Essays in Behavioural Finance and Investment

A thesis submitted for the Degree of Doctor of Philosophy

By

Mohamed Ahmed Shaker Ahmed

Department of Economics and Finance

College of Business, Arts and Social Sciences

Brunel University London

London, United Kingdom

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Abstract

This thesis is an attempt to bridge some research gaps in the area of behavioural finance and investment through adopting the three essays scheme of PhD dissertations.

There is a widespread belief that the traditional finance theory failed to provide a sufficient and plausible explanation for (1) what motivates individual investors to trade, (2) the pattern of their trading and the formation of their portfolios, (3) the determinants of cross section of expected returns other than risk. Behavioural Finance, however, offers more realistic assumptions based on two building blocks; behavioural biases of irrational investors and the limits of arbitrage that prevent the arbitrageurs from correcting mispricing and pushing prices back to fundamental values. This dissertation is structured as follows:

In the first essay, the disposition effect is defined as the propensity of investors to realize gains too early while being loath to realize losses. Capital gains overhang is a measure of unrealized capital gains and losses that is associated with the disposition effect and the trading activities of behaviourally biased investors. We discover that firm characteristics can play a role in explaining variations in the capital gains overhang that is consistent with the activities of behaviourally biased and disposition investors. Specifically, we find that capital gains overhang is increasing in firm attributes that attract behaviourally biased investors, namely, earnings per share, leverage, growth and size. Capital gains overhang is also declining in market liquidity, possibly because liquidity allows behaviourally biased investors to excessively trade shares and beta and corporate earnings, probably because when high risk and inefficient firms experience losses, disposition investors experience capital losses that they are reluctant to realize.

In the second essay, quantile regressions are employed to analyse the relationship between the unrealized capital gains overhang and expected returns. The ability of the disposition effect to generate momentum is also considered for the extreme expected return regions (0.05^{th}) and (0.95^{th}) quantiles. To do so, 450,617 observations belonging to 5176 US firms are employed, covering a time span from January 1998 to June 2015. Following the methodology of Grinblatt and Han (2005), the findings show significant differences across various quantiles in terms of signs and magnitudes. These findings indicate a nonlinear relationship between capital gains overhang and expected returns since the impact of capital gains overhang as a proxy for disposition effect on expected returns vary across the expected

return distribution. More precisely, the coefficients of capital gains overhang are significantly positive and decline as the expected returns quantiles increase from the lowest to the median expected return quantiles. However, they become significantly negative and rise with the increase in expected returns quantiles above median expected returns quantiles. The findings also suggest that the disposition effect is not a good noisy proxy for momentum at the lowest expected return quantile (0.05^{th}). However, interestingly it seems to generate contrarian in returns at the highest expected returns quantile (0.95^{th}).

In the third essays, we try to discover systematic disagreements in momentum, asymmetric volatility and the idiosyncratic risk-momentum return relationship between high-tech stocks and low-tech stocks. We develop several hypotheses that suggest greater momentum profits, fainter asymmetric volatility and weaker idiosyncratic risk-momentum return relation in the high-tech stocks relative to the low-tech stocks. To this end, we divide 5795 stocks that are listed in the Russell 3000 index from January 1995 to December 2015 into two samples SIC code and analysed them using the Fama-French with GJR-GARCH-M term. The results show that the high-tech stocks provide greater momentum profits especially for portfolios that have holding and ranking periods of less than 12 months. In most cases momentum returns in the high-tech stocks explain a symmetric response to good and bad news while the momentum returns in the low-tech stocks show an asymmetric response. Finally, the idiosyncratic risk-momentum return relation is insignificant for high-tech stocks while it is significant and negative for low-tech stocks. That is, as idiosyncratic risk increases, momentum decreases for low-tech stocks. These findings are robust to different momentum strategies and to different breakpoints.

Dedicated to my Family

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Declaration

"I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree or award, other than that of the PhD, being studied at Brunel University London. I declare that all the material presented for examination is entirely the result of my own investigations except where otherwise identified by references and that I have not plagiarised another's work. In this regard, this thesis has been evaluated for originality checking by the University library through Turnitin plagiarism detection software prior to the formal submission. I also grant powers of discretion to the University Librarian to allow this thesis to be copied in whole or in part without the necessity to contact me for permission. This permission covers only single copies made for study purpose subject to the normal conditions of acknowledgement."

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Chapter One

Introduction

The objective of this chapter is to present an overview of this thesis. In the first section, the motivation of the thesis is presented. In the second section, the theoretical development towards the behavioural paradigm shift is outlined. In the third section, we introduce an overview of the thesis including the research motivation, the objectives of each empirical paper, key contributions and main findings.

1.1- Motivation of the thesis

> *Traditional finance assumes that we are rational, while behavioural finance assumes we are normal.*
>
> ____*Meir Statman*[1]

The first and foremost motivation of this thesis is the unrealistic assumptions of the standard finance based on CAPM/EMH framework. The standard finance studies financial phenomena assuming all investors are rational, well-informed, process all available information properly, process it and take rational decisions. Empirical evidence in the literature denied these assumptions and documented that investors oftentimes behave differently.

Behavioural finance, however, is a research discipline that uses psychological theories for explaining and understanding investment decision-making. It studies finance from wider perspective that intersects finance and economics with psychology and sociology. In contrast to standard finance, the necessity of behavioural finance comes from a considerable amount of literature in psychology revealed that people commit systematic cognitive errors in decision making process based on bounded rationality and cognitive limitations. These errors stem from investors' preferences or improper beliefs such as overconfidence, regret avoidance, fear of loss, disposition effect, framing, mental accounting, naïve diversification, anchoring, availability bias, representativeness bias and conservatism bias, and cause impermanent excess supply or excess demand leading to temporary mispricing. Another

[1] See Gregory Curtis (2004) P.16

rationale for the necessity of behavioural finance is financial anomalies. Theses anomalies can be defined as systematic empirical patterns that are explained by traditional CAPM/EMH framework such as momentum, size effect, value effect and turn-of-the-year. While the CAPM was genuine idea to capture the risk-return relationship, it experienced many empirical failures in explaining such anomalies.

Additionally, under the framework of standard finance it is often said arbitrageurs sell overpriced stock short and buy underpriced stocks long to correct any mispricing caused by irrational investors who prone to cognitive errors. This claim is unrealistic due to risk embodied in the long and short position or constraints on short selling or implementation cost. Moreover, arbitrageurs sometimes prefer not to trade or enter the market when the mispricing is too large.

1.2- Towards a behavioural paradigm shift

The clue of efficient market hypothesis devised by Eugene Fama first appeared in Journal of Business (1965). According to this hypothesis, Stock prices reflect all available information on capital assets (Frankfurter & McGoun, 2002). Fama (1970) then developed three different forms of informational efficiency, namely, weak form, semi-strong and strong market efficiency.

Weak Form Market Efficiency- The current stock price fully reflects all information embodied in historical prices and volume.

Semi-Strong Market Efficiency- the current stock price reflects historical price and volume data as well as all publically available information including news, analysts' reports and company reports.

Strong Market efficiency- The current stock price reflects not only historical price and volume data, but also all public and private information.

Sharpe (1964) and Lintner (1965) develop the capital asset pricing model (CAPM) which is an intuitive model to measure the investment risk and to capture the relation between risk and expected returns. The CAPM depends on three assumptions: first, the capital market is perfect which means there are no transaction cost or taxes and information is available and can be obtained without costs. As a result, investors can lend and borrow at the risk-free rate. Second, the homogenous expectation assumption; this assumption is that all investors have the same expectations, and they are all rational and they are risk-averse. Third, the CAPM assumes all investors have only one holding period and they use expected return and standard deviation of return in evaluating their portfolios (Perold, 2004). However, the empirical tests indicate that unsatisfying performance of the CAPM is attributable to the very simplified and unrealistic assumptions (Fama & French, 2004). The efficient market hypothesis (EMH) and the capital asset pricing model (CAPM) framework are the hub of standard finance theory (Statman, 1999) and the word 'anomaly' is always used to refers to the stream of research that focuses on the empirical invalidity of EMH/CAPM framework.

Schwert (2003) provides a comprehensive summary of all anomalies in finance literature on the following lines:

Size effect- the term size effect is used to point out the negative relation between size and average returns. Banz (1981) proved that small firms provide 0.40% higher average monthly returns than the other stocks did, using data on NYSE from 1936 to 1975[2]. Reinganum (1981) empirically supports the same anomaly through proving the small firms give higher average returns than large firms do.

The value effect- the value effect is used to point out that the firms with high ratios of Earnings to price (E/P) and book-to-market provide higher average returns than firms with low ratios of Earnings to price (E/P) and book-to-market ratio do. Basu (1977) in his seminal paper was the first to document the value effect. Basu (1977) found that stocks with higher value-related variables such as earnings per share (P/E) can make positive abnormal returns. He also confirmed that the CAPM could not provide an explanation for this behaviour.

Momentum effect- Jegadees & Titman (1993) form wide range of momentum strategies using market data from 1965 to 1989. They reveal that momentum strategies which entail buying past winners (stocks that have high returns over the previous three months to one year) and selling past losers (stocks that have low returns over the previous three months to one year) can generate monthly average returns of 1% for the next year.

[2] See Van Dijk (2011) P.3264

The turn-of-the-year effect / 'January Effect'- this anomaly has two interpretations: the first hypothesis is the tax-loss-selling-pressure hypothesis. According to this hypothesis, individual investors tend to realize capital losses by selling stocks that have gone down in prices during the year. These capital losses help them reduce their year-end tax liability and create selling pressure through an increase in the number of transactions, leading to a drop in year-end stock prices (Berges, McConnell, & Schlarbaum, 1984). The second hypothesis is the window dressing hypothesis. According to this hypothesis, institutional investors tend to rebalance their portfolio holdings before the end of the year through selling losers and buying winners, hoping to enhance the perceived performance (Haug & Hirschey, 2006).

The weekend effect- French (1980) is the first to use the term 'weekend effect'. He employed data on S&P 500 composite index from 1953 through 1977, and found negative average returns on Mondays and positive otherwise.

The empirical success of previous anomalies and the challenging role they play in the traditional framework EMH/CAPM show the need for a change from traditional framework EMH/CAPM to behavioural theory. The behavioural theory of finance has two pillars:

Limits to arbitrage- Shleifer & Vishny (1997) criticize the description of arbitrage as a no capital and no risk process which entails buying and selling similar financial security in two different markets to make profits through benefiting from different prices. Traditional finance assumes that arbitrage mechanism maintains market efficiency by assuming investors mistakes would impact on the market prices and pushing prices away from the fundamental value, while arbitrageurs -'rational investors'- are always going to benefit from any mispricing to make profits and correct any devation from the fundemental value. However, behavioural finance defenders believe that market prices are not fair.

In theory institutional investors play the role of rational investors because they have the required knowledge, analysts and wealth but they also have benefits to urge the way of trading that causes mispricing and motivates inefficiency (Baker & Nofsinger 2010). Barberis & Thaler (2003) mention that the limits to arbitrage that may prevent arbitrage and keep the market inefficient include: (1) fundamental risk because the short and long positions are prone to mismatch; (2) noise trader risk because the mispicing could be too large to be corrected and may lead to bankrupting the arbitrageurs; (3) Implementation cost. Thus, the limits to arbitrage may hinder the arbitrageurs from correcting any mispricing.

Behavioural biases- Ritter (2003) lists the key behavioural biases in the literature of behavioural finance as follows:

1- Heuristics or rules of thumb: the employment of rules of thumb facilitates the decision making process but can also cause cognitive biases**.** Benartzi and Thaler (2001) discover that several investors follow the *1/N* rule. For instance, if they encounter three alternatives that are available for investing their money, they allocate one-third of their money to each fund[3].

2- Overconfidence: overconfidence means that people sometimes overestimate their skills and capabilities. There are several forms of overconfidence such as insufficient diversification that may lead investors to over-invest in one asset. For instance, the finance literature documents that men are usually have higher levels of confidence than women but that women tend to outperform men.

3- Mental Accounting: mental accounting means that people tend to split decisions that should not be split. This may also lead to cognitive biases, for example, if several people allocate separate budgets for food and entertainment. They eat simple fish at home because shrimp is more expensive than fish but they prefer to eat shrimp at restaurant although the cost is higher than that of simple fish. If they combined eating at home and in restaurants they could save money through choosing to have shrimp at home and simple fish in restaurants.

4- Framing : framing concerns how an idea or term is exhibited to people. In other words, it deals with ways of expression. For instance, cognitive pychologists found that doctors give one set of prescriptions and treatments if a diagnosis is presented in the form of survival probabilities and another set if it is presented in the form of mortality probabilities in spite of the fact that the survival probabilities and mortality probabilities together totalled 100%.

5- Representativeness /'Law of small numbers': representativeness means that people have a propensity to overweigh contemporary events and underweigh ancient events. For instance, if the equities generate a high return for many years in succession, some investors start to believe that a high average return is customary.

[3] See Ritter (2003) P. 431.

6- Conservatism: representativess and conservatisim battle against each other. While representativeness leads to underweighing rates, people sometimes romanticize the base rates. In other words, when a change occurs, people tend to stick to the initial values and react slowly to the change. Therefore, the consevatism bias can be considered one source of underreaction.

7- Dissposition effect: the disposition effect is the tendency of investors to realize gains too early and hold losers too long. For instance, if somebody purchases a stock at $10, which then goes down to $6 before going up to $8, most people are not willing to sell until the stock price exceeds $10. Through the disposition effect, investors try to realize plenty of small gains, and a few minimal losses. In other words, their decision conforms with taxes maximization behaviour. The disposition effect comes out in aggregate trading volume since stocks tend to have a higher trading volume during bull markets and a lower trading volume during bear markets.

1.3- Overview of the thesis

The main focus of this thesis is to shed more light on the field of behavioural finance as one of the most important topics in finance theory. In doing so, the researcher submits three empirical papers and adds a chapter for data. The overall structure is as follows:

In Chapter 2, we provide a brief description of the Russell 3000 index together with its key characteristics; it is used throughout the thesis. The survivorship bias and some potential ruinous effects of survivorship bias are discussed and reviewed in chapter 2, since we updated our list of stocks each month to free our dataset from survivorship bias. Finally, this chapter details the definitions of all the variables used throughout the thesis and gives some descriptive statistics for each variable.

The main motivation of chapter 3 is, there was a belief in the literature that irrational investors trade randomly and there is no systematic pattern beyond their trading. We motivated by whether the irrational investor trade systematically or not.

Chapter 3 is dedicated to testing whether or not irrational investors prefer to buy and keep stocks of good companies. As a result, a number of characteristics of good companies are chosen such as their earnings per share (‘EPS’) as proxy for profitability, leverage as proxy for debt burden of a company, cash flow to price as a proxy for corporate liquidity, market to book ratio as proxy for growth opportunities and market capitalization as proxy for corporate size, and two market variables, namely, turnover and company beta as independent variables to run a panel regression model against capital gains overhang which is estimated following Grinblatt and Han (2005). The sample in this chapter contains 5,091 stocks and 422,278 observations between January 1995 and September 2014. This chapter makes three contributions: the first contribution is highlighting the characteristics of good companies and linking these characteristics with capital gains overhang, which is novel and viable, to check how attractive these characteritics are to irrational investors and whether those investors really believe that "good stocks are the stocks of good companies" and decide to engage in trading it accordingly. The second contribution is our sample has several unique features: first, it contributes to the literature because we include all firms listed on Ruseell 3000 index, which consists of the large cap Russell 1000 index and the small cap Russell 2000 index. This means that our sample contains more smaller stocks than the literature has yet used; another unique feature is that, NASDAQ stocks represents up to 20% of our sample, while NASDAQ is completely ignored in the literature on disposition effect; Finally, to the best of our knowledge we are the first in the literature of disposition effect to construct a sample that is free from survivorship bias. The presence of survivorship bias leads to spurious findings and will make the reference price reflects stale price rather than disposition investors' beliefs.

Our findings suggest that market variables; turnover and beta are negatively related to capital gains overhang. The cash flow to price is the only firm characteristic that shows a negaive relation to capital gains overhang, but all other firm characteristics such as stock EPS, leverage, market to book ratio and size are positively related to capital gains overhang. The coefficients of most of the above variables are stable over time since we run a cross section regression for each year and they are robust to growth measured by market to book ratio, systematic risk measured by beta, size measured by market capitalization, turnover, and financial crisis, since we divided our sample into before and after crisis, and they are also robust to capital gains versus capital losses.

The main motivation of chapter 4 is the disadvatages of the conventional OLS methods that gives partial view of the relationship between dependent and independent variables through providing only one estimate that consider the average relationship of the dependent and each independent variable. Another important disadvantage of the conventional OLS technique is ignoring all information near the extreme regions.

Chapter 4 re-examines the momentum and disposition effect using the quantile regression approach. Quantile regression is suggested to address the shortcomings of conventional OLS methods that are: first, the OLS conventional technique is not a good tool for estimating the extreme observations or the tails of a probability distribution. Second, the OLS conventional technique produces one estimate to capture the mean relationship between the dependent and each independent variable and ignores the heterogenous impact of the independent variable on the dependent variable across the distribution. Finally, quantile regression is better at dealing with some unlikelable characteristics such as heteroscedasticity, skewness and heavy-tailed distribution.

Once again, we use all the stocks listed on the Russell 3000 index between January 1998 and June 2015. This sample involves 5,176 stock and 450,617 observations.

This chapter has many developments of the theory of disposition effect which can be summarized as follows. First, this paper is the first to use quantile regression in dealing with the determinants of capital gains overhang. Second, this paper is the first to investigate the relation between expected return and capital gains overhang using quantile regression technique. Third, this paper is the first to check the capability of disposition effect to generate momentum for the highest and lowest expected return quantiles (0.05^{th}) and (0.95^{th}). Fourth, this paper is the first to use all the stocks listed on the Russell 3000 index which is characterized by more smaller stocks and includes around 20% of NASDAQ stocks the way in which are ignored in the literature due to data unavailability. This paper is also the first in the literature of momentum and disposition effect to use a sample that is free of survivorship bias.

This chapter has many new findings that can be structured as follows:

1- the determinants of capital gains overhang

In this section, we regress capital gains overhang on: (1) Cumulative returns over three different horizons, namely, the short horizon of the last three months ($r_{-3:-1}$); the intermediate horizon between the last four months and 12 months ($r_{-12:-4}$); and the long horizon between the last 13 months and 36 months ($r_{-36:-13}$), (2) The average turnover over three different horizons, namely, the short horizon of the last three months ($V_{-3:-1}$), the intermediate horizon between the last four months and 12 months ($V_{-12:-4}$) and the long horizon between the last 13 months and 36 months ($V_{-36:-13}$). (3) Size. The most important findings here can be highlighted as follows:

There is a heterogeneous and systematic impact of short-term cumulative returns, long-term cumulative returns and size on capital gains overhang since the coefficients of short-term cumulative returns, long-term cumulative returns and size declines systematically with the increase in capital gains overhang quantiles. The relation between the three above-mentioned variables and capital gains overhang is significantly positive. Another new finding, the theory suggests a negative relation between average turnover and capital gains overhang because the higher the turnover, the faster the reference price converges to the market price. However, in the highest capital quantile (0.95^{th}), the relation between short and long-term average turnover and capital gains overhang is positive and significant. In the lowest capital gains overhang quantile (0.05^{th}), the relation between short-term average turnover and capital gains overhang is also positive, suggesting that the higher the turnover, the more slowly the reference price converges to the market price which creates a higher capital gains overhang. All the above findings are robust to size, leverage and institutional ownership.

2- The expected returns, past returns and unrealized capital gains

In this section, we regress capital gains overhang on: (1) Cumulative returns over three different horizons, namely, the short horizon of the last three months ($r_{-3:-1}$), the intermediate horizon between the last four months and 12 months ($r_{-12:-4}$), and the long horizon between the last 13 months and 36 months ($r_{-36:-13}$). (2) Average monthly turnover over the past 12 months. (3) Size. (4) Capital gains overhang. The most important findings here can be highlighted as follows: The first finding is the relation between expected returns and capital gains overhang is nonlinear since the relation is positive and significant at and below the median points. At the median and below the median points the coefficients systematically decrease with the increase in expected return quantiles. At the above median quantiles, the relation between expected returns and capital gains overhang is significantly negative and the coefficients systematically increase with the increase in expected returns quantiles. These findings can be interpreted to suggest that irrational investors follow the disposition behaviour at the median and below the median points but they follow the opposite behaviour at above the median data-points. The second finding is the relation between expected returns and short-term cumulative returns is always significant and positive (‘persistence in returns’).

The coefficients systematically increase with the increase in expected returns quantiles. All the above findings are robust to size, leverage and institutional ownership.

3- Disposition effect and momentum

Based on the Grinblatt and Han (2005), three stages are followed to examine the ability of the disposition effect to drive momentum by running Fama-MacBeth (1973) two-step procedures and quantile regression with and without capital gains overhang as follows:

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V \quad (1)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S \quad (2)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g \quad (3)$$

where ($r_{-3:-1}$), ($r_{-12:-4}$) and ($r_{-36:-13}$) are the cumulative return over the short, intermediate and long horizons respectively, V is the volume effect measured by average monthly turnover in the past 12 months. S is firm size proxied by the logarithm of market capitalization and g is unrealized capital overhang.

Using the mechanism of before and after controlling for capital gains overhang, we find that at the lowest (0.05^{th}) expected returns quantile, disposition effect is not a good noisy proxy for intermediate momentum, while at the highest (0.95^{th}) expected returns quantile, the disposition effect induces intermediate contrarian rather than momentum. All the above findings are robust to size, leverage and institutional ownership.

Before I go to the chapter 5, it looks plausible to link the first two empirical papers with the third empirical paper. Basically, the main cornerstone of this work to emphasize the key role of human being in forming social phenomena either this human exists inside the firm or outside it in the market. The first two papers address the investor behaviour in the equity market and how this behaviour creates some patterns in returns and prices. The third empirical paper emphasizes this role by focusing on human capital inside the firm and the way this human capital through research and development activities, whish is key feature of high-tech firms, may produce unique patterns and unique relations.

The main motivation of chapter 5 is the growing importance of intangible assets since it represents a significant portion of many leading companies. Moreover, this kind of assets has a unique nature. Therefore, we expect this uniqueness to produce new phenomena and new relationships in finance theory. In this chapter, we shed some light on momentum, asymmetric volatility and idiosyncratic risk-momentum returns relation.

Chapter 5 aims to detect the systematic differences in momentum returns, asymmetric volatility and idiosyncratic risk-momentum returns relationship between high-tech stocks and low-tech stocks using all stocks listed on Russell 3000 index between January 1995 and December 2015. To free our sample from survivorship bias, the list of stocks was updated every month which leads the number of stocks to go up to 5795 stocks. The methodology Jagadeesh and Titman (1993) is followed to construct a range of momentum portfolios and the Fama-French model with GJR-GARCH-M term is employed to test our hypotheses.

This chapter like the two previous chapter makes many contributions to the literature, which can be summarised as follows: to our knowledge, we are the first to investigate the systematic differences in momentum returns between high-tech stocks and low-tech stocks. Second, to our knowledge, we are the first to investigate the systematic differences between high-tech stocks and low-tech stocks as to whether the variance responds symmetrically or asymmetrically to good and bad news. Third, to our knowledge, we are the first to investigate the systematic differences in idiosyncratic risk-momentum return relation between high-tech stocks and low-tech stocks. Finally, to our knowledge, we are the first to compare the performance of the Fama-French model with GJR-GARCH-M term in explaining momentum returns in high-tech stocks with low-tech stocks.

This paper has many promising findings since we have succeeded in exploring several systematic differences in momentum returns, symmetric or asymmetric volatility, idiosyncratic risk-momentum returns relation and the performance of the Fama-French model with GJR-GARCH-M term in explaining momentum returns between high-tech stocks and low-tech stocks. The first finding has two integral dimensions: the first one indicates that the momentum returns in low-tech stocks never outperform the momentum returns in high-tech stocks. The second dimension indicates that four momentum strategies explain the larger and robust momentum returns in high-tech stocks relative to low-tech stocks, namely, the 3-3 strategy, the 3-6 strategy, the 6-3 strategy and the 6-6 strategy. This finding is robust to different breakpoints. The second finding indicates that the volatility of high-tech stocks responds symmetrically to good and bad news. However, the volatility of low-tech stocks responds asymmetrically to good and bad news. This finding is robust to different breakpoints. The third finding indicates that there is no relation between idiosyncratic risk and momentum returns for high-tech stocks, while there is a negative relation for low-tech stocks. This finding is robust to different breakpoints. It is also consistent with (Lesmond, Schill, & Zhou, 2004) and supports the role of high transaction cost in limiting the arbitrage process rather than idiosyncratic risk, which makes the relation of idiosyncratic risk and momentum is weaker among high-tech stocks relative to low-tech stocks. However, this relation is negative for low-tech stocks. This means, For the high-tech stocks that experience the higher transcation costs due to higher information asymmetry, the transaction costs limit arbitrage among momentum stocks. For the low-tech stocks that experience lower transaction cost due to lower information asymmetry, idiosyncratic risk limits arbitrage among the reversal stocks. Finally, the performance of the Fama-French model with GJR-GARCH-M term in explaining momentum returns is better for the high-tech stocks than for the low-tech stocks. This finding is robust to different breakpoints and robust to the simplified version of Fama-French with GARCH-M term.

Chapter 6 of this thesis highlights the main conclusions along with some policy implications. It also discusses the research limitations and ends with some recommendations for future research.

Chapter Two

Data

2.1-Sample Selection

This thesis focuses on all stocks listed on the Russell 3000 index throughout all chapters. According to Bloomberg, the Russell 3000 Index is composed of 3000 large US companies, as determined by market capitalization. This portfolio of securities represents approximately 98% of the investable US equity market and includes the large cap Russell 1000 and the small cap Russell 2000 Indices. The choice of the Russell 3000 index comes from its comprehensiveness and its being representative of the market among other advantages, as follows:

Transparent: The Russell 3000 index is designed with open, published, and easy methodology for any financial expert to understand.

Representative of the market: The Russell 3000 index is designed to provide a broad and complete description of the whole market because it provides complete coverage of all stocks without gaps or overlaps.

Accurate and Practical: The Russell 3000 index is developed to provide not only accurate data but also accurate representation.

Furthermore, the methodology of the Russell 3000 index relies on a float-adjusted and market capitalization-weighted index to provide an objective and accurate description of the market. Since the size of firms change over time, the Russell 3000 index is rebuilt annually in June to maintain the accurate description of the market and to guarantee that firms continue to be placed in the appropriate Russell indices.

The list of stocks in the Russell 3000 index was updated each month to free the dataset from survivorship bias. Survivorship bias means that stocks tend to disappear after poor performance, leading to bias in the performance of indices, funds or stocks. Survivorship bias happens when a financial expert computes the performance using the 'survivors' of the current list only at the end of the period and remove the funds, or stocks that no longer remain. Since survivorship bias comes from removing the underperforming stocks, the results always change in one direction and this makes the results look better than they actually are.

Recent research in the finance literature demonstrates the negative effect of survivorship bias. For instance, Brown, Goetzmann, Ibbotson, & Ross (1992) focus on performance measurements in the period 1976 and 1987 and infer that studying the survivors leads only to weighty bias in the first and second moments of returns. They also document that the survivorship bias may lead to a spurious relationship between volatility and return. Elton, Gruber, & Blake (1996) target the performance of mutual funds and the impact of survivorship bias on performance. Elton, Gruber, & Blake (1996) highlight the necessity of amending the sample to include the survivors and delisted funds. The potential pitfalls of survivorship bias range from exaggerating the estimated returns to producing spurious correlations for the performance-relevant variables. Carhart, Carpenter, Lynch, & Musto (2002) measure the survivorship bias in performance ('fund's return'). They find the annual bias to be 0.07% for short term samples ('usually one year') and reach 1% for long term samples ('15 years period'). They also ascertain that containing survivors only has an impact on the relationship between fund characteristics and persistence in performance and impairs the persistence in performance. However, Aggarwal & Jorion (2010) report a much higher survivorship bias, averaging more than 5% a year. Rohleder, Scholz, & Wilkens (2011) measure the survivorship bias in small and large funds separately. In their study, small funds are more probably to disappear. Large funds are more able to stay alive during periods of underperformance since they can maintain the revenues from management salaries and incentives.

The sample selection yields a total of 9060 stocks and up to 734741 observations and covers the period between January 1995 and December 2015. The items include closing price, trading volume, shares outstanding, company beta, earning per share ('EPS'), leverage, cash flow to price, market to book ratio, market capitalization, institutional ownership, excess market returns and the 4-digit SIC code. All data are collected from Bloomberg except the excess market return, which is collected from the Kenneth R. French data library. Table 2.1 provides detailed definitions of all variables.

<<Table 2.1 about here>>

2.2- Descriptive Statistics

Table 2.2 explains the summary statistics of the variables used in the three following chapters. The table contains mean, standard deviations, median, minimum and maximum. trading volume and shares outstanding are used to compute turnover which is a proxy for market liquidity. Company beta is used as a proxy for systematic risk. EPS is a proxy for company profitability. Leverage is a proxy for the debt burden of the companies. Cash flow to price is a proxy for firm liquidity. The market to book ratio is a proxy for growth opportunities and market capitalization is a proxy for company size. All the figures in Table 2.2 are reported after winsorizing the data at the level of 2% to handle the problem of outliers. It is woth noting that the leverage has a very high mean because the finance sector represents around one-fifth of our sample.

<<Table 2.2 about here>>

Tables of results

Table 2.1. A description of the variables.

Variable	Definition
Closing price	The monthly closing price at the end of each month.
Trading Volume	The monthly total number of shares traded on a security during a specific month.
Shares outstanding	The combined number of primary common share authorized by the company; the number is also listed on the companies' balance sheet.
Company Beta	The sensitivity measure of the security returns to the volatility of S&P 500 index, which is the proxy for market index. To calculate this variable, Bloomberg employs the CAPM model and the two past years of weekly data.
EPS	Computed as net income available to common shareholders divided by the basic weighted average shares outstanding. Sum of the previous most recent 12 months (trailing 12 months).
Leverage	The monthly ratio of equity to debt.
Cash flow to price (CF/P)	The monthly ratio of cash flow to price.
Market to Book ratio (M-B)	The monthly ratio of market capitalization to book value.
Market Capitalization	The proxy for corporate size. It is the monthly monetary value of all outstanding shares and is calculated by the number of shares outstanding times the monthly closing price.
Institutional Ownership	Percentage ratio of freely traded shares held by institutions to the number of float shares outstanding.
Returns	The change rate in monthly closing price. Gross dividends are included in the calculation.

Table 2.1. (Continued)

Variable	**Definition**
Market excess return (R_m-R_f)	The excess market returns and is computed as returns on market index minus risk-free. This variable is obtained from the Kenneth R. French data library.
SIC code	We depend on a 4-digit code. SIC stands for Standard Industrial Classification. This code was developed by US government in 1937 in order to indicate which industry the company was affiliated to.

Table 2.2. Summary statistics

Variables	**Mean**	**St. Deviation**	**Median**	**Minimum**	**Maximum**	**Obs**
Closing price	27.123	24.995	20.020	2.586	135.534	723251
Volume (in thousands)	871.992	1672.265	245.700	380.3	8797.800	730504
Shares Outstanding (in millions)	125.000	218.000	48.800	6.505	1190.000	724226
Beta	1.041	0.839	0.957	-0.685	3.365	734094
EPS	1.147	1.969	1.070	-4.380	6.930	692991
Leverage	2.737	3.744	1.255	0.080	16.800	701182
CF/P	0.119	0.103	0.090	0.008	0.531	577810
M-B ratio	3.104	3.241	2.124	-1.885	17.069	698035
Market Cap. (in billion)	3.550	7.720	2.124	0.103	42.700	721583
Institutional Ownership	63.814	45.286	82.490	0.000	129.450	644816
Return (percentage)	0.873	12.249	0.465	-30.491	34.529	734094
Market excess returns (R_m-R_f)	0.006	0.043	0.012	-0.101	0.082	240

Chapter Three

Determinants of capital gains overhang

Abstract

The disposition effect is the propensity of investors to realize gains too early while they are loath to realize losses. Capital gains overhang is a measure of unrealized capital gains and losses that is associated with the disposition effect and the trading activities of behaviourally biased investors. We discover that value irrelevant firm characteristics can play a role in explaining variations in the capital gains overhang that is consistent with the activities of behaviourally biased and disposition investors. Specifically, we find that capital gains overhang increases in firm attributes that attract behaviourally biased investors, namely, earnings per share, leverage, growth and size. Capital gains overhang declines in market liquidity, possibly because liquidity allows behaviourally biased investors to excessively trade shares and beta and corporate liquidity, probably because when high risk and inefficient firms experience losses, disposition investors experience capital losses that they are reluctant to realize.

Keywords: Capital Gains Overhang, Value-irrelevant Characteristics, Disposition Effect, Behavioural Finance

3.1- Introduction

We relate unrealized capital gains and losses (hereafter unrealized capital gains) to the disposition effect, the tendency of behaviourally biased investors to excessively realize capital gains and to reluctantly realize capital losses. We also relate unrealized capital gains to firm level value irrelevant factors which we hypothesize behaviourally biased investors believe to be value relevant. In general, there is no rational reason why unrealized capital gains should relate to these factors other than by random occurrence. Therefore, we conduct extensive robustness checks to be sure that these factors do in fact systematically relate to unrealized capital gains. We find that these firm level factors are significantly related to unrealized capital gains in ways that are consistent with the activities of disposition and otherwise behaviourally biased investors. For the most part, these relationships are consistent in the robustness tests and in the very few instances where the relationships do change; they do so within the behaviourally biased investor paradigm.

Over the past three decades, many authors have challenged the traditional notion that market prices are rational and reflect only relevant information. Importantly, Grinblatt and Han (2005) introduce an analysis of the way in which irrational behaviour can cause mispricing via a prospect theory and mental accounting (PT/MA) framework. The essence of prospect theory entails that investors are more risk adverse when dealing with gains, but are less risk adverse when dealing with losses, where gains and losses are proportional to a reference point. Mental accounting is the mechanism that investors follow to determine these reference points. Grinblatt and Han (2005) also distinguish between two types of investors in the economy: rational investors and behaviourally-biased irrational investors. If the demand and supply of irrational investors overcome the demand and supply of rational investors, irrational investors are expected, according to the Grinblatt and Han (2005) model, to push prices away from fundamental values.

If behaviourally biased investors do push prices away from fundamental values, it is more probably to occur due to excess demand rather than to by excess selling pressure by behaviourally biased investors. Restrictions in short selling inhibit irrational investors from causing excess selling pressure in reaction to bad news and inhibit the ability of rational investors from arbitraging excess buying pressure in reaction to good news.[4] However, there are no such restrictions on buying shares. Therefore, we investigate the demand side of Grinblatt and Han (2005)'s model. Specifically, we examine the characteristics of firms and how they relate to probably reference points. We hypothesize that firm factors that can be related in some way to increases in gains and losses will be inversely related to unrealized capital gains since disposition investors will react asymmetrically, immediately realizing gains but delaying losses. We also hypothesize that the characteristics of "good" firms would be positively related unrealized capital gains since "good" firms would be in demand by irrational investors who discount the importance of the more rational, future risk and return characteristics of these firms. In effect, we are trying to read the investor's mind about which stocks behaviourally biased investors feel attracted to and prefer to possess so that generally unrealized capital gains are positively related to the firm characteristics that behaviourally biased investors believe are attractive.

This paper contributes to the theoretical development of behavioural finance in two ways. First, we suppose that there is a relation between value irrelevant firm characteristics and unrealized capital gains. Most research to date has addressed the impact of irrational behaviours on the supply side, while the personal preferences of the behaviourally biased investors have not yet been covered. Our contribution helps to grasp investor behaviour better through identifying buying preferences and their possible impact on prices by detecting the firm characteristics that can attract irrational investors' attention and affect stock prices. More precisely, we examine the ability of the measurable BARRA, Inc.,[5] inspired company characteristics to act as explanatory variables for unrealized capital gains, namely, market liquidity (share trade volume), beta, earnings per share, leverage, corporate liquidity (cash flow to price), growth, and size. To the extent that these variables are associated with value, this information should be included in stock prices at the date of purchase and should not systematically affect future capital gains.

