portfolios 1 to 10 when portfolios are formed on the basis of component percentage solvency ratios: (a) debt to assets ratio (DA), (b) long-term debt to assets ratio (LDA), (c) debt to equity ratio (DE), and (d) equity multiplier (EM). Portfolios are held for 3, 6, 12 and 24 months. The risk-adjusted return is estimated using equation (4.2) and is used instead of returns. Following the first methodology, the first portfolio represents high solvency portfolios including stocks with low DA, LDA, DE, and EM. The low solvency portfolio is represented by the tenth portfolio including stocks with high DA, LDA, DE, and EM. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

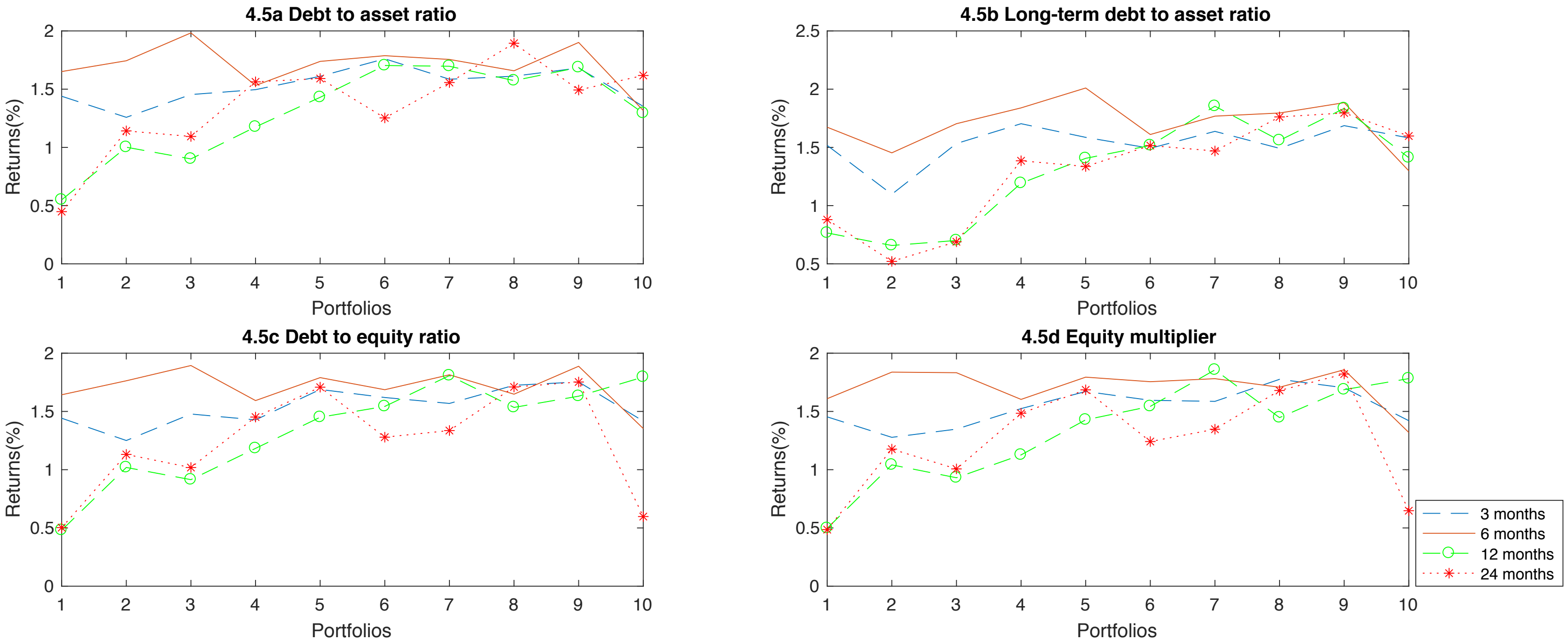

Figure 4.6: Risk-adjusted portfolios' returns (coverage solvency ratios)

Figure 4.6 presents portfolios' average risk-adjusted returns from portfolios 1 to 10 when portfolios are formed on the basis of coverage solvency ratios: (a) interest coverage ratio (IC), (b) fixed charge coverage ratio (FCC), (c) cash flow coverage ratio (CFC), and (d) cash flow to debt ratio (CFD). Portfolios are held for 3, 6, 12 and 24 months. The risk-adjusted return is estimated using equation (4.2) and is used instead of returns. Following the first methodology, the first portfolio represents low solvency portfolios including stocks with low IC, FCC, CFC, and CFD. The high solvency portfolio is represented by the tenth portfolio including stocks with high IC, FCC, CFC, and CFD. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors.

