# Asset Pricing Anomalies

By

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# Abstract

Asset pricing anomalies refer to the evidence that cannot be explained or captured by an asset pricing model, i.e. the return is inconsistent with the estimated return from an asset pricing model. Anomalies are often used as the evidence against the efficient market hypothesis because it is abnormal compared with a normal return from the rational model. Recently, Cooper, Gullen and Schill (2008) show an important new anomaly -- the asset growth anomaly -- which reveals the negative relation between firm asset growth and subsequent stock returns on the US market after controlling for the book-to-market ratio and firm size. In addition, international studies of the asset growth anomaly show that it is more apparent in developed markets than emerging markets (see Titman, Wei and Xie, 2013; Watanabe, Xu, Yao and Yu, 2013). The explanations for the asset growth anomaly can be grouped into two broad categories: rational explanations (Li and Zhang, 2009; Watanabe, Xu, Yao and Yu, 2013; Hou, Xue and Zhang 2015) and behavioural explanations (Cooper, Gullen and Schill, 2008; Lipson, Mortal and Schill, 2011).

In the first empirical chapter, the asset growth anomaly is tested across a long period and in different industries (Fama-French industry classification) on the US market. By using US data from 1963 to 2011, I show that 13 out of 44 industries feature the asset growth anomaly. Motivated by the different asset structure in different industries, I examine whether industry characteristics have influence on the asset growth anomaly. According to the empirical results, existing explanations (i.e. Q-theory with investment frictions and mispricing with limits-to-arbitrage) cannot fully explain the variations of the anomaly at the industry level. After controlling for existing explanations, I find the anomaly is a function of industry characteristics which proxy for industry competition and to a lesser degree the growth opportunities within an industry. The findings suggest that

the asset growth anomaly can be at least partly explained by the reaction of investors to the growth opportunities within less competitive industries.

In the second empirical chapter, I directly investigate if overreaction is the source of the asset growth anomaly. Investors have been warned not to pay too much for growth, yet empirically there is a strong negative relationship between asset growth and subsequent stock returns - the asset growth anomaly. It may suggest overreaction to firm asset growth. Previously, Cooper, Gullen and Schill (2008) show the reversal pattern of margin profit by comparing before and after the asset growth portfolio formation date. However, it does not test how the asset growth anomaly interacts with the degree of overreaction. In addition, some studies test how limits-to-arbitrage affect the asset growth anomaly. However, limits-to-arbitrage cannot state the source of mispricing. High limits-to-arbitrage cause high risk (or high transaction cost) for the arbitrage activity and hence anomalies cannot be traded away easily; but it does not tell us how investors' behavioural biases move price away from fundamental value. Overall, there is a lack of direct evidence of overreaction as the source of the asset growth anomaly. I propose that investors' expectation error on the trend and profitability of asset growth is the reason behind paying too much for growth and hence the anomaly. The empirical analyses provide strong evidence that investors use the historic growth trend to extrapolate future growth. Specifically, the asset growth effect is stronger when the consecutive growth trend is longer. The finding is robust to controls for existing explanations of the asset growth anomaly (Q-theory with investment frictions and limits-to-arbitrage) and traditional risk measures. To control all the proxies of investment frictions and limits-to-arbitrage but avoiding multicollinearity, I also conduct factor analysis to extract common factors. Prior literature compares Q-theory with investment frictions and limits-to-arbitrage by one on one comparison rather than controlling for all the proxies to avoid high correlation among these proxies (Li and Zhang, 2010; Lam and Wei, 2011; Watanabe, Xu, Yao and Yu, 2013).

In the third empirical chapter, I examine if other anomalies, like the asset growth anomaly, are more prominent in developed markets than emerging markets. Therefore, I study 16 extensively documented anomalies in 45 countries across the globe for the period between 1980 and 2013. The results show clear evidence that developed markets have more anomalies than emerging markets. And most importantly, I provide news watcher efficiency as an explanation of this phenomenon. Developed markets are considered more efficient than emerging markets and more efficient markets should have fewer anomalies based on the efficient market hypothesis. However, previous literature documents a puzzle that developed markets have more asset pricing anomalies than emerging markets. To understand the puzzle, I first apply the latest q-factor model (Hou, Xue and Zhang, 2015) and 5-factor model (Fama and French, 2015). Although these models provide explanatory power for some of the anomalies, the puzzle - a difference between developed and emerging markets - still remains. This test also provides an out-of-sample check for the new asset pricing model. Furthermore, the difference is more profound in equal-weighted than value-weighted anomaly returns.

Building on Hong and Stein (1999) I hypothesize and show that very slow information diffusion in emerging market stocks and especially for small stocks provides an explanation of the puzzle. News watcher efficiency determines information diffusion speed and there is a nonlinear relation between news watcher efficiency and anomalies. When information diffusion is slow which is the first stage, there is no apparent price change caused by news watchers. And, therefore, momentum traders have no trend to follow; namely, there should be no momentum activities. As a result, anomalies cannot be observed even if the price does not reflect information in the market. This is the case for

emerging markets. As information diffusion speeds up (which is the second stage), price will gradually incorporate information but not immediately. In this situation, there should be more momentum activities because momentum traders have a clear trend to follow. High momentum intensity, therefore, is more likely to overshoot the price and cause overreaction or price continuation. When investors realize the fundamentals, there is reversal in the long run. This information diffusion phase is the situation in developed markets. Consistent with the prediction, the empirical results show the nonlinear relation (the inverted U shape) between anomalies and news watcher efficiency proxies (higher education, investor sophistication and accounting standards).

Therefore, in summary, this thesis considers three aspects of anomalies. First, asset growth anomalies, to some extent, relates to industry characteristics. Second, overreaction is the source of the asset growth anomaly. Third, there are more anomalies in developed markets than emerging markets, and this is due to the slow information diffusion in emerging markets.

# Table of Contents

# List of Tables, Figures, and Equations

## Tables



## Figures

## Equations

# Chapter 1

# Introduction

## 1.1. Introduction

In an efficient market, all the information should be reflected by the asset price and the asset return should follow an asset pricing model. One of the main tasks of asset pricing is to find how asset prices behave. Asset pricing anomalies provide empirical evidence against the market efficiency hypothesis which indicates no predictability of information. In other words, asset pricing anomalies suggest return predictability or abnormal return over and above the expected return from the fair value model. Many anomalies have been documented in the past 30 years. In a recent study, Harvey, Liu and Zhu (2015) summarize at least 316 anomalies. And the most important question is how to explain anomalies, i.e. why there are anomalies in the market (is it due to risk or mispricing)? This motivates me to find the source of asset pricing anomalies. Further, if anomalies are evidence against market efficiency, one should expect less anomalies in developed markets than emerging markets because there are strong grounds for believing that developed markets are more efficient than emerging markets. The existing literature, however, shows some evidence inconsistent with the prediction. This also motivates me to resolve the puzzle and investigate the mechanism which generates the difference between developed and emerging markets.

Addressing these questions has implications for academics, professional market participants and policy makers. For academics, I provide out of sample evidence to the documented anomalies either by longer periods or in another market. In addition, we can have a better understanding of the source of anomalies. For professional market participants, they will know which anomaly is profitable and in which market the anomaly works. For policy makers, they will know how to improve market efficiency so that resources can be better allocated across the market.

The asset growth anomaly is one of the asset pricing anomalies which is found recently and has no clear conclusion of the explanation. Cooper, Gulen and Schill (2008) document this anomaly which refers to a negative relationship between asset growth and subsequent stock returns. Specifically, investors will earn a higher return by holding low asset growth stocks than high asset growth stocks. There are two reasons to start with this particular anomaly. First, this is a relatively new anomaly. Second, this is a kind of aggregate anomaly which incorporates both the investment side and the financing side. Any components from either investment activities or financing activities would be reflected in firm total assets. Therefore, the asset growth anomaly can be a representative anomaly for many other anomalies which are related to investment and financing. These component anomalies (relative to aggregate anomalies) include the investment growth anomaly (Xing, 2008), the abnormal capital investment anomaly (Titman, Wei and Xie, 2004), the accrual anomaly (Sloan, 1996; Richardson, Sloan, Soliman, and Tuna, 2005), and the equity issue anomaly (Pontiff and Woodgate, 2008).