[4] Restrictions that prevent disposition investors from causing excess selling pressure include "circuit breaker" regulations that ban short selling altogether during severe bear market conditions and the requirement that short sales can only occur on an uptick in stock prices. Restrictions that reduce the incentive by rational investors to arbitrage excess demand include limitations on the use of the proceeds from short selling.

[5] BARRA, inc is a software provider for portfolio risk and performance analytics. This company construct a proxy for quality companies and its stock based on 12 characteristics that are; market variability, success in the market, size, trading activity, growth, Earning-price ratio, Book-price ratio, Earnings variability, Leverage, foreign income, labour intensity, and dividend yield. For more details, see Clarke & Statman (1994).

Second, we employ a much broader sample size by including the stocks that underlie the Russell 3000 index, whereas most of the literature uses a narrower sample that employs stocks listed on the NYSE/AMEX exchanges. The Russell 3000 index contains the largest 3,000 US stocks representing 98% by market capitalization of the US market.[6] Consequently, our data contains many more of the smaller companies that still actively trade on regional and not necessarily national stock markets, thereby improving the chance of detecting excess demand by irrational investors. We adjust for survivorship bias by including firms for as long as they remain in the Russell 3000 index.[7] Having nearly 20 years of monthly data allows us to examine the robustness of our data over a wide variety of market conditions. Moreover, a significant portion of the literature focuses on NYSE and AMEX stocks and neglects stocks listed on NASDAQ. This also means that much of the literature ignores the technology sector, which is characterized by high volatility and high growth stocks and ignores the early performance of some of the best performers in the U.S stock market such as Apple and Microsoft. In contrast, our sample contains 986 stocks (around 20% of our sample) that are listed on NASDAQ.

Our results show that value irrelevant firm characteristics that we hypothesize irrational investors to find attractive, specifically earnings per share, financial leverage, growth and size are positively related to capital gains overhang while another firm characteristic, namely, corporate liquidity, is inversely related to unrealized capital gains. The later can turn negative because corporate liquidity could also be associated with underutilized corporate assets leading to capital losses which disposition investors hang on to. In addition, beta is inversely related to capital gains overhang probably because high risk stocks sometimes have poor performance resulting in capital losses that disposition investors are loath to realize. Moreover, we find that the market liquidity of the firm's shares is inversely related to capital gains overhang probably because more liquid stocks encourage disposition investors to realize capital gains too early while being irrationally reluctant to realize losses.

The next section briefly reviews the relevant literature while section 3.3 develops our hypotheses. Section 3.4 describes the sample and methodology. Section 3.5 presents our empirical analysis followed by concluding remarks and recommendations for future research in section 3.6.

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[6] http://www.russell.com/indexes/emea/indexes/

[7] Attempting to include companies that have dropped out of the Russell 3000 index would include stocks that do not actively trade. This would mean that the reference price would reflect stale prices and not the beliefs of disposition investors.

3.2- Literature review

The disposition effect is one of the best documented cognitive biases in the behavioural finance literature. The term "disposition effect" refers to the behaviour of realizing gains promptly and holding losing stock too long. Dechow and Sloan (1997) do not find any evidence that irrational investors commit systematic cognitive errors when perceiving firm performance. Later however, by using Ohlson's (1980) O-score, the return difference between high and low book to market stocks, Griffin and Lemmon (2002) do find that firms with current poor operating performance are more susceptible to mispricing.

Shefrin and Statman (1985) study how investors react to gains and losses. They develop a behavioural theory of the disposition effect through synthesizing prospect theory, mental accounting, regret aversion, and self-control. Odean (1998) uses 10,000 accounts of individual investors to investigate the disposition effect, showing that, while investors exhibit a strong preference for realizing winners rather than losers, they do not delay realizing losses in December so as to gain tax benefits. The latter is consistent with Lakonishok and Smidt (1986) who show that while investors delay realizing losses and recognize gains early, there has been a marked increase in tax loss motivated selling in December. Odean's (1998) results were generalized by Grinblatt and Keloharju (2001) who examine institutional as well as individual investors and by Locke and Mann (2005) who examine professional investors. Goetzmann and Massa (2008) use a large number of individual accounts to investigate the relationship between the percentage of disposition investors and the elasticity of stocks to financial bubbles confirming that returns, volatility and volume are inversely related to the disposition effect.

More recently, Hur et al. (2010) assume that individual investors suffer most from the disposition effect and find that stocks with greater individual ownership are also stocks where momentum profits are more strongly influenced by the disposition effect. Ben-David and Hirshleifer (2012) find that for short holding periods, investors are more probably to sell if the stock is a large loser. However, they affirm that the trading behaviour in the case of gains or losses is too complicated to be interpreted by direct tastes; factors such as future expectations, tax benefits and portfolios repositioning should be taken into account. Cici (2012) study U.S mutual funds, finding that most mutual funds like to realize losses more than gains to capture tax benefits. Ye (2014) focuses on institutional investors, providing evidence that institutional investors tend to ride losses too long.

Dhar and Zhu (2006) target the specification of individual differences in the disposition effect. While the study supports the notion that individual investors behave on average according to the disposition effect, 20% of investors react against the disposition effect by realizing losses immediately and holding winning stocks. Moreover, while white-collar, richer and financially savvy investors show only a slight disposition effect, investors who trade less frequently experience a higher disposition effect. Choe and Eom (2009) examine the disposition effect in the Korean futures market finding that individual, institutional and foreign investors all exhibit disposition. Choe and Eom (2009) as well as Da Costa et al. (2013) pay attention to investor characteristics, finding that there is less disposition among sophisticated and experienced investors.

Debondt and Thaler (1987) work on market overreaction to earnings that force prices to deviate from the intrinsic value. Frazzini (2006) examines 29,000 mutual funds using prospect theory and mental accounting (PT/MA) framework to examine the ability of the disposition effect to generate under-reaction to news and its contribution to predicting future returns. Frazzini (2006) supposes that disposition investors react predictably to information flowing from the firm so that price movements are foreseeable. He concludes that bad (good) news goes sluggishly (quickly) to the marketplace, generating negative (positive) price movements.

Fu and Wedge (2011) relate the managerial ownership of mutual funds to the disposition effect and gather data from statements prepared by investment companies. They report that funds without managerial ownership and funds with poorer performance suffer from a higher disposition effect while funds with more board independence manifest a lower one. Kaustia (2004) sheds light on the disposition effect of IPO investors and confirms that reference pricing is important for market wide activity.

Kaustia (2010) & Barberis and Xiong (2009) examine the ability of two models of prospect theory, the annual gains and the realized gains and losses models, to explain disposition. Barberis and Xiong (2009) find that while the annual gains and losses model is unable to predict the disposition behaviour, the realized gains/loss model is able to so. Kaustia (2010) uses a logit regression model to test the tendency to sell. Surprisingly, the results show that the prospect theory is unable to predict disposition. Later, Li and Yang

(2013) develop a theoretical equilibrium model to link prospect theory to disposition and asset pricing. Lehenkari (2012) uses Finnish data to explore the disposition effect by testing three possible sources of it, namely, prospect theory, mean reversion, and self-accountability in making the initial investment decisions. The results indicate that when they controlled for the ability of investors to make investment decisions by themselves, the disposition effect disappeared. Clearly, this implies that personal accountability for initial investments is the main source of the disposition effect. Frydman and Rangel (2014) & Weber and Camerer (1998) depend on the experimental approach to provide an explanation for the disposition effect behaviour.

Bhootra and Hur (2012) investigate the impact of cointegration on the relationship between stock prices and momentum profits. To do so, they divide the whole sample into cointegrated and non-cointegrated groups finding positive significant relationships between the capital gains overhang and stock returns for both groups. However, the relationships for the co-integrated group are weaker. More recently, Birru (2015) finds that investors do not follow disposition behaviour after stock splitting.

A. Value irrelevant cognitive biases

Hirshleifer et al. (2004), Hirshleifer and Teoh (2003) & Daniel et al. (2002) all agree that several cognitive errors can occur and create a deviation from fundamental values because the volume of information is too great to be handled by the limited capability of investors. Barber, Heath, and Odean (2003) assert that behaviourally biased investors usually require some rationale for choosing between different stocks. In this context, these reasons may be that the company excels in managing its operations, produces quality products and develops successful strategies. However, from a rational standpoint, the power of such reasons does not necessarily promote superior future stock performance.

Barber and Odean (2008) argue that each investor faces a large number of options but choose only a few because human beings have a limited ability to attend to and to process available information. Barber and Odean (2008) also find that investors are more attracted to information that leads to buying decisions rather than selling decisions. Shefrin and Statman (1995) claim that the fluctuations in asset prices are mainly due to cognitive errors committed by uninformed irrational investors when they evaluate the role firm characteristics play in explaining expected returns. As a result, irrational investors mistakenly think "good stocks are the stocks of good companies". The reality refutes this belief because some superior stocks subsequently experience inferior operating performance and some inferior stocks subsequently experience superior operating performance. Additionally, this systematic error is expected to push irrational investors to under or overreact, which eventually causes price distortion. Shefrin and Statman (1995) finally conclude that large companies with a moderately high book to market ratio are more probably to be viewed as good companies.

The previous arguments are empirically supported by Lakonishok et al. (1994) who seek to explain the superior performance of value strategies to those of glamour strategies as determined by different book to market and cash flow to price ratios. Lakonishok et al. (1994) find evidence that behaviourally biased investors can be the primary cause of the significant association between firm characteristics and stock prices. Evidently, some investors associate good investment with good companies irrespective of price and so push stock market prices away from the intrinsic values. They conclude that investors tend to overprice stocks that are characterized by low book to market ratios and underprice stocks that are characterized by high book-to-market ratios.

Clarke and Statman (1994) refer to two sets of criteria that make up the representative heuristics used by investors to describe a specific company as good and to romanticize the performance of its stock accordingly. The company focused set of criteria, prepared by Fortune Magazine, suggests that a company is good if it has quality management, financial soundness, quality products, highly talented people, efficiently use of corporate assets, value as a long term investment, innovation and community and environmental responsibility. The fundamental factor criteria are inspired by BARRA, Inc., and consist of stock volatility, prior success in the stock market, size, trading activity, growth, earnings price ratio, book to market value ratio, earnings variability, financial leverage, foreign income, labour intensity and dividend yield. All of these variables are irrelevant in a competitive market with rational investors because to the extent that these factors create value, this should already be reflected in stock prices. What should determine value are future earnings and the corresponding systematic risk of achieving them.

As is common in the literature, we employ unrealized capital gains based on cumulative past returns and trading volumes as a variable associated with the disposition effect and other cognitive biases. However, as far as we are able to determine, the role that firm characteristics play in explaining the disposition effect and other cognitive biases has not for the most part been examined in the literature.

3.3- Hypotheses Development

Representativeness heuristics of (Tversky & Kahnmann, 1974) is the tendency of people to oversimplify the decision-making process by ignoring the laws of probability and judge events and subjects on their typicality and similarity to well-known events or subjects (Hirshleifer, 2001) and (Barberis, Shleifer and Vishny, 1998). Eaton (2000) defines representativeness as a cognitive bias where brain resorts to simplify the complication of a problem. According to this bias, investors assume that things that have limited number of similar features are the same and classify stocks as "good" or "bad" depending on few numbers of superficial characteristics and ignoring some other relevant characteristics. Also, they ignore underlying probabilities. Another example of this bias is that some investors in the stock market sometimes may deal with some stocks as growth stocks depending on past growth in earnings and disregard that the number of companies that continue growing is few. Many studies in the literature evidenced that investors are prone to representativeness bias by believing that past returns are representative to future returns Chen, Kim, Nofsinger and Rui (2007). De Bondt and Thaler (1985) supported the previous findings by explaining that Bayes' rule represents the level of appropriate reaction to new information. They also found evidence that people expose to representativeness heuristics by overweight recent events and ignore base rates. They also confirm that this representativeness heuristics induce over-reaction to new information and lead past losing portfolios to outperform past winning portfolios. One kind of representativeness was reported in Cooper, Dimitrov & Rau (2001) who studied what so called investor mania by relating the change of companies' name to dotcom name with making abnormal returns. The findings documented that investors prefer to invest in internet companies and also documented that changing the company's name to dotcom name makes positive abnormal returns for the five days around the announcement date. Another kind of representativeness was documented in Shefrin & Statman (1995) who linked representativeness heuristics to characteristics of companies by examining whether investors believe good companies are representative of good stocks. They used Fortune magazine survey that was distributed to 8000 senior executives, outside directors and financial analysts from 311 companies in 32 industries. This survey aimed at asking respondents to rate companies based on eight characteristics that are quality of management, quality of products or services, innovativeness, long-term investment value, financial soundness, ability to attract, keep and develop talented people, social responsibility and wise use of corporate assets. Manzan & Westerhoft (2005) develop a model for speculators who are prone to representativeness heuristics in the foreign exchange market. This model assumes that these speculators perceive news incorrectly which ultimately influencing demand and supply interaction by overreacting or underreacting to this news. This impact depends on the magnitude of historical volatility. If the volatility is high (low), the current news will be important (unimportant), causing overreaction (under-reaction) to this news.

From the previous discussion we conclude that the belief of good stocks are stocks of good companies is kind of representativeness heuristics since some investors feel good companies are representative of good stocks and good investments. In other words, investors expect above mean expected returns from good operating performance companies, low risk "safe" companies and financially sound companies. In this case, representativeness leads investors to predict above mean returns from safe stocks.

We depended on some characteristics of BARRA's quality proxy that generally used to classify companies as "good" or "bad". BARRA's quality proxy includes 12 features that are; variability in the stock market, stock success, institutional popularity in the market, growth, earning-price ratio, book-price ratio, earnings variability, leverage, foreign income, labor intensity and dividend yield. These features are employed to describe and measure perceptions of admired companies.

Representativeness best explains the buying patterns or investors use representativeness heuristics when purchasing Barber, Odean & Zheng (2000) and Barber, Odean & Zhu (2009). This leads investors to give too much consideration to stocks of these admired companies which inducing overreaction Wu, Wu, & Liu (2009) and causing excess demand for them. We can also say investors pay premium for holding stocks of good companies or require lower required return on stocks of good companies leading to higher market price or positive spread between market price and reference price.

Our central hypotheses are first, that disposition investors react irrationally in the face of capital gains in accordance with a framework of mental accounting and prospect theory and, second, react to value irrelevant firm level characteristics. The latter assumes that firms with the characteristics irrational investors find attractive can be influenced by them provided that excessive demand by these investors overcomes supply by more rational investors. We measure the influence of disposition and behaviourally biased investors proxied by the unrealized capital gains and losses as proposed by Grinblatt and Han (2005) and use this as the dependent variable to see first, if this proxy is associated with the irrational reluctance to realize losses and second whether this proxy is associated with the factors that irrational investors mistakenly believe are value relevant.

A central aspect of the disposition effect is that disposition investors excessively sell winning stocks yet are reluctant to sell losing stocks. Lakonishok and Smidt (1986) and Odean (1998) show that with the exception of end of year tax loss selling, investors do delay realizing losses and recognize gains early. Later, Grinblatt and Keloharju (2001), Locke and Mann (2005), Choe and Eom (2009) and Ye (2014) all find evidence of the disposition effect. If so, the higher the trading volume of a given share, the more probably this is caused by disposition investors excessively realizing capital gains leading to lower unrealized capital gains. Moreover, the lower the volume of share trading, the more probably this is associated with disposition investors failing to realize losses, again leading to lower realized capital gains. In addition, high risk stocks will tend to have both higher losses and higher gains. Yet disposition investors will react asymmetrically, selling shares to realize capital gains early but holding shares with capital losses. Therefore, our first hypothesis can be stated as follows.

H1. Ceteris paribus, there is an inverse relation between unrealized capital gains and stock liquidity and systematic risk.

Shefrin and Statman (1995) suppose that behaviourally biased investors mistakenly think "good stocks are the stocks of good companies". Lakonishok et al. (1994) find that investors tend to overprice growth stocks that are characterized by low book to market ratios and underprice value stocks that are characterized by high book-to-market ratios. Similarly, Shefrin and Statman (1995) conclude that large companies with a moderately high book to market ratio are more probably to be viewed as good companies. None of these authors, however, have investigated the relationship between size and growth with unrealized capital gains. Inspired by the BARRA, Inc., listing of the measureable characteristics of a “good” company, we add earnings per share, and leverage, cash flow to price, growth and size as company characteristics that will attract the attention of behaviourally biased investors.

There is no reason why these factors should be related to past capital gains or losses because to the extent that there is any value associated with these factors, it should be reflected in the current stock price. In other words, earnings per share, leverage, growth and size should not predict future gains and losses hence they should not be

related to unrealized capital gains either. Therefore, buying these shares should be innocuous on a shares future return. However, because disposition investors believe these characteristics to be valuable, they will cause excessive buying pressure that rational investors may have difficulty in arbitraging. Therefore, we expect capital gains overhang will be positively associated with firms with these characteristics. Therefore, our second hypothesis is stated as:

H2. Ceteris paribus, there is a positive relation between capital gains overhang and the characteristics of "good" companies", namely, earnings per share, leverage, growth and size.

We are unable to sign a fifth company characteristic, corporate liquidity. On the one hand, we expect a high level of corporate liquidity to be viewed by behaviourally biased investors as an attractive characteristic. This suggests that if the demand by behaviourally biased investors overcomes the supply by rational investors, the stock price will rise leading to unrealized capital gains. On the other hand, for some firms, excess corporate liquidity can indicate inefficient use of resources via excess investment in inventories, a failure to collect receivables on time or, for financial firms, a failure to find quality lending opportunities. This can lead to losses by some but not all of these companies. Disposition investors will react asymmetrically by realizing gains for those companies with high corporate liquidity that have gains and by failing to realize losses for those companies with high corporate liquidity that have losses. This will lead to an inverse relationship between firms with high corporate liquidity and unrealized capital gains.

3.4- Description of the sample and methodology

We collect all the stocks listed on Russell 3000 index. To avoid survivorship bias, the list of companies was updated each month. We needed to estimate the capital gains overhang with respect to a reference price based on past data. Grinblatt and Han (2005) use five years of data to estimate the reference price and note that estimates of the reference price are robust to using three and seven years of data. To avoid losing too much data and enhance our ability to conduct robustness tests, we relied on three years of observations to calculate the reference price. Therefore, we excluded all stocks that had fewer than 36 observations so that we ended up with data on 5,091 stocks with 422,278 stock month observations over the period January 1995 to September 2014. Using the first three years of monthly data to estimate the initial reference price means that our empirical study commences in January1998 and ends in September 2014.

Our dependent variable, capital gains overhang, is a measure of unrealized capital gains calculated with respect to a reference price. Unlike Grinblatt and Han (2005), we use monthly rather than weekly data because our sample included many smaller stocks and we wished to avoid any issues with thin trading. The reference price RP_t is a turnover weighted average of past prices. We use Grinblatt and Han's (2005) calculation of the reference price RP_t because we too are unable to differentiate between rational and disposition investors. Therefore, the market's reference price will be calculated as follows.

$$RP_t = \frac{1}{k}\sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}\left[1-V_{t-n+\tau}\right]\right)P_{t-n} \tag{1}$$

where V_t is date t's number of shares traded in the stock, P_{t-n} is the closing price at t-n and k is a constant that makes the weights sum to one. In other words, (1) is a geometrically declining volume weighted average of the past prices of a stock. Our measure of unrealized capital gains (capital gains overhang) was measured as the percentage difference between the current price and the reference price.

$$CGO_t = \frac{P_t - RP_t}{P_t} \tag{2}$$

where CGO_t is a capital gains overhang at the end of month t, P_t is the closing price at the end of month t, and RP_t denotes the reference price at the end of month t.

To test our first hypothesis, we measure stock liquidity as TURNOVER, the monthly share trading volume of a given stock and systematic risk as BETA the CAPM measure of systematic risk and included them as explanatory variables of capital gains overhang. As mentioned previously, we expected both of these variables to be inversely related to capital gains overhang.

To test our second hypothesis, we include several variables that we hypothesized behaviourally biased investors would mistakenly believe to be associated with attractive investment candidates. These variables are earnings per share EPS, a measure of recent profitability, LEVERAGE, measured as the ratio of debt to equity, corporate liquidity CF/P measured as the ratio of cash flow to price, GROWTH measured as the ratio of the market to book value and SIZE, the log of monthly market capitalization. We included these factors as explanatory variables of capital gains overhang. As mentioned previously, if the demand by behaviourally biased investors is excessive, then these variables will be positively associated with capital gains overhang. All data were winsorized at 2% and 98% to reduce the harmful effect of outliers. A detailed description of the variables is reported in Table 3.1.

<<Table 3.1 about here>>

We used panel regressions because we wished to consider the time series and cross sectional behaviour of capital gains overhang. Following the approach of Petersen (2009), White (1980) standard errors were compared to standard error clustered by time to detect whether the data had time series dependence. The difference between White (1980) standard errors and standard errors clustered by time ranged from 50% to 260%, which clearly indicates that there is time series dependence in our data. White (1980) standard errors were compared again with standard errors clustered by firms to check the possibility of cross sectional dependence. In this case, the difference varies from 24% to 380%, which also indicated that our data suffered from cross sectional dependence. It is well known that a fixed effect model is more appropriate when the sample completely covers the whole population Brooks (2008). Since our sample "All stocks in Russell 3000 index" represents 98% of the US stock market and provides full and transparent coverage of the market as previously mentioned in Chapter 2, the fixed effects model was employed, also named the least square dummy variable approach (LSDV). To deal with joint time series and cross sectional dependence, the parametric approach was followed by including dummy variables for each time period and clustering our standard errors by firm. The same approach was previously used by Lamont and Polk (2001), Anderson and Reeb (2004), Gross and Souleles (2004), Sapienza (2004), and Faulkender and Petersen (2006)[8]. Our model is therefore

$$CGO_{it} = \beta_0 + \beta_1 Turnover_{it} + \beta_2 Beta_{it} + \beta_3 EPS_{it} + \beta_4 Leverage_{it} + \beta_5 CF / P_{it} + \beta_6 Growth_{it} + \beta_7 Size_{it} + u_{it} \tag{3}$$

where CGO_{it} is capital gains overhang, $TURNOVER_{it}$ is the turnover ratio, $BETA_{it}$ is the company beta, EPS_{it} is earnings per share, $LEVERAGE_{it}$ is our measure of the debt burden, CF/P_{it} is the cash flow to price ratio, $GROWTH_{it}$ is the growth rate in market to book ratio, $SIZE_{it}$ is the natural log of monthly market capitalization, and u_{it} is the error term.

In Table 3.2, we provide summary statistics for the dependent and independent variables that cover the period from January 1998 to September 2014. The table shows that the mean of capital gains overhang is -0.0935 meaning that overall; investors are experiencing an unrealized capital loss. This mean is larger than -0.15 as reported by Frazzini (2006) whose sample is drawn from mutual funds and is smaller than 0.056 as reported by Grinblat and Han 2005) whose sample was drawn from stocks listed on the NYSE and AMEX. The standard deviation of 0.54 and skewness of -2.4 of capital gains overhang was very similar to the findings of Frazzini (2006) who reports 0.52 and -2.3 respectively. In addition, financial companies comprised nearly one fifth of our sample so the mean of leverage is somewhat high.

<< Table 3.2 about here>>

Table 3.3 shows the summary statistics for the capital gains overhang for each industry. From this table, we can conclude that all industries provide negative capital gains overhang. The wholesale industry gives the highest mean capital gains overhang, while finance, insurance and real estate is the second highest industry in terms of mean capital gains overhang. It is also observed that the public administration industry gives the lowest capital gains overhang. Regarding the standard deviation, the services industry and mining industry experience the highest standard deviation in capital gains overhang.

[8] See Petersen (2009) P.458

<< Table 3.3 about here>>

We report the sample correlation amongst the variables in Table 3.4. According to Alm and Mason (2007), if the correlation coefficient amongst independent variables is less than 0.70, there should be no issues with high collinearity. According to this criterion, we do not expect to have issues with collinearity since all our correlations are far less than 0.70. The first and second highest correlation coefficients are between earnings per share and size (0.40) and between cash flow to price and beta (0.26). The other correlation coefficients are quite low, all less than 0.18. All the correlation coefficients are statistically significant at 1% or 5% level except for the correlation between growth and turnover.

<<Table 3.4 about here>>

3.5- Empirical analysis

Our main empirical results are shown in Table 3.5. According to the rational investor competitive market view, none of our variables should be systematically related to capital gains overhang, yet all of them are significant at the 1% level. Moreover, the R-square of the regression model is more than 20% and highly significant according to the F- Statistic.

<<Table 3.5 about here>>

We find very strong support for our first hypothesis. As expected, market liquidity TURNOVER and systematic risk BETA are inversely related to capital gains overhang. Both coefficients are significant at the 1% level. This is evidence of the activities of disposition investors who are reluctant to realize capital losses. Evidently, with higher stock market liquidity, disposition investors are realizing capital gains early yet are reluctant to realize capital losses and so induce an inverse relation between stock market liquidity and unrealized capital gains even though there is no rational reason why this relationship should exist.

We also find strong support for our second hypothesis. The four value irrelevant firm characteristics that we hypothesize will attract demand from behaviourally biased investors are indeed positively related to unrealized capital gains. All of these coefficients are significant at the 1% level. Evidently, firms with larger earnings per share, growth, size and leverage attract excess buying behaviour from behaviourally biased investors not counteracted by more rational investors.

A fifth firm characteristic, corporate liquidity CF/P is inversely related to unrealized capital gains and is also significant at the 1% level. This suggests that the disposition effect is operative here rather than the irrational demand by behaviourally biased investors since evidently; some firms with high corporate liquidity are inefficiently deploying resources leading to losses that disposition investors are reluctant to realize. This finding is also consistent with Lakonishok, Shleifer, and Vishny (1994) who find that investors tend to overvalue growth stock "low cash flow to price", while they undervalue high cash flow to price stocks.

Robustness checks

The main reason why we implement robustness check is to ensure regression estimates are insensitive to different market conditions and are insensitive to different assumptions. The first robustness check was conducted through running cross section regression for each year to check the stability of the coefficients over time (see Table 3.6). Sixth further robustness checks were conducted through splitting the whole sample into two subsamples, the first five are based on median growth, median beta, median size, median turnover, before and after the financial crisis and the sixth on the basis of capital gains versus losses. We first divided the entire sample into two subsamples based on median growth in the market to book ratio. Then, we ran the same model (1) (see Table 3.7). Similarly, the previous procedure is replicated in beta, size and turnover in Tables 3.8, 3.9, and 3.10. To check the robustness of the relation to different economic circumstances, the sample periods was split on the basis of occurring before August 2007 or After August 2007 (see the subsamples in Table 3.11). Finally, we divided the entire sample into two subsamples periods based on the capital gains overhang: capital gains and capital losses (see Table 3.12). The main conclusion in Tables 3.6, 3.7, 3.8, 3.9, 3.10, 3.11 and 3.12 is that the relation is stable over time except BETA. This instable relation between BETA and capital gains overhang can be attributed to the non-linear relation between them. The findings are also robust to higher- and lower- growth stocks, higher- and lower-beta stocks, higher- and lower-sized stocks, higher- and lower-liquidity stocks, boom and recession conditions and also robust to capital gains and capital losses. There are three differences between the main results and the robustness checks: the first difference lies in the main conclusion (see Table 3.7) that there is positive significant relationship between growth rate and capital gains overhang. But when we divided the whole sample according to growth rate (high growth vs low growth) (see Table 3.7), we noticed that the relation between growth rate and capital gains overhang became negative in the high growth subsample, indicating that the disposition investor to some extent prefers high growth stocks. However, he does not taste the extremely high growth stocks due to the high level of uncertainty that they represent. From this point, we can see also that there is a nonlinear relationship between growth rate and capital gains overhang. The second different story (see Table 3.12) is that we ran the panel regression model (1) to the capital gains and capital losses separately. In the case of capital gains the turnover coefficient became positive and significant at 10%, meaning that if the disposition investor expects to earn capital gains, he pays little attention to the stock's trading activity and likes to buy the higher-volume stocks rather than the lower-volume stocks, while he is very much concerned about the trading activity when facing capital losses as the turnover coefficient is highly significant in the capital losses subsample. The final different story is that, we still find in capital gains subsample (see Table 3.12) that the sign of the beta coefficient also becomes positive, referring to the fact that the disposition investors favour high-beta stocks when facing gains to maximize their benefits. All other robustness tests are quite consistent with the main conclusion.

Finally, we consider some subsamples statistics. The above median sized subsample of "large sized companies" has a mean capital gains overhang of 0.05, while the smaller sized "below median" mean subsample is -0.24. There is thus no size effect here and the difference between the two subsamples is 0.29. However, the mean unrealized capital gains overhang on the above median turnover subsample is -0.12, while it is -0.06 on the below median turnover. Similarly, the below median subsample has a higher unrealized capital gains overhang and the difference in unrealized capital gains overhang is 0.18.

3.6- Conclusion

In this study, we aimed to determine the main factors that might attract the disposition investors to trade in, generating temporary price distortions. In doing so, we followed Petersen (2009) methodology to attain efficient and unbiased standard errors in the context of the panel regression models. The purpose of using the panel regression model is to describe the time series and cross section behaviour of capital gains overhang. Turnover, firm beta, EPS, leverage, cash flow to price, growth, and size were chosen. The relationships between the capital gains overhang and turnover, beta and cash flow to price were negative, while it is positive between the capital gains overhang and earnings to price, leverage, growth and size. The conclusion introduced here is conformable with Lakonishok, Shleifer and Vishny (1994): that, - firm characteristics are the main reason for irrationality and price distortion.

The main conclusion can be summarized as follows: there is strong evidence that disposition investors believe that "good stocks are the stocks of good companies", especially the strongest significant variables are, cash flow to price, growth and size, are firm characteristics, while the turnover variable that is used as a proxy for market activity is far less significant than firm characteristics mentioned above. The robustness checks were implemented through running cross sectional regression year by year and through dividing the whole sample on the basis of median growth, median size, median turnover, median beta, before and after the financial crisis and capital gains and capital losses separately. In general, the robustness tests support the main result.

The main implication for this paper is that the rational investors who are less susceptible to cognitive errors can develop profitable trading strategies to benefit from the temporary mispricing caused by the irrational investors. In this context, we would encourage the rational investors to pay more attention to those good companies that attracted the irrational investors and in turn, provides a higher capital gains overhang such as more profitable firms, higher growth, higher levered firms, larger firms and firms with lower corporate liquidity. Finally, it may be useful to make some recommendations for theory development. Investigating other factors such as management efficiency, quality products, innovation and social responsibility and replicating this research in other developed and emerging markets would be interesting.

Tables of results

Table 3.1. A description of the variables

Variable	**Definition**
Capital gains overhang	The capital gains overhang is calculated as the percentage difference between current prices and the reference price. $CGO_t = \frac{P_t - RP_t}{P_t}$
Turnover	The turnover is a measure of shares monthly trading volume divided by monthly shares outstanding as a proxy for liquidity.
Company Beta	A measure of systematic risk: The beta value is determined by the CAPM for the past two years of weekly data using S&P 500.
EPS	Is the Earnings per share and computed as net income available to common shareholders divided by the basic weighted average shares outstanding. Sum of the most recent 12 months (trailing 12 months).
Leverage	A measure of the debt burden of a company. It is equal to the ratio of debt to equity.
CF/P	Is the ratio of cash flow to price.
The market to book ratio	Is a proxy for growth.
The company Size	Proxied by monthly market capitalization.

Table 3.2. Descriptive statistics

This table reports the descriptive statistics of the data. The capital gains overhang is $(P_t - RP_t)/P_t$ where P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured monthly and is the trading volume divided by the number of shares outstanding. Beta is the CAPM beta calculated over the previous two years using weekly data. EPS is the net income available to common shareholders divided by the weighted average number of shares outstanding (trailing 12 months). Leverage is calculated as the ratio of debt to equity. Cash flow to price CF/P is the ratio of cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) / (M/B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variable	Mean	Median	Std. Dev.	Min	Max	Skewness	Obs
CGO	-0.093	0.062	0.547	-2.395	0.493	-2.394	422278
Turnover	0.008	0.006	0.009	0.000	0.040	2.148	422278
Beta	1.129	1.044	0.754	-0.310	3.205	0.595	422278
EPS	1.298	1.200	2.014	-4.280	7.240	0.231	415244
Leverage	2.793	1.329	3.715	0.109	16.823	2.211	410603
CF/P	0.123	0.093	0.100	0.012	0.520	2.053	367977
Growth (%)	0.528	0.000	12.776	-32.075	39.204	0.345	410846
Size (in billions)	4.800	1.200	10.200	0.140	56.000	3.700	418730

Table 3.3. Summary statistics for capital gains overhang by industry

This table reports the capital gains overhang. The capital gains overhang = $(P_t - RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Using the first two digits of SIC codes, all stocks are assigned into ten industries as follows: Agriculture (01-09), Mining (10-14), Construction (15-17), Manufacturing (20-39), Transportation and public utlity (40-49), Wholesale trade (50-51), Retail trade (52-59), Finance, Insurance and Real Estate (60-67), Services (70-89), and Public Administration (91-99).

Industry	**Agriculture**	**Mining**	**Construction**	**Manufacturing**	**Transportation and Public Utility**	**Wholesale Trade**	**Retail Trade**	**Finance, Insurance and Real Estate**	**Services**	**Public Administration**
Mean	-.093	-0.115	-0.096	-0.110	-0.072	-0.0388	-0.060	-0.057	-0.136	-0.367
Std. Dev	0.464	0.597	0.576	0.559	0.520	0.480	0.528	0.494	0.604	0.569
Min	-2.395	-2.395	-2.395	-2.395	-2.395	-2.395	-2.395	-2.395	-2.395	-2.395
Max	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493
Obs	631	17171	5273	163231	41334	11163	29618	91255	62536	66

Table 3.4. Correlation Matrix

Table 3.4 reports the correlation coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = (P_t-RP_t)/P_t. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) / (M/B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variable	**CGO**	**Turnover**	**Beta**	**EPS**	**Leverage**	**CF/P**	**Growth M-B**	**Log size**
CGO	1.00							
Turnover	-0.113	1.00						
Beta	-0.136	0.181	1.00					
EPS	0.361	-0.078	- 0.168	1.00				
Leverage	-0.024	-0.078	0.004	0.039	1.00			
CF/P	-0.403	0.050	0.036	-0.085	0.263	1.00		
Growth (%)	0.136	-0.001*	0.033	-0.035	-0.018	-0.054	1.00	
Logsize	0.341	0.08	-0.112	0.402	0.039	-0.170	0.013	1.00

(*) denote significance at 10% and 5% otherwise

Table 3.5. Panel regression output

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t\text{-}RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M / B_t - M / B_{t-1}\right) \;/ (M / B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Coefficients**	
	β	t
Intercept	-7.005 (0.195)	-35.92
Turnover	-5.426 (0.259)	-20.94
Beta	-0.032 (0.002)	-13.24
EPS	0.035 (0.002)	12.35
Leverage	0.015 (0.002)	7.62
CF/P	-1.705 (0.056)	-35.60
Growth (%)	0.004 (0.000)	76.04
Size	0.341 (0.019)	37.09
R^2	40.49	
F-statitics P- Value	115.37 (0.000)	
Obs	351062	

Figures in the parenthesis are robust standard errors
Significant at 1% level

Table 3.6. Robustness analysis based on cross section regression (year by year)

This table reports the coefficients of the cross section regression. The dependent variable is a capital gains overhang. The capital gains overhang = (P_t-RP_t)/P_t. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right)\ /(M/B_{t-1})\times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market at the end of the month.