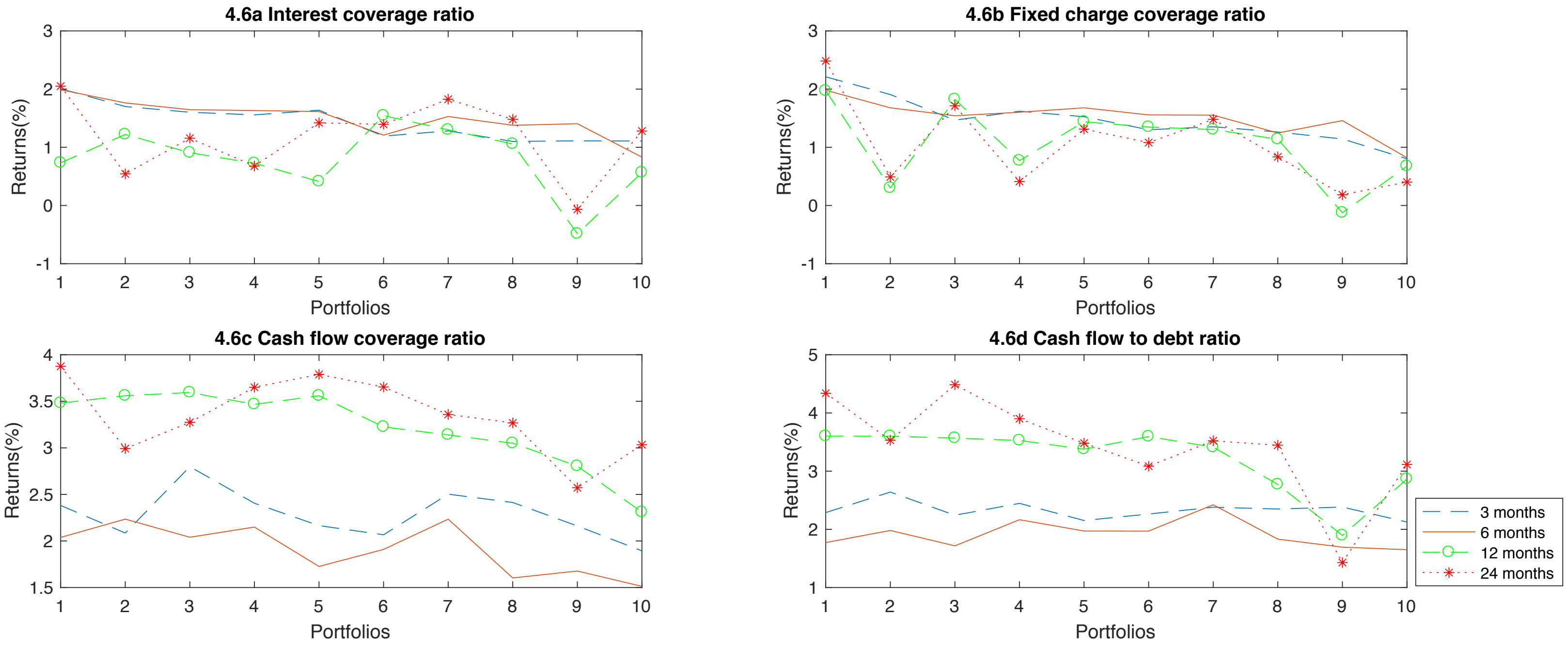

Table 4.4: Risk-adjusted solvency premiums

Table 4.4 presents the risk-adjusted solvency premium when sorting portfolios on the basis of the solvency ratios: debt to assets ratio (DA), long-term debt to assets ratio (LDA), debt to equity ratio (DE), equity multiplier (EM), interest coverage ratio (IC), fixed charge coverage ratio (FCC), cash flow coverage ratio (CFC), and cash flow to debt ratio (CFD). Equation (4.2) is employed to estimate the risk-adjusted returns. H represents the average risk-adjusted return from high solvency portfolios and L represents the average risk-adjusted return from low solvency portfolios. The risk-adjusted solvency premium is measured by the difference in risk-adjusted returns between high and low solvency portfolios that are represented in H-L. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tail test (equation (4.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Measure of Solvency							
		Component percentage solvency ratio				Interest coverage ratio			
		DA	LDA	DE	EM	IC	FCC	CFC	CFD
3	H	1.44%	1.52%	1.44%	1.45%	1.11%	0.80%	1.89%	2.13%
	L	1.35%	1.58%	1.42%	1.42%	2.00%	2.21%	2.38%	2.29%
	H-L	0.09%	-0.06%	0.02%	0.03%	-0.90%	-1.41%	-0.49%	-0.16%
	(T-stat)	(0.2248)	(-0.1805)	(0.0607)	(0.0774)	(-3.2263**)	(-3.2782**)	(-1.4129)	(-1.0936)
6	H	1.65%	1.67%	1.64%	1.61%	0.83%	0.82%	1.51%	1.65%
	L	1.32%	1.30%	1.35%	1.32%	1.99%	1.98%	2.04%	1.77%
	H-L	0.33%	0.37%	0.29%	0.29%	-1.16%	-1.16%	-0.53%	-0.12%
	(T-stat)	(0.7895)	(0.9437)	(0.8323)	(0.8133)	(-3.5667**)	(-3.5550**)	(-1.0427)	(-0.5323)

Table 4.4: Risk-adjusted solvency premiums (cont.)

Holding Periods	Return	Measure of Solvency							
		Component percentage solvency ratio				Interest coverage ratio			
		DA	**LDA**	**DE**	**EM**	**IC**	**FCC**	**CFC**	**CFD**
12	**H**	0.55%	0.77%	0.48%	0.50%	0.57%	0.68%	2.31%	2.87%
	L	1.29%	1.41%	1.80%	1.78%	0.73%	1.97%	3.48%	3.60%
	H-L	-0.74%	-0.65%	-1.31%	-1.28%	-0.17%	-1.29%	-1.17%	-0.74%
	(T-stat)	(-2.0001)	(-2.1676*)	(-3.3081**)	(-3.2875**)	(-1.7484)	(-2.2388*)	(-2.1621*)	(-2.9791**)
24	**H**	0.45%	0.88%	0.50%	0.49%	1.28%	0.40%	3.03%	3.11%
	L	1.62%	1.60%	0.60%	0.65%	2.05%	2.48%	3.88%	4.34%
	H-L	-1.17%	-0.72%	-0.10%	-0.16%	-0.77%	-2.08%	-0.84%	-1.22%
	(T-stat)	(-1.6015)	(-2.6625*)	(-2.4894*)	(-2.5476*)	(-1.0556)	(-2.0463)	(-0.3569)	(-1.1978)

Table 4.5: Solvency premiums during economic expansion and contraction

Table 4.5 presents the risk-adjusted solvency premium when (a) debt to assets ratio (DA), (b) debt to equity ratio (DE), (c) fixed charge coverage ratio (FCC), and (d) cash flow to debt ratio (CFD) are used as criteria for identifying solvent stocks during economic expansion and economic contraction. The business cycle turning point is defined using the OECD business cycle turning point. Equation (4.2) is employed to estimate the risk-adjusted returns. The risk-adjusted solvency premium is measured by the difference in average risk-adjusted returns between high and low solvency portfolios. The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors. The t-stat indicates the significance level of the two-tail test (equation (4.1)). * and ** denote the statistical significance levels of 5% and 1% respectively.