To understand the generation and the existence of the asset growth anomaly, many studies test both risk explanations and mispricing explanations. Cooper, Gullen and Schill (2008) do not favour the risk explanation as the Fama-French 3-factor model cannot capture the return pattern for asset growth portfolios. And they suggest that overreaction is the potential source of the anomaly due to the reversal profitability performance of firms for both high and low asset growth firms.

Following the original research of the asset growth anomaly, there are many other studies of the explanations. Li and Zhang (2010) employ both Q-theory with investment frictions and limits-to-arbitrage. The former is from the rational point and the latter is from a behavioural point of view. The comparison of the two explanations shows that limits-to-arbitrage is a more promising explanation. However, the debate is not over. Lam and Wei (2011) update the Li and Zhang (2010) article with a more comprehensive examination by using more proxies for investment frictions and limits-to-arbitrage. After direct comparison the conclusion is mixed as both of the two explanations have power and neither dominates the other. In terms of understanding the driver of the asset growth anomaly, Lipson, Mortal, and Schill (2011) show that there is a weaker asset growth effect when firms have lower idiosyncratic volatility. Gray and Johnson (2011) attribute the asset growth anomaly to mispricing in the Australian market. These studies tend to support mispricing or behavioural explanations.

Given the fact that limits-to-arbitrage is linked to the asset growth effect, there should be an initial overreaction and then limits-to-arbitrage can take effect. If there is overreaction initially, it is very straightforward that limits-to-arbitrage is a key factor to explain why the asset growth effect is stronger for firms with high limits-to-arbitrage than that with low-limits-to-arbitrage. High limits-to-arbitrage, for example, via low analyst coverage, high bid-ask spreads and high idiosyncratic volatility, would incur high risk and transaction costs. Hence, arbitragers or rational investors have difficulty in taking the arbitrage opportunities. In contrast, there is a weaker asset growth effect for low limits-to-arbitrage firms because the arbitrage activities can trade away the anomaly easily. However, the reason why investors overreact is not clear. And this initial mispricing is the prior condition that underpins limits-to-arbitrage. In terms of behavioural explanations, there are two seminal behavioural models which explain why behavioural biases cause overreaction or underreaction. Barberis, Shleifer and Vishny (1998) attribute overreaction to representativeness, while Daniel, Hirshleifer and Subrahmanyam (1998) argue that overconfidence contributes to overreaction.

Further, to provide out of sample evidence to the asset growth anomaly and to pursue its true source, recent studies show empirical results of the asset growth effect in a global context. The international markets provide a platform to compare different explanations. Watanabe, Xu, Yao and Yu (2013) and Titman, Wei and Xie (2013) find a stronger asset growth effect in more developed markets than less developed markets. The former supports Q-theory while the latter favours agency theory with market discipline. These international studies related to the asset growth anomaly increase the understanding of the asset growth effect. However, such international evidence is not only for the asset growth anomaly, but applies to many other asset pricing anomalies. These international studies include McLean, Pontiff and Watanabe (2009), Ang, Hodrick, Xing and Zhang (2009), Griffin, Kelly and Nardari (2010), Chui, Titman, and Wei (2010) and Kaniel, Ozoguz and Starks (2012).

The international evidence to date raises another question, that is, whether all anomalies are stronger in developed markets? If this is true for many anomalies, it challenges the traditional wisdom that there should be fewer anomalies in more developed markets because such markets are more efficient. Therefore, I may find an asset pricing puzzle in global markets. For existing international studies, the literature only provides explanations to a particular asset pricing anomaly. For example, investment-based Q-theory may be helpful for the asset growth anomaly or other investment related anomalies, but it is difficult to explain momentum and many other anomalies. Hence, a unified theory is required to solve the puzzle.

Motivated by the empirical evidence and existing explanations, there are three questions to be solved. First, to confirm the robustness of the asset growth anomaly. The previous literature already examines the asset growth effect during different time periods and in different size groups. However, in order to get a better understanding of this anomaly, the first empirical chapter tests the existence of the asset growth anomaly across different industries. The results will give us a robustness test of the asset growth effect from a different angle.

Secondly, if there is an initial overreaction to firm asset growth, what is the rationale behind the overreaction in explaining the asset growth anomaly? Following representativeness bias from the BSV model, the second empirical chapter tries to find whether firms with a longer growth trend show stronger asset growth effects than firms with a shorter growth trend. If the hypothesis is true, it means that overreaction is the source of the asset growth anomaly.

Third, some international studies show developed markets have stronger anomalies than emerging markets. The question is whether this is only a phenomenon for some particular anomalies or is this a general fact? In the third empirical chapter, I test many well-documented anomalies in the global markets and I do find more anomalies in developed markets than emerging markets. This is counter-intuitive because developed markets are more efficient and they should not have more anomalies. Therefore, in the third empirical chapter, I try to solve the puzzle. Following the Hong and Stein (1999) model, my explanation is that news watchers and information diffusion speed determine why I observe more anomalies in developed markets than emerging markets.

## 1.2. Motivations and Contributions

### 1.2.1 Asset Growth Anomaly across Industries

The first examination of the asset growth anomaly is by Cooper, Gullen and Schill (2008). They test the asset growth anomaly in different size groups and across different time periods to check its robustness. They find that the asset growth anomaly exists in each size group but it is weaker in large firms. They also show a significant asset growth effect during different time frames. Another way to check the robustness is to test the anomaly in different industries.

By using US market data from 1963 to 2011, I find a significant asset growth anomaly in the US market. However, the industry analysis shows that the anomaly is not significant in each of the industries. Following Fama and French (1997), all the firms are divided into 44 industries, and a significant asset growth effect (negative coefficient of asset growth) occurs in 13 out of 44 industries. Therefore, the fact is that although there is an asset growth effect in the US market, it is not a phenomenon in every industry. Besides, there are another 23 industries that show a negative slope of asset growth although they are insignificant. Accordingly, the majority of industries show the negative sign which is consistent with the relation between stock return and firm asset growth.

### 1.2.2 Overreaction is the Source of the Asset Growth Anomaly

Cooper, Gulen and Schill (2008) argue mispricing may cause the asset growth anomaly by looking at the profitability performance before and after asset growth portfolio formation. They show increasing (decreasing) profit margins for high (low) asset growth firms before formation date but decreasing (increasing) profit margins after the formation date. However, Cooper, Gullen and Schill (2008) only give this loose test (there is no test whether the asset growth anomaly is stronger when there is an expectation error) and there is no direct test if the degree of overreaction can determine the magnitude of the asset growth effect. Therefore, why investors overreact to firm asset growth is still unknown.

The Q-theory with investment frictions and limits-to-arbitrage have been more recently used to explain the asset growth effect (see Li and Zhang, 2010; Lam and Wei, 2011). Q-theory is a rational explanation and it stands at the point of firm manager rather than the investors view. Specifically, firm managers are rational and their aim is to maximize firm value. As a result, firms will invest in projects with a positive net present value. High expected return implies low present value and firms are likely to disinvest. And therefore there should be a negative return-investment relation. Furthermore, firms with high investment frictions should be less sensitive to the negative relation because such firms have higher investment costs. In other words, only a lower discount rate can induce them to invest. Therefore, if Q-theory has power to explain, we should expect that firms with higher investment frictions have a stronger asset growth effect. But this explanation cannot rule out limits-to-arbitrage (which is a mispricing explanation) in the direct comparison. Firms with high limits-to-arbitrage are much riskier and hence it is difficult to correct the price and arbitrage away any asset growth anomaly. Lam and Wei (2011) show a stronger asset growth effect for firms with high investment frictions even controlling for limits-to-arbitrage. They also show a stronger asset growth effect in high limits-to-arbitrage firms after controlling for investment frictions. Therefore, it is difficult to distinguish between the two explanations.