Coefficients	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Intercept	**-1.041**	**-1.474**	**-1.124**	**-0.407**	**0.610**	**-0.265**	**-0.222**	**-0.620**	**-0.778**	**-1.1261**	**-1.966**	**-2.420**	**-1.424**	**-1.258**	**-1.087**	**-0.698**	**-0.793**
	(-8.33)	**(-11.45)**	**(-8.27)**	**(-3.34)**	**(-3.30)**	**(-1.58)**	**(-2.22)**	**(-7.03)**	**(-8.94)**	**(-12.28)**	**(-14.44)**	**(-15.40)**	**(-11.89)**	**(-12.96)**	**(-8.26)**	**(-7.40)**	**(-8.67)**
Turnover	**-7.636**	**-6.384**	**-4.298**	**-6.215**	**-5.824**	**-2.590**	**-2.975**	**-1.101**	**-0.636**	**-3.441**	**-5.615**	**-0.390**	**0.769**	**-2.750**	**-4.810**	**-3.770**	**-1.261**
	(-6.22)	**(-5.03)**	**(-4.15)**	**(-5.05)**	**(5.81)**	**(-2.08)**	**(-3.66)**	**(-2.11)**	**(-1.43)**	**(-5.82)**	**(-7.74)**	**(-0.58)**	**(1.15)**	**(-4.40)**	**(-5.70)**	**(-4.32)**	**(-2.24)**
Beta	**-0.042**	**0.024**	**0.005**	**-0.149**	**-0.304**	**-0.072**	**-0.023**	**0.012**	**0.015**	**0.001**	**-0.163**	**-0.184**	**0.001**	**-0.003**	**-0.043**	**0.018**	**0.047**
	(-4.49)	**(3.05)**	**(0.70)**	**(-15.15)**	**(-20.22)**	**(-6.92)**	**(-4.41)**	**(3.13)**	**(4.27)**	**(0.19)**	**(-18.45)**	**(17.77)**	**(0.12)**	**(-0.42)**	**(-7.84)**	**(3.94)**	**(9.02)**
EPS	**0.058**	**0.063**	**0.062**	**0.090**	**0.099**	**0.117**	**0.049**	**0.041**	**0.033**	**0.030**	**0.051**	**0.039**	**0.047**	**0.032**	**0.038**	**0.032**	**0.024**
	(9.62)	**(10.47)**	**(10.02)**	**(15.11)**	**(14.79)**	**(16.39)**	**(11.51)**	**(12.27)**	**(10.64)**	**(9.63)**	**(11.43)**	**(9.94)**	**(12.77)**	**(9.14)**	**(10.33)**	**(10.60)**	**(8.91)**
Leverage	**0.010**	**-0.001**	**-0.002**	**0.007**	**0.010**	**0.009**	**0.004**	**0.001**	**0.000**	**-0.005**	**0.006**	**0.003**	**-0.007**	**-0.004**	**0.004**	**0.008**	**0.007**
	(4.56)	**(-0.42)**	**(-1.14)**	**(3.91)**	**(4.52)**	**(4.34)**	**(2.99)**	**(1.47)**	**(0.09)**	**(-3.11)**	**(2.90)**	**(1.36)**	**(-2.75)**	**(-1.62)**	**(1.56)**	**(4.59)**	**(4.40)**
CF/P	**-1.404**	**-1.561**	**-2.078**	**-1.217**	**-0.813**	**-1.141**	**-0.651**	**-0.653**	**-0.672**	**-1.304**	**-2.433**	**-1.905**	**-1.076**	**-1.187**	**-1.118**	**-0.874**	**-0.654**
	(-9.63)	**(-11.97)**	**(-16.94)**	**(-11.68)**	**(-7.42)**	**(-11.39)**	**(-6.65)**	**(-6.59)**	**(-7.49)**	**(-12.39)**	**(-28.24)**	**(-23.34)**	**(-12.70)**	**(-12.20)**	**(-11.72)**	**(-10.71)**	**(-8.69)**
Growth (%)	**0.007**	**0.007**	**0.008**	**0.005**	**0.003**	**0.004**	**0.003**	**0.006**	**0.004**	**0.006**	**0.007**	**0.006**	**0.004**	**0.005**	**0.004**	**0.005**	**0.005**
	(22.81)	**(24.02)**	**(25.70)**	**(18.20)**	**(17.94)**	**(12.43)**	**(19.87)**	**(24.02)**	**(26.09)**	**(24.23)**	**(35.67)**	**(22.25)**	**(20.26)**	**(23.31)**	**(17.79)**	**(18.70)**	**(15.35)**
Log size	**0.057**	**0.072**	**0.059**	**0.021**	**0.022**	**0.012**	**0.014**	**0.037**	**0.041**	**0.067**	**0.101**	**0.116**	**0.069**	**0.071**	**0.054**	**0.037**	**0.040**
	(9.92)	**(12.11)**	**(9.32)**	**(3.42)**	**(2.64)**	**(1.51)**	**(3.02)**	**(9.09)**	**(10.58)**	**(14.83)**	**(16.02)**	**(15.99)**	**(12.18)**	**(15.38)**	**(10.60)**	**(8.89)**	**(11.25)**
R^2	**34.77**	**33.99**	**37.08**	**30.51**	**33.06**	**29.25**	**16.73**	**19.48**	**18.25**	**31.04**	**54.40**	**48.49**	**31.19**	**30.40**	**25.93**	**21.36**	**21.67**
F-statistics	**88.08**	**52.94**	**47.91**	**24.69**	**24.45**	**22.60**	**14.86**	**15.59**	**15.32**	**15.99**	**62.61**	**44.29**	**23.03**	**17.45**	**8.11**	**8.93**	**8.12**
P-value	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Obs	**11559**	**14550**	**16029**	**17105**	**18686**	**18102**	**21196**	**22430**	**23052**	**22777**	**22795**	**22807**	**24717**	**25429**	**25315**	**25511**	**19002**

Figures in the parenthesis are t statistics. Significant at 1% level

Table 3.7. Robustness analysis based on growth subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t\text{-}RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) \; / (M/B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Above median growth**		**Below median growth**	
	β	t	β	t
Intercept	-6.111	-32.53	-7.274	-36.04
	(0.198)		(0.202)	
Turnover	-5.00	-19.22	-4.707	-16.77
	(0.26)		(0.281)	
Beta	-0.026	-14.62	-0.019	-6.63
	(0.000)		(0.003)	
EPS	0.026	13.08	0.022	10.21
	(0.002)		(0.002)	
Leverage	0.013	6.28	0.017	8.02
	(0.002)		(0.002)	
CF/P	-1.557	-32.46	-1.656	-34.71
	(0.045)		(0.047)	
Growth (%)	-0.002	-17.69	0.012	58.74
	(0.000)		(0.000)	
Size	0.304	34.21	0.355	37.25
	(0.009)		(0.009)	
R^2	37.59		44.71	
F-statitics	40.82		85.64	
P- Value	(0.000)		(0.000)	
Obs	179367		171696	

Figures in the parenthesis are robust standard errors

Significant at 1% level

Table 3.8. Robustness analysis based on beta subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t\text{-}RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right)\ /(M/B_{t-1})\times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Above median beta**		**Below median beta**	
	β	t	β	t
Intercept	-8.836 (0.243)	-36.30	-5.692 (0.190)	-30.02
Turnover	-6.158 (0.331)	-18.57	-3.572 (0.236)	-15.12
Beta	-0.0330 (0.004)	-8.13	-0.017 (0.003)	-5.40
EPS	0.023 (0.003)	8.61	0.022 (0.002)	11.44
Leverage	0.027 (0.002)	6.95	0.011 (0.002)	5.88
CF/P	-1.832 (0.058)	-31.70	-1.379 (0.049)	-27.88
Growth (%)	0.004 (0.001)	45.82	0.005 (0.000)	55.37
Size	0.429 (0.015)	37.30	0.277 (0.009)	31.10
R^2	45.72		34.51	
F-statitics P- Value	78.57 (0.000)		53.34 (0.000)	
Obs	172777		178286	

Figures in the parenthesis are robust standard errors
Significant at 1% level

Table 3.9. Robustness analysis based on size subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = (P_t-RP_t)/P_t. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right)\ /(M/B_{t-1})\times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	Above median size		Below median size	
	β	t	β	t
Intercept	-4.427 (0.233)	-19.00	-11.890 (0.267)	-44.58
Turnover	-4.342 (0.305)	-14.24	-7.261 (0.347)	-20.31
Beta	-0.025 (0.003)	-7.27	-0.034 (0.003)	-11.90
EPS	0.019 (0.002)	9.08	0.028 (0.004)	7.94
Leverage	0.012 (0.002)	5.83	0.019 (0.003)	6.45
CF/P	-1.429 (0.063)	-22.58	-1.533 (0.059)	-26.09
Growth (%)	0.004 (0.000)	58.87	0.004 (0.000)	50.60
Size	0.213 (0.011)	20.20	0.599 (0.013)	45.13
R^2	32.11		44.84	
F-statitics P- Value	55.33 (0.000)		78.42 (0.000)	
Obs	184338		166724	

Figures in the parenthesis are robust standard errors
Significant at 1% level

Table 3.10. Robustness analysis based on turnover subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t-RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) \ /(M/B_{t-1})\times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Above median turnover**		**Below median turnover**	
	β	t	β	t
Intercept	-8.618 (0.259)	-33.16	-6.154 (0.224)	-27.52
Turnover	-3.581 (0.256)	-14.00	-17.732 (1.321)	-14.18
Beta	-0.037 (0.003)	-11.62	-0.012 (0.002)	-4.94
EPS	0.018 (0.002)	7.33	0.032 (0.002)	12.60
Leverage	0.019 (0.002)	7.93	0.009 (0.002)	3.71
CF/P	-1.880 (0.059)	-31.47	-1.385 (0.054)	-25.76
Growth (%)	0.004 (0.000)	46.188	0.005 (0.000)	52.08
Size	0.412 (0.012)	34.08	0.303 (0.011)	28.34
R^2	45.86		34.01	
F-statitics P- Value	80.77 (0.000)		48.76 (0.000)	
Obs	175588		175474	

Figures in the parenthesis are robust standard errors
Significant at 1% level

Table 3.11. Robustness analysis based on before and after financial crisis subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t\text{-}RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) \ / (M/B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Before August 2007**		**After August 2007**	
	β	t	β	t
Intercept	-7.772 (0.245)	-31.67	-12.127 (0.293)	-41.39
Turnover	-3.572 (0.363)	-9.83	-2.434 (0.245)	-9.94
Beta	-0.015 (0.003)	-5.62	-0.017 (0.002)	-6.86
EPS	0.026 (0.000)	9.25	0.009 (0.002)	6.27
Leverage	0.019 (0.000)	6.49	0.011 (0.003)	3.65
CF/P	-1.341 (0.062)	-21.72	-1.597 (0.059)	-27.23
Growth (%)	0.004 (0.000)	57.64	0.003 (0.000)	40.98
Size	0.374 (0.011)	32.36	0.569 (0.014)	41.32
R^2	34.24		55.95	
F-statitics P- Value	52.7 (0.000)		106.95 (0.000)	
Obs	175958		175105	

Figures in the parenthesis are robust standard errors
Significant at 1% level

Table 3.12. Robustness analysis based on capital gains/losses subsamples

This table reports the coefficients of the panel regression model. The dependent variable is a capital gains overhang. The capital gains overhang = $(P_t - RP_t)/P_t$. P_t is the stock price at the end of month t and RP_t is the reference price calculated according to Grinblatt and Han (2005). Turnover is measured by monthly trading volume/ monthly shares outstanding. Company beta is the CAPM beta calculated over the previous two years using weekly data. EPS is computed as the net income available to common shareholders divided by the basic weighted average shares outstanding (trailing 12 months). Leverage is the ratio of debt to equity. CF/P is the ratio of the cash flow per share divided by the stock's price. The growth is the growth rate in a market to book ratio and computed as $\left(M/B_t - M/B_{t-1}\right) \ /(M/B_{t-1}) \times 100$, when M/B is the market to book ratio. Size is the natural logarithm of the market capitalization at the end of month t.

Variables	**Capital gains**		**Capital losses**	
	β	t	β	t
Intercept	-1.395 (0.063)	-22.19	-8.901 (0.278)	-32.06
Turnover	0.128 (0.076)	1.68*	-7.629 (0.347)	-21.96
Beta	0.009 (0.001)	11.85	-0.064 (0.004)	-17.73
EPS	0.003 (0.001)	4.18	0.023 (0.003)	9.08
Leverage	0.006 (0.001)	8.55	0.016 (0.002)	6.16
CF/P	-0.284 (0.018)	-15.52	-1.435 (0.051)	-28.26
Growth (%)	0.002 (0.000)	75.12	0.003 (0.003)	45.85
Size	0.077 (0.003)	26.06	0.418 (0.013)	31.71
R^2	14.44		37.40	
F-statistics P-value	52.37 (0.000)		57.66 (0.000)	
Obs	214535		136575	

Figures in the parenthesis are robust standard errors
(*) significant at 10% and 1% otherwise

Chapter Four

Revisiting disposition effect and momentum: A quantile regression perspective

Abstract

Adopting quantile regression, we analyse the relationship between the unrealized capital gains overhang and expected returns. The ability of the disposition effect to generate momentum is also considered for the extreme expected return regions 0.05th and 0.95th. To do so, we employ 450,617 observations belonging to 5176 US firms, covering a time span from January 1998 to June 2015. Following the methodology of Grinblatt and Han (2005), we find significant differences across various quantiles in terms of signs and magnitudes. These findings indicate a nonlinear relationship between capital gains overhang and expected returns since the impact of capital gains overhang as a proxy for disposition effect vary across the expected return distribution. More precisely, the coefficients of capital gains overhang are significantly positive and decline as the expected returns quantiles increase from the lowest (0.05th) to the median expected return quantiles. However, they become significantly negative and rise with the increase in expected returns quantiles at the highest ('above median') expected returns quantiles. The findings also suggest that disposition effect is not a good noisy proxy for inducing momentum at the lowest expected return quantile (0.05th). However, it seems interestingly to generate contrarian at the highest expected returns quantile (0.95th).

Keywords Disposition Effect, Momentum, Quantile Regression; Grinblatt and Han (2005)

4.1- Introduction and Background

The disposition effect is the tendency of investors to realize gains too early and hold losers too long. A main story is introduced by Grinblatt & Han (2005) who mentioned that the story has two sides. First, when good news arrives to the stock market, it leads the stock value to go up. Here the disposition investors sell the stock creating an excess supply resulting in downward pressure on the stock prices. This causes a smaller initial price impact and greater subsequent returns as the stock returns to its fundamental value. Second, when bad news arrives, it causes a decline in the fundamental value. Here the disposition investors prefer to hold the stock rather than selling it, leading to reduce the downward pressure on the stock prices which hinder the bad news to fully incorporating into prices. In this case, the subsequent returns will be smaller as the stock prices return to its fundamental value. In short, this investor behaviour together with the absence of perfectly elasticity demand for stocks generates return predictability and leads to under-reaction to news which eventually induces momentum in returns.

Contradictory findings have been reached in the literature review on capital gains overhang as a predictor for expected returns. These findings may be grouped into two main categories: the first category claims that the unrealized capital gains overhang is a good predictor for expected returns and there is a positive and significant relation between expected returns and unrealized capital gains overhang. In this category, investors are shown to follow the disposition behaviour. For instance, Grinblatt & Han (2005) develop new framework depending on prospect theory and mental accounting to describe disposition behaviour proxied by reference price and estimated by the following equation:

$$RP_t = \frac{1}{k}\sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}\left[1-V_{t-n+\tau}\right]\right)P_{t-n} \qquad (1)$$

where V_t is the turnover ratio at date *t*, P_{t-n} is the probability that an investor bought a specific stock at date *t-n* and still hold it. In the parentheses, the mathematical term is a weight, and all weights total one. They support the positive relationship between unrealized capital gains overhang and expected returns. Birru (2015) follows the procedures of Grinblatt and Han (2005) to test the relation between capital gains overhang and expected returns using a sample period from 1967 to 2011. Birru (2015) supports the positive relation between capital gains overhang and expected returns either for the whole sample or February-December subsample. Bhootra & Hur (2012) analyse the period from January 1980 to December 2005 and find result consistent with Grinblatt &Han (2005) since the top capital gains portfolio gives the highest future returns per month, while the bottom capital gains portfolio provides the lowest future returns. Bhootra & Hur (2012) also divide the sample into co-integrated and non co-integrated subsamples and then they test the relation between unrealized capital gains overhang and expected returns in each subsample. According to their finding, this relation is positive for the two samples but stronger among non co-integrated stocks. Shumway & Wu (2006) use data on 13,460 investors in the Chinese stock market and confirm that the unrealized capital gains factor is a successful predictor for future return, and the relation between them is statistically positive. Finally, Hur, Pritamani, & Sharma (2010) cover the period 1980-2005 and demonstrate that the relation between capital gains overhang and expected returns is significant and positive.

In contrast, the second category finds a negative relation between capital gains overhang and future returns. In this category, investors follow the opposite behaviour of the disposition effect through tending to sell losers too soon and holding winners too long. Kong, Bai, & Wang (2014) employ firm-level data in the Chinese market from January 1998 to June 2013. They conclude that this relation between unrealized capital gains and future returns is negative for the whole sample and for February to December subsample. Goetzmann & Massa (2008) use daily data, follow Grinblatt and Han's methodology to estimate the reference price and reach the conclusion that the disposition factor, at the market level and stock level, is strongly and negatively related to future returns. Choe & Eom (2009) test the relation between disposition effect and profits in the Korean futures market using account-level data including all transactions from January 2003 to March 2005. Using cross-sectional regression, they also discover negative relation between the disposition factor and account returns.

The common drawback in most of the aforementioned studies, we claim they represent the main streams in the literature review, is that they use a regression model based on the conventional OLS technique. Therefore, these conflicting findings may reflect a nonlinear relationship between the unrealized capital gains overhang and the expected returns.

The OLS technique is useful for estimating the average relationship of the dependent and independent variables. However, it is not probably to work well if one is considering the performance of extreme observations that represent the tails of a probability distribution (Gowlland, Xiao, & Zeng, 2009). To simplify, the OLS produces the conditional mean and relationship between the dependent variable and each independent variable is always specified through only one estimate (Hallock, Madalozzo, & Reck, 2010). This means that if the sensitivities or the coefficients vary across different expected return quantiles, then a conventional OLS technique can be criticized for assuming homogeneity and concealing the potential heterogeneity of the impact of the independent variables 'X' on the dependent variable 'Y' across the distribution (Sula, 2011). Therefore, we use quantile regression to describe how different are the relations between the capital gains overhang and the expected returns across the conditional distribution of expected returns. In addition, the quantile regression is robust to some common but undesirable characteristics in financial datasets such as heteroscedasticity, skewness and heavy-tailed distribution (Pires, Pereiro, & Martins, 2015), (Cameron & Trivedi, 2010) and (Gowlland, Xiao, & Zeng, 2009).

This paper makes five contributions to the literature. As far as we know this paper is the first to use quantile regression to investigate the determinants of capital gains overhang. Providing a comprehensive picture of the relation between capital gains overhang and expected returns by using quantile regression is the second contribution of the paper. The third contribution is that we think we are the first to examine how linear the relationship between capital gains overhang and expected returns is through testing the equality of coefficients across different levels of expected returns. In other words, one motivation in our research was that the shape of expected return and capital gains overhang relation was still unknown since the OLS conventional technique does provide information about the possible nonlinearity between the unrealized capital gains overhang and expected returns. The fourth contribution is that we are the first, to our knowledge, to investigate the ability of the disposition effect to induce momentum for the extreme regions (0.05^{th} and 0.95^{th}) of the expected return distribution. Our sample, the Russell 3000 constituents, represents in many ways the fifth contribution to the literature on the disposition effect and momentum: 1) we are the first, to our knowledge, to include NASDAQ stocks, which made up one-fifth of our sample. However, Grinblatt & Han (2005), Birru (2015), and Bhootra & Hur (2012) exclude NASDAQ stocks from their samples even though NASDAQ contains plenty of leading stocks especially the high-tech stocks, in the US stock market, which is characterized by high volatility and high growth stocks; 2) Another advantage that improves the reliability of our findings is that we free our sample of survivorship bias through updating the list of Russell

3000 index periodically; 3) depending on the Russell 3000 index which has the largest 3000 stocks makes our sample representative and properly captures investors' beliefs, while including stocks that are excluded from the Russell 3000 index may lead to a spurious findings since the prices would represent stale prices rather than investors' current beliefs.

The quantile regression findings explain that there is a heterogeneous impact on the unrealized capital gains overhang of past returns on three different horizons. Fortunately, the coefficients of short and intermediate past returns decline systematically with the increase in unrealized capital gains quantiles, meaning that the momentum is stronger in the lowest capital gains quantile and its strength reduces with the increase in capital gains quantiles. Regarding the relation between the unrealized capital gains overhang and expected returns, the coefficients are significantly positive and systematically decline with the increase in expected returns quantiles from the lowest quantile (0.05^{th}) to the median. However, they are significantly negative and systematically increase with the increase in the expected returns at the above median quantiles, indicating that investors follow the disposition behaviour at the median and below the median points, while they tend to engage in the opposite behaviour above the median. Regarding the ability of disposition effect to generate momentum in returns, at the lowest expected returns quantile (0.05^{th}), the disposition effect is not a good noisy proxy for inducing the intermediate momentum. Finally, it interestingly generates contrarian at the highest expected return quantile (0.95^{th}).

The reminder of this paper is organized as follows: the next section shows the hypotheses development, Section 4.3 presents a brief summary of the quantile regression model, section 4.4 describes our data, sample, and methodology, section 4.5 presents the empirical results, section 4.6 demonstrates momentum and the disposition effect, and conclusions are drawn in section 4.7.

4.2- Hypotheses Development

Jagadeesh and Titman (1993) define momentum, as past winners tend to overcome past losers. Grinblatt and Han (2005) argue that relating past returns to capital gains overhang and momentum trading is lucrative since stocks that experience a positive spread between market prices and reference prices are expected to be future winners while stocks that experience negative spread between market prices and reference prices are expected to be future losers. In addition, we can proxy the unrealized capital gains facing disposition investors by using past cumulative returns. The size of momentum mainly depends on the investors' reaction to new information. Some writers suggest that investors respond in different way to good and bad news. For instance, Epstein & Schneider (2008) claim that bad news is more effectual than good news and, in turn, investors' reaction to bad news is more powerful. Kelsey, Kozhan, & Pang, (2010) found various patterns in price persistence. They attribute this asymmetric momentum to investors' different reactions to past winners and losers. These different reactions are more probably to produce different relations between past returns and capital gains overhang acrosss the unrealized capital gains distribution, which cannot be proved by using the OLS technique of Grinblatt and Han (2005). In summary, our first hypothesis can be stated as follows:

H1. Ceteris paribus, the relation between past returns over the three horizons and unrealized capital gains is not uniform and varies across different quantiles.

Our second hypothesis addresses the relationship between capital gains overhang and expected returns. Some studies indicate a positive relation between capital gains overhang and expected returns Grinblatt and Han (2005), Birru (2015), Bhoora and Hur (2012) & Shumway and Wu (2006). This positive relation means that investors adopt disposition behaviour through realizing gains too soon and holding losers too long. Others discover a negative relation between capital gains overhang and expected returns (Kong, Bai and Wang, 2014), (Goetzmann and Massa, 2008) & (Choe and Eom, 2009). This negative relation refers to the converse of the disposition behaviour holding winners too long and realizing losses too soon. Because all of the above studies use the conventional OLS technique, which gives no information on possible nonlinearities, these conflicting findings may indicate a non-linear relation between unrealized capital gains and expected returns. The second hypothesis can be stated as follows:

H2. Ceteris paribus, the relation between expected returns and capital gains overhang is nonlinear.

4.3- Quantile regression technique

In this section, we first discuss the conventional regression based on central tendency including ordinary least square ('OLS') and least absolute deviation ('LAD'). Then we discuss the more advanced quantile regression model

4.3.1- OLS and LAD

Koenker and Basset (1978) devised a quantile regression technique to tackle the shortcomings of traditional regression based on the conventional OLS technique. The quantile regression runs multiple estimations at different data-points of the distribution of a dependent variable 'Y' rather than focusing only on the conditional mean (Davino, Furno, & Vistocco, 2014). The basic regression model can adopt the following formula:

$$y_{it}=x'_{it}.\beta + u_{it} \qquad (2)$$

where y is the dependant variable, x is the independent variable, u is the error term and β is the coefficient "slope". i= 1, 2, 3,….N and t= 1, 2, 3,….. t are the time and sample units respectively. The traditional regression technique seeks to minimize the sum of squared error ('SSE') using the following formula:

$$\min \sum_i (u_{it})^2 = \sum_i (y_{it} - x'_{it}.\beta)^2 \qquad (3)$$

However, the least absolute deviation ("LAD") takes the following formula:

$$\min \sum_i |u_{it}| = \sum_i | y_{it} - x'_{it}. \beta| \qquad (4)$$

It is worth mentioning that β refers to the conditional mean in the traditional regression method and refers to the conditional median in the LAD technique and that both rely on one central distribution tendency. This means that both techniques ignore the observations in the two extremes of the distribution (Li & Hwang, 2011). To deal with this issue, the quantile regression model should be used.

4.3.2- Quantile regression model

The quantile regression model is a developmental extension of the least square conventional techniques. According to the quantile regression model, the conditional quantile can be defined as a linear function of the independent variables. The basic formula of the quantile regression model can be expressed as follows:

$$Y = x'\beta + \varepsilon \qquad (5)$$

$$Q_{\theta}(YX = x) = x'(\theta) \text{ and } \quad 0 < \theta < 1 \qquad (6)$$

where Y is the dependant variable, x is a matrix of independent variables, ε is the error term. Q_{θ}(YX= x) stands for the θth quantile of Y Conditional X =x. From Equation (6), we can infer that the error term ε restricted by Q_{θ} (∊\X=x) = 0.

The quantile regression coefficient (θ) can be produced by solving the problem below:

$$Min_{\beta \in R^K} \sum_{Y \geq X'\beta} \theta\, Y - X'\beta + \sum_{Y < X'\beta} (1-\theta) Y - X'\beta \qquad (7)$$

If the quantile is set as 50^{th}, then we deal with the median, and by going up from 0 to 1, we pursue the distribution of Y, conditional on X. This should provide more information on the relationship between the variables of interest (Koenker & Hallock, 2001)[9].

Finally, it should be noted that segmenting the sample and employ OLS technique for each subsample will produce a completely different results from the quantile regression since the quantile regression uses all the data for each estimation procedure (Hallock, Madalozzo, & Reck, 2010).

4.4- Data, sample and methodology description

We collect the monthly data of all constituents of the Russell 3000 index from January 1995 to June 2015. To deal with the expected survivorship bias, the list of companies was updated every month. This leads the number of companies to increase substantially (about 5176 firms after removing all firms that have fewer than 36 observations). The data includes closing price, trading volume and the number of outstanding shares to calculate the unrealized capital gains overhang based on Grinblatt and Han (2005) as detailed in section (4.1). However, we used the previous 36 months instead of 60 months to avoid losing a great deal of data, meaning that the period from January 1998 to June 2015 was subjected to the empirical analysis. We also used monthly rather that weekly data in calculating the unrealized

[9] See Tsai (2012)

capital gains because our sample included a larger number of smaller stocks that that might have been affected by thin trading if weekly data had been used.

The closing price is also used to calculate the stock return (r), the past cumulative returns over the short horizon of the last three months ($r_{-3:-1}$), the intermediate horizon between the last four months and 12 months ($r_{-12:-4}$) and the long horizon between the last 13 months and 36 months ($r_{-36:-13}$). The monthly trading volume and number of shares outstanding were collected in order to calculate the average turnover over the short horizon ($V_{-3:-1}$), the intermediate horizon ($V_{-12:-4}$) and the long horizon ($V_{-36:-13}$). Monthly market capitalization was also collected and converted to a logarithm 'log'. Table 4.1 gives a detailed description of all the dependent and independent variables.

<<Table 4.1 about here>>

On the methodological side, we compare the Fama and MacBeth (1973) two step procedure with the quantile regression and we also control for the following: return effects, proxied by cumulative return over the short, intermediate and long horizons; the return premium effect of firm size proxied by logarithm of market capitalization, and the volume effect measured by average monthly turnover over the past 12 months. We can formulate the regression model as follows:

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g \qquad (8)$$

where r_t is the monthly stock return. $r_{-t1:-t2}$ is cumulative monthly return from t-t_1 to t-t_2. V is the average monthly turnover over the previous 12 months. S is log (monthly market capitalization. g is the capital gains overhang.

This quantile regression model is run at 5th, 10th, 25th, 50th, 75th, 90th and 95th of the expected returns quantiles. The bootstrapping resampling technique with 400 replications was also run to estimate the standard errors. This bootstrapping helps to develop joint distribution and develop F-statistics to examine the significant differences in the coefficients across the conditional distribution quantiles. To address the shape of the relation between capital gains overhang and expected returns and to test the heterogeneity of the capital gains overhang impact across different levels of expected returns, we follow Koenker and Bassett (1982) and Hendricks and Koenker (1991) who develop the following test

$$T_n = (\widehat{\beta}_{T1} - \widehat{\beta}_{T2})'(\mathrm{H}^{-1}\mathrm{J}\mathrm{H}^{-1})(\widehat{\beta}_{T1} - \widehat{\beta}_{T2}) \qquad (9)$$

We test the hypotheses H_0: $\beta_{T1} = \beta_{T2}$ against H_1: $\beta_{T1} \neq \beta_{T2}$ where $H^{-1}JH^{-1}$ is the "sandwich" formula developed by Hendricks and Koenker (1991). If the null hypothesis is not accepted, then we can confirm that there is a significant unequal coefficient across various expected return distribution quantiles.[10] In this case, we could say that the relation between capital gains overhang and expected returns was nonlinear. Finally, in this paper we tested the differences between coefficients or slopes at the θ against $(1- \theta)$ quantiles. For instance, we compare the 0.05th quantile versus the 0.95th quantile, the 0.10th quantile versus the 0.90th quantile and the 0.25th quantile versus the 075th quantile.

4.5- Empirical analysis

This section is divided into three subsections. The first of these discusses the descriptive statistics, the second section highlights the determinants of capital gains overhang and the third section focuses on the relation between capital gains overhang and expected returns.

4.5.1– Descriptive statistics

In Table 4.2, we present the summary statistics for more than 454,400 stock-month observations. We note that the capital gains overhang is negative (-0.08) with standard deviation (0.48). However, the average returns in our sample is positive (0.01) with standard deviation (0.11). We also report the summary for the 10th percentile, median and 90th percentile.

<<Table 4.2 about here>>

[10] Hallock, K.F, & et.al.(2010). CEO pay for performance heterogeneity using quantile regression. The financial Review, 45, 1-19

4.5.2- The cross sectional determinants of unrealized capital gains overhang

The first step in our analysis was to investigate the relation between capital gains overhang and its determinants, including past cumulative returns over three different horizons, past average turnover over three different horizons and size.

$$g_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S \quad (9)$$

where g_t is capital gains overhang. $r_{-t1:-t2}$ is cumulative monthly return from t-t_1 to t-t_2. $V_{-t1:-t2}$ is average monthly turnover from t-t_1 to t-t_2. Table 4.3 shows the correlation matrices.

<<Table 4.3 about here>>

Table 4.4 compare the Fama- MacBeth regression based on the conventional OLS technique with quantile regression at 0.05th, 0.10th, 0.25th, 0.50th, 0.75th, 0.90th, and 0.95th quantiles. This Table shows the consistent results of the Fama-MacBeth with Grinblatt and Han (2005), since there is a positive and significant relation between the unrealized capital gains and past cumulative returns over the past three horizons and a significantly negative relation between the unrealized capital gains and average turnover over the three different horizons and finally a positive relation between unrealized capital gains and size.

<<Table 4.4 about here>>

The quantile regression findings support our first hypothesis in terms of the impact of past returns over the three different horizons; Panel B shows significant differences for $r_{-3:-1}$ and $r_{-12:-4}$ across all capital gains overhang quantiles, while the long-term cumulative return $r_{-36:-13}$ explains the uniform impact in some quantiles and the heterogeneous impact in others. Interestingly, the coefficients of short-term and intermediate cumulative returns decline systematically as the capital gains overhang increases. These systematic patterns indicate that the ability of past winners (losers) to generate unrealized capital gains (losses) is higher in the lowest quantiles and declines with the increase in capital gains quantiles. In other words, the momentum is stronger in the lowest quantiles on the short and intermediate horizons. All the robustness checks in Tables 4.5, 4.6 and 4.7 support the previous conclusions.

<<Table 4.5 about here>>

<<Table 4.6 about here>>

<<Table 4.7 about here>>

Regarding the relationship between average turnover and capital gains overhang, the theory suggests a negative relation since the higher the turnover, the faster the reference price converges to the market price. However, the data-points close to the upper and lower extremes show surprising results especially the highest capital gains quantile (0.95^{th}). In this quantile, the relation between capital gains overhang and average turnover in the short and long- term is positive and significant in almost all cases either in the main analysis (see Table 4.4) or in all robustness checks (see Tables 4.5, 4.6 and 4.7). This result means that the higher the turnover, the more slowly the reference price converges to the market price, eventually creating larger unrealized capital gains. Finally, in the lowest capital gains quantile (0.05^{th}) the average turnover behaves the same as it does in the highest quantile (0.95^{th}) on the short and long- term.

Size is the last variable in this model. The quantile regression shows a conclusion completely consistent with the theory since the relation between capital gains overhang and size is positive across all quantiles and in all cases including all robustness checks except the below median institutional ownership. This finding reflects that the giant companies produce larger unrealized capital gains, probably because the past cumulative returns may not be able to capture the past growth made by the giant companies. The quantile regression also provides some useful insights into the relation between size and capital gains overhang. In the main finding (see Table 4.4) and all robustness (see Tables 4.5, 4.6 and 4.7), the size coefficients decline systematically with the increase in capital gains quantiles, suggesting that the ability of large companies to generate greater unrealized capital gains and capture the past growth declines with the increase in capital gains quantiles.

4.5.3- Expected returns, past returns and unrealized capital gains

The Fama-Macbeth regression based on OLS in Table 4.8 shows a strongly positive and significant cross-section relation between expected returns and capital gains overhang at 1% significance level. This result is consistent with Grinblatt and Han (2005) and Birru (2015). However, it is hard using the OLS technique to distinguish the impact of unrealized capital gains on expected returns between more and less profitable stocks across the distribution and in the extreme regions. Quantile regression can deal with this issue.

<<Table 4.8 about here>>

Table 4.15 and 4.16 provide a well-organized summary of the relation between expected returns and unrealized capital gains across all quantiles including the whole sample, the seasonality subsamples and all robustness checks. From these tables, we can observe that the coefficients of capital gains overhang are significantly positive and decline as the expected returns quantiles increase from the lowest to the median expected return quantiles (below median and median data-points). However, they become significantly negative and rise with the increase in expected returns quantiles at the highest ('above median') expected returns quantile. In Table 4.16, we compare the coefficients at θ against $(1-\theta)$ quantiles. F-statistics indicate significant differences in the coefficients of unrealized capital gains across various expected returns quantiles, meaning that the observed nonlinearities extracted from the quantile regression confirm a significant difference in the impact of unrealized capital gains across various levels of expected returns including the extremely lucrative and the extremely unprofitable stocks. This conclusion provides a strong support to our second hypothesis and asserts the nonlinear relation between unrealized capital gains and expected returns. This conclusion provides some insights into the conflicting findings in the literature, although confirming these conflicting findings might be attributed to the nonlinear relationship between the two variables of interest. In sum, the irrational investors follow the disposition behaviour of selling the winners too soon and holding losers too long at the median and below median expected returns points, while they follow the converse pattern of disposition behaviour at the above median expected returns points.