Holding Periods	Return	Measure of Solvency							
		Economic Contraction				Economic Expansion			
		DA	DE	FCC	CFD	DA	DE	FCC	CFD
3	H	-2.46%	-2.50%	-3.58%	1.81%	4.41%	4.45%	3.93%	2.03%
	L	-3.69%	-3.83%	-2.85%	1.22%	5.19%	5.41%	6.07%	2.96%
	H-L	1.23%	1.33%	-0.73%	0.59%	-0.78%	-0.96%	-2.14%	-0.93%
	(T-stat)	(2.2179*)	(2.1092*)	(-0.9502)	(1.3875)	(-1.6979)	(-2.1980*)	(-3.5720**)	(-2.8804**)
6	H	-1.20%	-1.23%	-2.26%	1.66%	3.83%	3.83%	3.16%	1.55%
	L	-1.30%	-1.82%	-1.06%	1.03%	3.31%	3.77%	4.17%	2.35%
	H-L	0.10%	0.59%	-1.20%	0.63%	0.52%	0.06%	-1.01%	-0.80%
	(T-stat)	(0.1292)	(1.1946)	(-2.6097*)	(0.9826)	(1.0329)	(0.1230)	(-2.4124**)	(-1.4421)

Table 4.5: Solvency premiums during economic expansion and contraction (cont.)

Holding Periods	Return (T-stat)	Measure of Solvency							
		Economic Contraction				Economic Expansion			
		DA	DE	FCC	CFD	DA	DE	FCC	CFD
12	H	-6.53%	-6.60%	-5.68%	0.80%	5.94%	5.92%	6.45%	3.90%
	L	-5.44%	-4.53%	-6.02%	1.99%	6.42%	6.56%	8.09%	4.69%
	H-L	-1.09%	-2.07%	-0.34%	-1.19%	-0.48%	-0.64%	-1.64%	-0.79%
	(T-stat)	(-1.8655)	(-3.6339**)	(-0.5728)	(-2.4322*)	(-0.9863)	(-1.3052)	(-2.4465**)	(-1.9119)
24	H	-6.67%	-6.60%	-6.12%	1.02%	6.87%	5.92%	6.98%	4.89%
	L	-6.11%	-5.36%	-5.78%	0.75%	7.40%	5.60%	8.03%	5.91%
	H-L	-0.56%	-1.24%	-0.34%	0.27%	-0.53%	0.32%	-1.05%	-1.02%
	(T-stat)	(-0.8705)	(-2.5446*)	(-0.8404)	(0.4499)	(-1.5215)	(-0.9021)	(-1.8904)	(-1.7248)

Table 4.6: Solvency premiums and stages of the business cycle

Table 4.6 presents the solvency premium, alphas and betas to three factors from Fama and French (1993): market factor (Rm-Rf); size factor (SMB); value factor (HML); betas to business cycle factor (CLI), which is the OECD CLI index; and the adjusted R-square from equation (4.3). The solvency premium is defined as the difference in average returns between two extreme portfolios, high and low solvency. Criteria for identifying solvent stocks are (a) debt to assets ratio (DA), (b) debt to equity ratio (DE), (c) fixed charge coverage ratio (FCC), and (d) cash flow to debt ratio (CFD). The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Measure of solvency	Holding periods	Solvency premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	Adj.RSQ
DA	3	0.91%	0.97%	0.56%	2.79%	-1.76%	-0.77%	18%
			(2.0967*)	(0.1823)	(0.7067)	(-0.6828)	(-2.4933*)	
	24	-0.92%	-1.07%	2.02%	3.48%	-1.52%	-0.55%	11%
			(-3.2954**)	(0.9463)	(1.2616)	(-0.8401)	(-2.5296*)	
DE	3	0.57%	0.70%	-0.55%	4.07%	-2.02%	-0.72%	20%
			(1.5568)	(-0.1871)	(1.0721)	(-0.8150)	(-2.4110*)	
	24	-0.80%	-0.97%	2.50%	4.47%	-4.15%	-0.27%	15%
			(-3.1110**)	(1.2407)	(1.6282)	(-2.4045*)	(-1.3206)	
FCC	3	0.33%	0.93%	-2.89%	-7.35%	-4.90%	-0.27%	37%
			(2.3553*)	(-1.1118)	(-2.2028*)	(-2.2432*)	(-1.0359)	
	24	-0.56%	-0.52%	-1.60%	7.49%	-2.43%	-0.51%	4%
			(-0.9575)	(-0.4874)	(1.5774)	(-0.8682)	(-1.4714)	
CFD	3	0.81%	0.80%	1.00%	4.07%	-2.82%	-0.82%	33%
			(2.0168)	(0.3857)	(1.2397)	(-1.3384)	(-2.7632*)	
	24	-0.64%	-0.22%	-3.32%	1.56%	0.33%	-0.44%	12%
			(-0.3286)	(-0.7990)	(0.2936)	(0.0973)	(-0.9352)	