To make the debate between rational and mispricing explanations clearer, in the second empirical chapter, I investigate whether investor's bias is a source of the asset growth anomaly after controlling for Q-theory and limits-to-arbitrage (Q-theory is from rational perspective; limits-to-arbitrage is from the mispricing point of view, but it is a constraint to arbitrage not the cause of mispricing). First, the reason behind overreaction is the investors' representativeness bias. Investors tend to overreact more when a firm experiences a longer sequence of asset growth than a shorter one. Further, the length of the sequence is significantly positive after controlling for investment frictions and limits-to-arbitrage. Second, I explicitly test whether there is an expectation error to asset growth portfolios by comparing the return around earnings announcement dates and the return outside the event window. The empirical results show that investors do have expectation errors when analysing asset growth information and investors make corrections when they realize the true value.

### 1.2.3. News Watchers and Asset Pricing Anomalies

Overreaction seems to be the source of the asset growth anomaly and it is still significant even after controlling for the Q-theory and limits-to-arbitrage. However, it does not exclude these explanations. To compare rational against irrational explanations further, Watanabe, Xu, Yao and Yu (2013) use the global context to distinguish the two explanations. Developed markets are seen as being more efficient and the optimal investment (asset growth) decision is seen as relying on efficient prices as indicated by Q-theory. Therefore, the asset growth effect should be stronger in developed markets according to Q-theory. In contrast, more efficient markets should have less mispricing and a low level of limits-to-arbitrage. Therefore, more efficient markets should have a weaker asset growth anomaly. They show evidence to support Q-theory that the asset growth effect is getting stronger when market efficiency is better after controlling for limits-to-arbitrage. This comparison, therefore, differentiates Q-theory and limits-to-arbitrage in explaining the asset growth anomaly.

However, global market studies bring some new questions. First, it is counter-intuitive to see anomalies being more prominent in developed markets than less developed markets. The question to answer is whether the asset growth anomaly is an individual case by chance or this is true for other anomalies. Second, Q-theory is related to investment- or production-based anomalies. It is hard to explain other types of anomalies, for example, momentum, the financial distress anomaly and the short-term reversal effect. Therefore if there are more anomalies in developed markets, Q-theory cannot be the unified explanation to apply to each anomaly. Therefore, a deeper explanation is needed to establish a more unified theory.

Therefore, I include another 15 popular asset pricing anomalies and cover 45 markets including 23 developed markets and 22 emerging markets based on MSCI market development. This comprehensive study finds that there are more anomalies in developed markets than emerging markets. To confirm this finding, not only are raw hedged returns examined, but alphas from the most recent asset pricing model have been checked. This results show that the risk factor model cannot explain the anomaly difference between developed markets and emerging markets. To solve the puzzle, I borrow and extend the agent model from Hong and Stein (1999). According to the model, news watchers affect the information diffusion speed which is the key to determine the activities of momentum traders. The interaction between news watchers and momentum traders produces an inverted U shape of anomaly generation. Hence, the number of anomalies is not a linear relationship with market efficiency or market development. The simulation results in chapter 5 show fewer anomalies when the markets have low level of news watcher efficiency, more anomalies when news watcher efficiency is improved, and fewer anomalies eventually if news watchers are more efficient. And the empirical results show significantly negative coefficients of the squared news watcher proxy in the quadratic regressions of anomaly number on the news watcher proxy. The negative squared term confirms the prediction of the inverted U shape.

In summary, my thesis will address three questions. In chapter 3, I will show the existence of the asset growth anomaly across industries. In chapter 4, I will show that investors are paying too much attention to firm asset growth and overreaction is the source of the asset growth anomaly. In chapter 5, I will test a unified theory to explain anomaly differences between developed markets and emerging markets by using multiple anomalies. In chapter 6, I conclude my thesis. Overall, my thesis contributes to the market anomalies and market efficiency literature. First, the asset growth anomaly does not exist in each industry in the US market and it is probably due to investors' overreaction to asset growth. Second, news watcher efficiency causes more anomalies in developed markets. Third, mispricing is likely to be the source of market anomalies globally. Fourth, most markets are not efficient but market efficiency is improved with the development of a market.

# Chapter 2

# Literature Review

In this chapter I review the existing literature. Section 2.1 reviews the empirical findings of the asset growth anomaly and other asset pricing anomalies. Section 2.2 covers explanations of asset pricing anomalies. Section 2.3 reviews the anomalies in global markets and the underlying explanations. Section 2.4 focuses on the Hong and Stein (1999) model, which is the foundation of the explanation in the third empirical chapter.

## 2.1. Empirical Findings in Asset Pricing Anomalies

Asset pricing anomalies offer evidence against the efficient market hypothesis. The evidence shows that investors are able to earn abnormal return or economic profits.

### 2.1.1. Asset Pricing Anomalies and the Efficient Market Hypothesis (EMH)

Fama (1970) describes the efficient market concept as prices reflect all the information in the market. It states that if information is available to investors without cost and investors are rational, then the price will incorporate all the information and there should be no pricing error between expected and realized price. The implication is that prices follow random walks and no variable can predict returns. After risk adjustment, there is no abnormal return for investors to earn. The only way to obtain a higher return is to take extra risk. This is why market efficiency depends on a correct asset pricing model which can incorporate all the risk factors. Otherwise, the abnormal return cannot represent a true anomaly if the asset pricing model is inadequate. The effort to have a benchmark model to test market efficiency includes CAPM (Sharpe, 1964), the Fama-French 3-factor model (Fama and French, 1992; Fama and French, 1993), the q factor model (Li and Zhang, 2010;

Lam and Wei, 2011; Hou, Xue and Zhang, 2015), and the Fama-French 5-factor model (Fama and French, 2015). These models try to capture the behaviour of cross sectional returns. The expected return or required rate of return from the model is also the stochastic discount factor (SDF) which determines the pricing of an asset.

Asset pricing anomalies are the facts that are inconsistent with efficient markets and anomalies are usually used as evidence to oppose EMH. There are a large number of anomalies challenging the EMH; well-documented anomalies include post earnings announcement drift, size effect, value premium and momentum with some of them even considered as risk factors from 1990s onwards. Harvey, Liu and Zhu (2015) summarize at least 316 anomalies. The findings of anomalies motivate the improvement of asset pricing models, agent behaviour models (Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999) and the understanding of the relationship between anomalies and market efficiency (Griffin, Kelly and Nardari, 2010).

### 2.1.2. Asset Growth Anomaly and Other Investment-related Anomalies

The first paper to test the asset growth anomaly is Cooper, Gullen and Schill (2008). Motivated by the asset expansion and asset contraction anomaly, (for example, the equity issue effect and accrual anomaly), they argue that asset growth is an aggregate measurement because both asset expansion and contraction are components of a firm's total assets. During 1963 to 2003 on the US market, they show significantly higher returns for low asset growth firms than high asset growth firms. The asset growth rate is defined as the percentage change of a firm's total assets as compared to the previous year. In other words, the asset growth effect refers to a negative relationship between asset growth and subsequent return. In their paper, the asset growth effect is confirmed by using both sort and regression techniques. For the deciles sort (i.e. the univariate test), both raw returns and the intercept (alpha) from the Fama-French three-factor model show that the low asset growth decile has significantly higher return than the high asset growth decile. For the Fama-MacBeth regression (i.e. multivariate test), the coefficient of asset growth is significantly negative after controlling for firm size, book-to-market ratio and previous 6-month returns. In addition, they show that the asset growth effect can last for five years and three years after the formation of asset growth portfolios for equal-weighted and value-weighted return respectively.