<<Table 4.15 about here>>

<<Table 4.16 about here>>

Finally, Tables 4.8, 4.9, 4.10, 4.11, 4.12, and 4.13, show strong persistence in the short-term cumulative returns (‘a_1’) in all cases using either the whole sample or seasonal subsamples or robustness checks subsamples across all quantiles. The main reason why we implement robustness check is to ensure regression estimates are insensitive to different market conditions and are insensitive to different assumptions. Fortunately, the coefficients of short-term a_1 and long-term cumulative returns a_3 tend to go up systematically with the increase in expected returns quantiles. However, the intermediate cumulative return a_2 shows a systematic pattern in December only since it increases with the increase in expected returns quantiles. Apart from December, there is robust evidence that the intermediate cumulative returns go up systematically from the lowest expected returns quantile to the median point and goes down systematically above the median to the highest expected returns quantile (0.95^{th}).

<<Table 4.8 about here>>

<<Table 4.9 about here>>

<<Table 4.10 about here>>

<<Table 4.11 about here>>

<<Table 4.12 about here>>

<<Table 4.13 about here>>

4.6- Disposition effect and momentum

This section checks the ability of the disposition effect to drive intermediate momentum. Grinblatt and Han (2005) conclude that the disposition effect alone can induce the intermediate momentum effect described by Jagadeesh and Titman (1993) since the intermediate momentum disappears once the unrealized capital gains overhang is controlled for. Birru (2015) doubts the ability of the disposition effect alone to induce momentum and demonstrate that the momentum is too complicated to be generated by disposition effect alone. Shumway & Wu (2006) also produce evidence that the disposition effect drives momentum using account-level data. Muga & Santamaría (2009) study the momentum and disposition effect in the spanish stock market. They recommend combining under-reaction theory based on the disposition effect with over-reaction theory when explaining the momentum effect since under-reaction and disposition successfully induce momentum in down markets, while over-reaction does the same in up markets. Hur, Pritamani, & Sharma (2010) relate the ability of the disposition effect to induce momentum with the proportional representation of individual investors. They believe that the higher the number of individual investors, the stronger the ability of the disposition effect to induce momentum. Despite the practical importance of the highest gains and the highest losses stocks, none in the literature, to our knowledge, attempts to check the sources of momentum for the most extreme expected returns quantiles (0.05^{th} and 0.95^{th}).

In this paper, we focus on the extreme expected return regions (0.05^{th} and 0.95^{th}). From a practical point of view, the behaviour of the extreme regions attracts the particular attention of risk managers as well as investors since they represent the stocks with the highest gains and the highest losses (Nath & Brooks, 2015). In addition, the OLS conventional technique used by Grinblatt and Han (2005) and the other previous studies is not only not useful for understanding the behaviour of the extreme regions but also very sensitive to outliers and ignores the behaviours of data-points which are very far from the mean (Gowlland, Xiao and Zeng, 2009) & (Naifar, 2015). Moreover, the use of the OLS technique always leads to ignoring the information on the tails of a probability distribution (Chiang, Li, & Tan, 2010). The quantile regression, however, is more effective in dealing with outliers and heavy-tailed distributions (Pires, Pereira, & Martins, 2015). We conclude from the above discussion that the uniqueness of the extreme regions justifies examining them alone.

Following Grinblatt and Han (2005), we proceed to examine in three stages the ability of the disposition effect to drive momentum by running Fama-MacBeth (1973) two-step procedures and quantile regression with and without capital gains overhang as follows:

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V \qquad (10)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S \qquad (11)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g \qquad (12)$$

where r_t is the monthly stock return. $r_{-t1:-t2}$ is cumulative monthly return from t-t_1 to t-t_2. V is the average monthly turnover over the previous 12 months. S is log (monthly market capitalization. g is capital gains overhang.

In this part, we were satisfied by presenting only the intermediate cumulative return ('a_2') from the model 10 and model 11 outputs because it is the variable of interest, and other regression outputs were not needed. Table 4.14 includes the intermediate cumulative returns for the three regressions ('before and after controlling for the unrealized capital gains') to facilitate reading and comparing the coefficients.

<<Table 4.14 about here>>

Focusing on the lowest (0.05^{th}) and highest (0.95^{th}) expected returns quantiles, it is worth noting that the intermediate cumulative return is strongly positive and significant in the lowest expected return quantile (0.05^{th}) before the unrealized capital gains overhang is controlled for. Once we added the unrealized capital gains overhang, most of the intermediate cumulative returns coefficients turned significantly negative, meaning that the disposition effect was not a good noisy proxy to generate momentum at the lowest expected return quantile (0.05^{th}). This finding is robust to institutional ownership, leverage and size. However, most of the highest expected returns quantiles (0.95^{th}) have strongly significant and negative intermediate cumulative returns, which means that there is a reversal in return. In other words, the intermediate momentum of Jagadeesh and Titman (1993) is not profitable in the highest expected returns quantile (0.95^{th}). Interestingly, when we control for unrealized capital gains, almost all the negative coefficients, except below median institutional ownership and large size subsamples, became insignificant. This conclusion means that the opposite behaviour of disposition can successfully drive intermediate contrarian rather than momentum at the highest expected return quantile (0.95^{th}) in all cases except the above median size and below median institutional ownership stocks since the contrarian disappears when we control for unrealized capital gains. This occurs, when stocks experience significant capital gains and the investors tend to be risk lovers because the current gains protect them against future losses and, the prices are usually high. As a result, the investors look forward to lower expected returns. However, if the stocks experience unrealized capital losses and the investors are more risk-averse, the investors look forward to higher expected returns.

4.7- Conclusion

In this paper, we have tried to extend the literature through using an unconventional quantile regression technique since previous studies on the relation between expected returns and capital gains overhang provide mixed findings. One important conclusion in our paper is that these contradictions in the literature can, to some extent, be attributed to the nonlinear relationship between the unrealized capital gains overhang and expected returns. Second, the disposition-prone investors follow disposition behaviour at the below median and median expected returns quantiles but they follow the converse behaviour at the above median expected returns quantiles. Our findings also explain that the disposition effect is not a good noisy proxy for inducing intermediate momentum at the lowest expected returns quantile (0.05^{th}). Therefore, it would be of interest for future research to examine the other sources of momentum such as the risk-based explanation at the lowest expected return quantile (0.05^{th}). At the highest expected returns quantile (0.95^{th}) the opposite disposition effect contributes entirely in generating contrarian rather than momentum. These findings are robust to institutional ownership, leverage and size.

In sum, we can conclude that the OLS estimates that neglect the embodied heterogeneity in the stocks can produce incorrect conclusions. Finally, this paper suggests several research points for future consideration, such as using the quantile regression to investigate the relation between the unrealized capital gains overhang and expected returns, and the ability of disposition effect to generate momentum in returns in a range of developed and emerging markets.

Tables of results

Table 4.1. Description of the independent variables.

Variable	Definition
Capital gains overhang	The capital gains overhang is calculated as the percentage difference between current prices and the reference price. $$CGO_t = \frac{P_t - RP_t}{P_t}$$ Where P_t is the closing price at time t and RP_t is reference price calculated based on equation (1).
Stock return	The change rate in monthly closing price $r_t^i = \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ Where P_t^i is the closing price at month *t* and P_{t-1}^i is the closing price at month *t-1*.
$r_{-3:-1}$	The past cumulative returns over the short horizon of the last three months.
$r_{-12:-4}$	The intermediate horizon between the last four months and 12 months.
$r_{-36:-13}$	The long horizon between the last 13 months and 36 months.
$V_{-3:-1}$	The average turnover over the short horizon of the last three months.
$V_{-12:-4}$	The average turnover between the last four months and 12 months.
$V_{-36:-13}$	The average turnover between the last 13 months and 36 months.
V	A proxy for volume effect and computed as average monthly turnover over the past 12 months.
Institutional Ownership	The percentage ratio of freely traded shares held by institutions to the number of Float Shares Outstanding.
Leverage	A measure of the debt burden of a company. It is equal to the monthly ratio of debt to equity
The company Size (S)	Proxied by monthly market capitalization.

Table 4.2. Summary statistics

This table demonstrates various descriptive statistics such as mean, median, standard deviations, minimum, maximum and skewness for capital gains overhang *g*, expected returns *r*, past returns over three horizons $r_{-3:-1}$, $r_{-12:-4}$ and $r_{-36:-13}$, Size *S* and average volume *V*.

Variables	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Skew**	**10th Pct.**	**90th Pct.**	**Obs**
g	-0.0772	0.0633	0.4846	-1.8358	0.4454	-2.0530	-0.6490	0.3320	454432
r	0.0096	0.0086	0.1072	-0.2316	0.2651	0.0911	-0.1251	0.1446	454467
$r_{-3:-1}$	0.0293	0.0253	0.1919	-0.3850	0.4931	0.1734	-0.2136	0.2728	454474
$r_{-12:-4}$	0.0895	0.0692	0.3469	-0.5831	0.9948	0.4692	-0.3417	0.5341	454474
$r_{-36:-13}$	0.2569	0.1789	0.6226	-0.7460	2.0176	0.8622	-0.4776	1.0745	454474
S	21.1036	20.9056	1.4325	18.8261	24.3868	0.5002	19.3370	23.2082	450658
V	0.0086	0.0066	0.0071	0.0008	0.0308	1.4827	0.0018	0.0250	454474

Table 4.3. Correlation matrices and Heteroscedasticity

where *g* is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month $t\text{-}t_1$ through $t\text{-}t_2$ computed over three past return horizons; $r_{-t1:-t2}$; $V_{-t1:-t2}$ = average monthly turnover from $t\text{-}t_1$ through $t\text{-}t_2$; *V*= average monthly turnover ratio (share volume divided by the number of shares outstanding) over the previous 12 month. *S* = natural logarithm of monthly market capitalization; *return* is the month-*t* return.

Panel A correlation matrix for the determinants of capital gains overhang

Variable	CGO	$r_{-3:-1}$	$r_{-12:-4}$	$r_{-36:-13}$	$v_{-3:-1}$	$v_{-12:-4}$	$v_{-36:-13}$	S
g	1.00							
$r_{-3:-1}$	0.39	1.00						
$r_{-12:-4}$	0.59	0.53	1.00					
$r_{-36:13}$	0.66	0.30	0.52	1.00				
$v_{-3:-1}$	-0.14	-0.03	-0.04	-0.01	1.00			
$v_{-12:-4}$	-0.16	-0.03	-0.06	-0.04	0.87	1.00		
$v_{-36:13}$	-0.17	-0.02	-0.04	-0.07	0.76	0.88	1.00	
S	0.35	0.09	0.17	0.28	0.07	0.06	0.05	1.00

Panel B correlation matrix for expected returns, past returns and capital gains overhang

Variable	return	$r_{-3:-1}$	$r_{-12:-4}$	$r_{-36:-13}$	V	S	CGO
return	1.00						
$r_{-3:-1}$	0.54	1.00					
$r_{-12:-4}$	0.30	0.53	1.00				
$r_{-36:-13}$	0.18	0.30	0.52	1.00			
V	-0.01	-0.03	-0.05	-0.05	1.00		
S	0.05	0.09	0.17	0.28	0.06	1.00	
g	0.24	0.39	0.59	0.66	-0.17	0.35	1.00

Significance level at 5%

Panel C: Heteroscedasticity (Breusch-Pagan test)

Model	Model one	Model two	Model three	Model four
P- Value	0.000	0.000	0.000	0.000

These results indicate that all models suffer from Heteroscedasticity which can be taken as a justification for using quantile regression because quantile regression is robust to heteroscedastictic data.

Table 4.4. Determinants of capital gains overhang: Fama-MacBeth and Quantile regression

Panel A: Determinants of capital gains overhang: Fama-MacBeth and Quantile regression

$$g_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; $V_{-t1:-t2}$ = average monthly turnover from t-t_1 through t-t_2; S = natural logarithm of monthly market capitalization.

Explanatory Variables	**Fama-MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	-1.2126	-6.2631	-3.7825	-1.6731	-0.6914	-0.2888	-0.0343	0.1185
	(-30.98)	(-151.13)	(-177.15)	(-179.18)	(-155.05)	(-87.95)	(-8.96)	(27.08)
a_1	0.2889	0.5066	0.3899	0.2571	0.1985	0.1718	0.1518	0.1467
	(23.37)	(26.10)	(33.13)	(47.81)	(65.15)	(79.36)	(71.05)	(52.87)
a_2	0.3786	0.3984	0.3415	0.2976	0.2754	0.2589	0.2448	0.2338
	(33.11)	(31.27)	(44.88)	(73.71)	(118.26)	(156.74)	(136.15)	(109.94)
a_3	0.3213	0.1641	0.1909	0.2209	0.2236	0.2126	0.1921	0.1707
	(33.37)	(31.59)	(50.67)	(100.13)	(154.69)	(198.30)	(196.35)	(160.24)
a_4	-1.7863	0.0017	0.0012	0.0002	0.0002	0.0003	0.0004	0.0004
	(-4.38)	(1.80) *	(1.75) *	(1.04)	(1.49)	(3.96)	(4.62)	(3.36)
a_5	-1.6324	0.0008	0.0005	0.0005	0.0000	-0.0004	-0.0008	-0.0011
	(-2.51)	(0.56)	(0.48)	(1.97)	(0.21)	(-3.73)	(-5.37)	(-6.11)
a_6	-6.3299	-0.0040	-0.0027	-0.0008	-0.0002	0.0003	0.0008	0.0012
	(-12.41)	(-4.23)	(-3.79)	(-5.18)	(-1.55)	(5.11)	(8.57)	(13.05)
a_7	0.0538	0.2435	0.1489	0.0674	0.0296	0.0151	0.0064	0.0014
	(31.51)	(145.65)	(166.39)	(162.73)	(146.02)	(98.14)	(37.00)	(7.34)
R^2	60.40	15.12	16.16	18.67	22.18	25.63	27.31	27.11

Panel B: Tests of the equality-of-slope estimates across quantiles

Variables	**Quantiles**					
	0.05 vs. 0.95		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	353.75	(0.0000)	449.86	(0.0000)	378.40	(0.0000)
a_2	179.76	(0.0000)	198.52	(0.0000)	150.84	(0.0000)
a_3	1.77	(0.1839)	0.12	(0.7248)	28.45	(0.0000)
a_4	1.73	(0.1878)	1.19	(0.2743)	0.35	(0.5546)
a_5	1.75	(0.1853)	1.58	(0.2088)	15.19	(0.0001)
a_6	30.63	(0.0000)	24.92	(0.0000)	60.64	(0.0000)
a_7	20862.43	(0.0000)	26125.98	(0.0000)	19139.35	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth. R^2 for Fama-MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.5. Determinants of Capital gains overhang: Robustness analysis based on institutional ownership subsamples

$$g_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4\, V_{-3:-1} + a_5\, V_{-12:-4} + a_6\, V_{-36:-13} + a_7\, S$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; $V_{-t1:-t2}$ = average monthly turnover from t-t_1 through t-t_2; S = natural logarithm of monthly market capitalization.

	Above median institutional ownership								**below median institutional ownership**							
Coefficients	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	-1.0901	-5.7405	-3.5719	-1.6788	-0.7636	-0.3631	-0.0866	0.0609	-1.2090	-7.4464	-4.2877	-1.7434	-0.6551	-0.2207	0.0261	0.1797
	(-28.48)	(-112.42)	(-129.23)	(-137.31)	(-121.58)	(-70.04)	(-14.67)	(9.25)	(-30.31)	(-103.92)	(-131.93)	(-135.30)	(-111.86)	(-51.82)	(5.20)	(27.68)
a_1	0.2590	0.3916	0.3148	0.2241	0.1863	0.1605	0.1417	0.1368	0.3073	0.6161	0.4558	0.2939	0.2103	0.1846	0.1647	0.1584
	(21.82)	(16.69)	(23.47)	(34.70)	(50.40)	(55.57)	(52.39)	(38.70)	(21.91)	(16.47)	(21.22)	(31.24)	(39.19)	(51.69)	(40.74)	(30.48)
a_2	0.3440	0.3313	0.2953	0.2690	0.2554	0.2421	0.2297	0.2203	0.4080	0.4521	0.3961	0.3299	0.2994	0.2773	0.2643	0.2520
	(30.97)	(28.71)	(40.87)	(64.61)	(94.74)	(118.01)	(109.72)	(85.38)	(32.39)	(18.71)	(29.63)	(46.33)	(71.85)	(101.45)	(95.02)	(76.68)
a_3	0.2835	0.1460	0.1708	0.1953	0.1991	0.1934	0.1794	0.1637	0.3679	0.1659	0.2082	0.2543	0.2555	0.2360	0.2044	0.1745
	(32.99)	(30.33)	(50.87)	(83.02)	(123.48)	(154.97)	(150.40)	(130.82)	(33.28)	(15.45)	(29.45)	(58.33)	(97.96)	(118.80)	(120.77)	(82.99)
a_4	-1.5006	-0.0006	-0.0004	0.0001	0.0002	0.0001	0.0001	0.0000	-2.2312	0.0030	0.0019	0.0002	0.0003	0.0004	0.0006	0.0008
	(-3.58)	(-2.33)	(-1.95)*	(0.24)	(1.07)	(0.76)	(0.80)	(0.01)	(-4.49)	(2.76)	(2.51)	(0.74)	(2.27)	(3.97)	(6.45)	(5.29)
a_5	-2.0000	-0.0004	-0.0003	-0.0001	-0.0003	-0.0003	-0.0006	-0.0007	-1.0557	-0.0000	0.0002	0.0009	0.0002	-0.0005	-0.0009	-0.0015
	(-3.02)	(-1.38)	(-1.09)	(-0.56)	(-1.65)	(-1.44)	(-2.55)	(-2.44)	(-1.37)	(-0.01)	(0.23)	(2.04)	(0.99)	(-3.85)	(-5.16)	(-7.44)
a_6	-5.3234	0.0009	0.0005	0.0001	0.0002	0.0004	0.0008	0.0012	-8.0421	-0.0045	-0.0033	-0.0014	-0.0005	0.0004	0.0008	0.0013
	(-9.41)	(10.43)	(5.28)	(1.31)	(2.67)	(2.35)	(7.01)	(6.05)	(-13.81)	(-3.36)	(-4.47)	(-5.37)	(-4.00)	(4.93)	(6.42)	(13.22)
a_7	0.0492	0.2309	0.1450	0.0698	0.0340	0.0194	0.0096	0.0046	0.0527	0.2857	0.1658	0.0684	0.0267	0.0109	0.0028	-0.0019
	(29.47)	(106.98)	(121.31)	(128.16)	(119.08)	(81.35)	(35.35)	(15.32)	(30.57)	(101.00)	(125.33)	(123.16)	(101.72)	(55.12)	(12.37)	(-6.73)
R^2	60.38	18.90	20.12	23.20	27.22	30.50	32.10	31.95	61.65	13.32	14.18	16.12	18.79	21.87	23.53	23.32

Panel B: Tests of the equality-of-slope estimates across quantiles

	Above median Institutional ownership					
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	121.95	(0.0000)	185.70	(0.0000)	147.68	(0.0000)
a_2	99.17	(0.0000)	97.55	(0.0000)	72.85	(0.0000)
a_3	15.11	(0.0001)	8.41	(0.0037)	1.39	(0.2390)
a_4	3.83	(0.0504)*	4.62	(0.0317)	0.07	(0.7892)
a_5	0.56	(0.4561)	0.85	(0.3577)	0.30	(0.5835)
a_6	1.56	(0.2122)	5.05	(0.0246)	1.92	(0.1660)
a_7	10844.25	(0.0000)	12963.84	(0.0000)	10539.38	(0.0000)

	Below median institutional ownership					
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	156.09	(0.0000)	205.59	(0.0000)	202.78	(0.0000)
a_2	72.55	(0.0000)	109.58	(0.0000)	89.07	(0.0000)
a_3	0.73	(0.3942)	0.35	(0.5550)	35.71	(0.0000)
a_4	3.78	(0.0517)*	3.14	(0.0763)*	0.21	(0.6445)
a_5	0.53	(0.4666)	1.01	(0.3144)	11.83	(0.0006)
a_6	19.22	(0.0000)	32.67	(0.0000)	57.10	(0.0000)
a_7	10521.31	(0.0000)	16214.41	(0.0000)	14428.61	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.6. Determinants of Capital gains overhang: Robustness analysis based on leverage subsamples

$$g_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; $V_{-t1:-t2}$ = average monthly turnover from t-t_1 through t-t_2; S = natural logarithm of monthly market capitalization.

Above median Leverage									**Below median Leverage**							
Explanatory Variables	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	-1.2241	-7.2931	-4.2155	-1.7050	-0.6510	-0.27	-0.0375	0.1139	-1.2111	-5.3972	-3.4387	-1.6568	-0.7525	-0.3320	-0.0538	0.1012
	(-26.82)	(-102.42)	(-105.53)	(-123.23)	(-116.09)	(-58.71)	(-7.31)	(18.35)	(-34.90)	(-114.61)	(-125.88)	(-130.71)	(-107.56)	(-64.73)	(-8.56)	(15.89)
a_1	0.2983	0.5130	0.3659	0.2373	0.1859	0.1645	0.1471	0.1449	0.2840	0.5309	0.4108	0.2787	0.2093	0.1770	0.1546	0.1491
	(21.25)	(17.61)	(20.18)	(27.99)	(39.94)	(44.13)	(41.71)	(32.93)	(22.46)	(21.31)	(30.49)	(40.58)	(52.07)	(63.48)	(51.82)	(35.16)
a_2	0.3837	0.4010	0.3404	0.2868	0.2678	0.2566	0.2447	0.2330	0.3768	0.3927	0.3527	0.3069	0.2813	0.2607	0.2465	0.2351
	(33.24)	(22.53)	(27.92)	(47.38)	(73.05)	(94.38)	(95.05)	(74.56)	(30.93)	(29.83)	(45.53)	(69.91)	(99.98)	(121.22)	(107.80)	(97.71)
a_3	0.3377	0.2231	0.2398	0.2575	0.2494	0.2321	0.2063	0.1810	0.3040	0.1158	0.1498	0.1888	0.2003	0.1953	0.1785	0.1611
	(31.69)	(28.78)	(42.54)	(85.95)	(127.54)	(157.85)	(130.47)	(104.03)	(33.28)	(15.22)	(30.64)	(66.66)	(107.15)	(125.98)	(118.94)	(104.49)
a_4	-2.6433	0.0020	0.0009	0.0000	0.0001	0.0003	0.0005	0.0001	-0.8526	0.0015	0.0019	0.0005	0.0002	0.0003	0.0005	0.0007
	(-5.32)	(1.75)*	(1.19)	(0.06)	(1.12)	(4.37)	(5.87)	(3.75)	(-2.14)	(0.88)	(2.05)	(1.33)	(1.12)	(1.97)	(3.18)	(3.22)
a_5	-2.1620	-0.0000	0.0011	0.0006	0.0001	-0.0005	-0.0009	-0.0006	-0.7337	0.0002	-0.0008	0.0003	-0.0001	-0.0006	-0.0012	-0.0015
	(-2.86)	(-0.04)	(0.83)	(1.68) *	(0.83)	(-3.48)	(-7.87)	(-4.99)	(-1.12)	(0.05)	(-0.46)	(0.56)	(-0.71)	(-2.60)	(-4.56)	(-6.01)
a_6	-6.1900	-0.0034	-0.0031	-0.0008	-0.0003	0.0003	0.0007	0.0010	-7.3536	-0.0028	-0.0016	-0.0007	0.0002	0.0007	0.0013	0.0015
	(-11.41)	(-2.65)	(-3.46)	(-3.65)	(-3.16)	(3.63)	(10.22)	(8.25)	(-12.43)	(-1.92)	(-1.58)	(-2.26)	(2.27)	(4.37)	(7.38)	(11.07)
a_7	0.0542	0.2851	0.1664	0.0682	0.0273	0.0136	0.0061	0.0009	0.0542	0.2085	0.1350	0.0672	0.0328	0.0176	0.0078	0.0027
	(27.25)	(97.80)	(100.40)	(113.59)	(108.86)	(63.93)	(26.31)	(4.47)	(35.66)	(107.07)	(115.53)	(118.55)	(101.57)	(72.17)	(26.23)	(8.91)
R^2	60.61	15.13	15.41	17.06	20.10	23.47	25.15	24.99	60.90	16.32	17.95	21.07	24.96	28.35	29.84	29.47

Panel B: Tests of the equality-of-slope estimates across quantiles

Above median Leverage						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	160.85	(0.0000)	159.09	(0.0000)	112.12	(0.0000)
a_2	95.13	(0.0000)	70.35	(0.0000)	44.66	(0.0000)
a_3	31.86	(0.0000)	43.36	(0.0000)	142.98	(0.0000)
a_4	1.55	(0.2133)	0.34	(0.5576)	2.51	(0.1129)
a_5	0.24	(0.6279)	2.40	(0.1214)	10.32	(0.0013)
a_6	11.35	(0.0008)	18.06	(0.0000)	28.38	(0.0000)
a_7	9540.41	(0.0000)	9543.94	(0.0000)	9893.68	(0.0000)

Below median leverage						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	241.62	(0.0000)	387.34	(0.0000)	303.72	(0.0000)
a_2	150.49	(0.0000)	209.34	(0.0000)	175.68	(0.0000)
a_3	37.29	(0.0000)	43.35	(0.0000)	10.89	(0.0010)
a_4	0.21	(0.6502)	2.46	(0.1169)	0.17	(0.6814)
a_5	0.32	(0.5689)	0.03	(0.8550)	3.23	(0.0723)*
a_6	8.88	(0.0029)	8.27	(0.0040)	20.12	(0.0000)
a_7	11139.65	(0.0000)	12235	(0.0000)	9369.66	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise

Table 4.7. Determinants of Capital gains overhang: Robustness analysis based on size subsamples

$$g_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; $V_{-t1:-t2}$ = average monthly turnover from t-t_1 through t-t_2; S = natural logarithm of monthly market capitalization.

Above median size									Below median size							
Explanatory Variables	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	-0.3684	-2.3130	-1.4017	-0.6135	-0.2567	-0.0787	0.0539	0.1346	-3.4445	-32.6994	-18.8849	-7.5017	-2.7913	-1.0659	-0.4919	-0.2192
	(-18.03)	(-58.37)	(-66.29)	(-63.03)	(-49.63)	(-17.30)	(9.40)	(21.69)	(-47.60)	(-67.20)	(-89.90)	(-100.70)	(-91.6)	(-63.20)	(-25.30)	(-8.90)
a_1	0.2234	0.3762	0.3051	0.2303	0.1924	0.1600	0.1329	0.1213	0.3140	0.4632	0.3631	0.2703	0.2052	0.1813	0.1682	0.1764
	(20.08)	(22.68)	(27.30)	(40.10)	(55.54)	(55.20)	(48.81)	(35.81)	(22.00)	(19.30)	(23.50)	(33.70)	(41.30)	(53.70)	(41.60)	(31.00)
a_2	0.3070	0.2698	0.2659	0.2524	0.2411	0.2290	0.2160	0.2089	0.3892	0.2946	0.3089	0.2990	0.2949	0.2877	0.2772	0.2569
	(27.27)	(25.18)	(42.76)	(62.66)	(85.27)	(104.86)	(117.24)	(96.57)	(34.10)	(20.60)	(33.00)	(50.80)	(79.90)	(98.30)	(92.60)	(67.60)
a_3	0.2502	0.0805	0.1033	0.1349	0.1564	0.1665	0.1666	0.1604	0.3640	0.2798	0.3048	0.3308	0.3204	0.2783	0.2237	0.1815
	(32.68)	(16.83)	(35.63)	(58.58)	(93.19)	(122.37)	(129.60)	(123.96)	(32.10)	(38.60)	(62.0)	(88.20)	(142.70)	(163.60)	(119.39)	(81.90)
a_4	-2.2672	-0.0006	-0.0003	0.0000	0.0001	0.0002	0.0003	0.0003	-2.8833	0.0029	0.0021	0.0013	0.0003	0.0007	0.0006	0.0010
	(-6.15)	(-3.51)	(-1.40)	(0.40)	(1.21)	(2.29)	(3.91)	(2.29)	(-5.80)	(2.60)	(1.90)	(1.90) *	(0.97)	(3.20)	(2.70)	(4.20)
a_5	-5.5843	0.0004	0.0002	0.0001	-0.0003	-0.0005	-0.0008	-0.0011	-0.7065	-0.0016	-0.0008	0.0013	0.0012	-0.0001	-0.0009	-0.0015
	(-8.53)	(1.04)	(0.68)	(0.73)	(-2.12)	(-4.11)	(-6.83)	(-5.99)	(-0.90)	(-0.90)	(-0.40)	(1.00)	(3.10)	(-0.21)	(-3.30)	(-5.30)
a_6	0.9152	-0.0004	0.0003	-0.0002	0.0002	0.0005	0.0008	0.0011	-10.8376	-0.0053	-0.0048	-0.0041	-0.0017	-0.0002	0.0010	0.0015
	(1.61)	(-1.15)	(-2.62)	(-2.45)	(3.15)	(6.43)	(9.21)	(8.64)	(-18.40)	(-4.90)	(-3.90)	(-5.50)	(-6.60)	(-0.70)	(5.00)	(13.80)
a_7	0.0164	0.0823	0.0504	0.0233	0.0119	0.0068	0.0033	0.0011	0.1676	1.5547	0.8966	0.3549	0.1324	0.0528	0.0287	0.0180
	(20.86)	(48.21)	(54.69)	(55.04)	(52.34)	(34.22)	(12.87)	(4.07)	(47.80)	(65.80)	(87.70)	(97.30)	(87.80)	(62.70)	(29.60)	(14.60)
R^2	63.38	13.61	16.83	22.61	29.26	34.87	38.19	38.90	60.66	20.01	19.27	19.12	20.09	21.53	21.65	20.50

Panel B: Tests of the equality-of-slope estimates across quantiles

Above median size						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	238.79	(0.0000)	251.74	(0.0000)	220.82	(0.0000)
a_2	33.48	(0.0000)	73.68	(0.0000)	63.56	(0.0000)
a_3	323.95	(0.0000)	674.60	(0.0000)	494.68	(0.0000)
a_4	18.23	(0.0000)	7.49	(0.0062)	1.76	(0.1845)
a_5	11.80	(0.0006)	15.39	(0.0001)	18.18	(0.0000)
a_6	19.17	(0.0000)	56.86	(0.0000)	55.13	(0.0000)
a_7	2232.31	(0.0000)	2456.70	(0.0000)	1579.40	(0.0000)

Below median size						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	146.99	(0.0000)	171.78	(0.0000)	178.70	(0.0000)
a_2	7.42	(0.0065)	13.14	(0.0003)	6.15	(0.0131)
a_3	182.00	(0.0000)	283.58	(0.0000)	299.96	(0.0000)
a_4	2.70	(0.1005)	1.73	(0.1880)	0.98	(0.3216)
a_5	0.00	(0.9815)	0.00	(0.9513)	1.33	(0.2486)
a_6	39.87	(0.0000)	23.20	(0.0000)	31.48	(0.0000)
a_7	4222.17	(0.0000)	7237.63	(0.0000)	7887.91	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.8. Expected returns, past returns and capital gains overhang: Comparison between Fama-MacBeth two step procedure and quantile regression

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5\, S + a_6\, g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Explanatory Variables	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	0.0176	-0.3547	-0.2770	-0.1556	-0.0204	0.1513	0.3351	0.4656
	(2.01)	(-65.80)	(-67.11)	(-56.12)	(-10.91)	(56.65)	(73.04)	(68.03)
a_1	0.2983	0.2348	0.2521	0.2786	0.2972	0.3094	0.3454	0.3772
	(61.28)	(93.12)	(130.44)	(175.80)	(219.47)	(180.57)	(137.38)	(99.51)
a_2	-0.0000	-0.0060	-0.0029	0.0033	0.0079	0.0049	0.0033	0.0019
	(-0.02)	(-4.30)	(-2.96)	(4.11)	(11.95)	(7.00)	(2.58)	(1.15)
a_3	-0.0026	-0.0100	-0.0065	-0.0018	0.0008	0.0003	0.0058	0.0113
	(-2.75)	(-16.40)	(-15.36)	(-5.42)	(3.62)	(1.10)	(9.28)	(12.56)
a_4	0.1505	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0001
	(1.88) *	(-6.90)	(-3.96)	(-3.99)	(-0.79)	(2.74)	(3.28)	(2.54)
a_5	-0.0007	0.0105	0.0083	0.0048	0.0007	-0.0049	-0.0107	-0.0147
	(-1.80) *	(43.25)	(45.16)	(39.07)	(8.44)	(-40.88)	(-52.51)	(-47.67)
a_6	0.0124	0.0757	0.0546	0.0232	0.0013	-0.0044	-0.0401	-0.0748
	(7.96)	(37.47)	(36.61)	(19.12)	(2.53)	(-4.57)	(-18.12)	(-26.62)
R^2	34.06	28.93	24.96	19.33	15.88	14.67	15.93	18.29

Panel B: Tests of the equality-of-slope estimates across quantiles

Variables	**Quantiles**					
	0.05 vs. 0.95		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	1104.69	(0.0000)	1036.18	(0.0000)	254.13	(0.0000)
a_2	13.09	(0.0003)	15.35	(0.0001)	3.47	(0.0624) *
a_3	348.56	(0.0000)	235.77	(0.0000)	25.90	(0.0000)
a_4	18.89	(0.0000)	29.43	(0.0000)	27.95	(0.0000)
a_5	3864.52	(0.0000)	4077.00	(0.0000)	3044.06	(0.0000)
a_6	1256.39	(0.0000)	787.88	(0.0000)	188.21	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.9. Expected returns, past returns and capital gains overhang: February to November subsample

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5\, S + a_6\, g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Explanatory Variables	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	0.0172	-0.3627	-0.2818	-0.1563	-0.0209	0.1509	0.3355	0.4697
	(1.76) *	(-66.79)	(-64.50)	(-50.47)	(-10.10)	(51.39)	(61.50)	(63.89)
a_1	0.3019	0.2434	0.2612	0.2893	0.3078	0.3200	0.3570	0.3883
	(60.19)	(91.26)	(125.13)	(178.23)	(208.17)	(175.01)	(129.52)	(98.97)
a_2	-0.0006	-0.0069	-0.0045	0.0007	0.0047	0.0004	-0.0019	-0.0026
	(-0.26)	(-4.67)	(-3.93)	(0.75)	(6.82)	(0.53)	(-1.41)	(-1.53)
a_3	-0.0029	-0.0106	-0.0066	-0.0015	0.0012	0.0008	0.0060	0.0113
	(-2.74)	(-14.15)	(-13.30)	(-3.83)	(4.82)	(2.47)	(8.83)	(10.75)
a_4	0.1493	-0.0000	-0.0001	-0.0000	-0.0000	0.0000	0.0000	0.0000
	(1.70) *	(-3.92)	(-5.23)	(-3.22)	(-1.42)	(1.58)	(3.35)	(2.49)
a_5	-0.0006	0.0109	0.0086	0.0049	0.0008	-0.0048	-0.0107	-0.0148
	(-1.42)	(44.61)	(43.78)	(35.46)	(8.32)	(-36.17)	(-43.69)	(-45.35)
a_6	0.0142	0.0771	0.0549	0.0234	0.0013	-0.0041	-0.0396	-0.0741
	(8.60)	(34.61)	(33.05)	(17.95)	(2.49)	(-4.04)	(-16.69)	(-23.16)
R^2	34.63	29.63	25.73	20.06	16.47	15.11	16.34	18.77

Panel B: Tests of the equality-of-slope estimates across quantiles

Variables	**Quantiles**					
	0.05 vs. 0.95		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	1010.75	(0.0000)	877.54	(0.0000)	235.38	(0.0000)
a_2	3.41	(0.0648) *	1.96	(0.1618)	0.04	(0.8381)
a_3	257.99	(0.0000)	216.53	(0.0000)	22.46	(0.0000)
a_4	18.23	(0.0000)	35.08	(0.0000)	14.37	(0.0002)
a_5	3550.94	(0.0000)	3316.27	(0.0000)	3432.88	(0.0000)
a_6	965.82	(0.0000)	643.32	(0.0000)	160.93	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.10. Expected returns, past returns and capital gains overhang: January and December subsamples

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5\, S + a_6\, g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