Table 4.7: Solvency premiums, stages of the business cycle and investors' sentiment

Table 4.7 presents the solvency premium, alphas and betas to the three factors from Fama and French (1993): market factor (Rm-Rf); size factor (SMB); value factor (HML); betas to business cycle factor (CLI), which is the OECD CLI index; betas to investors' sentiment factor (SENT), which is the investors' sentiment by Baker and Wurgler (2006); and the adjusted R-square from equation (4.4). The solvency premium is defined as the difference in average returns between two extreme portfolios, high and low solvency. Criteria for identifying solvent stocks are (a) debt to assets ratio (DA), (b) debt to equity ratio (DE), (c) fixed charge coverage ratio (FCC), and (d) cash flow to debt ratio (CFD). The sample stocks include stocks that are listed in the three main US stock markets: NYSE, AMEX, and NASDAQ from January 1973 to December 2015 covering 43 years but excluding the financial and utility sectors. The t-stat indicates the significance level. * and ** denote the statistical significance levels of 5% and 1% respectively.

Measure of solvency	Holding periods	Solvency premium	α (T-stat)	Rm-Rf (T-stat)	SMB (T-stat)	HML (T-stat)	BUS (T-stat)	SENT (T-stat)	Adj.RSQ
DA	3	0.91%	0.76%	1.29%	3.63%	-4.39%	-0.86%	0.97%	21%
			(1.5964)	(0.4241)	(0.9265)	(-1.4235)	(-2.7749**)	(1.4850)	
	24	-0.92%	-1.34%	2.90%	4.54%	-4.77%	-0.66%	1.17%	27%
			(-4.3143**)	(1.4766)	(1.7939)	(-2.3621*)	(-3.2760**)	(2.7592**)	
DE	3	0.57%	0.45%	0.29%	5.03%	-5.04%	-0.82%	1.11%	25%
			(1.0014)	(0.1007)	(1.3576)	(-1.7258)	(-2.7901**)	(1.7999)	
	24	-0.80%	-1.05%	2.81%	4.86%	-5.19%	-0.30%	0.37%	14%
			(-3.2037**)	(1.3657)	(1.7361)	(-2.4353*)	(-1.4562)	(0.8398)	
FCC	3	0.33%	0.87%	-2.75%	-7.14%	-5.53%	-0.29%	0.22%	36%
			(2.0756*)	(-1.0309)	(-2.0812*)	(-1.9916)	(-1.0742)	(0.3773)	
	24	-0.56%	-0.94%	-0.86%	8.19%	-5.39%	-0.54%	1.18%	14%
			(-1.6545)	(-0.2750)	(1.8093)	(-1.7201)	(-1.6427)	(1.7832)	
CFD	3	0.81%	0.75%	1.21%	4.46%	-4.23%	-0.83%	0.57%	32%
			(1.8882)	(0.4620)	(1.3424)	(-1.6079)	(-2.8008**)	(0.9027)	
	24	-0.64%	-0.57%	-2.28%	4.26%	-6.67%	-0.55%	2.71%	44%
			(-1.0426)	(-0.6859)	(0.9886)	(-1.9378)	(-1.4563)	(3.2768**)	

Chapter 5 – Summary and Conclusions

As trading strategy can be defined a certain plan that aims to generate significant profits by going long (buy) or short (sell) in stocks traded in the financial markets. A trading strategy can generally be based on two main types of analysis: (a) technical analysis and (b) fundamental analysis. The technical analysis allocates assets on the basis of several statistics such as historical price movements while the fundamental analysis tries to identify the intrinsic value of assets. A good trading strategy helps investors allocate their funds efficiently. The key question that needs to be answered is which stocks to buy and which ones to sell. This thesis investigates three different trading strategies. Namely, trading strategies based on historical patterns, value versus growth trading strategies, and trading strategies based on corporate solvency. It also examines whether the generated profits are influenced by risk, business cycle, and/or investors' sentiment.

Firstly, this thesis builds on the literature on momentum (see e.g. Blitz et al. (2011)) and contrarian (see e.g. Blitz et al. (2013)) trading strategies in order to investigate the profitability of trading strategies that are based on historical patterns and the relation between investors' sentiment and stock returns (see e.g. Baker and Wurgler (2006)). The momentum profit is documented in medium horizon investments while contrarian profits are found in short and long horizon investments. Scholars have used risk-based and behavioural-based factors in an attempt to explain the profitability of historical pattern based trading strategies. Previous studies generally agree that the profitability of trading strategies that are based on historical patterns cannot be explained by risk. Some studies claim that the profits can be partially explained by behavioural-related factors. The relative empirical evidence is, however, mixed. This thesis fills this gap by examining whether the profitability of historical pattern based trading strategies can be explained by the risk and investors' sentiment factors developed by Baker and Wurgler (2006). Following, Blitz et al. (2011) and Blitz et al. (2013), this thesis also investigates the profitability of historical pattern based trading strategies using residual stock returns.