Furthermore the asset growth anomaly is robust to various considerations. First, the asset growth effect is robust in terms of both equal- and value-weighted returns. Second the asset growth effect is weaker in large firms, but the anomaly still exists across most different firm size groups (see Cooper, Gullen and Schill, 2008; Fama and French, 2008; Lipson, Mortal and Schill, 2011). The third consideration is the asset growth anomaly across different time periods. Cooper, Gullen and Schill (2008) show a significant asset growth effect in 1968-1980, 1981-1990 and 1991-2003. Lastly, Lipson, Mortal and Schill (2011) also confirm the asset growth effect by examining different measurements of asset growth, for example, fixed asset growth.

Asset growth reflects the change of firm investments, namely, any change of investment will increase or decrease firm total assets. In addition, there are some other anomalies which are related to firm investment, for instance, investment growth, abnormal capital expenditures, investment-to-asset ratio and net operating assets.

Xing (2008) explicitly tests the relationship between investment growth (capital expenditure) and future returns. The empirical results show that subsequent stock returns are negatively related to investment growth. They also argue that the investment growth factor plays a similar role to the book-to-market ratio. Titman, Wei and Xie (2004) also find that abnormal capital investment is negatively related to stock returns. For the investment-to-asset anomaly, both Lyandres, Sun, and Zhang (2008) and Xing (2008) document a negative relation between investment-to-asset and future stock returns. Hirshleifer, Hou, Teoh, and Zhang (2004) find another negative investment-return relationship, i.e. net operating assets.

In terms of interpretation of investment-related anomalies there is no clear conclusion so far. Cooper, Gulen and Schill (2008) find little support for the risk explanation. Since then, Li and Zhang (2010) employ an investment-based asset pricing model (Q-theory) as an explanation. Lam and Wei (2011) compare Q-theory and limits-to-arbitrage and both are found to have only partial explanatory power.

### 2.1.3. Accrual Anomaly

Sloan (1996) discovered a negative relation between the level of firm accrual and stock returns. Following the paper, other researchers investigate firm accruals including Richardson, Sloan, Soliman, and Tuna (2005) and Hirshleifer, Hou, and Teoh (2009). The latter not only confirms the negative accrual-return relation at the firm level (cross sectional level), but also shows a positive relationship of accrual and stock returns at the market level (aggregate or time series level).

The accrual anomaly is the evidence which rejects that price can reflect information contained in firm accrual, because there should be no significant hedge return if price already incorporates accrual information.

An explanation of this anomaly is the earnings fixation hypothesis provided by Sloan (1996). This hypothesis argues that there are two components of earnings—accruals and cash flow. However, the effect of the two components on earnings forecasts is different. The earnings forecast based on cash flow is more positive than that based on accruals. Consequently, stocks are mispriced when investors make earnings forecasts and they cannot distinguish the difference between the two components. Stocks are overvalued if there is high accrual but low cash flow. In contrast, stocks are undervalued if there is low accrual and high cash flow.

### 2.1.4. Value Premium

It is well known that value stocks earn higher returns than growth stocks – the value premium. To identify value stocks, previous literature uses the value of book equity relative to market value (book-to-market ratio), and value stocks are stocks with a higher book-to-market ratio. Rosenberg, Reid, and Lanstein (1985) show that there is positive relationship between the book-to-market ratio and stock returns on the US market. Fama and French (1992) also find higher returns for high book-to-market ratio stocks than low book-to-market ratio stocks. Other studies of the relation between the book-to-market ratio and stock returns are Stattman (1980), DeBondt and Thaler (1987), Chan, Hamao and Lakonishok (1991) and Dechow and Sloan (1997). Asness, Moskowitz and Pedersen (2013) find a value premium not only in stock markets but fixed income, commodity and currency markets.

In addition to the book-to-market ratio, there are many other measurements of book value relative to market value. Basu (1977) finds that the ratio of earnings to price is positively associated with stock returns. Fama and French (1992) also show a positive relation between asset-to-market (total asset divided by market value) and stock returns. Lakonishok, Shleifer and Vishny (1994) find the cash flow-to-market ratio and the earnings-to-market ratio are positively correlated with stock returns.

Explanations of the value premium are controversial. One interpretation is fundamental risk. Fama and French (1992, 1993) argue that value stocks are much riskier than growth stocks and hence value stocks have superior returns. Alternatively, DeBondt and Thaler (1985) suggest market overreaction as an explanation. Lakonishok, Shleifer and

Vishny (1994) assert that investors extrapolate good (bad) performance in the past too far into the future (investors expect good (bad) performance based on past good (bad) performance); but the performance actually cannot persist. The growth firms with good performance in the past are overvalued while the value firms with bad performance in the past are undervalued. As a result, value stocks have higher return and growth stocks have lower returns subsequently.

### 2.1.5. Profitability Anomaly

Novy-Marx (2013) finds a positive relationship between gross profits and stock returns. The author measures firm gross profits as revenue minus cost of goods and then divides by firm total assets. Similarly, Haugen and Baker (1996) show that return on equity is positively related to stock returns. Balakrishnan, Bartov and Faurel (2010) sort firms into earnings deciles and firms in the top decile earn superior abnormal returns than firms in the bottom decile.

Q-theory provides the explanation to these profitability anomalies (see Li and Zhang, 2010; Hou, Xue and Zhang, 2015). According to Q-theory, the discount rate or cost of capital depends on two channels—profitability and investment. Intuitively, lower discount rates suggest higher present values and therefore it induces more investment. This causes a negative relationship between the discount rate and investment. However, due to decreasing marginal profit as investment increases, profitability is negatively correlated with investment. As a result, the discount rate should be positively related to profitability.

### 2.1.6. Financial Distress Anomaly

Fama and French (1993) suggest that the book-to-market factor may be linked to financial distress risk. Given this interpretation, a positive relation between financial distress risk and stock returns should be observed. Dichev (1998) argues that bankruptcy risk is a good proxy for financial distress. Ohlson (1980) constructs this O score to measure the risk of firm bankruptcy. By using O score, Dichev (1998) finds that firms experiencing a higher bankruptcy risk have a lower return than firms with lower bankruptcy risk.

### 2.1.7. Price Continuation and Reversal Anomalies

Price continuation and reversal are two of most widely investigated anomalies. Price continuation is the phenomenon that stock prices continue the trend after portfolio formation. In contrast, the reversal of return demonstrates that price goes in the opposite direction after portfolio formation.

Momentum is an example of price continuation. Jegadeesh and Titman (1993) find that the past winner stocks earn higher returns than past loser stocks. Specifically, the stocks with a high return (based on the return in the past 6 months) have higher 6-month holding period returns than stocks with low return (based on the past 6-month return). Their empirical results also show that the momentum effect exists when the formation period return and holding period return are within one year. Other price continuation anomalies include earnings surprise and earnings forecast revisions (see Foster, Olsen and Shevlin, 1984; Bernad and Thomas, 1989; Chan, Jegadeesh and Lakonishok, 1996).

On the reversal side, Jegadeesh (1990) reports significantly negative serial correlation between last month and current month. This first order monthly return relation is the short-term reversal anomaly. In addition, another price reversal anomaly is the long-term reversal effect. DeBondt and Thaler (1985) find that higher return stocks in the past three to five years have worse performance than lower return stocks in the past three to five years. This result is widely referred as evidence of market overreaction and evidence against the efficient market hypothesis.

### 2.1.8. Trading Friction Anomalies

There are many studies investigating anomalies related to trading frictions. These trading frictions include risk, trading volume and the visibility of stocks which can either raise the cost of trading or have an influence on investors' attention. These empirical results extend the list of asset pricing anomalies. More specifically, we have the followings:

1. Beta anomaly. Frazzini and Pedersen (2014) show that abnormal returns are superior for firms with a low beta than those with a high beta. This negative beat-return relation can even spread into bond markets and futures markets.

2. Maximum daily return anomaly. Bali, Cakici, and Whitelaw (2011) show that firms in the high maximum daily return group in the last month tend to earn lower returns in the next month than firms in the low maximum daily return portfolio.

3. Idiosyncratic volatility anomaly. Ang, Hodrick, Xing and Zhang (2006) provide evidence that high idiosyncratic volatility stocks have a lower return that low idiosyncratic volatility stocks. This cannot be explained by traditional risk factors. The idiosyncratic volatility is firm specific risk which is left unexplained by the asset pricing model.