	January								**December**							
	Fama - MacBeth	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	-0.0333	-0.3648	-0.2883	-0.1800	-0.0550	0.0965	0.2741	0.4223	0.0756	-0.2735	-0.2100	-0.1058	0.0283	0.2105	0.3853	0.5357
	(-1.58)	(-27.23)	(-26.14)	(-19.63)	(-6.86)	(10.64)	(17.75)	(18.91)	(2.62)	(-18.95)	(-18.79)	(-13.39)	(4.30)	(20.08)	(23.48)	(26.55)
a_1	0.3249	0.2514	0.2682	0.3039	0.3435	0.3793	0.4279	0.4535	0.2327	0.1343	0.1405	0.1642	0.1828	0.2001	0.2291	0.2531
	(21.10)	(37.40)	(45.68)	(56.19)	(61.46)	(67.83)	(49.57)	(38.75)	(11.42)	(19.56)	(24.12)	(33.81)	(42.03)	(34.03)	(26.33)	(21.12)
a_2	-0.0092	-0.0266	-0.0208	-0.0121	-0.0086	-0.0192	-0.0281	-0.0339	0.0155	0.0164	0.0222	0.0292	0.0345	0.0366	0.0426	0.0446
	(-0.77)	(-6.13)	(-6.47)	(-4.00)	(-3.29)	(-7.13)	(-7.36)	(-7.14)	(1.95) *	(5.03)	(9.81)	(13.09)	(17.30)	(15.38)	(10.56)	(9.86)
a_3	-0.0001	-0.0089	-0.0048	-0.0021	-0.0002	0.0004	0.0077	0.0119	-0.0022	-0.0054	-0.0043	-0.0008	0.0000	0.0007	0.0113	0.0168
	(-0.03)	(-4.03)	(-2.95)	(-2.00)	(-0.21)	(0.48)	(4.25)	(4.48)	(-0.62)	(-3.18)	(-2.98)	(-0.85)	(0.03)	(0.49)	(5.60)	(4.88)
a_4	0.5540	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0001	0.0001	-0.2637	-0.0000	0.0000	0.0000	0.0000	0.0001	0.0002	0.0002
	(1.84) *	(0.90)	(0.30)	(-0.75)	(0.48)	(0.65)	(1.31)	(1.95) *	(-1.14)	(-0.33)	(0.81)	(0.44)	(0.50)	(1.79) *	(1.91) *	(2.95)
a_5	0.0007	0.0105	0.0082	0.0052	0.0016	-0.0031	-0.0089	-0.0136	-0.0030	0.0075	0.0060	0.0031	-0.0012	0.0075	-0.0132	-0.0178
	(0.82)	(17.29)	(16.62)	(12.60)	(4.43)	(-7.36)	(-12.84)	(-13.19)	(-2.35)	(11.37)	(11.90)	(8.70)	(-3.90)	(-16.26)	(-17.95)	(-20.01)
a_6	-0.0006	0.0676	0.0506	0.0248	0.0053	-0.0011	-0.0217	-0.0476	0.0085	0.0707	0.0509	0.0200	0.0002	-0.0123	-0.0552	-0.0872
	(-0.10)	(15.64)	(14.68)	(7.63)	(2.08)	(-1.05)	(-5.88)	(-8.61)	(1.44)	(14.42)	(11.83)	(8.31)	(0.14)	(-2.34)	(-8.11)	(-9.84)
R^2	34.31	27.62	23.96	19.28	17.10	17.27	18.15	19.12	27.97	24.01	19.34	13.43	10.76	10.95	13.72	16.24

Panel B: Tests of the equality-of-slope estimates across quantiles

January						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	253.24	(0.0000)	270.88	(0.0000)	172.32	(0.0000)
a_2	1.30	(0.2542)	2.23	(0.1355)	4.43	(0.0354)
a_3	36.01	(0.0000)	29.58	(0.0000)	4.77	(0.0289)
a_4	1.78	(0.1820)	1.41	(0.2355)	1.14	(0.2867)
a_5	427.90	(0.0000)	390.45	(0.0000)	247.27	(0.0000)
a_6	206.52	(0.0000)	142.84	(0.0000)	52.98	(0.0000)

December						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	78.62	(0.0000)	77.77	(0.0000)	33.21	(0.0000)
a_2	27.17	(0.0000)	20.40	(0.0000)	7.18	(0.0074)
a_3	31.16	(0.0000)	35.81	(0.0000)	0.80	(0.3698)
a_4	6.31	(0.0120)	2.72	(0.0988) *	2.94	(0.0863) *
a_5	504.61	(0.0000)	441.47	(0.0000)	326.07	(0.0000)
a_6	169.59	(0.0000)	113.80	(0.0000)	21.39	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.11. Expected returns, past returns and unrealized capital gains: Robustness analysis based on institutional ownership subsamples

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Coff	**Above median institutional ownership**								**Below median institutional ownership**							
	Fama - MacBeth	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	0.0236	-0.3425	-0.2659	-0.1509	-0.0132	0.1542	0.3294	0.4614	0.0148	-0.3656	-0.2839	-0.1540	-0.0194	0.1427	0.3335	0.4745
	(2.30)	(-47.84)	(-56.64)	(-42.71)	(-4.07)	(36.99)	(46.43)	(50.43)	(1.75)*	(-49.66)	(-48.42)	(-39.40)	(-9.00)	(47.49)	(55.27)	(51.07)
a_1	0.3026	0.2395	0.2530	0.2772	0.2925	0.3109	0.3427	0.3694	0.2949	0.2311	0.2491	0.2777	0.2985	0.3117	0.3520	0.3876
	(59.47)	(78.70)	(96.47)	(142.02)	(146.94)	(120.04)	(99.28)	(74.45)	(59.58)	(54.72)	(76.27)	(104.09)	(143.53)	(127.18)	(93.38)	(66.47)
a_2	-0.0017	-0.0122	-0.0071	-0.0001	0.0068	0.0093	0.0091	0.0080	0.0013	-0.0039	-0.0017	0.0044	0.0074	0.0015	-0.0009	-0.0029
	(-0. 67)	(-7.48)	(-6.42)	(-0.09)	(7.88)	(8.45)	(6.66)	(4.22)	(0.55)	(-2.28)	(-1.20)	(3.26)	(7.56)	(1.22)	(-0.40)	(-1.15)
a_3	-0.0023	-0.0137	-0.0096	-0.0044	-0.0008	0.0021	0.0101	0.0158	-0.0030	-0.0088	-0.0048	-0.0003	0.0011	0.0000	0.0037	0.0090
	(-2.09)	(-19.17)	(-19.40)	(-10.68)	(-2.65)	(4.55)	(11.26)	(16.45)	(-3.04)	(-9.10)	(-5.88)	(-0.74)	(3.95)	(0.00)	(4.13)	(7.61)
a_4	0.1783	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.1342	-0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0001
	(1.93)*	(-1.43)	(-1.59)	(-1.22)	(-0.09)	(1.04)	(1.80)	(2.41)	(1.57)	(-3.58)	(-4.27)	(-3.37)	(-1.68)*	(2.78)	(3.04)	(2.53)
a_5	-0.0010	0.0100	0.0078	0.0046	0.0004	-0.0050	-0.0105	-0.0145	-0.0005	0.0109	0.0087	0.0048	0.0007	-0.0046	-0.0107	-0.0150
	(-2.18)	(29.93)	(35.85)	(28.05)	(2.72)	(-26.00)	(-31.83)	(-34.31)	(-1.48)	(33.94)	(33.68)	(27.86)	(6.88)	(-33.56)	(-40.37)	(-37.19)
a_6	0.0127	0.1027	0.0755	0.0388	0.0092	-0.0149	-0.0653	-0.1022	0.0119	0.0635	0.0451	0.0176	0.0007	-0.0017	-0.0295	-0.0582
	(6.53)	(45.89)	(47.00)	(36.35)	(11.03)	(-12.00)	(-24.57)	(-35.40)	(7.42)	(24.81)	(19.32)	(11.60)	(3.03)	(-2.79)	(-11.97)	(-16.05)
R^2	35.16	28.52	24.89	19.68	16.03	14.71	16.15	18.45	34.27	29.44	25.29	19.28	15.76	14.67	16.09	18.53

Panel B: Tests of the equality-of-slope estimates across quantiles

Above median institutional ownership						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	543.79	(0.0000)	519.43	(0.0000)	213.58	(0.0000)
a_2	70.91	(0.0000)	105.94	(0.0000)	74.02	(0.0000)
a_3	691.90	(0.0000)	410.58	(0.0000)	144.80	(0.5070)
a_4	8.36	(0.0038)	5.68	(0.0171)	3.06	(0.0804)
a_5	2072.26	(0.0000)	2271	(0.0000)	1922.84	(0.0000)
a_6	2936.84	(0.0000)	1889.56	(0.0000)	986.53	(0.0000)

Below median institutional ownership						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	507.87	(0.0000)	499.03	(0.0000)	153.98	(0.0000)
a_2	0.11	(0.7411)	0.07	(0.7857)	3.92	(0.0477)
a_3	132.53	(0.0000)	46.19	(0.0000)	0.44	(0.5070)
a_4	12.02	(0.0005)	27.35	(0.0000)	23.52	(0.0000)
a_5	2125.62	(0.0000)	2299.42	(0.0000)	2030.63	(0.0000)
a_6	478.37	(0.0000)	285.60	(0.0000)	95.83	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.12. Expected returns, past returns and unrealized capital gains: Robustness analysis based on leverage subsamples

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Above median leverage									**Below median leverage**							
Variable	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	0.0160	-0.3471	0.2645	-0.1423	-0.0201	0.1370	0.3147	0.4481	0.0198	-0.3412	-0.2736	-0.1556	-0.0161	0.1528	0.3377	0.4667
	(1.83)*	(-48.05)	(-49.15)	(-36.46)	(-9.20)	(39.81)	(43.54)	(43.97)	(2.14)	(-47.26)	(-60.18)	(-40.97)	(-5.58)	(37.55)	(56.13)	(48.46)
a_1	0.2967	0.2156	0.2390	0.2717	0.2928	0.3032	0.3440	0.3783	0.2994	0.2534	0.2655	0.2854	0.3009	0.3171	0.3488	0.3765
	(57.27)	(59.71)	(78.27)	(103.86)	(150.46)	(132.31)	(94.53)	(71.44)	(61.12)	(87.89)	(133.48)	(143.88)	(151.25)	(123.03)	(101.35)	(70.19)
a_2	0.0010	-0.0029	-0.0009	0.0057	0.0089	0.0055	0.0030	0.0024	-0.0005	-0.0124	-0.0100	0.0002	0.0063	0.0043	0.0033	0.0021
	(0.42)	(-1.84)*	(-0.77)	(4.80)	(10.36)	(5.37)	(1.63)	(1.09)	(-0.20)	(-6.14)	(-5.01)	(0.14)	(6.82)	(3.54)	(1.84)*	(0.79)
a_3	-0.0034	-0.0053	-0.0020	0.0009	0.0011	-0.0012	0.0005	0.0048	-0.0020	-0.0145	-0.0100	-0.0047	-0.0001	0.0030	0.0104	0.0169
	(-2.95)	(-7.42)	(-3.13)	(2.10)	(3.54)	(-3.29)	(0.75)	(4.36)	(-2.12)	(-19.66)	(-18.15)	(-9.83)	(-0.29)	(6.09)	(14.14)	(13.90)
a_4	0.1444	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0001	0.1616	-0.0001	-0.0000	-0.0000	-0.0000	0.0008	0.0000	0.0001
	(1.99)	(-4.64)	(-4.27)	(-4.67)	(-0.24)	(2.56)	(3.43)	(2.63)	(1.87)*	(-4.04)	(-4.72)	(-1.13)	(-1.55)	(1.24)	(2.24)	(2.27)
a_5	-0.0006	0.0103	0.0079	0.0043	0.0007	-0.0044	-0.0100	-0.0141	-0.0008	0.0097	0.0080	0.0047	0.0005	-0.0048	-0.0106	-0.0145
	(-1.58)	(32.16)	(33.09)	(25.15)	(7.29)	(-28.22)	(-31.14)	(-30.96)	(-1.97)	(29.07)	(38. 47)	(27.18)	(3.87)	(-26.01)	(-38.02)	(-32.73)
a_6	0.0122	0.0734	0.0524	0.0205	0.0007	-0.0028	-0.0367	-0.0758	0.0129	0.0818	0.0588	0.0279	0.0042	-0.0088	-0.0438	-0.0731
	(6.94)	(28.56)	(23.40)	(11.68)	(2.58)	(-2.90)	(-12.12)	(-17.28)	(7.84)	(34.11)	(40.58)	(21.36)	(4.80)	(-7.47)	(-29.74)	(-21.14)
R^2	34.41	30.64	25.62	19.08	15.65	14.34	15.78	18.87	34.12	27.46	24.39	19.57	16.13	14.99	16.05	17.80

Panel B: Tests of the equality-of-slope estimates across quantiles

Above median Leverage						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	653.44	(0.0000)	512.57	(0.0000)	113.56	(0.0000)
a_2	3.62	(0.0572)*	2.99	(0.0840)	0.04	(0.8472)
a_3	46.54	(0.0000)	5.86	(0.0155)	14.78	(0.0001)
a_4	18.10	(0.0000)	26.55	(0.0000)	25.89	(0.0000)
a_5	1597.77	(0.0000)	1583.28	(0.0000)	1304.49	(0.0000)
a_6	554.33	(0.0000)	336.83	(0.0000)	85.06	(0.0000)

Below median Leverage						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	438.82	(0.0000)	464.78	(0.0000)	163.92	(0.0000)
a_2	21.16	(0.0000)	22.94	(0.0000)	9.11	(0.0025)
a_3	439.30	(0.0000)	442.92	(0.0000)	130.85	(0.0000)
a_4	12.78	(0.0004)	16.50	(0.0000)	4.00	(0.0374)
a_5	1842.90	(0.0000)	3037.09	(0.0000)	1746.77	(0.0000)
a_6	1139.29	(0.0000)	1810.33	(0.0000)	326.75	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.13. Expected returns, past returns and unrealized capital gains: Robustness analysis based on size subsamples

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5\, S + a_6\, g$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Above median size									**Below median size**							
Variables																
	Fama - MacBeth	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**	**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_0	0.0145	-0.2781	-0.2200	-0.1111	-0.0094	0.1077	0.2579	0.3790	0.0277	-0.3644	-0.3087	-0.2168	-0.0565	0.2058	0.4350	0.5576
	(1.67)*	(-36.80)	(-46.21)	(-34.12)	(-3.43)	(29.09)	(42.65)	(45.17)	(1.99)	(-15.33)	(-15.31)	(-15.37)	(-6.51)	(16.49)	(17.01)	(14.66)
a_1	0.3006	0.2525	0.2623	0.2806	0.2947	0.3075	0.3334	0.3602	0.2966	0.2183	0.2402	0.2712	0.2952	0.3171	0.3607	0.3990
	(53.27)	(82.56)	(100.56)	(137.27)	(162.35)	(138.78)	(106.04)	(76.26)	(62.86)	(64.29)	(77.83)	(113.26)	(137.99)	(122.45)	(91.53)	(77.42)
a_2	-0.0035	-0.0254	-0.0178	-0.0067	0.0040	0.0109	0.0122	0.0109	0.0012	-0.0004	0.0006	0.0058	0.0078	0.0039	0.0012	-0.0008
	(-1.20)	(-13.87)	(-12.91)	(-7.52)	(4.32)	(10.30)	(10.38)	(4.86)	(0.55)	(-0.25)	(0.43)	(4.44)	(8.97)	(3.32)	(0.67)	(-0.36)
a_3	-0.0034	-0.0253	-0.0183	-0.0098	-0.0013	0.0053	0.0166	0.0258	-0.0027	0.0023	0.00٤0	0.0047	0.0028	-0.0041	-0.0048	-0.0023
	(-2.97)	(-32.19)	(-32.70)	(-21.47)	(-3.95)	(10.09)	(23.30)	(20.54)	(-3.03)	(3.02)	(4.51)	(6.94)	(6.74)	(-7.66)	(-5.79)	(-1.57)
a_4	0.1658	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.1655	-0.0001	-0.0001	-0.0000	-0.0000	0.0001	0.0001	0.0001
	(1.88)*	(-5.17)	(-4.56)	(-2.68)	(-0.31)	(2.12)	(3.62)	(20.54)	(2.03)	(-3.78)	(-5.27)	(-1.35)	(-1.80)*	(1.95)*	(4.63)	(6.29)
a_5	-0.0006	0.0074	0.0060	0.0029	0.0002	-0.0030	-0.0000	-0.0110	-0.0012	0.0105	0.0096	0.0078	0.0025	-0.0075	-0.0154	-0.0189
	(-1.58)	(22.01)	(28.29)	(20.55)	(1.98)	(-18.61)	(-28.30)	(-30.02)	(-1.72)*	(8.92)	(9.64)	(11.19)	(5.81)	(-12.11)	(-12.19)	(-10.01)
a_6	0.0192	0.1451	0.1111	0.0624	0.0147	-0.0263	-0.0075	-0.1305	0.0116	0.0555	0.0398	0.0162	0.0007	-0.0018	-0.0271	-0.0571
	(7.87)	(53.93)	(58.82)	(39.25)	(11.56)	(-15.22)	(-30.71)	(-29.59)	(7.78)	(28.72)	(19.99)	(11.51)	(2.52)	(-3.31)	(-12.79)	(-17.23)
R^2	35.66	27.62	24.22	19.48	16.25	15.14	16.08	17.65	32.89	27.70	24.00	18.71	15.52	14.43	15.35	17.52

Panel B: Tests of the equality-of-slope estimates across quantiles

Above median size						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	420.85	(0.0000)	382.69	(0.0000)	150.17	(0.0000)
a_2	171.05	(0.0000)	325.18	(0.0000)	254.93	(0.0000)
a_3	1182.08	(0.0000)	1495.19	(0.0000)	483.27	(0.0000)
a_4	37.37	(0.0000)	41.12	(0.0000)	15.55	(0.0001)
a_5	1432.85	(0.0000)	1937.23	(0.0000)	1081.83	(0.0000)
a_6	2834.35	(0.0000)	3181.98	(0.0000)	1480.98	(0.0000)

Below median size						
	Quantiles					
Variable	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistics	**P-value**	**F-statistics**	**P-value**	**F-statistics**	**P-value**
a_1	968.78	(0.0000)	767.53	(0.0000)	315.36	(0.0000)
a_2	0.03	(0.8709)	0.08	(0.7834)	1.96	(0.1613)
a_3	6.97	(0.0083)	44.67	(0.0000)	127.03	(0.0000)
a_4	51.59	(0.0000)	40.67	(0.0000)	8.61	(0.0033)
a_5	168.72	(0.0000)	216.39	(0.0000)	292.62	(0.0000)
a_6	589.92	(0.0000)	333.26	(0.0000)	101.39	(0.0000)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

R^2 for Fama and MacBeth is an average R^2, however it is Pseudo R^2 for Quantile regression. (*) Significance at 10% and 5% otherwise.

Table 4.14. Capital gains coefficients across three models

This table summarizes the ability of disposition effect to generate momentum at the lowest and highest quantiles (5% and 95% respectively). The table reports the intermediate cumulative return and t values in three cases; before size is added, after adding size and after capital gains overhang is added

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V \quad (10)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S \quad (11)$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 g \quad (12)$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Quantiles		**Fama-MacBeth**			**5%**			**95%**		
Models		**Model 10**	**Model 11**	**Model 12**	**Model 10**	**Model 11**	**Model 12**	**Model 10**	**Model 11**	**Model 12**
Whole sample		0.0049	0.0048	-0.0000	0.0207	0.0177	-0.0060	-0.0174	-0.0150	0.0019
		(1.99)	(1.96)	(-0.02)	(16.30)	(13.40)	(-4.30)	(-10.98)	(-8.55)	(1.15)
Institutional	Above median	0.0025	0.0029	-0.0017	0.0205	0.0194	-0.0122	-0.0147	-0.0130	-0.0080
		(0.96)	(1.12)	(-0.67)	(14.17)	(11.87)	(-7.48)	(-9.92)	(-6.63)	(4.22)
	Below median	0.0066	0.0064	0.0013	0.0203	0.0165	-0.0039	-0.0207	-0.0171	-0.0029
		(2.62)	(2.55)	(0.55)	(9.35)	(8.51)	(-2.28)	(-7.27)	(-5.18)	(-1.15)
Leverage	Above median	0.0059	0.0058	0.0009	0.0219	0.0200	-0.0029	-0.0149	-0.0141	0.0024
		(2.38)	(2.37)	(0.42)	(11.85)	(10.08)	(-1.84)	(-6.49)	(-5.56)	(1.09)
	Below median	0.0045	0.0044	-0.0005	0.0172	0.0153	-0.0124	-0.0195	-0.0178	0.0021
		(1.69)*	(1.69)*	(-0.20)	(10.39)	(8.98)	(-6.14)	(-8.29)	(-7.91)	(0.79)
Size	Above median	0.0029	0.0025	-0.0035	0.0125	0.0123	-0.0254	-0.0095	-0.0099	0.0108
		(1.01)	(0.84)	(-1.20)	(6.08)	(6.14)	(13.87)	(-3.93)	(-3.79)	(4.86)
	Below median	0.0060	0.0057	0.0012	0.0214	0.0150	-0.0004	-0.0187	-0.0144	-0.0008
		(2.61)	(2.49)	(0.55)	(11.55)	(8.12)	(-0.25)	(-8.81)	(-6.70)	(-0.36)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth.

(*) Significance at 10% and 5% otherwise.

Table 4.15. Capital gains coefficients across different quantiles

The coefficients below belong to the capital gains overhang variable only which is included in the following regression.

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5\, S + \boldsymbol{a_6}\, \boldsymbol{g} \qquad (12)$$

where g is capital gains overhang; $r_{-t1:-t2}$ = cumulative returns from month t-t_1 through t-t_2 computed over three past return horizons; $r_{-t1:-t2}$; V= average monthly turnover ratio (share volume divided by number of shares outstanding) over the previous 12 months. S = natural logarithm of monthly market capitalization; r_t is the month-t return.

Explanatory Variables		**Fama - MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
Whole Sample		0.0124 (7.96)	0.0757 (37.47)	0.0546 (36.61)	0.0232 (19.12)	0.0013 (2.53)	-0.0044 (-4.57)	-0.0401 (-18.12)	-0.0748 (-26.62)
Seasonality (Feb-Nov)		0.0142 (8.60)	0.0771 (34.61)	0.0549 (33.05)	0.0238 (17.95)	0.0013 (2.49)	-0.0040 (-4.04)	-0.0395 (-16.69)	-0.0741 (-23.16)
Seasonality (January)		-0.0006 (-0.10)	0.0676 (15.64)	0.0506 (14.68)	0.0248 (7.63)	0.0053 (2.08)	-0.0011 (-1.05)	-0.0218 (-5.88)	-0.0476 (-8.61)
Seasonality (December)		0.0085 (1.44)	0.0707 (14.42)	0.0509 (11.83)	0.0200 (8.31)	0.0002 (0.14)	-0.0123 (-2.34)	-0.0552 (-8.11)	-0.0872 (-9.84)
Institutional	Above median	0.0127 (6.53)	0.1027 (45.89)	0.0755 (47.00)	0.0388 (36.35)	0.0092 (11.03)	-0.0149 (-12.00)	-0.0653 (-24.57)	-0.1022 (-35.40)
	Below median	0.0119 (7.42)	0.0635 (24.81)	0.0451 (19.32)	0.0176 (11.60)	0.0007 (3.03)	-0.0017 (-2.79)	-0.0295 (-11.97)	-0.0582 (-16.05)
Leverage	Above median	0.0122 (6.94)	0.0734 (28.56)	0.0524 (23.40)	0.0205 (11.68)	0.0007 (2.58)	-0.0028 (-2.90)	-0.0367 (-12.12)	-0.0758 (-17.28)
	Below median	0.0129 (7.84)	0.0818 (34.11)	0.0588 (40.58)	0.0279 (21.36)	0.0042 (4.80)	-0.0088 (-7.47)	-0.0438 (-29.74)	-0.0731 (-21.14)
Size	Above median	0.0192 (7.87)	0.1451 (53.93)	0.1111 (58.82)	0.0624 (39.25)	0.0146 (11.56)	-0.0263 (-15.22)	-0.0846 (-30.71)	-0.1305 (-29.59)
	Below Median	0.0116 (7.78)	0.0555 (28.72)	0.0398 (19.99)	0.0162 (11.51)	0.0007 (2.52)	-0.0018 (-3.31)	-0.0271 (-12.79)	-0.0571 (-17.23)

Figures in brackets are t-statistics. Standard errors are corrected by bootstrapping for quantile regression (400 runs) and corrected by Newey-West for Fama-MacBeth. (*) Significance at 10% and 5% otherwise.

Table 4.16. Tests of the equality-of-slope estimates across quantiles between expected returns and capital gains overhang

		Quantiles					
		0.05 vs. 0.95		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
		F-statistics	**P-Value**	**F-statistics**	**P-Value**	**F-statistics**	**P-Value**
Whole Sample		1256.39	(0.0000)	787.88	(0.0000)	188.21	(0.0000)
February-November		965.82	(0.0000)	643.32	(0.0000)	160.93	(0.0000)
January		206.52	(0.0000)	142.84	(0.0000)	52.98	(0.0000)
December		169.59	(0.0000)	113.80	(0.0000)	21.39	(0.0000)
Institutional	Above Median	2936.84	(0.0000)	1889.56	(0.0000)	986.53	(0.0000)
	Below Median	478.37	(0.0000)	285.60	(0.0000)	95.83	(0.0000)
Leverage	Above Median	554.33	(0.0000)	336.83	(0.0000)	85.06	(0.0000)
	Below Median	1139.29	(0.0000)	1810.33	(0.0000)	326.75	(0.0000)
Size	Above Median	2834.35	(0.0000)	3181.98	(0.0000)	1480.98	(0.0000)
	Below Median	589.92	(0.0000)	333.26	(0.0000)	101.39	(0.0000)

(*) Significance at 10% and 5% otherwise

Chapter Five

Momentum, asymmetric volatility and idiosyncratic risk: A comparison of high-tech and low-tech stocks

Abstract

This paper seeks to discover systematic disagreements in momentum, asymmetric volatility and the idiosyncratic risk-momentum return relationship between high-tech stocks and low-tech stocks. We develop several hypotheses that suggest greater momentum profits, fainter asymmetric volatility and weaker idiosyncratic risk -momentum return relation in the high-tech stocks relative to the low-tech stocks. To do so, 5795 stocks that are listed in the Russell 3000 index from January 1995 to December 2015 were divided into two samples based on SIC code 3-digits into high and low-tech categories. We analyzed them using the Fama-French with GJR-GARCH-M term. The results show that the high-tech stocks provide greater momentum profits especially for portfolios that have holding and ranking periods of less than 12 months. In most cases the momentum returns in the high-tech stocks explain symmetric response to good and bad news while the momentum returns in the low-tech stocks show an asymmetric response. Finally, the idiosyncratic risk-momentum return relation is insignificant for the high-tech stocks while it is significant and negative for the low-tech stocks. That is, as idiosyncratic risk increases, momentum decreases for low-tech stocks. These findings are robust to different momentum strategies and to different breakpoint.

Keywords: R&D intensity, High-tech stocks, Momentum, Asymmetric Volatility, Idiosyncratic Risk

5.1- Introduction

According to many studies in the literature high-tech stocks invest more in R&D activities or knowledge-based investments and have higher level of unreported assets Watanabe, Hur & Lei (2006), Kwon and Yin (2015), Lim (2015), Junttila, et al (2005) & Kwon and Yin (2006). The key value drivers have lately become less peculiar to tangible assets. A contemporary study indicates that only 15% of the S&P 500 market capitalization belonged to tangible assets in 1988. However, it was 62% in 1982[11]. During the last quarter century, there has been renewed interest in knowledge-based organizations. These organizations possess a large proportion of unique intangible assets such as patents, R&D, brands and talented human capital. This uniqueness changes the shape and nature of organizations. According to Zingales (2000), the appearance of knowledge-based organizations challenges several aspects of the traditional theory of the firm: the traditional firm is vertically integrated and heavily monopolized by physical assets while knowledge-based organizations are human capital-intensive organizations and non-vertically integrated. Moreover, the nature of the traditional firm enforces the power of the top management and control is practised through the ownership of the indispensable physical assets, whereas to gain a sustainable competitive advantage knowledge-based organizations must run a rigorous innovation process and product research and development activities which increases the need for talented human resources. In the knowledge-based economy human capital is, by nature, less specific to its current employers which diminishes the power and control of top management; in addition, the use of corporate governance and managerial incentives in the traditional firm eases the shareholders' control while putting in question the transparency and, accountability of top managers and coping with shareholder wealth maximization in the knowledge-based organizations.

The theory of investment endorses the uniqueness of R&D, which like other intangible assets is more distinctive than typical investments because such assets have several unique features. One important feature is mentioned by Hall (2002) who reveals that more than 50% of R&D expenditures goes to financial allocations to scientists and engineers who work to produce intangible assets and are likely to contribute to increased firm's future earnings. The value of scientists and engineers is equal to the value of the tacit knowledge they have. This kind of assets can be transferred to another organization if they depart or are

[11] See Bagella, Becchetti, & Adriani (2005), P.550

dismissed. This means that part of a firm's assets can disappear if the knowledgeable workers leave. This feature has valuable implications; for example, companies usually distribute the R&D expenditures over time to guarantee the continuation of knowledge workers and avoid high amendment cost. Covering this cost needs a high required rate of return and makes it harder to measure the change in the cost of capital in consequence of a departure of intangible assets. The second important feature is that the outcome of R&D activity is also associated with a high level of uncertainty, especially in the initial stages of new proposals. In addition, some R&D proposals that have a low probability of great future benefits may be worth implementing even if the required rate of return does not exceed the cost of capital. In this case, the uncertainty is very high and cannot be simply captured by mean and variance.

The stock market and finance theory are never far from these advances, show coincident attention with them. Some scholars note the importance of R&D, for example Chan, Lakonishok, & Sougiannis (2001) who document that the technology sector and the pharmaceutical sector have intensive R&D activities and investments represent around 40 percent of the market capitalization of the S&P 500 index. Callimaci & Landry (2004) study the Canadian stock market and find that research and develoment costs are among the largest incurred by Canadian companies. We also found some support for the growing importance of research and development in emerging markets. In Taiwan, Chiao, Hung, & Lee (2008) found that the ratio of aggregate R&D to GDP rose from 1.14 percent in 1987 to 2.42 percent in 2003 and the number of companies that had R&D activities went up from 48 companies in 1987 to 393 companies in 2003.

Others link the R&D with other financial puzzles; for instance, Doukas & Switzer (1992) collect announcements that represent around 58% of US's firms-funded R&D in 1984 to explore the link between R&D activity and market value and find significant relationship. Bhagat & Welch (1995) investigate the determinants of R&D using data on the US, European, British, Canadian and Japanese companies. They show that last year's debt ratio, two-year lagged stock return, size, and last year' tax payments play a role and correlated either positively or negatively with the current R&D expenditures. Aboody & Lev (2000) choose the period between 1985 and 1997 to examine the relation between R&D activity and insider profits. They find evidence that the information asymmetry is primarily caused by the R&D which creates an informational advantage to the insiders at the expense of outsiders. This informational advantage gives the insiders in the R&D-intensive firms the opportunity to make more generous profits than insiders in firms without R&D can make. Schmutz &

Santerre (2013) also specify the determinants of R&D expenditures in the medical device industry covering the period between 1962 and 2008. Schmutz & Santerre (2013) confirm that the previous year's cash flow and market value are positively related to the R&D expenditures. The relation between debt ratio and R&D expenditures is tested by Czarnitzki, Hottenrott, & Thorwarth (2011) who find that an increase in debt causes a reduction in R&D investments.

The uniqueness of the intensive R&D firms is not limited to financial phenomena, but should be extended to accounting theories and practices. On the accounting side, Sougiannis (1994) tries to tie the corporate R&D with accounting earnings and the market value of equity. He uses cross sectional data and find that, on average, a one dollar investment in R&D increases profits by two dollars over a seven years period and raises market value by five dollars. Lev & Sougiannis (1996) use a huge sample of public companies to assess the value of R&D. They obtain statistically and economically significant values and a significant relation between corporate R&D value and stock returns. This significant relation can be attributed to either a systematic mispricing in the R&D-intensive firms, or an extra premium for bearing the additional market risk associated with R&D. Eng & Shackell (2001) examine the impact of institutional holding and long-term performance plans on the level of R&D expenditures. Their findings explain the positive relation between institutional holding and R&D expenditures because the horizon of institutional holding encourages managers to adopt long-term investments; however, the relation between preparing long-term performance plans and R&D expenditures is insignificant. Barron, Byard, Kile, & Riedl (2002) who target the degree of analyst consensus in the high-tech stocks using estimates over the period from 1986 to 1988. They believe that if the R&D expenditures and the corresponding asymmetric information are high, the level of consensus thereby goes down. Kothari, Laguerre, & Leone (2002) devote a study to measuring the uncertainty embodied in the predictable earnings generated by R&D and that generated by Property, Plant and Equipment (PP&E) between 1972 and 1997. Their findings stress that the future earnings generated by R&D embody a far higher degree of uncertainty relative to the predictable earnings generated by PP&E. Kwon and Yin (2015) introduce evidence that intensive R&D firms have lower earnings persistence than non-intensive R&D firms. Moreover, they catch stronger ties between earnings persistence and discretionary accruals in the intensive R&D firms.

The above studies show the main issues discussed in the literature of accounting and finance among R&D-intensive firms. This paper makes four research contributions. To begin with, this paper is the first to our knowledge to discover the systematic differences in momentum profits between high-tech stocks and low-tech stocks; Second, we are the first to discover the systematic differences in asymmetric volatility between high-tech stocks and low-tech stocks; Third, we are the first to discover the systematic differences in the idiosyncratic risk -momentum return relation between stocks with high-tech and stocks with low-tech; Finally, we are the first to compare the performance of the Fama-French model with GJR-GARCH-M term in explaining momentum return between stocks with high-tech and stocks with low-tech.

Results indicate that the momentum profits in low-tech stocks never outperform those profits in high-tech stocks and some momentum portfolios, namely, the 3-3 strategy, the 3-6 strategy, the 6-3 strategy and the 6-6 strategy, show robust higher momentum profits for high-tech stocks. The second finding is that high-tech stocks exhibit symmetric volatility in momentum returns or the variance in momentum returns responds symmetrically to good and bad news. However, low-tech stocks exhibit significant asymmetric volatility. This second finding is robust to different momentum strategies and to different breakpoints. Our third finding focuses on the idiosyncratic risk -momentum return relation; there is robust evidence on the no-idiosyncratic risk -momentum return relation for high-tech stocks and robust evidence on the significantly negative idiosyncratic risk -momentum return relation for stocks with low-tech. Finally, there is robust evidence on the better ability of the Fama-French with conditional variance term to explain momentum returns for high-tech stocks than for low-tech.

The rest of this paper is structured as follows. Section 5.2 reviews the previous literature. Section 5.3 demonstrates the research hypotheses. Section 5.4 presents the econometric framework. Section 5.5 contains the research data and the methodology. Section 5.6 explains the empirical analysis. Section 5.7 contains the main concluding remarks and some recommendations for future research.

5.2- Literature review

In this paper, we discuss three main issues; momentum, asymmetric volatility and the idiosyncratic risk and momentum relation. Therefore, it may be useful to divide the literature accordingly.