Secondly, this thesis builds on the literature on value versus growth trading strategies (see e.g. Zhang (2005)) and the relation between value premium and (a) risk (see e.g. Ang and Chen (2007)), (b) business cycle (see e.g. Chen et al. (2008)) and (c) investor behavioural (see e.g. Xing (2008)). Some studies claim that risk is one of the factors that can explain the value premium (see e.g. Parker and Julliard (2005)) while others do not agree with this view (see e.g. Ang and Chen (2007)). The empirical evidence regarding the relation between value premium and risk remains ambiguous. Another factor to be considered is the business cycle. There are few studies that investigate the relationship between value premium and business cycle such as that of Petkova and Zhang (2005). The business cycle factor that is employed in earlier studies is based on the National Bureau of Economic Research (NBER) business cycle turning point while this thesis uses the Organization for Economic Co-operation and Development Composite leading indicator (OECD CLI) index and the OECD business cycle turning point which is different from the methodology used in earlier studies. The last factor to be examined is the investors' sentiment. Lakonishok et al. (1994) argue that the value premium can be explained by investor behavioural whereas other studies (see e.g. Xing (2008)) do not share the same opinion. Therefore, the relation between value premium and investors' sentiment remains ambiguous too. An important number of studies suggest that value investing strategies generate superior returns. However, the reason behind this remains unidentified. This thesis bridges this gap by investigating the relation between value premium and the above mentioned factors: (a) risk, (b) business cycle, and (c) investors' sentiment.

Lastly, this thesis also contributes to the literature on financial leverage and financial distress examining whether these factors can affect stocks returns (see e.g. Gomes and Schmid (2010)). Aiming to shed new light into the debate, a new trading strategy is introduced based on corporate solvency. On the one hand, some scholars (see e.g. Gill and Obradovich (2012)) suggest that high solvency firms experience lower return relative to low solvency firms due to risk differentials. On the other hand, other studies (see e.g. George and Hwang (2010)) show that high solvency firms earn higher returns than low solvency firms. It becomes clear that the empirical evidence regarding the relation between firms' solvency and stock returns is mixed and are the underlying factors not yet rigorously examined. This thesis fills this gap by examining the relation between firms' solvency and stock returns in four different holding periods and also by classifying solvency stocks according to eight different definitions. This thesis also investigates whether risk, business cycle and investors' sentiment can explain the documented profitability of trading strategies that are based on corporate solvency.

The findings suggest that these three trading strategies generate positive and statistical significant profits to investors. The results also show whether risk, business cycle and investors' sentiment can explain these profits. Specific findings with relation to each of these trading strategies are described below.

5.1 Historical Return and Trading Strategies: Can risk and investors' sentiment explain the profit?

The first issue that is examined in this thesis is the profitability of historical pattern based trading strategies (i.e. momentum and contrarian trading strategies) and whether these profits can be explained by risk and/or investors' sentiment. This thesis, following momentum trading strategy, developed a portfolio of long positions in past winner stocks and short positions in past loser stocks. However, the previously documented profitability of momentum investing is not observed in this case. The thesis, then, forms winner and loser portfolios based on residual stock returns following Blitz et al. (2011). Similar to the conventional momentum strategy, the previously documented momentum profits from residual momentum trading strategy are not evident in this thesis. Therefore, the thesis cannot empirically support the view that conventional momentum and residual momentum trading strategies can result in consistent profits.

The contrarian trading strategy, however, generates statistically significant profits during relatively short holding periods (one month) as well as during longer holding periods (36 and 60 months). The presence of contrarian profits during these holding periods is consistent with earlier studies, (De Bondt and Thaler (1985) and Avramov and Chordia (2006)). This finding offers an alternative way to invest in loser stocks. Investors normally prefer to hold portfolios with different holding-periods depending on their investment objectives. If an investor prefers a short investment horizon, the empirical findings suggest that the investor should form winners and losers portfolios based on past 6-month average returns. This strategy results in contrarian profits of 0.40% per month, which is the highest contrarian profits over a short-term holding period (one month). In the case of long-term investment horizons, if investors prefer to hold their portfolios between 36 and 60 months, the empirical findings suggest that investors should form portfolios based on 12-months average historical returns. The contrarian profit of 0.67% (per month), which is the highest contrarian profit among all portfolio formations and investment holding periods, is observed when portfolios are formed based on past 12-month average returns and are held for 36 months. A contrarian profit of 0.48% per month is observed following the same portfolio formation when a longest holding period (60 months) is employed. Therefore, in order to earn the highest possible contrarian profits, investors should follow a 12-36 strategy, which means to form portfolios on the basis of 12-month- average historical returns and hold their portfolios for 36 months.

Blitz et al. (2013) find that the contrarian trading strategy based on historical residual returns can earn significantly superior returns compared to the conventional contrarian trading strategy. This thesis, however, cannot find any significant contrarian profits when portfolios are formed on the basis of historical residual returns. In other words, residual contrarian trading strategy cannot earn significant returns. The different result between this thesis and Blitz et al. (2013) is due to different sample specifications and methodology. The study of Blitz et al. (2013) is mainly focused on short-term contrarian profits when winner and loser stocks are classified based on past month (one month) residual returns, which is difference from the methodology followed in this thesis. This thesis focuses on average returns of past 3, 6, 9, and 12-month periods rather than just one month. The insignificant residual contrarian strategy returns lead to the conclusion that the conventional contrarian trading strategy outperforms the residual contrarian trading strategy during the sample periods under consideration.

The documented contrarian profits from the conventional momentum trading strategy (winner and loser portfolios formed on the basis of historical returns) leads to the next question: can these profits be explained by risk? The unconditional Fama and French (1993) three-factor model is employed to investigate whether risk differences are able to explain contrarian profits. A statistically significant intercept of the three-factor model is observed which suggests that there are contrarian profits left unexplained even after controlling for risk. In other words, risk factors based on the Fama and French (1993) three-factor model is unable to explain contrarian profits. This evidence is consistent with the findings of Avramov and Chordia (2006).