4. Trading volume anomaly. Brennan, Chordia, and Subrahmanyam (1998) show a significantly negative correlation between stock returns and trading volume. This phenomenon can be attributed to liquidity risk -- low trading volume stocks face higher liquidity risk and, therefore, require higher premiums.

5. Illiquidity anomaly. Amihud and Mendelson (1986) discovered a positive relation between stock returns and bid-ask spreads. They argue that the bid-ask spread is a natural proxy of illiquidity because the bid-ask spread reflects the ease or cost of immediate execution. There are numerous other empirical studies of the illiquidity-return relation. Although the measurement of liquidity is different, the positive illiquidity-return relation holds (see Brennan and Subrahmanyam, 1996; Amihud, 2002; Bekaert, Harvey and Lundblad, 2007). For the reason of illiquidity premium, investors need compensation to hold illiquid stocks because such stocks cannot be traded immediately at a favourable price.

## 2.2. Explanations of Asset Pricing Anomalies

This section reviews the theory in explaining asset pricing anomalies. Broadly, all these explanations can be grouped into two categories—rational and behavioural explanations. For the rational explanations, both risk factor models (e.g. CAPM, Fama-French 3-factor model) and investment-based models (e.g. q-factor model) can be used to explain asset pricing anomalies. On the other hand, behavioural explanations assert that investors are irrational and they have a behavioural bias (psychology bias) in their decision making -- the anomalies are generated by overreaction or underreaction.

### 2.2.1. Traditional Asset Pricing Model

A factor model is considered as a benchmark to determine the existence of anomalies. This is because a factor model is used to describe the return or price behaviour and hence the required rate of return (or compensation) that should come from the factors.

The first asset pricing model is the capital asset pricing model (CAPM) delivered by Sharpe (1964) and Lintner (1965). It summarizes the positive relationship between stock returns and systematic risk (beta). It implies that higher stock returns should compensate higher systematic risk to induce investors to hold the assets. CAPM works very well to capture stock return movements before 1963. For example, Cochrane (2011) shows that the average return of each 10 book-to-market portfolio is very close to the predicted line of the CAPM model. In addition, lower book-to-market portfolios (growth stocks) with lower betas have lower return while higher book-to-market portfolios (value stocks) with higher betas have higher return. This evidence confirms the success of CAPM in describing the behaviour of stock returns. However, Cochrane (2011) finds that the book-to-market portfolios are located far away from the predicted line from 1963 onwards and value and growth stocks, most surprisingly, seem to have the same beta more or less. This implies that value stocks with higher return are not riskier than growth stocks with lower returns. In other words, the risk-adjusted return of value stocks is still higher than the risk-adjusted return of growth stocks. Therefore, systematic risk fails to explain the return pattern and the value premium is left as an anomaly which is referred to as evidence against market efficiency.

However, it difficult to deny the efficient market hypothesis. The existence of abnormal return does not necessarily mean market inefficiency. The abnormal return may be either by chance or the current asset pricing model is not adequate. If the abnormal return is significant in a few years over a long period, this means that abnormal return is not persistent. It implies that the abnormal return occurs by chance. If the asset pricing model cannot capture the return pattern completely, then the asset pricing model is not adequate. In this case, it may appear as a market anomaly if the anomaly is tested using an inadequate asset pricing model even if the market is efficient. Therefore, the examination of market efficiency also needs an out-of-sample test and a prefect asset pricing model. With the development of financial markets, there are more trading data available for researchers to conduct such tests. The value premium does exist within longer periods. Similar to the value premium, many other anomalies are uncovered. For instance, the size effect and post earnings announcement drift are found to be inconsistent with the beta-return relation (see Banz, 1977; Ball and Brown, 1968).

To solve these puzzles, Fama and French (1992, 1993) construct a three-factor model (FF3) to describe stock return movements. As mentioned above, the robustness of an anomaly is also used to improve asset pricing models. FF3 is much more powerful in explaining cross sectional stock returns. Therefore, the confirmation of anomalies should be checked via FF3. The FF3 states that expected return is determined by not only market return (systematic risk) but also by a size factor and the book-to-market factor. Fama and French (1996) argue size and book-to-market are measurements of firm distress risk. A higher factor loading indicates higher risk and, therefore, it should have a higher return with respect to the high risk. However, it is not clear whether the two factors reflect the firm risk level. Dichev (1998) finds the conflicting result that higher book-to-market stocks do not have higher bankruptcy risk than low book-to-market stocks.

### 2.2.2 Q-theory (Investment-based Asset Pricing Model)

The initial effort to build the relation between return and firm investment is by Cochrane (1991). The prior consumption-based asset pricing model describes the relation between return and an investor's decision to save or consume. As an analogue of the consumption-based asset pricing model, he constructs a production-based asset pricing model to uncover the relation between return and firms' decisions relating to production plans.

The asset growth anomaly is related to firm investment in a very intuitive way, because if a firm increases (decreases) investment, there is positive (negative) asset growth. Therefore, it is reasonable to expect that an investment-based or production-based asset pricing model should have the power to explain the negative relation between return and asset growth. In addition, all other investment-related anomalies should also be explained in this framework. Li and Zhang (2010) start from a Q-theory of investment to explain the asset growth anomaly and other investment related anomalies. Intuitively, Q-theory argues that firms increase investment when there is a positive present value after deduction of investment cost because positive profits can increase firm value. Therefore, firms tend to invest when there is a higher net present value. The net present value of a project or investment depends on future cash flows and the discount rate or expected return. This links the investment decision to the expected return. Net present value is the sum of discounted future cash flows minus investment costs. And the expected return is in the denominator, so it is negatively related to net present value. As a result, investment should connect to expected return negatively. Specifically, firms tend to invest when the expected return is lower, because the net present value is higher with a low discount rate; while firms would not invest if expected return is higher, because the net present value may be negative after investment cost. Consequently, the Q-theory predicts the negative relation between investment and subsequent stock returns. The asset growth anomaly documented by

Cooper, Gullen and Schill (2008) is just the negative asset growth-return relation. Therefore, Q-theory may be one of the explanations to the asset growth anomaly. However, Q-theory relies on the assumption that firm managers

The asset growth anomaly is in line with the prediction of Q-theory; the difficulty, however, is how to test Q-theory to explain the asset growth anomaly, i.e. how to apply the investment-based asset pricing model to quantify the relationship between asset growth and future stock returns. To examine the Q-theory to explain the asset growth anomaly, Li and Zhang (2010) construct an investment-based model with investment frictions. There are two advantages of adding investment frictions into the model. First, investment frictions are important to firms' investment decisions. Kaplan and Zingales (1997) find that firms with less financial constraints are more likely to pay attention to internal cash flows when making investment decisions. Cleary (1999) shows that investment decisions are conditional on firm creditworthiness. Besides, financial constraints are also correlated with returns. Livdan, Sapriza and Zhang (2009) model the relationship of return and financial frictions. Previous literature does not include the important factor into the production-based model -- for example, Cochrane (1991, 1996). Second, with investment friction proxies, it provides a testable hypothesis that firms with high (low) investment frictions should have a stronger (weaker) asset growth anomaly. This will be shown in the following model demonstration.