5.2.1- Momentum

Jagadeesh and Titman (1993) are the first to document the momentum profits. They confirm that using momentum strategies which entail buying past winners and selling past losers can generate significant abnormal returns. Rouwenhorst (1998) studies market return data from 12 European stock markets between 1978 and 1995 and found economically and statistically significant intermediate-term return persistence. Moskositz & Grinblatt (1999) contend that profitable momentum strategies involve a significant industry effect. An explanation of industry momentum comes from Hong and Stein (1999) model; they suggest that under-reaction to news due to the slowness of information spread can induce momentum[12]. In a different work, Hong et al. (2000) discover the higher momentum profits among smaller size firms and attribute this phenomenon to lower analyst coverage and the slower information spread experienced by smaller firms. This concept can be extended to the industry momentum since the information takes time to reach all firms in an industry and the leading firms capture the new information earlier than smaller firms in the same industry can, since the analysts cover the impact of the new information on the whole industry. This behaviour may lead to the lead-lag effect between the leading firms and the smaller ones within the same industry and eventually generate momentum. Chui, Titman, & Wei (2003) examine the momentum using REITs data. They conclude that the momentum returns for REITs are higher than for common stocks. Pan, Liano, & Huang (2004) investigate the sources of industry momentum and find empirical evidence that it is due to the returns autocorrelation in industry momentum portfolios.

5.2.2- Asymmetric volatility

It is well known that the asymmetric volatility means the different response of volatility to bad news and good news. In particular, negative shocks have a larger impact on volatility than positive shocks of the same magnitude do. One interpretation for this phenomenon is that investors react more quickly to bad news than good, which contributes more volatility to the market (Jones, Walker, & Wilson, 2004).

Volatility has a pivotal role in modern finance theory. Black (1976) and Christie (1982) introduced the first explanation of this phenomenon. They attributed the negative relation between volatility and price to the 'Leverage effect'. This explanation suggests that a decline in stock prices leads to an increase in leverage measured by the debt to equity ratio,

[12] See Moskowitz & Grinblatt (1999) P.42

resulting in an increase in the risk of the stock which causes a surge in volatility. Ericsson, Huang, & Mazzotta (2016) find a vastly higher leverage effect than is documented in Christie (1982). Talpsepp & Rieger (2010) document the larger importance of asymmetry over time. They study the asymmetric volatility for 49 countries and find evidence that the asymmetry in most countries increases constantly. In the US where the market of interest is, Ederington & Guan (2010) measure the impact of positive and negative return news of the same size on the predictive volatility. They find that the surge of predictive volatility after negative returns is much greater than that after positive returns. On the behavioural finance side, Avramov, Chordia, & Goyal (2006) offer a behavioural explanation for the asymmetric volatility. According to their research, it can be fully interpreted by the interplay between contrarian and herding investors. They base their analysis on the clue that irrational 'uniformed' investors divert the market prices away from the intrinsic value. The irrational investors purchase when the stock prices are high and vend when the stock prices are low. Rational 'informed' investors push asset prices back to the intrinsic value through following the opposite behaviour. In other words, the rational 'informed' vend when the stock prices are high and purchase when the stock prices are low. In their context, when stock prices fall, the herding investors control the volatility of the following period because they trade in the same direction as the change. They exaggerate the change and drive volatility upward. However, when the stock prices surges, contrarian investors control the volatility of the following period, which leads to declines in volatility because they trade in the opposite direction of change.

EGARCH and GJR are well documented in the literature of asymmetric volatility because they are the most effective models for caliberating the asymmetry. Nelson (1991) introduces the exponential GARCH ('EGARCH') model. The EGARCH is characterized as overcoming the non-negativity constraints in GARCH modelling and allows the capture of asymmetric responses to good and bad news. According to Heynen, Kemna, & Vorst (1994), the EGARCH model outperforms the basic GARCH of Bollerslev (1986). The second asymmetric GARCH is the GJR model developed by Glosten, Jagannathan, & Runkle (1993). Engle & Ng (1993) compare the GJR and EGARCH and conclude that the GJR is better at capturing asymmetric volatility. Barone-Adesi, Engle, & Mancini (2008) support the superiority of the GJR over the EGARCH model. Those two papers provide our justification for using the GJR model. Another virtue of the GJR is mentioned in Pilar & Rafael (2002), who prefer it for its lower sensitivity than the EGARCH model to outiers. One paper that used the GJR model to examine the asymmetric response of winners' and losers' portfolios to good and bad news is written by Li, Miffre, Brooks, & O'Sullivan (2008). They demonstrate that the effect of positive return news ('past winners') on volatility is smaller than the effect in case of negative returns news ('past losers'), because past winners tend more to reveal news than past losers.

5.2.3- Idiosyncratic risk -momentum return relation

Pindyck (1984) and Kenneth, Schwert, & Stambaugh (1987) provide another explanation for this negative relation between the unexpected change in volatility and an unexpected change in price, namely, the 'volatility feedback theory'. According to this theory, if the increase in stock price volatility leads to an increase in future returns, then, ceteris paribus, stock prices should drop when stock price volatility goes up.

The most common econometric model in the literature for testing the risk-return relation is GARCH in mean ('GARCH-M'). This model was developed by Engle, Lilien, & Robins (1987) to caliberate the relation between conditional variance and time-varying expected returns. In other words, the GARCH-M model embodies the impact of conditional variance on the conditional mean of the returns. A much debated question is whether the risk-return relation is positive or negative. For example Corrado & Miller (2006) used two measures of volatility, namely, past volatility and implied volatility and discover insignificant relation between historical volatility and expected returns, while the relation between implied volatility and expected returns is positive. Chan, Karolyi, & Stulz (1992) support the insignificant relation between future return and its conditional variance. Similarly, Poon & Taylor (1992) and Li, Yang, Hsiao, & Chang (2005) bring evidence for the insignificant risk-momentum return relation. Nyberg (2012) uses monthly U.S stock market returns and contributed to the literature through allowing the business cycle to influence the risk-momentum return relation. The business cycle apart, the risk-momentum return relation is significantly positive. A positive relationship is also demonstrated in Lundblad (2007), and Ludvigsona & Ng (2007). Lee, Jiang, & Indro (2002), and Whitelaw (2000) calculate that the risk-momentum return relation is negative. Finally, Baillie & DeGennaro (1990) infer from their data that any portfolio's risk-momentum return relation is weak.

Several papers in the literature address the relation between idiosyncratic risk and momentum returns. For instance, Arena, Haggard, & Yan (2008) adopt the behavioural approach in investigating the sources of momentum profits through examining the relation between momentum and idiosyncratic risk. They used data to cover the period between 1965 and 2002 and find a relation between momentum and idiosyncratic risk which is in line with the view that the momentum is sourced by the underreaction to firm-specific information and the limits to arbitrage deters arbitrageurs from correcting the momentum mispricing. Hung & Glascock (2010) use GARCH-M model to test the relation between time-varying idiosyncratic volatility and momentum in REIT. Hung & Glascock (2010) find evidence that momentum returns exhibit time-varying behaviour and also find that losers experience greater idiosyncratic volatility than winners and investors demand a smaller risk premium for bearing the higher idiosyncratic volatility of losers. This smaller risk premium leads to smaller returns, and hence to momentum in returns. McLean (2010) studies the possibility that the momentum effect is sourced by idiosyncratic risk hindering the arbitrage mechanism. In his paper, he emphasizes the role of transaction cost in preventing the arbitrageurs from correcting the momentum mispricing, supports the negative relation between idiosyncratic risk and momentum and specifies that the limits to arbitrage can induce momentum when the benefits of arbitrage are lower than the costs. He also confirms that reversal is predominant only among the stocks that experience higher idiosyncratic risk. Pyo & Shin (2013) use Korean data in replicating the study by Arena, Haggard, & Yan (2008). They find higher momentum among stocks with a higher level of idiosyncratic risk in particular among high idiosyncratic risk winners. Chichernea & Slezak (2013) provide evidence that the cross-sectional variation in idiosyncratic risk premium can explain momentum profits using a sample of individual stocks, except for the momentum among lower idiosyncratic risk stocks. Under the incomplete information assumption, less diversified investors require higher risk premia ("idiosyncratic risk premia") for bearing idiosyncratic risk. Di Iorio & Liu (2015) examine the relation between idiosyncratic risk and momentum using a sample of Australian equity pension funds. Their results are consistent with Arena, Haggard, & Yan (2008) and find that relation between momentum and idiosyncratic risk takes the form of U, which means that winners funds and losers funds both experience higher levels of idiosyncratic risk. The explanation here is that higher idiosyncratic risk embodies a higher level of information uncertainty, driving investors to under-react to news on the stocks with higher idiosyncratic risk and in turn induce momentum.

5.3- Hypotheses development

As mentioned previously, high-tech stocks have intensive R&D expenditures. There are two channels why the intensity of R&D should be related to momentum profits. They are dividends channel and disclosure channel. According to the dividends channel, most stocks with intensive R&D activities pay little dividends and more frequent zero dividend payments than others because they tend to invest free cash in developing new products and services Bagella, Becchetti, & Adriani (2005) & Kwon and Yin (2015). Paying dividends imparts information from the management about the expected future earnings (Bhattacharya, 1979). Chordia & Shivakumar (2006) link momentom returns with firms' future earnings and argue that past losers encounter a decrease in earnings while past winners encounter an increases in earnings, suggesting dividend payment by past winners and past losers imparts different information.

The previous argument is an extension to (Asem, 2009) who analyzed the relation between paying dividends and momentum. Asem (2009) compares the momentum profits in dividend-paying-firms and non-dividend-paying firms separately. He provides empirical evidence that momentum profits are higher among non-paying-dividend firms. The explanation here is for example, not paying dividend by high-tech stocks when the performance is bad may impart negative sign to investors Cuellar, Callen, & Gadea (2011) due to their inability to value the R&D activities, the intentional ambiguity and secrecy by most firms associated with developing new products and service in the current rude competitive environment to protect these proposals from reaching their competitors as well as the outcome of R&D activities is highly uncertain. This may lead investors to predict the bad performance to continue 'persist' in the future and generate momentum accordingly.

On the other side, paying dividends 'low-tech stocks' in the face of declining earnings indicates that management predicts the bad performance will not continue in the future, which is positive information for the losers 'positive and good news but does not include persistence and does not lead to momentum accordingly because momentum linked to future earnings'. For winners, dividend maintaince does not indicate that increase in their earnings are persistent and, hence, it does not convey good news. The above disscusion is called asymmetry in the dividend news conveyed by winners and losers.

According to the disclosure channel, the disclosure of R&D new proposals is voluntary and firms have strategic interest in not disclosing or supplying any details of their proposals to develop new products, new services or new technologies simply because this kind of disclosue may advantage their rivals (Jones, 2007). Cohen, Goto, Nagata, Nelson, & Walsh (2002) received surveys from 1478 of 3240 managers of R&D department in US industrial firms. Most of the respondents believe that secrecy is an effective way of avoiding competitive imitations. In addition, the future earnings generated by R&D activities are highly uncertain and difficult to measure (Kothari, Laguerre, & Leone, 2002). Lang & Lundholm (1996) argue that if the analysts play an intermediary role, i.e. if they acquire information and disseminate it in the stock market, it is cheaper for them to acquire information from the firm directly than try to capture it from other sources. In this case, the increase in disclosure and details provided by the firms, leads to a coincident increase in the quality of the reports sold by analysts and an increase in the demand for these reports which eventually attracts more analysts to follow the stock news and speed up the flow and dissemination of information in the stock market. As a result, we can expect the high-tech stocks that deliberately conceal information to have lower levels of analysts' coverage. Hong, Lim, & Stein (2000) use the analysts' coverage as a proxy for the flow of information and attibute the momentum effect to underreaction to the firm-specif information caused by the gradual dissemination of such information. This is because the lower level of analysts' coverage, all things being equal, slows the flow of information to the public investors and hinders the news from being fully reflected by the market prices. This means that the momentum effect is stronger among stocks that experience a slower dissemination of information. Our first hypothesis can be stated as follows:

H1. Ceteris paribus, high-tech stocks experience higher momentum profits than do stocks with low-tech.

Once more, high-tech stocks have intensive R&D expenditures. Our definition of the term 'high-tech stocks' conforms to Kwon and Yin (2015). This definition uses the intensity of R&D investments and the heaviness of intangible assets to classify stocks and pick out the high-tech stocks. R&D investments have several unique characteristics such as not being recognized, being difficult to value, having related future earnings that embody higher levels of uncertainty, being untradeable, showing no related assets in the financial statement and not being disclosed in financial reporting. These characteristics harm the coordination between managers and investors and create an information gap between them, which induces a higher level of information asymmetry and inhibits the firm's investment decisions (Aboody & Lev, 2000), (Smith &Watts, 1992)[13] (Choi, Mao, & Upadhyay, 2013), (Mohd, 2005), (Barth, Kasznik, & McNichols, 2001) & (Alam, Liu, & Peng 2014).

A wide strand of literature has documented the tendency of investors, analysts and stocks to herd. For example, Hirshleifer & Teoh (2003) mention that investors may herd in deciding whether to participate in the market, what securities to trade, and whether to buy or sell. Analysts are also prone to herding in their estimates, while managers are also prone to herd in their investment and finance decisions. The relation between herding behaviour and information asymmetry is discussed in Choi & Skiba (2015), who observe widespread herding in 41 countries, including the US stock market, which is the market of interest in this research. Choi & Skiba (2015) provide empirical evidence that higher herding behaviour can be found where lower information asymmetry exists. Choi & Skiba (2015) focus on unintentional herding, which means that the investors receive the same information at the same time, form the same expectations and eventually trade similarly. In the case of low-tech stocks, firms disclose much more information relative to the high-tech stocks, which makes the probability of herding is higher among such stocks because the investors receive more information that has higher quality about them. Avramov et al (2006) propose that the asymmetric volatility[14] can be fully accounted for herding behaviour and the interaction between herding and contrarian investors. Their model shows that when stock prices fall, herding investors control the volatility of the subsequent period, since they all act in the direction of price change. They exacerbate the move and cause the volatility to increase. However, when the stock prices rise, contrarian investors control the volatility of following period, which reduces the volatility because they trade in the opposite direction to the price change. In sum, the interaction between contrarian and herding investors can fully account for asymmetric volatility. In the low-tech stocks that disclose more information and have lower information asymmetry, the probability of investors to herd is higher as explained above and the probability of interacting with contrarian investors to induce asymmetric volatility is also higher. The second hypothesis can be stated as follows:

H2. Ceteris paribus, low-tech stocks experience higher asymmetric volatility than high-tech stocks that have intensive R&D activities.

[13] See Kwon & Yin, (2015), P.649

[14] Means the negative relation between price and its volatility comes from the changes in firm's financial leverage which leads to changes in expectations over a firm's risk and hence its volatility

Behavioural finance provides two explanations why idiosyncratic risk relates to the momentum effect. First, the idiosyncratic risk works as a measure to the amount of firm-specfic information. If the underreaction to firm-specific information is the proper source for momentum, idiosyncratic risk should be positively related to the momentum effect and firms with higher idiosyncratic risk, all else being equal, could be expected to have higher momentum returns (Arena, Haggard, & Yan, 2008). Second, the idiosyncratic risk successfully limits the arbitrage process and prevent arbitrageurs from correcting the momentum effect (Shleifer & Vishny, 1997). In other words, the arbitrageurs do not trade on mispricing because arbitrage is risky. According to (Shleifer & Vishny, 1997), arbitrage risk consists of systematic and idiosyncratic components but the idiosyncratic risk is more important in limiting the arbitrage mechanism.

Nevertheless, Lesmond, Schill, & Zhou, (2004) and McLean (2010) provide empirical evidence that when the transaction cost is high, it can alone, rather than idiosyncratic volatility, play the major role in preventing the arbitrage process from correcting the momentum effect, which weakens the relation between idiosyncratic risk and momentum. In this paper, we separate our sample into high-tech that have higher R&D expenditure versus low-tech stocks. Aboody & Lev (2000) argue that the R&D is the key source of information asymmetry which means that high-tech stocks experience a greater level of information asymmetry. In theory transaction costs have two main components; 1) the inventory holding and clearing cost which is due to costs incurred by the dealer when organizing trades and executing transaction; 2) the adverse selection cost, which is due to information asymmetry. Glosten & Harris (1988) study the US stock market and find that a greater proportion of the bid-ask spread as a proxy for transaction costs comes from information asymmetry. This finding is consistent with Callahan, Lee, & Yohn (1997) who confirm that an increase in information asymmetry leads to a coincident increase in transaction costs. The third hypothesis can be stated as follows:

H3. Ceteris paribus, high-tech stocks that have higher R&D expenditure experience a weaker idiosyncratic risk *-momentum return relation than do low-tech stocks.*

5.4- Econometric framework

The use of GARCH (1,1) family models has two advantages: first, it successfully deals with the conditional heteroskedasticity problem. Second, the static asset pricing models assume that the variances of the error terms are constant. This assumption contradicts the empirical evidence provided by several studies, which emphasizes the time varying nature of error terms Li, Brooks & Miffre (2009). In this paper, we have two models as follows:

5.4.1- The GARCH in mean ('GARCH-M') model

The GARCH-M model was developed by Engle, Lilien, & Robins (1987) to measure the relation between expected return and variance. This model can be represented as follows:

$$R_t = \alpha + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + \delta\sigma_t + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \tag{4}$$

where $(R_{mt}-R_{ft})$, SMB and HML make up the Fama-French three factor model (1993). $\varepsilon_{i,t}$ is a white noise error term, σ_t^2 is conditional variance of the momentum portfolios. γ is the lagged squared error term which measures the impact of recent news on volatility. θ is the lagged conditional volatility which measures the impact of old news on volatility. The $\delta\sigma_t$ is the time-varying risk premium and δ measures the relation between idiosyncratic risk and momentum returns. This framework is used to test the third hypothesis.

5.4.2- The GJR –GARCH-M model

According to Glosten, Jagannathan, & Runkle (1993), good news means positive return shocks and bad news means negative return shocks. The conditional variance of expected returns responds asymmetrically to this news. More precisely, the conditional variance of negative returns is higher than that of positive returns of the same magnitude. The GJR can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \delta_i \sigma_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$\sigma^2_{i,t} = \omega_i + \gamma_i \varepsilon^2_{i,t-1} + \eta_i I_{i,t-1} \varepsilon^2_{i,t-1} + \theta_i \sigma^2_{i,t-1} \quad (2)$$

where $R_{i,t}$ is the return on momentum portfolio. $(R_{mt} - R_{ft})$, *SMB* and *HML* are the Fama-French three factor model (1993). $\varepsilon_{i,t}$ is the white noise error term. $\sigma^2_{i,t}$ is conditional variance of momentum portfolios. γ_i is the lagged squared error term which measures the impact of recent news on volatility. η_i is the measure of the asymmetric response of volatility to bad and good news (commonly attributed to the leverage effect). $I_{i,t-1} = 1$ if $\varepsilon^2_{i,t-1} < 0$ (bad news, also called negative return shocks, and $I_{i,t-1} = 0$ otherwise, θ_i is the lagged conditional volatility which measures the impact of old news on volatility. The $\delta_i \, \sigma_{i,t}$ is the time-varying risk premium. This framework is used to test the second hypothesis. The coefficients of the conditional volatility refer to the impact and speed of the momentum portfolios respond to good and bad news.

5.5- Data and methodology

Monthly data for all stocks listed on the Russell 3000 index was collected and winsorized at 2%. To avoid survivorship bias, the list of companies was updated every month to include the delisted companies. All the poor representation stocks that had less than 30 observations were deleted. Following Kwon and Yin (2015) we classified all sample stocks into high-tech versus low-tech using the SIC 3-digit code and defined the high-tech stocks as stocks listed in the computer, electronic, pharmaceutical, technology and telecommunications industries. The technology stocks, as specified by CNNFN.com, are also included. These stocks are tech blue chips, cable, chips, computer/peripherals, internet, networking, satellite, software, tech retail, telecommunication and wireless, while the low-tech stocks include everything else. The pharmaceutical industry was added to the high-tech stocks because it shares the same characteristics especially heavy R&D expenditures and higher level of unreported assets. As a result, 2086 stocks of high-tech and 3709 of low-tech are considered. Table 5.2 presents a full description of each subsample.

The methodology of Jagadeesh & Titman (1993) was followed to construct equally weighted portfolios using two breakpoints 10% and 30%. This means that the securities in the bottom 10 (30) percent are positioned in the loser portfolio, while the securities in the top 10 (30) percent are positioned in the winner portfolio. For the robustness checks, the 30% breakpoint was chosen following Chui, Titman, & Wei (2003). The main reason why we implement robustness check is to ensure regression estimates are insensitive to different market conditions and are insensitive to different assumptions. At the end of each month all stocks in the high-tech and low-tech samples were ranked in ascending order based on their past J-months cumulative returns with dividends (J= 3, 6, 12 months). Each of these portfolios is held for K-months (K=3, 6, 12 months). The momentum portfolio was measured as a J-K portfolio. This gaves a total of 18 portfolios (nine for the high-tech stocks and nine for the low-tech stocks). We skipped one -month between the portfolio formation period and the holding period to relieve the effect of nonsynchronous trading and bid-ask spread, leading to greater strength in our test. We constructed an overlapping portfolio that consisted of the winner (loser) portfolios in the previous K months. The returns on the winner/loser portfolios were the simple average of the returns on the K winner (loser) portfolios. For example, if we had been going to form a portfolio with 6-months holding period, we would have computed the simple average of the returns on the six winner (loser) portfolios. In other words, it is August return on the winner (loser) portfolio is the simple average of the August returns on the winner (loser) portfolios that constructed from January to June and July that was skipped. The momentum portfolio ('zero-cost') in this context equals winners-minus-losers portfolio. All momentum portfolios were regressed on the three-factor model of Fama-French (1993), which is described as model 1. Table 5.1 provides detailed descriptions of all the dependent and independent factors.

<<Table 5.1 about here>>

5.6- Empirical analysis

5.6.1- Summary statistics

Table 5.2 provides the contribution of each industry in the high-tech stocks and low-tech stocks determined by the SIC three digits for high-tech stocks and the Fama-French industrial classification for low-tech stocks. The computer and data processing industry is the largest industry among the high-tech stocks, which represents 21.43%. The second largest industry is the pharmaceutical and represents 15%. They together make up one-third of the high-tech stocks. In the other category, construction materials and banks dominate 41.5% of the low-tech stocks.

<<Table 5.2 about here>>

Table 5.7 compares the descriptive statistics between the high-tech and low-tech stocks for each 6-6 momentum portfolio including price, institutional ownership, Beta, EPS, leverage, turnover and size. We did not notice any difference between the high-tech stocks and the low-tech stocks. For both subsamples, there is a U-shaped relationship between momentum returns and both of Beta and Turnover. However, the relationship between momentum returns and each of Price, Institutional Ownership, EPS, Leverage and Size formed an inverted U-shape. This means that the loser portfolio has lower Price, Institutional Ownership, EPS, Leverage and Size but has higher Beta and Turnover than the winner portfolio in both samples. Nevertheless, on average the high-tech portfolios had lower Price, lower Institutional Ownership, much lower EPS, much lower Leverage, and lower Size than the low-tech stocks but they had higher Beta and Turnover than the low-tech stocks. The t-statistics in Panel B shows significant differences between the high-tech and low-tech for all variables and portfolios.

<<Table 5.7 about here>>

The noticeably high Leverage measured by debt to equity can be attributed to the finance sector since both categories have some financial companies; the miscellaneous investing in high-tech subsample represents 13% of the sample and the finance sector, including banks, insurance, financial trading and real estate represent about 25% of the low-tech R&D sample.

5.6.2- Momentum

Table 5.8 and 5.9 compare the summary statistics between the high-tech stocks and low-tech stocks including mean returns, standard deviation and reward-to-risk for each momentum portfolios. The rows represent the ranking periods (J=3, 6 and 12 months) and the columns represent the holding periods (K=3, 6 and 12 months). Our robust findings for the high-tech stocks, using the breakpoints 10% and 30%, challenge the rational expectation theory, since the portfolios with higher risk do not provide higher returns. For example, the 6-6 strategy provides the highest risk-adjusted returns 0.205 and 0.169 for the breakpoints 10% and 30% respectively, while they do not embody the highest risk. Moreover, the 3-3 strategy is the lowest volatile strategy, but it does not provide the lowest risk-adjusted returns using the 10% and 30% breakpoints. For low-tech stocks, the finding provides strong support for inconsistency with the rational expectation theory. For example, the 12-12 strategy using the breakpoints 10% and 30%, is the highest volatile strategy, but it does provide the lowest risk-adjusted returns for the two breakpoints.

<<Table 5.8 about here>>

<<Table 5.9 about here>>

Panel D in Tables 5.8 and 5.9 provides t-statistics that are needed to test our first hypothesis. To facilitate the exposition, we can say that four strategies show larger significant momentum profits in high-tech stocks than low-tech stocks do, namely, the 3-3 strategy, the 3-6 strategy, the 6-3 strategy and the 6-6 strategy, since the t-statistics show significant difference between them at 5% significance level. This finding is robust to different breakpoints. Another important support for the first hypothesis comes from the fact that the low-tech momentum portfolios never outperform the high-tech ones. In sum, we accept the first hypothesis for the above mentioned strategies and reject it otherwise. This finding appears consistent with that of (Wang, 1993) who develops a model of asset pricing under information asymmetry. In his model, the economy has two kinds of investors, informed and uninformed investors. He assumes that all investors know current dividends and stock prices, but informed investors (‘insiders in our case’) have certain expectations of the growth rate of future dividends and uninformed ones ('outsiders in our case') do not. It is known that the increase in stock prices depends on the growth rate of dividends. As a result, any change in stock prices can be attributed to the growth rate of dividends. If we assume that the uninformed investors build rational expectation about the state of the economy using prices and dividends, then the stocks prices should be considered as true and fundamental values because the market has frictions and is incomplete. Under the incomplete market assumptions, investors face different information which leads them to reach different return expectations. Therefore, the less informed investors, the outsiders in our case who do not have sufficient information on future dividends and prices, base their trading on realized returns only to know about the state of the economy, which increases the reliance of their expected returns on past returns and creates higher momentum for high-tech stocks compared to low-tech stocks. Therefore, it seems plausible for investors to follow the opposite of momentum strategy by adopting a long position in the loser portfolio and a short position in the winner portfolio for low-tech stocks

5.6.3 Asymmetric volatility

Consistently with the GARCH family models, the coefficients of the variance equation should be positive, except for the asymmetric coefficient in the GJR framework. We check this condition for all portfolios and it satisfied all of them except the 3-6 strategy in the high-tech stocks, which has a negative intercept. Fortunately, however, it is insignificant.

Table 5.10 and 5.11 report estimates of Fama-French models (1) and (2) that include a GJR-GARCH-M term. To facilitate the exposition, the average estimates across the ranking and holding periods of the coefficients are discussed. The coefficients of γ and η In system (1) and (2) associate with the lagged square error term and, calibrate the effect of recent news on the volatility of momentum returns. For the high-tech stocks, using the 10% and 30% breakpoints the average $\gamma + \eta /2$ of the Fama-French model equals 0.597 and 0.643 respectively, and 0.312 and 0.338 for low-tech stocks respectively. From this discussion, we found robust and valuable conclusions. The first is that the impact of recent news on the volatility of high-tech stocks is greater than this impact for low-tech stocks. This is consistent with the information asymmetry view since the flow of information in the case of higher levels of information asymmetry creates higher levels of dispersion of belief and leads to a higher level of volatility (Shalen, 1993).

<<Table 5.10 about here>>

<<Table 5.11 about here>>

The coefficient θ in systems (1) and (2) reflects the effect of old news ('lagged conditional variance') on the volatility of momentum returns. For high-tech stocks, the average θ coefficients are 0.430 and 0.378 using 10% and 30% respectively. For low-tech stock, the average θ coefficients are 0.554 and 0.416 using 10% and 30% respectively. The above discussion reaches the robust conclusion that the impact of old news on volatility for the high-tech stocks is smaller than that impact for the low-tech stocks. This result is robust to different breakpoints.

In testing our second hypotheses, the empirical evidence provides a reasonably robust support. For high-tech stocks, the asymmetric coefficients are insignificant at 5% level for the whole nine momentum portfolios using the 10% breakpoint, while 7 out of 9 momentum portfolios show insignificant asymmetric coefficients η using 30% breakpoint at 5% significance level. The insignificant coefficients indicate that the variance responds symmetrically to good and bad news, indicating high-tech stocks, which are characterized by higher information asymmetry, leading the investor to lack the required information to herd and to interact with contrarian investors to induce asymmetric volatility. This symmetric volatility is robust to different momentum strategies and to different breakpoints. However, for the low-tech stocks, the asymmetric coefficient η in 7 out of 9 momentum portfolios is significant and 6 out of 9 momentum portfolios have significant asymmetric coefficients η at the 5% significance level using 10% and 30% breakpoints respectively. The significant coefficient means that the impact of bad news ('negative return shocks') on volatility is greater than the impact of good news ('positive return shocks'), indicating that the non-intensive firms disclose more information, which helps the irrational investors to herd and to interact with contrarian investors to induce asymmetric volatility.

Finally, the last row in each panel in Tables 5.10 and 5.11 presents the persistence in volatility proxied by $\gamma + \eta/2 + \theta$. The above tables present robust evidence that the volatility of high-tech stocks is more persistent than that of low-tech stocks. For the high-tech stocks, the average $\gamma+ \eta/2+ \theta$ is 1.026 and 1.013, respectively, using 10% and 30% breakpoints. For the low-tech stocks, however, it is 0.886 and 0.754 respectively. In theory, volatility persistence means that shocks of current conditional variance have a significant impact on the variance of the next periods and this persistence is attributed to the persistence in the information flow proxied by trading volume. The explanation here is that when new information reaches the stock market, investors react by trading until stock prices attain a equilibrium point. Investors, then, form new expectations concerning the new equilibrium point (Andersen, 1996). Therefore, the more persistent volatility for the high-tech stocks is due to the higher ratio of turnover based on trading volume as shown in Table 5.7 as a proxy for information flow since the turnover for the high-tech stocks is 0.009 compared with 0.007 for low-tech stocks. Table 5.7 shows that high-tech stocks experience higher levels of systematic risk measured by beta and smaller size. This conclusion is consistent with Koutmos, Lee, & Theodossiou (1994) who confirm that volatility persistence is stronger among stocks with higher systematic risk and among stocks with smaller size.

5.6.4- Idiosyncratic risk -momentum return relation

Tables 5.10 and 5.11 also present the impact of conditional volatility on return through δ coefficients that measure the idiosyncratic risk -momentum return relationship. For the high-tech stocks, 8 out of 9 momentum strategies show an insignificant relation between idiosyncratic risk and momentum returns at 5% significance level using the 10% breakpoint and 8 out of 9 δ coefficients are insignificant using the 30% breakpoint, which obviously indicates that there is no idiosyncratic risk -momentum return relation at 5% significance level. These results mean that idiosyncratic risk does not limit arbitrage among momentum stocks, while momentum is induced as a consequence of mispricing that continues due to limited arbitrage; and that the transaction cost is high enough to prevent the arbitrageurs from correcting the momentum effect.

At the same time, for the low-tech stocks 6 out of 9 show a significant and negative idiosyncratic risk -momentum return relation using the 10% breakpoint and 9 out of 9 are significant and negative using the 30% breakpoint at 5% significance level. This finding strongly supports our third hypothesis that the idiosyncratic risk -momentum return for the high-tech stocks is weaker than that for the low-tech stocks and upholds the role of high transaction cost rather than idiosyncratic risk in limiting arbitrage (Lesmond, Schill, & Zhou, 2004).

Since the negative relation between idiosynctratic risk and momentum return denies the standard finance theory, Another robustness check is ran using GARCH-M model to provide additional support for this negative relation using the same breakpoints 10% and 30%. The finding of GARCH-M supports the previous finding of GJR-GARCH-M which indicates the first conclusion is robust to the simplified GARCH-M model in Tables 5.12 and 5.13. For the high-tech stocks using GARCH-M, all nine δ coefficients are insignificant using 10% and 30% breakpoints at 5% significance level. However, 8 out 9 of the δ coefficients of the low-tech stocks are significant and negative using the 10% and 30% breakpoints at 10% significance level. Tables 5.8 and 5.9 show that most low-tech stocks generate losses and the corresponding t-statistics are significant for the longest holding period. This finding is consistent with De Bondt & Thaler (1985) who document the reversal pattern on the long - term. This finding suggests that the transaction cost for low-tech stocks is too small to limit arbitrage, due to lower information asymmetry. Therefore, the idiosyncratic risk is the key player in limiting arbitrage and inducing reversal in returns.

In contrast to the traditional asset pricing theory and risk-return trade-off, the negative relation between time-varying idiosyncratic risk and momentum returns means investors do not require greater risk premium for bearing higher risk and also means momentum returns are greater among stocks with low idiosyncratic volatility. Instead, in the absence of R&D, investors who bear higher idiosyncratic risk are penalized with lower momentum returns. This is consistent with Glosten, Jagannathan, & Runkle (1993) who confirm that this negative sign is possible in special circumstances such as in times of peak interest rate on savings and scarce investment opportunities are available. From a behavioural perspective, this negative relation between predicted volatility and the corresponding risk premium is consistent with Black & McMillan (2006) and Nam, Pyun, & Kim (2003) who attribute this to investors' overreaction to certain market news, especially the negative ones ('bad news'). This news increases predicted volatility which results in higher required rate of return and lower current stock prices. The explanation here is, some investors, who believe in mean reversion, become more optimistic about the future after negative return shocks, accepting lower risk premium.

While McLean (2010) confirms that transaction costs limit arbitrage for the smaller mispricing and idiosyncratic risk limits the arbitrage among the reversal stocks for the greater mispricing, we find that the high-tech stocks that experience higher transcation costs due to higher information asymmetry, transaction costs limit the arbitrage among momentum stocks, while for the low-tech stocks that experience lower transaction cost due to lower information asymmetry, idiosyncratic risk limits the arbitrage among reversal stocks.

5.6.5- The Performance of Fama-French model

Li, Miffre, Brooks, & O'Sullivan (2008) contributed to the literature through demonstrating that momentum profits can be explained by a GJR-GARCH-M without following Lesmond et al. (2004)'s methodology based on transaction costs since all α coefficients were insignificant in the framework of GJR-GARCH-M. In our result, Tables 5.10 and 5.12 show the following:

For the high-tech stocks, the Fama-French with GJR-GARCH-M terms can moderately describe the momentum returns since Table 5.10 shows that 5 out of 9 momentum portfolios have insignificant α coefficients using the 10% breakpoint and Table 5.11 shows that 6 out of 9 have insignificant α coefficients using the 30% breakpoint at 5% significance level. Using Fama-French with GARCH-M in Tables 5.12 and 5.13 provides robust support for the previous finding, since Table 5.12 shows that 8 out of 9 α coefficients are insignificant using the 10% breakpoint and all 9 α coefficients are insignificant using the 30% breakpoint at 5% significance level.

For the low-tech stocks, the Fama-French with GJR-GARCH-M terms acts very poorly in describing momentum returns. Table 5.10 shows that only 2 out 9 α coefficient are insignificant using the 10% breakpoint and 1 out 9 α coefficients is insignicant using the 30% breakpoint in Table 5.11 at 5% significance level. Using Fama-French with GARCH-M term provides a robust support, since only 2 out 9 α coefficients are insignificant using the 10% breakpoint at 10% significance level in Table 5.12 likewise in Table 5.13 with the 30% breakpoint at 10% significance level.

<<Table 5.12 about here>>

<<Table 5.13 about here>>

From the analysis above, we can conclude that there is robust evidence that Fama-French with its conditional variance term can apparently better explain momentum returns for high-tech stocks. Though there is no relation between idiosyncratic risk and momentum, the model performs better at explaining momentum returns. This confirms the third hypothesis and means that something else ('transaction cost') other than idiosyncratic risk limits the arbitrage and induce momentum.

5.7- Conclusion

This research focused on investigating the systematic disagreements in momentum, asymmetric volatility and the idiosyncratic risk-momentum return relation between high-tech stocks and low-tech stocks. The SIC code was used to split the whole dataset into two samples based on the intensity of R&D expenditures; and the Fama-French with GJR-GARCH-M term was also used to test our hypotheses. We find that; (1) the high-tech stocks, relative to low-tech stocks, show greater momentum profits in all portfolios that have a ranking or holding period of less than 12 months and an insignificant difference between the two samples otherwise; (2) the high-tech stock show symmetric response to good and bad news while the low-tech stocks show asymmetric response to good and bad news; (3) for the high-tech stocks there was no idiosyncratic risk- momentum return relation, while this relation was significant and negative for the low-tech stocks. Our results are robust to different breakpoints; (4) there is robust evidence that the ability of Fama-French with conditional variance term to explain momentum returns is better for high-tech stocks than to low-tech stocks.