The above empirical results are also similar to the findings of De Bondt and Thaler (1985) who show that risk cannot explain superior returns from past loser stocks. Instead, De Bondt and Thaler (1985) suggest that investor overreaction can be a good explanation of contrarian profits. The investors' sentiment proxy developed by Baker and Wurgler (2006), is incorporated into the Fama and French (1993) three-factor model and a statistically insignificant of coefficient of investors' sentiment is found. This result suggests that investors' sentiment is also unable to explain contrarian profits. In other words, contrarian profits cannot be explained by investor behavioural. Therefore, this thesis shows that the observed contrarian profit cannot be unexplained by either risk-based or behavioural-based factors.

5.2 Business Cycles and the Profitability of Value vs. Growth Trading Strategies

Value versus growth trading strategies is among the oldest trading strategies. According to this type of strategy, value stocks can outperform growth stocks. Therefore, investors should take a long position in value stocks and short position in growth stocks. The profitability of this trading strategy is widely documented. This thesis employs dividend yield, book to market ratio, earnings to price ratio, and cash-flow to price ratio as a measure to identify value and growth stocks. The profitability of value versus growth trading strategies is called value premium. The findings suggest that value premium persistently exists when stocks are classified as value or growth stocks based on book to market ratio, earnings to price ratio, and cash-flow to price ratio but not when the dividend yield is used as a classification criterion. Evidence of value premium is found consistently over all given holding periods[40]. This is in line with the findings of Fama and French (2012). The highest value premium of 1.01% (per month) is observed when cash-flow to price ratio is employed to identify value and growth stocks and portfolios are held for 6 months. This finding suggests that if investors would like to earn the highest possible return from value investing, they should classify stocks on the basis of their cash-flow to price ratio and then hold their portfolios for 6 months. The value premium is also observed at industry level. More specifically, the value premium is documented in the industries of Consumer Nondurables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Shops, and Health. These findings lead to the question; what is the underlying reason behind the superior returns on value stocks? Consequently, the second issue that is examined in this thesis is whether the

[40] The holding periods are 3, 6, 12 and 24 months.

value premium can be explained by risk, business cycle, and/or investors' sentiment factors.

Fama and French (1992) suggest that one of the factors that can possibly explain value premium is risk. The Fama and French (1993) three-factor model is employed to examine whether risk is able to explain value premium. The results show positive and statistical significant risk-adjusted returns in the hedge portfolio (risk-adjusted return in value portfolio *minus* risk-adjusted return in growth portfolio). This suggests that value premium exists even after controlling for risk; in other words, the superior returns on value stocks cannot be explained by risk. This finding is consistent with the finding of Avramov and Chordia (2006). If value premium cannot be explained by risk, there must be another factor to explain this abnormal return.

The value premium could possibly be attributed to business cycles. Zhang (2005) claim that there is a relation between value premium and business cycle. This thesis, in turn, examines whether value premium can be explained by the stages of the business cycle. The OECD CLI index is used as a proxy of the business cycle factor. The business cycle factor is added to the three-factor model. A positive and statistically significant coefficient of the business cycle factor is observed. This suggests that the value premium is positively associated with the stages of the business cycle. Therefore, the value premium increases during economic expansion and decreases during economic contraction. During economic expansion, investors are more optimistic and have more confident to invest in value stocks (which are riskier than growth stocks). A possible explanation of the positive relation between value premium and business cycle is that the increase in investment volume of value stocks leads to increases in their price and as a result higher returns. .

The value premium of some industries is also partially explained by business cycles i.e. the value premiums of Consumer Durables, Manufacturing, Business Equipment, Shops, and Health. These industries (except Health) produce luxurious goods, which tend to produce higher profits during economic expansion relative to economic contraction periods. The purchase and consumption of such products can be postponed during economic downturns. Regarding the Health industry, during economic contraction people may be unable to afford the high cost of private hospitals. Therefore, people tend to use government healthcare (i.e. public hospitals) during that period. During an economic boom, people are more able to afford the high cost of private hospitals in order to receive a higher quality service. The Health industry, thus, also experiences higher profits during economic boom. The business cycle, however, is unable to explain value premiums in Consumer Nondurables, Chemicals, and Energy industries. These three industries produce goods whose consumption is not considerably different between economic expansion and contraction periods. It can be concluded thus that the, value premium is affected by different factors depending on the type of industry under consideration. To the best of the author's knowledge, this is a new finding regarding the relation between value premium and stages of the business cycle.

This finding is, however, inconsistent with the that of Zhang (2005) who argue that the value premium is expected to be higher during economic contraction. This inconsistent result is possibly due to the measurement of business cycle. Zhang (2005) employed NEBR business cycle turning point, which indicates economic expansion and contraction based on the classic cycle approach. This thesis, however, uses the OECD CLI index, which indicates economic expansion and contraction based on the growth cycle approach. Another possible explanation is sample specific. This thesis covers a longer sample period expanding after 2005. Consequently, the length of economic expansion and contraction are different.

As shown above, stages of the business cycle partially can explain the value premium. An increase in value premium is documented during periods of economic expansion due to investor overconfidence. As a result, investors' sentiment may be another factor related to value premium. Investors' sentiment, is, in turn, incorporated into the three-factor model to investigate its association with the value premium. The statistical insignificant coefficient of investors' sentiment suggests that there is no important relation between value premium and investors' sentiment. This is consistent with the findings of Xing (2008) that the value premium cannot be attributed to investor under/over reaction. Similarly, investors' sentiment does not seem to be able to explain value premium in at industry level. This thesis, then, concludes that value premium is left unexplained by risk and investors' sentiment but can be explained by the business cycle factor.