In the Li and Zhang (2010) model, the inputs are capital ($K_i$), the long-term average of return on asset ($\Pi$) and the discount rate ($R_i$). There are two periods in the model, time 0 and time 1. Firm invests $I_{i0}$ at time 0 with capital $K_{i0}$ and operating profits $\Pi K_{i0}$. The investment cost occurs due to investment frictions (there should be more costs for more constrained firms). The cost of investment frictions follows a quadratic function of investment and capital, $C(I_{i0}, K_{i0}) = \frac{\lambda_i}{2}\left(\frac{I_{i0}}{K_{i0}}\right)^2 K_{i0}$, where $\lambda_i$ indicates cost level (high $\lambda_i$ means high cost or investment frictions and $\lambda_i > 0$). Therefore, the total cost at time 0 is $I_{i0} + C(I_{i0}, K_{i0})$. At time 1, the firm has capital $K_{i1}$ which follows the equation $K_{i1} = I_{i0} + (1-\delta)K_{i0}$, where $\delta$ is depreciation ($0 \le \delta \le 1$). In the two period model, the object of the firm is to maximize the sum of value at time 0 and the discounted value with discount rate $R_i$ at time 1. Intuitively, firms are facing an investment decision to trade-off between today's cash flow and future cash flow (either investing at time 0 to exchange higher cash flow at time 1 or disinvesting to have cash flow at time 0 by foregoing the cash flow in time 1).

To maximize the market value of the firm at time 0 which is the sum of cash flow at time 0 and the discounted value of cash flow at time 1, so the objective function is (see Equation (2) of Li and Zhang (2010)):

$$\max_{I_{i0}} V = \Pi K_{i0} - \left[I_{i0} + \frac{\lambda_i}{2}\left(\frac{I_{i0}}{K_{i0}}\right)^2 K_{i0}\right] + \frac{1}{R_i}\left[\Pi K_{i1} + (1-\delta)K_{i1}\right] \quad \text{(Eq. 2-1)}$$

To solve the optimization problem, we first need the first-order derivative with respect to $I_{i0}$ and let it equal to zero:

$$\frac{\partial V}{\partial I_{i0}} = -1 - \lambda_i \frac{I_{i0}}{K_{i0}} + \frac{1}{R_i}\left[\Pi + (1-\delta)\right] = 0 \quad \text{(Eq. 2-2)}$$

After we rearrange the equation (2-2), the optimal solution can be written as the following equation (see Equation (3) of Li and Zhang (2010)):

$$R_i = \frac{\Pi + 1 - \delta}{1 + \lambda_i (I_{i0}^* / K_{i0})} \quad \text{(Eq. 2-3)}$$

Therefore, this equation links the return and investment. Given that the investment is in the denominator, there should be a negative relation between return and investment. To explicitly show the return-investment relationship, the equation (2-3) can be further differentiated with respect to $I_{i0}^{*}/K_{i0}$:

$$\boldsymbol{dR_i = \frac{\partial R_i}{\partial(I_{i0}^{*}/K_{i0})} d(I_{i0}^{*}/K_{i0}) = (\Pi + 1 - \delta) \frac{-\lambda_i}{[1+\lambda_i(I_{i0}^{*}/K_{i0})]^2} d(I_{i0}^{*}/K_{i0})} \quad \text{(Eq. 2-4)}$$

After rearranging $d(I_{i0}^{*}/K_{i0})$ in equation (2-4) to the left hand side, we can get the ratio of $d(I_{i0}^{*}/K_{i0})$ and $dR_i$ (see Equation (4) in Li and Zhang (2010)):

$$\boldsymbol{\frac{d(I_{i0}^{*}/K_{i0})}{dR_i} = -\frac{[1+\lambda_i(I_{i0}^{*}/K_{i0})]^2}{\lambda_i(\Pi+1-\delta)} < 0} \quad \text{(Eq. 2-5)}$$

Equation (2-5) will always be less than zero because both the numerator and denominator are greater than zero. The negative value exactly describes that investment change is negatively related to expected returns, i.e. the increase in investment will lead to a decrease of stock return. This implies that the slope to regression of stock returns on asset growth should be negative, i.e. the asset growth effect.

Further, the Li and Zhang (2010) model also examines the effect of investment friction on this negative relationship, namely, how the investment-return relation changes given changes in investment friction. This can be shown by using the total differentiate of the absolute value of equation (2-5) with respect to $\lambda_i$. The reason for taking the absolute value is to measure the magnitude of the return-investment relation responding to the change of investment frictions:

$$\boldsymbol{\begin{aligned} d\left|\frac{d(I_{i0}^{*}/K_{i0})}{dR_i}\right| &= \frac{\partial\left(\frac{[1+\lambda_i(I_{i0}^{*}/K_{i0})]^2}{\lambda_i(\Pi+1-\delta)}\right)}{\partial(I_{i0}^{*}/K_{i0})} d(I_{i0}^{*}/K_{i0}) + \frac{\partial\left(\frac{[1+\lambda_i(I_{i0}^{*}/K_{i0})]^2}{\lambda_i(\Pi+1-\delta)}\right)}{\partial\lambda_i} d\lambda_i \\ &= \frac{2[1+\lambda_i(I_{i0}^{*}/K_{i0})]}{\lambda_i(\Pi+1-\delta)} \lambda_i\, d(I_{i0}^{*}/K_{i0}) + \\ &\quad \frac{2[1+\lambda_i(I_{i0}^{*}/K_{i0})]}{\lambda_i(\Pi+1-\delta)} (I_{i0}^{*}/K_{i0}) d\lambda_i - \\ &\quad \frac{[1+\lambda_i(I_{i0}^{*}/K_{i0})]^2}{\lambda_i^{2}(\Pi+1-\delta)} d\lambda_i \end{aligned}} \quad \text{(Eq. 2-6)}$$

Divided by $d\lambda_i$ of both sides of equation (2-6), we can get the ratio of the return-investment relation and investment frictions:

$$d\left|\frac{d(I_{i0}^*/K_{i0})}{dR_i}\right|/d\lambda_i = \frac{2[1+\lambda_i(I_{i0}^*/K_{i0})]}{\lambda_i(\Pi+1-\delta)}\,\lambda_i\,\frac{d(I_{i0}^*/K_{i0})}{d\lambda_i} +$$

$$\frac{2[1+\lambda_i(I_{i0}^*/K_{i0})]}{\lambda_i(\Pi+1-\delta)}\left(\frac{I_{i0}^*}{K_{i0}}\right) - \frac{[1+\lambda_i(I_{i0}^*/K_{i0})]^2}{\lambda_i^{\,2}(\Pi+1-\delta)}$$

$$= \frac{2[1+\lambda_i(I_{i0}^*/K_{i0})]}{\lambda_i(\Pi+1-\delta)}\left(\lambda_i\frac{d(I_{i0}^*/K_{i0})}{d\lambda_i} + \frac{I_{i0}^*}{K_{i0}}\right) -$$

$$\frac{[\mathbf{1}+\boldsymbol{\lambda_i}(\boldsymbol{I_{i0}^*}/\boldsymbol{K_{i0}})]^{\mathbf{2}}}{\boldsymbol{\lambda_i}^{\mathbf{2}}(\boldsymbol{\Pi}+\mathbf{1}-\boldsymbol{\delta})} \qquad \text{(Eq. 2-7)}$$

To simplify equation (2-7) we can differentiate both sides of equation (2-3):

$$\frac{\partial R_i}{\partial(I_{i0}^*/K_{i0})}d(I_{i0}^*/K_{i0}) = -\frac{\partial R_i}{\partial\lambda_i}d\lambda_i$$

$$\Rightarrow \frac{\Pi+1-\delta}{[1+\lambda_i(I_{i0}^*/K_{i0})]^2}\,\lambda_i d(I_{i0}^*/K_{i0}) = -\frac{\Pi+1-\delta}{[1+\lambda_i(I_{i0}^*/K_{i0})]^2}\,\frac{I_{i0}^*}{K_{i0}}\,d\lambda_i$$

$$\Rightarrow \lambda_i d(I_{i0}^*/K_{i0}) + \frac{I_{i0}^*}{K_{i0}}\,d\lambda_i = 0$$

$$\Rightarrow \frac{\lambda_i d(I_{i0}^*/K_{i0})}{d\lambda_i} + \frac{I_{i0}^*}{K_{i0}} = 0 \qquad \text{(Eq. 2-8)}$$

Then we substitute equation (2-8) into equation (2-7) (see Equation (6) of Li and Zhang (2010)):

$$d\left|\frac{d(I_{i0}^*/K_{i0})}{dR_i}\right|/d\lambda_i = -\frac{[1+\lambda_i(I_{i0}^*/K_{i0})]^2}{\lambda_i^{\,2}(\Pi+1-\delta)} < 0 \qquad \text{(Eq. 2-9)}$$

The equation (2.9) indicates how the negative return-investment relation responds given the change in investment frictions. The reciprocal of $\left|\frac{d(I_{i0}^*/K_{i0})}{dR_i}\right|$ on the left hand side can be considered as the absolute value of the regression slope, hence, the lower the absolute value of $\left|\frac{d(I_{i0}^*/K_{i0})}{dR_i}\right|$ the steeper the slope of asset growth from the regression of return on asset growth; namely, the stronger the asset growth effect. Intuitively, the increase in investment frictions will make $\left|\frac{d(I_{i0}^*/K_{i0})}{dR_i}\right|$ flatter, and, therefore, the firm's investment is not sensitive to the discount rate. As a result, a firm chooses to invest only if the discount rate has a larger decrease that induces a stronger asset growth effect. Overall, if the negative relationship between asset growth and stock return is caused by firms' optimal investment (as implied by Q-theory) then it should predict that the asset growth anomaly is stronger for firms with high investment frictions.