These conclusions have many implications: (1) the investor should increase the proportion of high-tech stocks when constructing the momentum portfolios at the expense of low-tech stocks to generate greater momentum profits; (2) for the high-tech stocks, the asymmetric coefficients are econmically and statistcally insignificant, which means that the variance responds similarly to the positive and negative shocks (good and bad news), while for the low-tech stocks, the asymmetric coefficients are economically and statistcally significant, which means that the variance responds to a greater degree in negative returns shock (bad news) than in positive returns shocks (good news); (3) the finding on idiosyncratic risk-momentum return relation indicates that, in the case of high-tech stocks, the momentum returns are compensation for market friction and transcation costs are the key player in limiting the arbitrage and persisting momentum, while with low-tech stocks that experience lower transaction costs due to lower information asymmetry, idiosyncratic risk limits the arbitrage and persists reversal in returns. We believe that the next steps in this research should be to check the robustness of our findings either to data from the emerging markets or to higher frequency data, such as daily and weekly data or to the other aymmetric conditional variance models, such as EGARCH model.

Tables of results

Table 5.1. Description of the independent variables

Variable	Definition
$R_{i,t}$	Is the return on momentum portfolio.
Winner	Includes the stocks in the top 10% (30%) based on past J-months cumulative returns with dividends.
Loser	Includes the stocks in the bottom 10% (30%) based on past J-months cumulative returns with dividends.
Momentum	Is a zero-cost portfolio and measured by winners' minus losers' portfolio.
$(R_{mt} - R_{ft})$	The excess market returns.
SMB (small minus big)	The returns to small firms less the returns to large firms. We measure a firm's size by the market value of equity at the end of the fiscal year.
HML (high minus low)	The returns to high book-to-market firms less The returns to low book-to-market firms. We measure the book to market ratio as the fiscal year-end book value of common equity over the calendar year-end market equity (December).
$\varepsilon_{i,t}$	White noise error term.
$\sigma^2_{i,t}$	Conditional variance of the momentum portfolios.
γ_i	Lagged squared error term measuring the impact of recent news on volatility.
η_i	Measure of the asymmetric response of volatility to bad and good news (commonly attributed to the leverage effect).
θ_i	Lagged conditional volatility measureing the impact of old news on volatility.
$\delta\sigma_t$	Time-varying risk premium.

Table 5.2. Summarizes the proportion of each industry in the high-tech stocks versus low-tech stocks

High-tech stocks				Low-tech stocks			
3-Digits SIC code	**Industry**	**Number of firms per industry**	**Percentage (%)**	**4-Digits SIC code**	**Industry**	**Number of firms per industry**	**Percentage (%)**
272	Periodicals	8	0.38	0100-0799	Agriculture	16	0.40
283	Drugs	318	15.20	1000-1119 1400-1499	Mining	33	0.90
355	Special industry Machinery	26	1.20	1200-1299	Coal	17	0.40
357	Computer and office equipment	99	4.75	1300-1389	Petroleum and Natural gas	204	5.50
361	Electronic distribution Equipment	2	0.09	1500-1799	Construction	63	1.70
362	Electronic industrial apparatus	16	0.70	2000-2099	Food, Soda and Beer	94	2.50
363	Household appliances	8	0.38	2100-2199	Tobacco	9	0.20
364	Electronic lighting and writing equipment	15	0.72	2200-2399	Textiles	48	1.30
365	Household audio and video equipment	8	0.38	2400-3996	Construction materials and steel works	931	25.10
366	Communication equipment	111	5.32	4000-4789	Transportation	145	3.90
367	Electronic components and accessories	213	10.21	4822-4839	Telegraph, Radio-TV broadcaster and communication providers	71	1.90
369	Miscellaneous Electronic components and supplies	28	1.34	4900-4991	Utilities, and power producer	213	5.70

Table 5.2. (continued)

High-tech stocks				Low-tech stocks			
3-Digit SIC Code	**Industry**	**Number of firms per industry**	**Percentage (%)**	**4-Digits SIC code**	**Industry**	**Number of firms per industry**	**Percentage (%)**
381	Search and navigation equipment	19	0.91	5000-5199	Wholesale	147	4.00
382	Measuring and controlling devices	96	4.60	5200-5999	Retail	326	8.80
386	Photographic equipment and supplies	8	0.38	6000-6199	Banks	610	16.40
481	Telephone Communication	122	5.85	6200-6299 6700-6799	Financial trading	53	1.40
484	Cable and other pay TV services	33	1.60	6300-6411	Insurance	231	6.20
573	Radio TV and Electronic stores	19	0.91	6500-6611	Real estate	35	0.90
621	Security brokers and dealers	51	2.44	7020-8999	Personal and Business services	463	12.50
679	Miscellaneous investing	274	13.13				
733	Mailing, reception and stenographic	5	0.24				
737	Computer and data processing	447	21.43				
738	Miscellaneous business services	112	5.37				
873	Research and testing services	47	2.25				
Total		2086	99.79	Total		3709	99.7

Table 5.3. Unit root test (Augmented Dickey-Fuller) Breakpoint 10%

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
ADF	-4.280	-3.796	-4.822	-5.087	-4.609	-4.008
% Critical value	-3.469	-3.470	-3.472	-3.469	-3.470	-3.472
Panel B: Ranking period 6 months						
ADF	-3.525	-3.626	-5.001	-4.079	-3.744	-3.572
% Critical value	-3.470	-3.471	-3.473	-3.470	-3.471	-3.473
Panel C: Ranking period 12 months						
ADF	-3.509	-4.556	-4.987	-3.810	-4.031	-3.855
% Critical value	-3.472	-3.473	-3.475	-3.472	-3.473	-3.475
Panel D: Fama-French Factors						
	High-tech stocks			**Low-tech stocks**		
	(R_m-R_f)	**SMB**	**HML**	**(R_m-R_f)**	**SMB**	**HML**
ADF	-4.030	-4.746	-4.043	-4.030	-5.409	-3.814
% Critical value	-3.467	-3.467	-3.467	-3.467	-3.467	-3.467

The regression is used to estimate Augmented Dickey-Fuller statistics. The regression includes up to 12 lags of the dependent variable with a constant and no trend. It is obvious that all ADF estimates are more negative than the critical value. This indicates that the null hypothesis H0: series contains a unit root should be rejected. This means the time series in the table are stationary.

Table 5.4. Unit root test (Augmented Dickey-Fuller) Breakpoint 30%

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
ADF	-5.023	-4.120	-4.723	-4.495	-4.298	-3.660
% Critical value	-3.469	-3.470	-3.472	-3.469	-3.470	-3.472
Panel B: Ranking period 6 months						
ADF	-3.916	-3.778	-4.757	-4.380	-3.897	-3.531
% Critical value	-3.470	-3.471	-3.473	-3.470	-3.471	-3.473
Panel C: Ranking period 12 months						
ADF	-3.777	-4.889	-4.572	-3.833	-3.775	-3.639
% Critical value	-3.472	-3.473	-3.475	-3.472	-3.473	-3.473
Panel D: Fama-French Factors						
	High-tech stocks			**Low-tech stocks**		
	(R_m-R_f)	**SMB**	**HML**	**(R_m-R_f)**	**SMB**	**HML**
ADF	-4.030	-4.746	-4.043	-4.030	-5.409	-3.814
% Critical value	-3.467	-3.467	-3.467	-3.467	-3.467	-3.467

The regression is used to estimate Augmented Dickey-Fuller statistics. The regression includes up to 12 lags of the dependent variable with a constant and no trend. It is obvious that all ADF estimates are more negative than the critical value. This indicates that the null hypothesis H0: series contains a unit root should be rejected. This means the time series in the table are stationary.

Table 5.5. ARCH effect '10% Breakpoint'

	High-tech stocks			**Low-tech stocks**		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
Chi2	45.010	36.948	41.238	59.135	98.489	137.941
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Ranking period 6 months						
Chi2	60.609	118.515	99.505	105.136	123.858	136.470
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Ranking period 12 months						
Chi2	61.273	109.938	99.099	87.141	118.337	106.318
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Before running a GARCH-family model, it is plausible to check whether ARCH exists in the residuals or not by employing Engle (1982) test for ARCH effect. The presence of ARCH helps justify a GARCH-family model. P-values here indicate that all test statistics are significant at 1%, meaning that ARCH exists in all momentum returns in both subsamples.

Table 5.6. ARCH effect '30% Breakpoint'

	High-tech stocks			**Low-tech stocks**		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
Chi2	25.927	39.720	71.674	69.522	126.990	174.258
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Ranking period 6 months						
Chi2	68.324	93.349	115.380	118.479	139.339	162.204
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Ranking period 12 months						
Chi2	88.480	127.754	106.696	110.825	133.583	152.618
P-Value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Before running a GARCH-family model, it is plausible to check whether ARCH exists in the residuals or not by employing Engle (1982) test for ARCH effect. The presence of ARCH helps justify a GARCH-family model. P-values here indicate that all test statistics are significant at 1%, meaning that ARCH exists in all momentum returns in both subsamples.

Table 5.7. portfolios characteristics based on 6-6 momentum strategy using 10% breakpoint

	High-tech stocks							Low-tech stocks						
Portfolios	**Price**	**INS**	**Beta**	**EPS**	**LEV**	**TUR**	**Size (billions)**	**Price**	**INS**	**Beta**	**EPS**	**LEV**	**TUR**	**Size (billions)**
P1	16.061	50.834	1.390	-0.279	1.491	0.013	1.430	24.034	72.568	1.119	1.140	2.848	0.010	2.670
P2	20.385	58.433	1.292	0.231	1.422	0.010	2.860	28.069	73.021	1.017	1.648	3.075	0.008	4.020
P3	23.016	61.568	1.209	0.516	1.476	0.009	3.750	30.203	72.433	0.980	1.846	3.263	0.007	4.760
P4	24.991	64.044	1.163	0.701	1.606	0.009	4.460	31.716	72.226	0.951	1.957	3.411	0.006	5.190
P5	27.119	65.222	1.118	0.814	1.671	0.008	4.990	32.972	71.892	0.936	2.022	3.487	0.006	5.470
P6	28.529	66.913	1.094	0.877	1.738	0.008	5.400	33.184	72.743	0.935	2.042	3.511	0.006	5.630
P7	29.346	67.186	1.085	0.930	1.730	0.008	5.600	33.556	72.988	0.933	2.029	3.485	0.006	5.550
P8	30.052	66.712	1.098	0.875	1.710	0.008	5.390	34.176	73.768	0.956	2.001	3.365	0.007	5.550
P9	29.880	65.382	1.179	0.700	1.656	0.009	4.920	33.854	75.019	0.985	1.887	3.214	0.007	5.090
P10	28.818	61.632	1.329	0.270	1.558	0.012	3.350	33.572	76.578	1.085	1.557	2.924	0.009	4.010
Average	25.820	62.793	1.196	0.563	1.606	0.009	4.215	31.534	73.324	0.990	1.813	3.258	0.007	4.794

This table shows several characteristics of ten momentum portfolios that are formed following Jagadeesh and Titman (1993) and based on six-month returns and held for six months. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Price is the average monthly closing prices. INS denotes institutional ownership and proxied by the average percentage ratio of free traded shares held by institutions to the number of float shares outstanding. BETA is the average systematic risk and was calculated by the CAPM for the past two years of weekly data using the S&P 500 in addition. EPS is computed as net income available to common shareholders divided by the basic weighted average shares outstanding and the most recent 12 months (trailing 12 months) are summed. LEV denotes leverage and is the average ratio of debt to equity. TUR denotes turnover and is the average ratio of a shares monthly trading volume divided by the monthly shares outstanding. Size is the average monthly market capitalization.

Table 5.7. (Continued)

Panel B: t-statistics for each portfolio and each factor

Portfolio	**Price**	**Institutional**	**Beta**	**EPS**	**Turnover**	**Leverage**	**Size (in billions)**
P1	-37.044	-49.771	30.153	-78.443	24.540	-42.717	-23.473
P2	-34.989	-33.966	34.686	-80.949	28.890	-53.057	-14.974
P3	-31.721	-25.701	30.849	-76.881	29.306	-57.141	-11.303
P4	-28.955	-19.600	29.847	-72.639	26.615	-56.044	-7.506
P5	-24.268	-16.045	26.565	-68.520	25.964	-55.803	-4.688
P6	-19.159	-14.100	23.466	-66.485	23.619	-53.713	-2.205
P7	-17.274	-14.019	22.561	-63.464	21.088	-53.507	0.481
P8	-16.528	-16.886	20.767	-63.750	21.356	-51.048	-1.57
P9	-15.766	-22.646	26.842	-66.995	21.824	-48.191	-1.705*
P10	-18.183	-34.141	29.627	-69.285	25.857	-42.149	-8.846

(*) Significant at 10%, otherwise all is either significant at 5% or insignificant in two tailed tests.

Table 5.8. Summary statistics of momentum portfolios based on 10% breakpoint

	High-tech stocks			**Low-tech stocks**		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
Mean	0.009 (1.67)*	0.017 (1.44)	-0.007 (-2.31)	-0.007 (-0.67)	-0.007 (-1.20)	-0.015 (-2.05)
St. Deviation	0.081	0.123	0.178	0.063	0.097	0.122
Reward-to-risk	0.111	0.138	-0.039	-0.111	-0.072	-0.123
Panel B: Ranking period 6 months						
Mean	0.017 (2.53)	0.026 (2.85)	-0.018 (-1.37)	-0.005 (-1.35)	-0.007 (-1.05)	-0.023 (-2.59)
St. Deviation	0.097	0.127	0.197	0.066	0.108	0.136
Reward-to-risk	0.175	0.205	-0.091	-0.076	-0.065	-0.169
Panel C: Ranking period 12 months						
Mean	0.010 (1.37)	-0.001 (-0.10)	-0.055 (-3.69)	-0.006 (-1.30)	-0.016 (-2.20)	-0.047 (-4.23)
St. Deviation	0.105	0.150	0.219	0.076	0.115	0.167
Reward-to-risk	0.095	-0.007	-0.251	-0.079	-0.139	-0.281

Panel D: t-statistics between the two groups

	Holding Period 3 months	**Holding Period 6 months**	**Holding Period 12 months**
Ranking Period 3 months	2.159	2.553	0.637
Ranking Period 6 months	2.840	2.863	0.389
Ranking Period 12 months	1.876	1.301	-0.385

Momentum is a portfolio that buys the winner portfolio (top 10% of stocks) and sells the loser portfolio (bottom 10% of stocks) short. Returns are measured as proportions rather than percentages. Reward-to-risk ratio is the ratio of monthly mean to the monthly standard deviation. The t-statistics in parentheses are for the significance of the mean. (*) indicates 10% significant level and we use 5% otherwise.

Table 5.9. Summary statistics of momentum portfolios: Robustness analysis based on 30% breakpoint

	High-tech stocks			**Low-tech stocks**		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
Mean	0.001	0.005	-0.003	-0.007	-0.008	-0.014
	(0.35)	(1.27)	(-0.50)	(-3.46)	(-2.86)	(-3.26)
St. Deviation	0.049	0.067	0.107	0.030	0.046	0.063
Reward-to-risk	0.020	0.075	-0.028	-0.233	-0.174	-0.222
Panel B: Ranking period 6 months						
Mean	0.007	0.012	-0.006	-0.005	-0.005	-0.014
	(1.89)*	(2.37)	(-0.96)	(-2.33)	(-1.56)	(-3.00)
St. Deviation	0.056	0.071	0.112	0.031	0.052	0.071
Reward-to-risk	0.125	0.169	-0.053	-0.129	-0.096	-0.197
Panel C: Ranking period 12 months						
Mean	0.004	-0.000	-0.031	-0.001	-0.005	-0.019
	(0.98)	(-0.07)	(-3.87)	(-0.87)	(-1.58)	(-3.57)
St. Deviation	0.059	0.081	0.120	0.032	0.054	0.079
Reward-to-risk	0.068	0.000	-0.258	-0.031	-0.092	-0.240

Panel D: t-statistics between the two groups

	Holding Period 3 months	**Holding Period 6 months**	**Holding Period 12 months**
Ranking Period 3 months	2.107	2.712	1.257
Ranking Period 6 months	2.848	2.829	0.787
Ranking Period 12 months	1.293	0.880	-1.262

Momentum is a portfolio that buys the winner portfolio (top 30% of stocks) and sells the loser portfolio (bottom 30% of stocks) short. Returns are measured as proportions rather than percentages. Reward-to-risk ratio is the ratio of monthly mean to the monthly standard deviation. The t statistics in parentheses are for the significance of the mean. We use 5% significance level.

Table 5.10. Fama-French with a GJR-GARCH-M based on 10% breakpoint

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
α	0.000	0.007	-0.004	0.011	0.045	0.011
	(0.01)	(1.42)	(-0.53)	(2.08)	(5.34)	(1.49)
β	-0.092	0.150	0.200	-0.021	-0.399	-0.064
	(-1.07)	(1.49)	(1.65)	(-0.28)	(-4.35)	(-0.57)
s	-0.108	-0.094	-0.084	-0.020	-0.098	0.017
	(-0.74)	(-0.78)	(-0.41)	(-0.15)	(-0.68)	(0.08)
h	-0.381	-0.288	-0.450	-0.573	-0.120	-0.513
	(-2.51)	(-2.14)	(-2.24)	(-4.24)	(-0.84)	(-2.42)
δ	1.738	-0.091	-0.435	-4.057	-6.262	-1.025
	(1.90)	(-0.25)	(-1.06)	(-1.91)	(-3.21)	(-1.37)
ω	0.000	-0.000	0.000	0.000	0.001	0.001
	(1.15)	(-0.55)	(0.41)	(2.15)	(3.19)	(2.26)
γ	0.288	0.332	0.481	0.457	0.676	0.698
	(2.32)	(3.55)	(2.50)	(3.19)	(4.37)	(2.88)
η	0.192	0.190	-0.236	-0.305	-0.627	-0.446
	(1.17)	(1.23)	(-1.34)	(-2.19)	(-4.10)	(-1.93)
θ	0.609	0.609	0.697	0.606	0.533	0.420
	(7.29)	(13.12)	(9.30)	(8.40)	(8.37)	(4.74)
$\gamma+\eta/2+\theta$	0.993	1.036	1.060	0.912	0.896	0.895
Panel B: Ranking period 6 months						
α	0.015	0.017	-0.003	0.010	0.135	0.030
	(3.07)	(2.76)	(-0.39)	(1.85)	(6.25)	(5.27)
β	-0.138	0.028	-0.202	-0.084	-0.274	-0.190
	(-1.61)	(0.28)	(-1.30)	(-1.08)	(-3.68)	(-1.80)
s	-0.097	0.265	-0.687	-0.186	-0.174	0.246
	(-0.80)	(1.67)	(-2.73)	(-1.71)	(-1.26)	(1.43)
h	-0.549	-0.151	-0.069	-0.731	-0.550	-0.664
	(-3.76)	(-1.03)	(-0.32)	(-5.07)	(-7.78)	(-4.36)
δ	0.379	0.082	-0.582	-2.538	-31.798	-1.230
	(0.51)	(0.17)	(-2.20)	(-1.26)	(-5.19)	(-3.22)
ω	0.000	0.001	0.001	0.001	0.001	0.002
	(1.77)	(2.52)	(1.68)	(2.74)	(3.75)	(3.09)
γ	0.387	0.591	0.819	0.616	0.249	0.922
	(3.25)	(3.47)	(3.21)	(3.12)	(4.54)	(3.56)
η	0.396	0.183	-0.346	-0.122	-0.342	-0.601
	(1.54)	(0.72)	(-1.31)	(-0.51)	(-4.91)	(-2.29)
θ	0.430	0.294	0.423	0.240	0.777	0.205
	(5.59)	(3.45)	(6.03)	(2.02)	(19.76)	(2.83)
$\gamma+\eta/2+\theta$	1.015	0.977	1.069	0.795	0.855	0.827

Table 5.10. (Continued)

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel C: Ranking period 12 months						
α	0.002	0.014	-0.024	0.025	0.098	0.185
	(0.37)	(2.52)	(-2.35)	(4.15)	(4.91)	(5.70)
β	-0.074	-0.030	-0.179	-0.044	0.014	-0.268
	(-0.87)	(-0.29)	(-1.01)	(-0.61)	(0.19)	(-2.99)
s	-0.141	0.021	-0.628	-0.221	0.215	-0.603
	(-0.87)	(0.17)	(-2.61)	(-1.79)	(1.28)	(-3.74)
h	-0.793	-0.096	-0.069	-0.710	0.017	-0.566
	(-5.02)	(-0.86)	(-0.29)	(-4.99)	(0.16)	(-2.98)
δ	0.480	-0.621	-0.452	-7.075	-17.336	-19.890
	(0.56)	(-1.76)	(-1.47)	(-2.53)	(-4.11)	(-4.71)
ω	0.000	0.001	0.005	0.000	0.001	0.001
	(1.64)	(2.26)	(3.38)	(2.59)	(5.30)	(2.80)
γ	0.191	1.334	0.961	0.479	0.205	0.060
	(2.67)	(3.00)	(2.77)	(3.38)	(4.35)	(4.47)
η	0.473	-0.615	-0.263	-0.244	-0.216	-0.214
	(1.89)	(-1.32)	(-0.67)	(-1.99)	(-4.25)	(-4.87)
θ	0.574	0.115	0.110	0.497	0.740	0.971
	(5.92)	(2.13)	(1.50)	(4.49)	(16.86)	(41.66)
$\gamma + \eta/2 + \theta$	1.002	1.141	0.939	0.854	0.837	0.924

This table reports the coefficient estimates for systems (1) and (2) for the momentum portfolios. Momentum is a portfolio that buys the winner portfolio (top 10% of stocks) and sells the loser portfolio (bottom 10% of stocks) short. α measures a portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings based on size and book-to-market factors as measured by Fama and French (1993), δ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GJR-GARCH structure as $\sigma_{i,t}^2 = \omega_i + \gamma_i \varepsilon_{i,t-1}^2 + \eta_i I_{i,t-1} \varepsilon_{i,t-1}^2 + \theta_i \sigma_{i,t-1}^2$ where ω, γ, η and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. We use 5% significance level. The t-statistics are in parentheses.

Table 5.11. Fama-French with a GJR-GARCH-M: Robustness analysis based on 30% breakpoint

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
α	0.002	0.001	0.004	0.001	0.022	0.060
	(0.93)	(0.41)	(0.82)	(0.46)	(5.02)	(4.40)
β	-0.195	0.026	0.124	-0.055	-00.123	0.066
	(-4.80)	(0.36)	(1.32)	(-1.74)	(-3.09)	(1.24)
s	-0.275	-0.027	-0.278	-0.149	-0.186	-0.014
	(-3.75)	(-0.27)	(-1.74)	(-2.40)	(-2.36)	(-0.19)
h	-0.200	-0.089	-0.210	-0.309	-0.183	-0.162
	(-3.28)	(-1.30)	(-1.80)	(-5.15)	(-2.83)	(-2.16)
δ	0.506	0.173	-0.786	-8.330	-20.002	-42.575
	(0.33)	(0.17)	(-1.37)	(-1.99)	(-4.10)	(-3.89)
ω	0.000	0.000	0.000	0.000	0.000	0.000
	(1.50)	(2.36)	(2.01)	(2.25)	(2.33)	(4.19)
γ	0.181	0.499	0.779	0.257	0.338	0.265
	(2.36)	(3.12)	(2.99)	(3.01)	(3.95)	(3.66)
η	0.334	-0.013	-0.292	-0.072	-0.360	-0.386
	(3.22)	(-0.08)	(-1.13)	(-0.75)	(-3.82)	(-3.69)
θ	0.689	0.542	0.367	0.737	0.741	0.661
	(10.16)	(7.33)	(3.98)	(13.10)	(17.69)	(10.54)
$\gamma+\eta/2+\theta$	1.037	1.034	1.000	0.958	0.899	0.733
Panel B: Ranking period 6 months						
α	0.002	0.011	-0.023	0.005	0.015	0.015
	(0.70)	(2.88)	(-5.52)	(2.51)	(4.66)	(4.35)
β	-0.118	-0.038	-0.024	-0.098	-0.147	-0.024
	(-2.92)	(-0.64)	(-0.30)	(-3.02)	(-4.13)	(-0.43)
s	-0.194	0.024	-0.367	-0.148	-0.187	0.050
	(-2.88)	(0.25)	(-3.12)	(-2.50)	(-2.45)	(0.64)
h	-0.216	-0.139	-0.061	-0.282	-0.218	-0.143
	(-3.00)	(-1.61)	(-0.63)	(-6.10)	(-2.99)	(-1.58)
δ	2.291	-0.809	0.820	-8.913	-6.468	-2.698
	(1.96)	(-0.91)	(1.53)	(-2.35)	(-2.60)	(-3.86)
ω	0.000	0.001	0.000	0.000	0.000	0.001
	(2.11)	(3.34)	(1.61)	(2.85)	(4.56)	(4.05)
γ	0.328	0.769	0.491	0.662	0.840	0.980
	(3.67)	(2.89)	(3.42)	(3.37)	(3.20)	(4.33)
η	0.712	-0.100	0.630	-0.264	-0.663	-0.744
	(2.32)	(-0.34)	(1.62)	(-1.30)	(-2.30)	(-3.17)
θ	0.405	0.210	0.272	0.321	0.041	0.065
	(4.95)	(2.47)	(3.14)	(3.00)	(0.48)	(0.87)
$\gamma+\eta/2+\theta$	1.089	0.929	1.078	0.851	0.549	0.673

Table 5.11. (Continued)

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel C: Ranking period 12 months						
α	0.004	0.004	-0.029	0.024	0.040	0.035
	(1.50)	(0.97)	(-5.05)	(4.56)	(7.55)	(8.24)
β	-0.143	-0.024	-0.047	-0.221	-0.130	0.054
	(-3.06)	(-0.36)	(-0.49)	(-9.07)	(-3.48)	(1.21)
s	-0.118	-0.037	-0.215	-0.223	-0.331	0.350
	(-1.49)	(-0.41)	(-1.58)	(-4.30)	(-4.91)	(3.48)
h	-0.330	-0.155	0.068	-0.430	-0.418	0.038
	(-3.82)	(-1.85)*	(0.59)	(-9.55)	(-6.43)	(0.38)
δ	-0.115	-0.910	-0.004	-30.224	-29.832	-6.943
	(-0.09)	(-1.17)	(-0.01)	(-2.82)	(-4.78)	(-3.65)
ω	0.000	0.001	0.000	0.000	0.000	0.000
	(1.52)	(4.12)	(1.81)	(6.61)	(2.91)	(2.43)
γ	0.451	0.945	0.590	0.426	0.458	0.613
	(3.17)	(2.50)	(2.63)	(3.08)	(3.62)	(3.90)
η	0.151	-0.313	0.251	-0.522	-0.460	-0.117
	(0.61)	(-0.80)	(0.80)	(-3.34)	(-3.72)	(-1.32)
θ	0.473	0.156	0.293	0.133	0.633	0.409
	(4.84)	(2.02)	(3.07)	(1.73)	(8.27)	(6.58)
$\gamma+\eta/2+\theta$	0.999	0.944	1.008	0.298	0.861	0.964

This table reports the coefficient estimates for systems (1) and (2) for the momentum portfolios. Momentum is a portfolio that buys the winner portfolio (top 10% of stocks) and sells the loser portfolio (bottom 10% of stocks) short. α measures the portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings based on size and book-to-market factors as measured by Fama and French (1993), δ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GJR-GARCH structure as $\sigma^2_{i,t} = \omega_i + \gamma_i \varepsilon^2_{i,t-1} + \eta_i I_{i,t-1}\varepsilon^2_{i,t-1} + \theta_i \sigma^2_{i,t-1}$ where ω, γ, η and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. We use 5% significance level. The t-statistics are in parentheses.

Table 5.12. Fama-French with a GARCH (1,1)-M based on 10% breakpoint

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
α	-0.000	-0.001	-0.003	0.007	0.039	0.013
	(-0.09)	(-0.15)	(-0.50)	(1.80)*	(3.89)	(1.35)
β	-0.170	-0.024	0.203	0.019	-0.394	-0.108
	(-1.90)	(-0.13)	(1.34)	(0.22)	(-3.21)	(-0.71)
s	-0.207	-0.077	-0.029	-0.004	-0.177	-0.008
	(-1.56)	(-0.43)	(-0.12	(-0.03)	(-1.00)	(-0.03)
h	-0.277	-0.433	-0.372	-0.544	0.029	-0.430
	(-1.92)	(-1.69)	(-1.21)	(-2.77)	(0.13)	(-1.08)
δ	1.283	0.084	-0.132	-2.569	-3.451	-0.896
	(1.26)	(0.15)	(-0.63)	(-2.47)	(-3.02)	(-1.67)*
ω	0.000	-0.000	0.000	0.000	0.001	0.001
	(1.36)	(-0.00)	(0.78)	(1.30)	(2.24)	(1.77)
γ	0.366	0.213	0.333	0.238	0.484	0.390
	(1.84)	(2.33)	(4.70)	(3.62)	(2.53)	(3.76)
θ	0.660	0.814	0.700	0.748	0.467	0.561
	(5.22)	(11.50)	(13.52)	(10.43)	(3.85)	(4.38)
$\gamma + \theta$	1.026	1.027	1.033	0.986	0.951	0.951
Panel B: Ranking period 6 months						
α	0.016	0.017	-0.008	0.011	0.046	0.053
	(2.95)	(1.93)	(-0.81)	(1.70)*	(2.15)	(3.57)
β	-0.097	0.079	0.112	-0.082	-0.082	-0.134
	(-1.01)	(0.50)	(-0.62)	(-1.00)	(-0.45)	(-0.96)
s	-0.127	0.324	-0.823	-0.190	-0.174	0.057
	(-1.02)	(1.59)	(-3.26)	(-1.25)	(-0.96)	(0.28)
h	-0.491	-0.089	-0.037	-0.739	-0.168	-0.508
	(-2.54)	(-0.30)	(-0.09)	(-3.91)	(-0.63)	(-2.19)
δ	-0.394	0.027	-0.404	-3.329	-4.765	-3.785
	(-0.72)	(-0.07)	(-1.39)	(-1.78)*	(-1.86)*	(-2.87)
ω	0.001	0.001	0.001	0.000	0.001	0.001
	(1.75)	(2.01)	(1.59)	(1.78)	(2.12)	(3.22)
γ	0.583	0.517	0.527	0.364	0.479	0.478
	(3.77)	(4.31)	(4.02)	(3.97)	(4.62)	(5.36)
θ	0.443	0.441	0.520	0.478	0.415	0.475
	(3.79)	(4.35)	(5.09)	(3.30)	(3.34)	(8.62)
$\gamma + \theta$	1.026	0.958	1.047	0.842	0.894	0.953

Table 5.12. (Continued)

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel C: Ranking period 12 months						
α	0.008	0.012	-0.037	0.022	0.038	0.119
	(1.20)	(1.76)	(-1.72)	(3.17)	(0.95)	(3.73)
β	-0.079	-0.015	-0.097	-0.008	-0.068	-0.113
	(-0.60)	(-0.11)	(-0.54)	(-0.10)	(-0.73)	(-0.73)
s	-0.102	0.010	-0.614	-0.192	0.056	-0.343
	(-0.54)	(0.06)	(-2.26)	(-1.29)	(0.21)	(-1.32)
h	-0.815	-0.166	-0.386	-0.678	-0.477	-0.222
	(-4.15)	(-0.96)	(-0.97)	(-3.51)	(-1.71)	(-0.92)
δ	-0.425	-0.157	-0.110	-5.467	-3.322	-9.865
	(-0.69)	(-0.67)	(-0.35)	(-3.40)	(-0.60)	(-3.20)
ω	0.000	0.001	0.005	0.000	0.001	0.001
	(1.95)	(2.00)	(3.45)	(2.44)	(2.24)	(3.71)
γ	0.331	0.923	0.952	0.398	0.634	0.300
	(3.46)	(5.47)	(5.01)	(4.23)	(1.52)	(6.53)
θ	0.642	0.201	0.054	0.491	0.208	0.590
	(7.49)	(1.87)	(0.76)	(5.43)	(0.56)	(20.44)
$\gamma+\theta$	0.973	1.124	1.006	0.889	0.842	0.890

This table reports the coefficient estimates for systems (3) and (4) for the momentum portfolios. Momentum is a portfolio that buys the winner portfolio (top 10% of stocks) and sells the loser portfolio (bottom 10% of stocks) short. α measures the portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings based on size and book-to-market factors as measured by Fama and French (1993), δ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GARCH (1.1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$ where ω, γ and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. (*) indicates 10% significant level and we use 5% significance level otherwise. The t-statistics are in parentheses.

Table 5.13. Fama-French with a GARCH (1,1)-M: Robustness analysis based on 30% breakpoint

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel A: Ranking period 3 months						
α	0.004	0.001	-0.004	0.001	-0.001	0.010
	(1.09)	(0.31)	(-0.51)	(0.48)	(-0.31)	(2.52)
β	-0.183	0.027	0.141	-0.051	-0.095	0.055
	(-2.59)	(0.35)	(1.59)	(-1.15)	(-1.56)	(1.09)
s	-0.231	-0.027	-0.283	-0.146	-0.255	-0.106
	(-2.50)	(-0.27)	(-1.88)	(-1.84)	(-2.53)	(-1.11)
h	-0.125	-0.089	-0.223	-0.305	-0.355	-0.132
	(-1.23)	(-0.69)	(-1.40)	(-3.23)	(-2.67)	(-1.22)
δ	-1.212	0.205	-0.107	-7.579	3.168	-3.185
	(-0.63)	(0.33)	(-0.20)	(-2.92)	(1.12)	(-2.26)
ω	0.000	0.000	0.000	0.000	0.000	0.001
	(1.30)	(1.68)	(2.42)	(1.31)	(1.58)	(3.22)
γ	0.192	0.491	0.489	0.213	0.179	0.824
	(2.14)	(3.83)	(4.33)	(2.86)	(3.79)	(3.79)
θ	0.803	0.542	0.509	0.753	0.800	0.124
	(10.56)	(4.92)	(5.66)	(8.00)	(17.04)	(0.97)
$\gamma+\theta$	0.995	1.033	0.998	0.966	0.979	0.948
Panel B: Ranking period 6 months						
α	0.004	0.005	-0.009	0.007	0.014	0.063
	(1.39)	(0.97)	(-0.80)	(1.92)*	(2.23)	(5.22)
β	-0.116	-0.084	-0.064	-0.084	-0.163	-0.018
	(-1.98)	(-0.90)	(-0.59)	(-2.07)	(-2.26)	(-1.04)
s	-0.223	0.047	-0.480	-0.185	-0.261	-0.004
	(-2.49)	(0.51)	(-309)	(-2.19)	(-2.45)	(-0.03)
h	-0.171	-0.081	-0.004	-0.258	-0.234	-0.225
	(-1.32)	(-0.64)	(-0.03)	(-3.10)	(-0.87)	(-4.09)
δ	-0.211	0.589	-0.153	-9.538	-4.688	-25.336
	(-0.18)	(1.01)	(-0.35)	(-2.61)	(-1.81)*	(-3.24)
ω	0.000	0.001	0.000	0.000	0.000	0.000
	(1.93)	(2.15)	(1.55)	(1.46)	(1.28)	(2.63)
γ	0.471	0.637	0.409	0.443	0.448	0.394
	(4.12)	(4.79)	(3.80)	(3.62)	(2.58)	(3.18)
θ	0.544	0.316	0.580	0.424	0.545	0.434
	(6.58)	(2.28)	(4.75)	(2.21)	(3.36)	(5.77)
$\gamma+\theta$	1.015	0.953	0.989	0.867	0.993	0.828

Table 5.13. (Continued)

	High-tech stocks			Low-tech stocks		
	Holding period 3 months	**Holding period 6 months**	**Holding period 12 months**	**Holding period 3 months**	**Holding period 6 months**	**Holding period 12 months**
Panel C: Ranking period 12 months						
α	0.005	0.002	-0.025	0.014	0.011	0.055
	(1.77)	(0.32)	(-1.12)	(2.35)	(3.83)	(9.10)
β	-0.126	-0.017	0.026	-0.085	-0.036	-0.030
	(-2.03)	(-0.19)	(0.25)	(-1.33)	(-0.67)	(-0.89)
s	-0.104	-0.052	-0.151	-0.249	-0.090	0.018
	(-1.30)	(-0.49)	(-0.91)	(-2.56)	(-0.87)	(0.24)
h	-0.358	-0.151	-0.072	-0.418	-0.756	-0.182
	(-3.56)	(-1.08)	(-0.23)	(-3.56)	(-6.80)	(-2.42)
δ	-0.620	-0.325	-0.444	-14.737	-1.750	-19.259
	(-0.68)	(-0.73)	(-0.66)	(-1.91)*	(-3.21)	(-6.88)
ω	0.000	0.001	0.001	0.000	0.000	0.000
	(1.75)	(3.03)	(2.19)	(1.29)	(4.44)	(2.83)
γ	0.391	0.792	0.694	0.417	1.066	0.409
	(4.21)	(5.35)	(5.28)	(2.35)	(3.84)	(7.41)
θ	0.624	0.150	0.296	0.352	0.010	0.595
	(10.10)	(1.27)	(3.33)	(1.27)	(0.32)	(15.95)
$\gamma + \theta$	1.015	0.942	0.990	0.769	1.076	1.004

This table reports the coefficient estimates for systems (3) and (4) for the momentum portfolios. Momentum is a portfolio that buys the winner portfolio (top 30% of stocks) and sells the loser portfolio (bottom 30% of stocks) short. α measures the portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings based on size and book-to-market factors as measured by Fama and French (1993), δ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GARCH (1.1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$ where ω, γ and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. (*) indicates 10% significant level and we use 5% significance level otherwise. The t-statistics are in parentheses.