5.3 Corporate Solvency and Investment Profitability

The final issue that is investigated in this thesis is whether high solvent stocks generate superior returns compared to low solvent stocks and the extent to which these returns can be explained by risk, business cycle and investors' sentiment. The trading strategy that is based on corporate solvency suggests taking long positions (buying) in high solvent stocks and short positions (selling) in low solvent stocks.

Stocks are classified as solvent according to 8 different measures, namely debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, equity multiplier, interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio. The findings show that this trading strategy generates statistically significant profits, known as solvency premium. The solvency premium is documented during short-term holding periods (3 and 6 months). The highest solvency premium of 0.96% (per month) is observed when stocks are characterized as solvent or non-solvent based on their cash-flow coverage ratio and portfolios are held for 3 months. This finding suggests that investors should take long positions in stocks with high cash-flow coverage ratios and short positions in stocks with low cash-flow coverage ratios.

The solvency premium, however, reverses to solvency discount when portfolios are held for longer periods, in particular for 12 and 24 months. This finding suggests that investors should take long positions in low solvency stocks and short positions in high solvency stocks during long-term holding periods (12 and 24 months). The highest solvency discount of 1.21% (per month) is documented when the level of solvency is measured by the debt to equity ratio and portfolios are held for 12 months. Overall, in order to profit from this trading strategy, investors should take long positions in high solvent stocks (low solvent stocks) and short positions in low solvent stocks (high solvent stocks) during short-term (long-term) holding periods. For example, if investors would like to invest for a long period (i.e. holding portfolios for two years), they should take long positions in low solvent stocks and short positions in high solvent stocks to make profits. The empirical results confirm the profitability of this solvency-based trading strategy which has never been rigorously observed before. This finding sheds new light into the area of stock trading introducing a novel equity trading strategy based on corporate solvency.

As explained above, the results confirm the existence of solvency premium and solvency discount. The next question is whether risk, business cycle, and investors' sentiment can explain this solvency premium/discount. Firstly, the three-factor model (Fama and French, 1993) is employed to investigate whether solvency premium can be explained by risk. There is evidence that the solvency premium disappears or decreases after controlling for risk. This result suggests that the solvency premium can partially be explained by risk differences.

However risk cannot completely explain solvency premiums. Therefore, the thesis also investigates whether the business cycle can be an important explanatory factor of the solvency premium. Negative and statistically significant coefficients of business cycle factors are found indicating a negative relation between business cycle and solvency premium. In other words, the solvency premium is negatively affected by stages of the business cycle. The negative relation between the solvency premium and the stages of the business cycle suggests that there are high solvency premiums during economic contraction and low (or solvency discounts) during economic expansion. In terms of trading strategies, a high solvency premium during economic contraction suggests that investors should take long positions in high solvent stocks and short positions in low solvent stocks to make profits. On the other hand, during economic boom, investors should take long positions in low solvent stocks and short positions in high solvent stocks in order to earn superior returns.

Another explanatory factor that is examined with respect to the solvency premium/discount is investors' sentiment. A positive and statistically significant coefficient of the investors' sentiment factor is documented. This positive relationship between investors' sentiment and solvency premium suggests that investors tend to invest in high solvency stocks when they have more confidence in equity markets (the period of high investors' sentiment).

To sum everything up, the empirical evidence provided by this thesis confirms that the trading strategy which is based on corporate solvency generates superior profits that are partially explained by risk, business cycle, and investors' sentiment. This is a novel trading strategy revealed by this thesis and a contribution to style investing due to the superior returns associated with a specific group of asset.

5.4 Implication of Findings and Recommendations for Future Research

5.4.1 Implications of Finding

This thesis reveals that superior returns can be earned following conventional contrarian trading strategy, value versus growth trading strategy, and solvency based trading strategy. The contrarian trading strategy, based on historical patterns of stock returns, uses technical analysis to identify profitable investment choices. Even if the random walk theory suggests that stock prices should be independent and should not be predictable based on past movements (Horne and Parker, 1967), the technical analysis suggests that historical trend is a good indicator of future movements. This thesis provides evidence in support of the technical analysis's claim that trading strategies based on historical patterns can be profitable.

The other two trading strategies (i.e. value versus growth and corporate solvency based trading strategies) are based on fundamental analysis using the fundamentals value of assets to form portfolios. The value investing style is based on the belief that value stocks can outperform growth stocks while the corporate solvency investing style supports that high solvent stocks generate higher returns relative to low solvent stocks during short-term holding periods. In other words, firms with good fundamentals are expected to experience higher stock returns.

The finding of this thesis provides several insights to investors into the cause of superior returns from these three trading strategies. Firstly, the relation between the business cycle factor and solvency premium/discount is revealed. During economic expansion, solvency discount is expected to be high due to investors' overconfidence. Investors have more confident about investing in riskier assets (i.e. low solvent stocks) to earn higher returns during economic boom. The increase in demand of these assets leads to increase in asset prices and, consequently, to higher stock returns. Therefore, solvency discount increases during economic boom. On the other hand, during economic contraction the investors have to deal with uncertain situations. They tend to avoid investing in high risk assets and they prefer to invest in assets with good fundamentals (i.e. high solvent stocks). As a result, the solvency discount reverses to solvency premium during this economic stage. The implication of these findings for investors is that they should invest in low solvent stocks during economic boom and in high solvent stocks during economic contraction to maximise their profits.

However, it's not only investors who can benefit from these findings but also fund manager. The finding show that the value premium in Consumer Durables, Manufacturing, Business Equipment, Shops, and Health sectors can be explained by business cycle. These types of business experience higher profits during economic expansion relative to periods of economic contraction. Allocating fund based on this finding should be another choices for fund manager. The fund manager should consider investing in these types of business only during economic expansion but avoiding these types of business during economic contraction. The fund manager may consider investing in Consumer Nondurables, Chemicals, and Energy industries during economic contraction. These three industries are neutral in different business cycles. Specifically, there is no negative impact during economic contraction.