Following Li and Zhang (2010), Lam and Wei (2011) conduct a more comprehensive empirical study by including more proxies of investment frictions. They find a fair amount of evidence to support Q-theory with investment frictions in explaining the asset growth anomaly, that is, firms with higher investment frictions tend to have a stronger asset growth effect.

However, Q-theory relies on the assumption that firm manager will maximize firm value. And therefore, firm managers will make investment decisions based on the net present value which adds value or reduces the value of firm. The limitation of the assumption is that there is an agency problem, because firm managers will not always have goals consistent with shareholders. In the case of empire building, firm managers will invest when it can increase firm assets regardless of the net present value. As a result, there should be no negative relation between investment and stock return for firms with agency problem.

### 2.2.3. Behavioural Explanations

Both risk factor models and Q-theory consider that investors or firm managers are rational. It implies that investors update newly received information correctly and the decision making is based on subjective expected utility (SEU, see Sargent (1993)). Instead of assuming investors are rational, behavioural finance asserts that investors have behavioural biases which can be used to explain anomalies in the market. In general, two consequences caused by psychological biases are overreaction and underreaction[1]. A large number of behavioural studies apply the behavioural approach to tackle the anomalies. For overreaction applications, Cooper, Gullen and Schill (2008) suggest that overreaction is a potential source of the asset growth anomaly. DeBondt and Thaler (1985) find that stocks which have higher (lower) returns in the past three to five years earn lower (higher) returns in the next three to five years: this indicates the past winners (losers) over the past three to five years are overvalued (undervalued). Lakonishok, Shleifer and Vishny (1994) argue that investors exploit past firm performance too far into the future when making forecasts and, therefore, investors are more likely to overreact to firm performance. They find evidence to support the overreaction explanation for many contrarian strategies, for instance, the book-to-market ratio, the cash flow-to-price ratio, the earnings-to-price ratio and the five-year average growth rate. Haugen (1995) also supports overreaction as an interpretation of the high return for high book-to-market ratio stocks. Hirshleifer, Hou, Teoh and Zhang (2004) argue that overreaction is the reason why net operating assets are negatively related to future stock returns. Bali, Cakici and Whitelaw (2011) attribute maximum daily return effects to overreaction to stocks that have a small chance to earn large returns. For the underreaction stream of research, Bernard and Thomas (1990) show

[1] For example, investors who are more overconfident tend to overreact to news; while investors who are conservative tend to underreact to news.

that investors underreact to earnings because they do not recognize the positive autocorrelation of earnings. Abarbanell and Bernard (1992) show that analysts tend to underreact to firms' earnings which is consistent with post earnings announcement drift. Titman, Wie and Xie (2004) argue that the negative relation between investment and stock returns is due to the underreaction to a firm manager's overinvestment. Hong, Lim and Stein (2000) show that momentum is because of slow information incorporation into price and, therefore, momentum is stronger for firms with poor analyst coverage and small size. Zhang (2006) supports the underreaction explanation for short-term price continuation because information uncertainty (more information uncertainty should lead to more underreaction) makes price continuation even more obvious.

Another block of behavioural finance is limits-to-arbitrage (see Barberis and Thaler, 2002). If those anomalies have resulted from mispricing, then arbitrageurs will take advantage of it and eventually trade away (buy undervalued stocks and sell overvalued stocks) the anomalous phenomenon. However, arbitrage is not riskless and not free of cost. For example, DeLong, Shleifer, Summers and Waldmann (1990) and Morck, Yeung and Yu (2000) argue that arbitrage is risky because of noisy trading. Mashruwala, Rajgopal and Shevlin (2006) point out that arbitrage activity may have significant transaction costs. Mitchell, Pulvino and Stafford (2002) suggest that imperfect information and market frictions make arbitrage difficult. Further, arbitrage is complicated in real markets even for the simplest arbitrage (see Shleifer and Vishny, 1997). Due to the above difficulties for arbitrage, high limits-to-arbitrage will impede the arbitrage activities and hence the anomalies can exist for a longer time periods. As the result of limits-to-arbitrage, it provides a prediction that if an anomaly is generated by mispricing then it should be more prominent when firms have high limits-to-arbitrage.

Although the above literature shows that mispricing (over- or under-reaction) has reasonable power to explain asset pricing anomalies, the underlying reason why investors over- or under-react to information and how investors experience behavioural bias are not clarified entirely. There are three seminal theoretical models which help with this purpose.

Barberis, Shleifer and Vishny (1998, thereafter BSV) argue that investors have behavioural bias when they forecast the future cash flow and therefore the stock price is mispriced. The incorrect expectation of future cash flow comes from two psychological elements. One is the representativeness bias that leads to neglect of the base rate and neglect of the sample size. For neglect of the base rate, when investors evaluate the probability of an event, they are more likely to focus on new information and put little weight on the base rate, i.e. prior probability. For neglect of the sample size, even though the small sample may not represent the population, investors tend to ignore the size of sample and infer from it based on a small sample too quickly rather than knowing more evidence. Another bias is conservatism. In contrast to representativeness, conservatism results in too much weight being placed on the base rate and little weight on new information.

According to the two biases mentioned above, BSV uses mean reversion and trend to capture representativeness and conservatism. When there is a series of good news about future cash flows, investors tend to over weight the good news due to representativeness and believe the trend of cash flows will continue into future. Consequently, the price will be pushed too high which causes a lower return after correction in the future and a reversal phenomenon (i.e. the negative relationship between anomaly variable and return is observed). On the other hand, when there is an unexpected future cash flow increase or positive surprise, investors are reluctant to update their belief because of conservatism and believe in mean reversion of future cash flows. Therefore, the price incorporates new information inadequately which leads to underreaction and the observation of a price continuation effect, i.e. the positive relationship between the anomaly variable and stock returns.

Daniel, Hirshleifer and Subrahmanyam (1998, hereafter DHS) also build a model to interpret the under- and over-reaction based on psychological biases. One difference from BSV is that they include different biases in their model. DHS considers overconfidence and self-attribution as the reason for over- and under-reaction. Overconfidence refers to investors being too confident about the precision of their private information, namely, investors generate a signal by the means of their own analysis and therefore the price suffers from overreaction. Then the correction of the overvalued price occurs when the public information fully uncovers the fair value of stock. This is why a stock return reversal is to be found. Self-attribution also plays an important role when investors update their beliefs. After investors analyse their private information, information which confirms their analysis will increase their confidence even more. However, they are less likely to update this private signal when there is opposite information or a counter event in the market. So the confirmation of a private signal fuels the overreaction caused by overconfidence and this is the process of price continuation. The reversal and continuation generated by overconfidence and the interaction with self-attribution imply another difference between BSV and DHS. BSV argue that the investors over- and under-react to public information; while DHS suggest that investors overreact to private information and underreact to public information.