Chapter Six

Concluding Remarks

The traditional framework EMH/CAPM has faced plenty of criticisms concerning its empirical failures that are attributed to its unrealistic assumptions such as assuming that all agents in financial markets are rational and able to perceive all information and form proper expectations. In addition, this traditional framework suffers from a failure to explain how individual investors take their investments decisions and a failure to explain the way that they follow in forming their portfolios. Behavioural Finance employs the principles of cognitive psychology to construct a more realistic body of knowledge and is formed of two building blocks: (1) people are susceptible to systematic cognitive biases and these biases have an impact on asset prices; (2) involving human beings in financial markets studies helps improve our understanding of financial phenomena.

This thesis makes a number of concluding remarks and suggests several policy implications that can be organized as follows:

The main conclusion of Chapter 3 is that irrational investors think “good stocks are the stocks of good companies”. As a result, they prefer to buy the stocks of good companies that are characterized by higher earnings per share as profitability, higher financial leverage, higher growth, larger size and lower CF/P since the lower level of liquidity reflects the underuse of corporate assets leading to corporate losses. The policy implications come from the idea in behavioural finance that stipulated irrational (‘uniformed’) investors destabilize or divert prices away from fundamental value. Rational (‘informed’) investors stabilize asset prices and back prices to the fundamental value through exploiting the systematic cognitive biases of the irrational investors. In this paper, we use the capital gains overhang as a proxy for the unrealized capital gains encountered by the PT/MA investors to forecast a cross section of expected returns. Therefore, we expect the momentum in stock returns to be the most important implication of the PT/MA framework. In this context, our paper has wide implications because it guides the momentum traders to increase the proportion of stocks of good companies that are characterized by higher earnings per share, higher financial leverage, higher growth, larger size and lower turnover in their portfolios, because stocks of this kind are more susceptible to being traded by irrational investors and accordingly generate a higher capital gains overhang. Finally, further research is required especially in emerging markets to provide empirical support for the applicability of our findings to emerging markets.

Chapter 4 contains new findings. For instance, the impact of capital gains overhang on expected returns differs across the expected returns distribution, which indicates that the relation between capital gains overhang and expected returns is nonlinear. This finding offers implications for researchers that the OLS conventional technique is less informative and not appropriate for introducing a full description of the relation between capital gains overhang and expected returns; instead, a broader and more flexible quantile regression technique should be used. The second contribution of this chapter is to show how well the disposition effect works in driving momentum profits at the 0.05^{th} and 0.95^{th} expected returns quantiles. However, there is robust evidence that the disposition effect is not a good noisy proxy for inducing intermediate momentum at the lowest 0.05^{th} expected returns quantile. At the highest 0.95^{th} expected returns quantile, the disposition effect induces contrarian rather than momentum returns. The implications are that the disposition effect can be considered the principal element in discerning return persistence anomalies at the 0.95^{th} expected return quantile and the principal element in discerning the price reversal anomaly. However, it seems that the risk-based explanation plays the major role at the lowest 0.05^{th} expected returns quantile. Finally, future works might do to shed light on emerging markets especially fast growing markets such as the Chinese stock market, to empirically support these interesting new findings.

Chapter 5 bridges at least three research gaps through examining the systematic differences in momentum, asymmetric volatility and the idiosyncratic risk-momentum returns relation between high-tech stocks and low-tech stocks. The first conclusion is that four momentum strategies explain the significant and robust larger momentum returns in high-tech stocks than low-tech stocks. These strategies are the 3-3 strategy, the 3-6 strategy, the 6-3 strategy and the 6-6 strategy. The implication here is that the momentum traders should increase the fraction of high-tech stocks in their portfolios at the expense of low-tech stocks to make greater momentum profits. The second conclusion is that there is robust evidence that the volatility responds symmetrically to good and bad news in high-tech stocks, while it responds asymmetrically in low-tech stocks. This finding has many implications for investors and policy makers. For instance, in low-tech stocks the risk and cost of equity may surge more when facing negative market returns shocks than when facing positive market returns shocks, because of the asymmetric volatility. However, in the high-tech stocks the negative and positive market returns shocks make the same impact on volatility and in turn they make the same impact on risk and the cost of capital. Another implication is in the area of option pricing because the stock market volatility is a key determinant of option prices. For low-tech stocks, the arrival of good and bad news leads to higher volatility in response to negative return shocks than to positive return shocks which results in higher option price in the case of negative return shocks than positive return shocks. For the high-tech stocks, the arrival of good and bad news should have the same impact on option prices.

The third conclusion is that, there is no robust evidence of idiosyncratic risk-momentum return relation in the high-tech stocks, while this relation is significantly negative in the low-tech stocks. This finding is robust to different breakpoints. It is also consistent with the behaviourally-based explanation and supports the role of high transaction cost in limiting the arbitrage process rather than idiosyncratic risk, which makes the relation of idiosyncratic risk and momentum is stronger among low-tech stocks than high-tech stocks. However, this relation is negative for low-tech stocks. This means that, for the high-tech stocks which experience the higher transcation costs associated with higher information asymmetry, the transaction costs limit arbitrage among momentum stocks, while for the low-tech stocks that experience lower transaction cost due to lower information asymmetry, idiosyncratic risk limits arbitrage among reversal stocks.

Finally, a replication of this research using emerging markets data is recommended to ensure that these findings are generalizable to emerging markets. The implication for researchers here is that this finding improves our understanding of the relative importance of idiosyncratic risk and transaction costs in the limiting arbitrage mechanism and inducing momentum. It also serves the theoretical debate on the sources of momentum between the risk-based school of thought and behaviourally-based school of thought.

This first limitation in this thesis is that it considers two cognitive biases only, namely, disposition effect and herding behaviour. However, other cognitive biases such as heuristics, representativeness, framing, overconfidence and conservatism are part of our research agenda for future works. The data used throughout the thesis focused mainly on the US stock market.

Therefore, our findings can be generalized to developed markets. However, the uncertain applicability of our thesis to emerging markets can be considered as another of its limitations because the emerging markets are characterized by unique features and require empirical evidence before our findings can be generalize to.

Bibliography

Aboody, D., & Lev, B. (2000). Information asymmetry, R&D, and insider gains. *The Journal of Finance 55 (6)*, 2747-2766.

Aggarwal , R. K., & Jorion, P. (2010). Hidden survivorship in hedge fund returns. *Financial Analysts Journal 66 (2)*, 69-74.

Alam, P., Liu, M., & Peng, X. (2014). R&D expenditures and implied equity risk premums. *Review of Quantitative Finance and Accounting 43*, 441-462.

Alm, l. R., & Mason, S. G. (Eds.). (2007). Linear correlation and regression (2^{ed}). United States: Taylor & Francis Group.

Andersen, T. G. (1996). Return volatility and trading volume in financial markets: An information of stochastic volatility. *The Journal of Finance 51 (1)*, 169-204.

Arena, M. P., Haggard, K. S., & Yan, X. (2008). Price momentum and idiosyncratic volatility. *The Financial Review 43*, 159--190.

Asem, E. (2009). Dividends and price momentum. *Journal of Banking and Finance 33*, 486-494.

Avramov, D., Chordia, T., & Goyal, A. (2006). The impact of trades on daily volatility. *The Review of Financial Studies 1 (19)*, 1241-1277.

Bagella, M., Becchetti, L., & Adriani, F. (2005). Observed and 'fundamental' price-earning ratios: A comparative analysis of high-tech stock evaluation in the US and in Europe. *Journal of International Money and Finance 24*, 549-581.

Baillie, R. T., & DeGennaro, R. P. (1990). Stock returns and volatility. *The Journal of Financial and Quantitative Analysis 25 (2)*, 203-214.

Baker, H. K., & Nofsinger, J. R. (2010). Behavioural finance: An overview. In B. K. H. , & J. R. Nofsinger, *Behavioural Finance: Investors, Corporations and Markets* (pp. 3-23). New Jersey: JohnWiley & Sons, Inc.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance 61 (4)*, 1645-1680.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics 9 (1)*, 3-18.

Barber, B. M., Heath, C., & Odean, T. (2003). Good reasons sell: Reason-based choice among group and individual investors in the stock market. *Management Science 49 (12)*, 1636-1652.

Barber, B., Odean T., & Zhu, N. (2009). Systematic noise. *Journal of Financial Markets 12*, 547-569.

Barber, B., Odean T., & Zheng, N. (2000). The behavior of mutual fund investors. Unpublished working paper, University of California.

Barberis, N., & Huang, M. (2001). Mental accounting, loss aversion, and individual stock returns. *The Journal of Finance 56 (4)*, 1247- 1292.

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. *The Quarterly Journal of Economics 116*, 1-53.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics 49*, 307-343.

Barberis, N., & Thaler, R. (2003). A survey of behavioural finance. In G. M. Constantinides, M. Harris, & R. M. Stulz, *Handbook of the Economics of Finance* (pp. 1052-1119). Netherlands: Elsevier Science.

Barberis, N., & Xiong, W. (2009). What drives the disposition effect? An analysis of long-standing preference-based explanation . *The Journal of Finance 64*, 751-784.

Barone-Adesi, G., Engle, R. F., & Mancini, L. (2008). A GARCH option pricing model with filtered historical simulation. *The Review of Financial Studies 21 (3)*, 1223- 1258.

Barron, O. E., Byard, D., Kile, C., & Riedl, E. J. (2002). High-technology intangibles and analysts' forecasts. *Journal of Accounting Research 40 (2)*, 289-312.

Barth, M. E., Kasznik, R., & McNichols, M. F. (2001). Analyst coverage and intangible assets. *Journal of Accounting Research 39 (1)*, 1-34.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance 32 (3)*, 663-682.

Baur, D. G., Dimpfl, T., & Jung, R. C. (2012). Stock return autocorrelations revisited: A quantile regression approach. *Journal of Empirical Finance 19*, 254-265.

Baysinger, B., & Hoskisson, R. E. (1990). The composition of boards of directors and strategic control: Effects on corporate strategy. *The Academy of Management Review 15 (1)*, 72-87.

Ben-David, I, & Hirshleifer, D. (2012). Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. *The Review of Financial Studies 25 (8)*, 2485-2532.

Berges, A., McConnell, J. J., & Schlarbaum, G. G. (1984). The turn-of-the-year in Canada. *The Journal of Finance 39 (1)*, 185-192.

Bhagat, S., & Welch , I. (1995). Corporate research & development investments international comparisons. *Journal of Accounting and Economics 19*, 443 470.

Bhattacharya, S. (1979). Imperfect information, dividend policy, and 'the bird in the hand' fallacy. *Bell Journal of Economics 10*, 259-270.

Bhootra, A., & Hur, J. (2012). On the relationship between concentration of prospect theory/mental accounting investors, cointegration, and momentum. *Journal of Banking and Finance 36*, 1266-1275.

Bilinski, P., & Strong, N. (2013). Managers' private information, investor underreaction and long-run SEO performance. *European Financial Management 19 (5)*, 956-990.

Birru, J. (2015). Confusion of confusions: A test of the disposition effect and momentum. *The Review of Financial Studies 28 (7)*, 1849-1873.

Black, F. (1976). Studies in stock volatility changes. *American Statistical Association, Business and Economics statistics section.*

Black, A., J., & McMillan, D. G. (2006). Asymmetric risk premium in value and growth stocks. *International Review of Financial Analysis 15*, 237-246.

Bolton, P., & Scharfstein, D. S. (1990). A theory of predation based on agency problems in financial contracting. *American Economic Review 80 (1)*, 93-106.

Bond, S. R., & Cummins, J. G. (2000). The stock market and investment in the new economy: Some tangible facts and intangible fictions. *Brookings Papers on Economic Activity 1*, 61-124.

Brooks, C. (2008). Introductory econometrics for finance (2^{ed}). New York: Cambridge University Press.

Brown, S. J., Goetzmann, W., Ibbotson, R. G., & Ross, S. A. (1992). Survivorship bias in performance studies. *The Review of Financial Studies 3 (4)*, 553-580.

Brunnermeier, M. K., & Nagel, S. (2004). Hedge funds and technology bubble. *The Journal of Finance 59 (5)*, 2013-2040.

Callahan, C. M., Lee, C. M., & Yohn, T. L. (1997). Accounting information and bid-ask spreads. *Accounting Horizons 11 (4)*, 50-60.

Callimaci, A., & Landry, S. (2004). Market valuation of research and development spending under Canadian GAAP. *Canadian Accounting Perspectives 3 (1)*, 33–53.

Cameron, C., & Trivedi, , P. (2010). *Microeconometrics using STATA.* Texas: STATA press.

Carhart, M. M., Carpenter, J. N., Lynch, A. W., & Musto, D. K. (2002). Mutual fund survivorship. *The Review of Financial Studies 15 (5)*, 1439-1463.

Chan, K., Karolyi, A., & Stulz, R. M. (1992). Global financial markets and the risk premium on U.S. equity. *Journal of Financial Economics 32*, 137-167.

Chan, W. S., Frankel, R, & Kothari, S.P. (2004). Testing behavioural finance theories using trends and consistency in financial performance. *Journal of Accounting and Economics 38*, 3–50.

Chan, L. K., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance 56 (6)*, 2431-2456.

Chang, X., Dasgupta , S., & Hilary , G. (2006). Analyst coverage and financing decisions. *The Journal of Finance 61 (6)*, 3009-3048.

Chen, G., Kim, K.A., Nofsinger, J.R., & Rui, O.M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making 20*, 425-451.

Chiang, T. C., Li, J., & Tan, L. (2010). Empirical investigation of herding behaviour in Chinese stock markets: Evidence from quantile regression analysis. *Global Finance Journal 21*, 111–124.

Chiao, C., Hung, W., & Lee, C. F. (2008). Mispricing of research and development investments in a rapidly emerging and electronics-dominated market. *Emerging Markets Finance and Trade 44 (1)*, 95–116.

Chichernea, D. C., & Slezak, S. L. (2013). Idiosyncratic risk premia and momentum. *The Journal of Financial Research 36 (3)*, 389–412.

Choe, H., & Eom, Y. (2009). The disposition effect and investment performance in the future market. *The Journal of Futures Markets 29 (6)*, 496-522.

Choi, J. J., Mao, C. X., & Upadhyay, A. D. (2013). Corporate risk management under information asymmetry. *Journal of Business Finance and Accounting 40 (1)*, 239-271.

Choi, N., & Skiba, H. (2015). Institutional herding in international markets. *Journal of Banking and Finance 55*, 246-259.

Chordia, T., & Shivakumar, L. (2006). Earnings and price momentum. *Journal of Financial Economics 80*, 985-1019.

Chou, P.-H., Chou, R. K., & Ko, K.-C. (2009). Prospect theory and risk-return paradox: Some recent evidence. *Review of Quantitative Finance and Accounting 33*, 193-208.

Christie, A. A. (1982). The stochastic behaviour of common stock variances. *Journal of Financial Economics 10 (2)*, 407-432.

Chui, A. C., Titman, S., & Wei, J. K. (2003). Intra-industry momentum: The case of REITs . *Journal of Financial Markets 6 (3)*, 363–387.

Cici, G. (2012). The prevalence of the disposition effect in mutual funds' trades. *Journal of Financial and Quantitative Analysis 47 (4)*, 795–820.

Clarke, R, & Statman, M. (1994). Growth, value, good, and bad. *Financial Analyst Journal 50 (6)*, 82-86.

Cohen, W. M., Goto, A., Nagata, A., Nelson, R. R., & Walsh, J. P. (2002). R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research Policy 31*, 1349–1367.

Cooper, M., Dimitrov, O., & Rau, P.R. (2001). A Rose.com by any other name. *The Journal of Finance 56 (6)*, 2371-2388.

Corrado, C. J., & Miller, T. W. (2006). Estimating expected excess returns using historical and an option-implied volatility. *The Journal of Financial Research 29 (1)*, 95–112.

Cuellar, B., Callen, Y. F., & Gadea, J. A. (2011). Stock price reaction to non-financial news in European technology companies. *European Accounting Review 20 (1)*, 81–111.

Curtis, G. (2004). Modern portfolio theory and behavioural finance. *The Journal of Wealth Management 7 (2)*, 16-22.

Czarnitzki, D., Hottenrott, H., & Thorwarth, S. (2011). Industrial research versus development investment: The implications of financial constraints. *Cambridge Journal of Economics 35*, 527–544.

Da Costa, N, Goulart, M, Cupertino, C, Macedo, J, & Da Silva, S. (2013). The disposition effect and investor experience. *Journal of Banking & Finance 37 (5)*, 1669-1675.

Daniel, K, Hirshleifer, D, & Teoh, S. H. (2002). Investor psychology in capital markets: Evidence and policy implications. *Journal of Monetary Economics 49 (1)*, 139–209.

Davino, C., Furno, M., & Vistocco, D. (2014). *Quantile regression: Theory and applications.* West Sussex, UK: John Wiley and Sons.

De Bondt, W. F.M, & Thaler, R. H. (1985). Does the market overreact? *Journal of Finance 40*, 793-805.

Debondt, W. F. M., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock-market seasonality. *Journal of Finance 42 (3)*, 557-581.

Dechow, P. M., & Sloan, R. G. (1997). Returns to contrarian investment strategies: Tests of native expectations hypotheses. *Journal of Financial Economics 43 (1)*, 3-27.

Dhar, R, & Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science 52 (5)*, 726-740.

Di Iorio, A., & Liu , B. (2015). Idiosyncratic volatility and momentum: The performance of Australian equity pension funds. *2015 Annual Meetings* (pp. 1-30). Amsterdam, NETHERLANDS: European Financial Management Association.

Doukas, J., & Switzer, L. (1992). The stock market's valuation of R&D spending and market concentration. *Journal of Economics and Business 44*, 95-114.

Eaton, D. (April, 2000). The psychology behind common investor mistakes. *AAII Journal*, 2-5.

Ederington, L. H., & Guan, W. (2010). How asymmetric is U.S stock market volatility. *Journal of Financial Markets 13*, 225-248.

Elton, E. J., Gruber, M. J., & Blake, C. R. (1996). Survivorship bias and mutual fund performance. *The Review of Financial Studies 9 (4)*, 1097-1120.

Eng, L. L., & Shackell, M. (2001). The implications of long-term performance plans and institutional ownership for firms' research and development investments. *Journal of Accounting, Auditing and Finance 16 (2)*, 117-139 .

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance 48 (5)*, 1749-1778.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The Arch-M Model. *Econometrica 55 (2)*, 391-407.

Epstein , L. G., & Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *The Journal of Finance 63 (1)*, 197-228.

Ericsson, J., Huang, X., & Mazzotta, S. (2016). Leverage and asymmetric volatility: The firm-level evidence. *Journal of Empirical Finance 38*, 1–21.

Fabozzi, F. J., Forcardi, S. M., Rachev, S. T., & Arshanapalli, B. G. (2014). *The basics of financial econometrics: Tools, concepts, and asset management applications.* New Jersey: Wiley.

Fama, E. F. (1965). The behaviour of stock-market prices. *The Journal of Business 38 (1)*, 34-105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance 25 (2)*, 383-417.

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *The Journal of Economic Perspectives 18 (3)*, 25-46.

Fattouh, B., Scaramozzino, P., & Harris, L. (2005). Capital structure in South Korea: A quantile regression approach. *Journal of Development Economics 76*, 231-250.

Foster, G. (1973). Stock market reaction to estimates of earnings per share by company officials. *Journal of Accounting Research 11 (1)*, 25-37.

Frankfurter, G. M., & McGoun, E. G. (2002). Resistance is futile: The assimilation of behavioural finance. *Journal of Economic Behaviour & Organization 48*, 375–389.

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance 61*, 2017-2046.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics 8*, 55-69 .

Frydman, C, & Rangel, A. (2014). Debiasing the disposition effect by reducing the saliency of of information about a stock's purchase price. *Journal of Economic Behaviour & Organization 107(part (B),* 541-552.

ftserussell.com. (2016, 08 09). *Russell U.S Equity Indexes*. Retrieved from FTSE: www.ftse.com/products/.../Russell-US-indexes.pdf?32.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics 91*, 24–37.

Fu, R, & Wedge, L. (2011). Managerial ownership and the disposition effect. *Journal of Banking & Finance 35 (9)*, 2407-2417.

Glosten, L. R., & Harris, L. E. (1988). Estimating the components of Bid-Ask spread. *Journal of Financial Economics 21*, 123-142.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess. *The Journal of Finance 48 (5)*, 1779-1801.

Goetzmann, W. N., & Massa, M. (2008). Disposition matters: Volume, volatility, and price impact of a behavioural bias. *The Journal of Portfolio Management Winter*, 105-125.

Goetzmann, W., & Kumar, A. (2004). Why do individual investors hold under-diversified portfolios? *Unpublished working paper, Yale University*. .

Gowlland, C., Xiao, Z., & Zeng , Q. (2009). Beyond the central tendency: Quantile regression as a tool in quantitative investing. *Journal of Portfolio Management 35 (3)*, 106-120.

Green, W. H. (2000). Econometric Analysis (4 ed.). Englewood Cliffs, New Jersey: Prentice Hall.

Griffin, J. M., & Lemmon, M. L. (2002). Book-to-market equity, distress risk, and stock returns. *Journal of Finance, 57 (5)*, 2317-2336.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting and momentum. *Journal of Financial Economics 78*, 311-339.

Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? *The Journal of Finance 56 (2)*, 589-616.

Hall, B. H. (2002). The financing of research and development. *Oxford Review of Economic Policy 18 (1)*, 35-51.

Hallock, K. F., Madalozzo, R., & Reck, C. G. (2010). CEO pay-for-performance heterogeniety using quantile regression. *The Financial Review 45*, 1-19.

Haug, M., & Hirschey, M. (2006). The January effect. *Financial Analysts Journal 62 (5)*, 78-88.

Heynen, R., Kemna, A., & Vorst, T. (1994). Analysis of the term structure of implied volatilities. *The Journal of Financial and Quantitative Analysis 29 (1)*, 31-56.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance 56 (4)*, 1533- 1597.

Hirshleifer, D, H., Kewei, T., Siew H., & Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics 38*, 297–331.

Hirshleifer, D, & Teoh, S, H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics 36 (1-3)*, 337–386.

Hirshleifer, D., & Teoh, S. H. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management 9 (1)*, 25-66.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55 (1)*, 265-295.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance 54 (6)*, 2143-2184.

Houge, T., & Loughran, T. (2000). Cash Flow is king? Cognitive errors by investors. *Journal of Psychology and Financial Markets 1 (3 &4)*, 161-175.

Hung, S.-Y. K., & Glascock, J. L. (2010). Volatilities and momentum returns in Real Estate Investment Trusts. *Journal of Real Estate Finance and Economics 41*, 126–149.

Hur, J., Pritamani, M., & Sharma, V. (2010). Momentum and the disposition effect: The role of individual investors. *Financial Management 39 (3)*, 1155-1176.

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance 11*, 585–616.

Jagadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48 (1)*, 65-91.

Jegers, M. (1991). Prospect theory and the risk-return relation: Some Belgian evidence. *The Academy of Management Journal 34 (1)*, 215-225.

Jones, D. (2007). Voluntary disclosure in R&D-intensive industries. *Contemporary Accounting Research 24 (2),* 489–522

Jones, C. P., Walker, M. D., & Wilson, J. W. (2004). Analyzing stock market volatility using extreme day measures. *The Journal of Financial Research 27 (4)*, 585–601.

Junttila, J., Kallunki, J., Karja, A., & Martikainen, M. (2005). Stock market response to analysts' perceptions and earnings in a technology-intensive environment. *International Review of Financial Analysis 14*, 77-92.

Kaustia, M. (2004). Market-wide impact of the disposition effect: Evidence from IPO trading volume. *Journal of Financial Markets 7 (2)*, 207-235.

Kaustia, M. (2010). Prospect theory and the disposition effect. *Journal of Financial and Quantitative Analysis 45 (3)*, 791- 812.

Kelsey, D., Kozhan, R., & Pang, W. (2010). Asymmetric momentum effects under uncertainty. *Review of Finance 15 (3)*, 1-29.

Kenneth, F. R., Schwert, W., & Stambaugh, R. F. (1987). Expected returns and volatility. *Journal of Financial Economics 19*, 3-29.

Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives 15 (4)*, 143-156.

Kong, L., Bai, M., & Wang, P. (2014). Is disposition effect related to momentum in Chinese market? *Managerial Finance 41 (6)*, 600-614.

Kothari, S., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies 7*, 355–382.

Koutmos, G., Lee, U., & Theodossiou, P. (1994). Time-varying betas and volatility persistence in international stock markets. *Journal of Economics and Business 46*, 101-112.

Kwon, S. S., & Yin, J. (2015). A comparison of earnings persistence in high-tech and non-high-tech firms. *Review of Quantitative Finance and Accounting 44*, 645-668.

Kwon, S. S., & Yin, J. (2006). Executive compensation, investment opportunities, and earnings management: High-tech firms versus low-tech firms. *Jounral of Accounting, Auditing and Finance 21 (2)*, 119-148.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics 32*, 23-43.

Lakonishok, J, & Smidt, S. (1986). Volume for winners and losers: Taxation and other motives for stock trading. *Journal of Finance 41 (4)*, 951-974.

Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behaviour. *The Accounting Review 71 (4)*, 467-492.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance 26*, 2277–2299.

Lehenkari, M. (2012). In search of the underlying mechanism of the disposition effect. *Journal of Behavioural Decision Making 25 (2)*, 196-209.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics 71*, 349–380.

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics 21*, 107-138.

Lev, B., & Zarowin, P. (1999). The boundaries of financial reporting and how to extend them. *Journal of Accounting Research 37 (2)*, 353-385.

Li, M.-Y. L., & Hwang, N.-C. R. (2011). Effects of firm size, financial leverage and R&D expenditures on firm earnings: An analysis using quantile regression approach. *ABACUS 47 (2)*, 182-204.

Li, Y., & Yang, L. (2013). Prospect theory, the disposition effect, and asset prices. *Journal of Financial Economics 107 (3)*, 715-739.

Li, Q., Yang, J., Hsiao, C., & Chang, Y.-J. (2005). The relationship between stock returns and volatility in international stock markets. *Journal of Empirical Finance 12*, 650–665.

Li, X., Brooks, C., & Miffre, J. (2009). The value premium and time-varying volatility. *Journal of Business Finance & Accounting 36 (9,10)*, 1252–1272.

Li, X., Miffre, J., Brooks, C., & O'Sullivan, N. (2008). Momentum profits and time-varying unsystematic risk. *Journal of Banking & Finance 32*, 541–558.

Lim, E. (2014). The role of reference point in CEO restricted stock and its impact on R&D intensity in high-technology firms. *Strategic Management Journal 36*, 872-889.

Llorente, G., Michaely, R., Saar, G., & Wany, J. (2016). Dynamic volume-return relation of individual stocks. *The Review of Financial Studies 15 (4)*, 1005-1047.

Locke, P. R., & Mann, S. C. (2005). Professional trader discipline and trade disposition. *Journal of Financial Economics 76 (2)*, 401-444.

Ludvigsona, S. C., & Ng, S. (2007). The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics 83*, 171-222.

Lundblad, C. (2007). The risk return tradeoff in the long run: 1836–2003. *Journal of Financial Economics 85*, 123–150.

Manzan, S., & Westerhoft, F. (2005). Representativeness of news and exchange rate dynamics. *Journal of Economic Dynamic and Control 29*, 677-689.

McLean, D. (2010). Idiosyncratic risk, long-term reversal and momentum. *Journal of Financial and Quantitative Analysis 45 (4)* , 883-906.

Mohd, E. (2005). Accounting for software develoment costs and information asymmetry. *The Accounting Review 80 (4)*, 1211-1231.

Moskowitz, T. J. & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance 54 (4)*, 1249–1290.

Muga, L., & Santamaría, R. (2009). Momentum, market states and investor behaviour. *Empirical Economics 37*, 105–130.

Naifar, N. (2015). Do global risk factors and macroeconomic conditions affect global islamic index dynamics? A quantile regression approach. *The Quarterly Review of Economics and Finance 61*, 29–39.

Nam, K., Pyun, C., S., & Kim, S. (2003). Is asymmetric mean-reverting pattern in stock returns systematic? Evidence from Pacific-basin markets in the short-horizon. *Journal of International Financial Markets, Institutions and Money 12*, 481-502.

Nath, H. B., & Brooks, R. D. (2015). Assessing the idiosyncratic risk and stock returns relation in heteroskedasticity corrected predictive models using quantile regression. *International Review of Economics and Finance 38*, 94-111.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica 59 (2)*, 347-370.

Nyberg, H. (2012). Risk-return tradeoff in U.S. stock returns over the business cycle. *Journal of Financial and Quantitative Analysis 47 (1)*, 137–158.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance 53 (5)*, 1775–1798.

Pan, M.-S., Liano, K., & Huang, G.-C. (2004). Industry momentum strategies and autocorrelations in stock returns. *Journal of Empirical Finance 11 (2)* , 185–202.

Pantzalis, C., & Park, J. C. (2009). Equity market valuation of human capital and stock returns. *Journal of Banking & Finance 33*, 1610–1623.

Perold, A. F. (2004). The capital asset pricing model. *The Journal of Economic Perspectives 18 (3)*, 3-24.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial studies 22 (1)*, 435-480.

Pilar, C., & Rafael, S. (2002). Does derivatives trading destabilize the underlying assets? Evidence from the Spanish stock market. *Applied Economics Letters 9*, 107-110.

Pindyck, R. S. (1984). Risk, inflation and the stock market. *The Amercian Economic Review 74 (3)*, 335-351.

Pires, P., Pereira, J., & Martins, L. (2015). The empirical determinants of credit default swap spreads: A quantile regression approach. *European Financial Management 21 (3)*, 556–589.

Poon, S.-H., & Taylor, S. J. (1992). Stock returns and volatility: An empirical study of the UK stock market. *Journal of Banking and Finance 16*, 37-59.

Pyo, U., & Shin, Y. J. (2013). Momentum profits and idiosyncratic volatility: The Korean evidence. *Review of Accounting and Finance 12 (2)*, 180-200.

Reinganum, M., R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics 9 (1)*, 19-46.

Ritter, J. R. (2003). Behavioural finance. *Pacific-Basin Finance Journal 11*, 429–437.

Rohleder, M., Scholz, H., & Wilkens, M. (2011). Survivorship bias and mutual fund performance: Relevance, significance, and methodological differences. *Review of Finance 15 (2)*, 441–474.

Rouwenhorst, G. (1998). International momentum strategies. *The Journal of Finance 53 (1)*, 267–284

Rozeff, M. S., & Zaman, M. A. (1998). Overreaction and insider trading: Evidence from growth and value portfolios. *Journal of Finance 53 (2)*, 701-716.

Schmutz, B. P., & Santerre, R. E. (2013). Examining the link between cash flow, market value, and research and development investment spending in the medical device industry. *Health Economics 22*, 157–167.

Schwert, W. G. (2003). Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. Stulz, *Handbook of the Economics of Finance* (pp. 937-972). Elsevier Science.

Shalen, C. T. (1993). Volume, volatility, and the dispersion of beliefs. *The Review of Financial Studies 6 (2)*, 405-434.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: theory and evidence. *Journal of Finance 40 (3)*, 777-790.

Shefrin, H, & Statman, M. (1995). Making sense of beta, size, and book-to-market. *Journal of Portfolio Management 21 (2)*, 26-34

Shleifer, A., & Vishny, R. W. (1997). The Limits of arbitrage. *The Journal of Finance 52 (1)*, 35–55 .

Shumway, T., & Wu, G. (2006). Does disposition drive momentum? *Working Paper, University of Michigan*.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies 17 (1)*, 165-206.

Sougiannis, T. (1994). The accounting based valuation of corporate R&D. *The Accounting Review 69 (1)*, 44-68.

Statman, M. (1999). Behaviourial finance: Past battles and future engagements. *Financial Analysts Journal 55 (6)*, 18-27.

Sula, O. (2011). Demand for international reserves in developing nations: A quantile regression approach. *Journal of International Money and Finance 30*, 764-777.

Talpsepp, T., & Rieger, M. O. (2010). Explaining asymmetric volatility around the world. *Journal of Empirical Finance 17*, 938-956.

Tinic, S. M., & West, R. R. (1984). Risk and return: Janaury vs. the rest of the year. *Journal of Financial Economics 13 (4)*, 561-574.

Van Dijk, M. A. (2011). Is size dead? A review of the size effect in equity returns. *Journal of Banking & Finance 35*, 3263–3274.

Vanguard. (2015, March). *What is 'survivorship bias'? and why does it matter?* Retrieved from Vanguard:https://www.vanguard.co.uk/documents/adv/literature/survivorship-bias.pdf

Wang, J. (1993). A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies 60*, 249-282.

Weber, M., & Camerer, C. F. (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behaviour & Organization 33 (2)*, 167-184.

What is SIC code? (2016, 08 10). Retrieved from SICCODE: http://siccode.com/en/pages/what-is-a-sic-code

Watanabe, C., Hur, J. Y., & Lei, S. (2006). Converging trend of innovation efforts in high technology firms under paradigm shift- a case of Japan's electrical machiery. *Omega 34*, 179-188.

Whitelaw , R. F. (2000). Stock market risk and return: An equilibrium approach. *Review of Financial Studies 13 (3)*, 521-547.

Wu, G. (2001). The determinants of asymmetric volatility. *Review of Financial Studies 14 (3)*, 837-859.

Wu, C., Wu., & Liu, V. (2009). The conservatism bias is an emerging stock market: Evidence from Taiwan. *Pacific-Basin Finance Journal 17*, 494-505.

Xing, X., & Howe, J. S. (2003). The empirical relationship between risk and return: Evidence from the UK stock market. *International Review of Financial Analysis 12*, 329-346.

Ye, P. (2014). Does the disposition effect matter in corporate takeovers? Evidence from institutional investors of target companies. *Journal of Financial and Quantitative Analysis 49 (1)*, 221–248.

Zingales, L. (2000). In search of new foundations. *The Journal of Finance 55 (4)*, 1623-1653 .