The second implication of the results is related to the profitability of these three trading strategies (i.e. conventional contrarian trading strategy, value versus growth trading strategy, and corporate solvency based trading strategy) and can form evidence against the weak form of efficient market hypothesis (EMH). Efficient market hypothesis claims that stock prices completely reflect all available information and it is therefore impossible to outperform the market (earn superior returns) by investing in specific group of assets.

The profitability of historical pattern-based trading strategies is documented in several studies (see e.g. Blitz et al. (2013)) and confirmed in this thesis. The profitability of these trading strategies is also evident at international level (see e.g. Kang et al. (2002)). The evidence provided by this thesis suggests that past winners will experience a stock price underperformance while past losers will experience a stock price overperformance. As a result, the thesis shows that past losers outperform past winners in terms of stock price returns.

The value versus growth trading strategy is associated with superior return in earlier studies (see e.g. Chen et al. (2008)) which is also confirmed in this thesis. Apart from the US stock market, value premium is also documented in 3 other regions worldwide: Asia Pacific, Europe, and North America (Fama and French

2012). The value investing strategy uses the financial ratios (i.e. book to market ratio, earnings to price ratio, and cash-flow to price ratio) to form portfolios. This thesis provides empirical evidence in support of the view that value firms outperform growth firms which in turn suggests that value versus growth trading strategies can generate superior returns.

The solvency-based investing style also employs the ratios of assets (i.e. debt to assets ratio, long-term debt to assets ratio, debt to equity ratio, equity multiplier, interest coverage ratio, fixed charge coverage ratio, cash flow coverage ratio, and cash flow to debt ratio) to form portfolios in order to generate superior returns. The solvency premium is documented during short-term holding periods while the solvency discount is evident during long-term holding periods. The profitability of corporate solvency based trading strategies is documented in this thesis.

Overall this thesis shows that investing in specific group of assets generates superior return i.e. contrarian profits (investing in past losers), value premiums (investing in value stocks), and solvency premium/discount (investing in high solvency stocks in short-term holding periods and in low solvency stocks in long-term holding periods). The findings from this thesis can, therefore, be considered as evidence against the weak form of efficient market hypothesis.

5.4.2 Recommendations for future research

The findings of this thesis can be the root to explain real investing. Short selling was employed to capture the profitability of historical pattern-based trading strategies, value versus growth trading strategies, and corporate solvency based trading strategies. The profitability of these strategies is defined as the difference in returns between a long position portfolio and a short position portfolio. Short selling, however, is not feasible for all stocks; in other words, short selling is not allowed for all type of stocks. The analysis presented in this thesis is subject to this limitation.

The second limitation of this thesis is related to transaction costs. Previous studies (see e.g. Avramov and Chordia (2006)) claim that abnormal returns from market anomalies will decrease or disappear when transaction costs are taken into account. This thesis, however, does not take the transaction costs into account due to data limitation. Therefore further research is suggested in order to take those aspects into consideration.

This thesis is examined based on many financial assumptions such as (a) short selling and (b) no transaction cost that are difference from the real investing. The investor should not follow only the results of this thesis in order to make a decision to invest. However, this thesis can be one of supporting reasons before the investor make a decision.

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Appendices

Appendix A

The OECD business cycle turning point provides a business cycle based on the growth cycle approach. The expansion starts immediately after the economy reaches a trough of economic activity and ends when the economy reaches its peak. From its peak to its trough, economy is in a contraction. The business cycle turning points are reported in the table below.

Business cycle turning references date		**Duration in months**	
Peak	**Trough**	**Peak to Trough**	**Trough to next peak**
	October 1949	-	22
August 1951	June 1954	34	15
September 1955	April 1958	31	14
June 1959	February 1961	20	14
April 1962	March 1963	11	36
March 1966	September 1967	18	18
March 1969	November 1970	18	30
May 1973	April 1975	23	43
November 1978	November 1982	48	34
September 1985	March 1987	18	27
June 1989	August 1991	26	37
September 1994	December 1995	15	53
May 2000	February 2003	33	56
October 2007	May 2009	19	35
April 2012	April 2013	12	24
April 2015		-	-

Appendix B

The table below represents the total number of firms and number of firms in 12 different fiscal year-ends for each ratio. The considered ratios are (a) the component percentage solvency ratios: debt to assets ratio (DA), long-term debt to assets ratio (LDA), debt to equity ratio (DE), and equity multiplier (EM), and (b) coverage solvency ratios: interest coverage ratio (IC), fixed charge coverage ratio (FCC), cash flow coverage ratio (CFC), and cash flow to debt ratio (CFD).

Measure of solvency	Fiscal year-end (number of firms)												Total (number of firms)
	1	2	3	4	5	6	7	8	9	10	11	12	
DA	708	274	1095	369	362	1484	368	351	1128	428	275	9119	15961
LDA	708	274	1095	369	362	1484	368	351	1128	428	275	9120	15962
DE	707	272	1076	363	358	1470	360	344	1106	419	269	8976	15720
EM	707	272	1076	363	358	1471	360	344	1106	419	269	8984	15729
IC	586	221	816	273	277	1107	286	280	870	345	219	6785	12065
FCC	584	222	814	274	275	1099	287	281	866	350	220	6756	12028
CFC	445	166	659	196	194	850	196	195	699	239	158	6149	10146
CFD	447	166	676	197	195	879	201	189	722	244	155	6380	10451