In addition to the two theoretical models based on the assumption of investors' psychological bias and single agent in the market, Hong and Stein (1999, thereafter HS) consider a model including two types of investors—news watcher and momentum trader. There is no need to clarify a particular psychological bias to cause over- or under-reaction, and hence the HS model avoids the problem about why investors overreact to particular types of information and underreact to another type of information. HS argue that price continuation and the later reversal come from the interaction between news watcher traders and momentum traders who are not fully rational. News watchers form expectations only based on news or information about fundamentals and do not follow past price changes. In contrast, momentum traders make forecasts only based on past price change regardless of any information relevant to fundamentals. Firstly, when there is new information in the market, news watchers incorporate this information into price slowly due to gradual information diffusion. As a result, HS show evidence of a positive return correlation in the short-term which is consistent with short-term momentum. If there are only news watchers in the market, we should observe underreaction but no overreaction. If there are momentum traders in the market, momentum traders will trade conditional on the price change. Accordingly, when there is good news about fundamentals there is an uptrend of price change and hence momentum traders will make a buy decision when they see the price change caused by news watchers. These early momentum traders will accelerate the process that price reaches long-run value. However, momentum traders trade only according to price change rather than fundamental information. Therefore, late momentum traders will trade based on the price change fuelled by early momentum traders. The late momentum traders drive the price in the same direction even more and the overreaction is generated. HS show negative return autocorrelation in the long-run which is consistent with long-term reversal. Further, HS show the simulated results to describe how news watchers interact with momentum traders. There is a negative relationship between information diffusion and momentum intensity, that is, momentum activities are stronger when the information travels slower which indicates stronger overreaction. HS compare the results by using various parameters.

### 2.2.4. Recent Development of Asset Pricing Model

Using asset pricing anomalies as evidence against market efficiency can never bypass the question if there is an asset pricing model to capture all risks. Some anomalies (for example, the size anomaly) which cannot be explained by CAPM are captured successfully by the Fama-French three-factor model (see Fama and French, 1992; Fama and French, 1993). Therefore, there is always the motivation to construct new asset pricing models to subsume new anomalies. Hou, Xue and Zhang (2015) construct a four-factor model based on Q-theory including the market return premium, the size premium, the investment premium and the profitability premium. They show evidence that the four-factor model works better than FF3. In the meantime, Fama and French (2015) suggest a new five-factor model by incorporating investment and profitability factors in addition to the existing three factors.

### 2.2.5 International Evidence of Asset Pricing Anomalies

The finding of anomalies is originally from the US market. The global examination of these anomalies can show an out-of-sample evidence to check the existence of an anomaly and the variation of an anomaly in different markets also provides a platform to justify possible explanations.

Watanabe, Xu, Yao and Yu (2013) show a stronger asset growth effect in developed markets than in less developed markets. This result can be attributed to an optimal investment effect implied by the Q-theory model. The firm decision relies on discounting the cash flow by using discount rate and this requires correct prices in the market (i.e. the level of market efficiency). In other words, if the price cannot reflect the information conveyed by optimal investment, then firm investment or asset growth should have weaker links between stock return and investment. Therefore, the asset growth effect should be stronger in developed markets because they are more efficient at reflecting information. Motivated by the prediction, Watanabe, Xu, Yao and Yu (2013) compare the Q-theory prediction with limits-to-arbitrage and the results support Q-theory. Lam and Wei (2011) run a horse race between Q-theory and limits-to-arbitrage in the US market and find no winner between the two explanations. Therefore, Watanabe, Xu, Yao and Yu (2013) contribute to the literature by distinguishing between the two explanations in the context of global markets. Titman, Wei and Xie (2013) also find a stronger asset growth anomaly in more developed markets and they also support Q-theory. They argue that firms are more likely to make decisions based on the investment-return relation in more developed markets because firm managers follow the rule of maximizing firm value in developed markets. Griffin, Hirschey and Kelly (2011) investigate how different markets react to news announcement and show that developed markets have a stronger reaction than emerging markets. They suggest that the source of this response is insider trading. Specifically, there are more leakages of news before news announcements in emerging markets than developed markets. And this leakage causes less reaction to news in emerging markets. Kaniel, Ozoguz and Starks (2012) find more developed markets have a stronger extreme volume effect. They argue that more developed markets have less visibility of stocks and, therefore, investors ask for a higher premium.

Overall, there are two gaps which will be addressed in empirical chapters of the thesis. The first gap is the source of the asset growth anomaly. The existing evidence has no conclusion given that both rational and irrational explanations show explanatory power. Second, in the context of global markets with the fact that developed markets are more efficient than emerging markets, why are there more anomalies in developed markets than emerging markets will be examined.

# Chapter 3

# Asset Growth Anomaly across Industries

## 3.1. Introduction

The efficient market hypothesis has faced a long line of challenges from anomalies (see Schwert, 2003, for a survey). The asset growth anomaly (where subsequent returns are negatively related to asset growth) is one of the latest challenges to be investigated. Cooper et al. (2008) provide empirical evidence in support of a mispricing explanation of the anomaly. They find that there is a clear reversal pattern of returns for the high and low asset growth groups between the pre- and post-formation date. Li and Zhang (2010) construct an optimal investment model for firms with investment frictions based on Q-theory which provides testable hypotheses. Intuitively, firms with high investment frictions are less sensitive to the discount rate and, therefore, only a large change of the discount rate can induce firms to invest. From a mispricing perspective, they argue that the anomaly will be stronger for firms with high limits-to-arbitrage because it will be more difficult to trade away the anomaly. Empirically, a stronger anomaly is observed for firms with high investment frictions and firms with high limits-to-arbitrage. They offer weak evidence in support of Q-theory with investment frictions to explain the asset growth anomaly but find that limits-to-arbitrage is a better explanation[2]. Lam and Wei (2011) use more comprehensive proxies for investment frictions and limits-to-arbitrage to test the two explanations and they show that firms with high investment frictions or high limits-

[2] They proposed that managers make investment decisions conditional on future required rates of return. Therefore, lower future returns are associated with higher current period investment. This relationship will be stronger for high investment friction firms which, therefore, have a stronger anomaly.

to-arbitrage have a stronger asset growth anomaly; neither explanation, however, is found to dominate. They indicate that the difficulty in distinguishing between the two explanations is due to the high correlation between the proxies for investment frictions and limits-to-arbitrage.

Given the mixed evidence for the Q-theory with investment frictions or mispricing with limits-to-arbitrage explanations of the asset growth anomaly, I analyze the asset growth anomaly from a new angle; namely, I examine whether the anomaly is different across industries and industry characteristics determine variations in the anomaly. The research is motivated by different industries having radically different asset structures and performance/asset structure relationships (for example, compare IT, retailing and shipbuilding). It is clear that the asset structures of firms reflect the nature of the industry they belong to. For example, firms in the heavy chemicals industry need very significant investment (large chemical plants) in assets to generate profits, while the asset investment needed to produce similar profits in retailing is likely to be less. Asset structures also affect the competitive structure of industries through barriers to entry and economies of scale. There is an extensive literature concerned with the relationship between firm performance and industry characteristics. Mann (1966) and Kilpatrick (1968) find a positive relation between concentration and profits, Grabowski and Muller (1978) show that firms in research intensive industries earn greater returns and Vernon and Nourse (1973) find a positive association between the advertising-to-sales ratio and industry profit. Furthermore, there is evidence that investors' valuation of firms is conditional on industry characteristics. For example, Moskowitz and Grinblatt (1999) show that momentum profits derive partially from industry components of stock returns and Waring (1996) finds that industry characteristics can explain the persistence of firm investment returns.

The industry characteristics provide a platform to test a possible explanation of the asset growth effect. Lakonishok, Shleifer and Hirshleifer (1994) argue that overreaction is due to investors' extrapolation of firm's past good (bad) performance far into future so that it is more likely to have a negative (positive) shock and lower (higher) returns. If overreaction is a potential explanation of the asset growth anomaly (i.e. investors overestimate the chance to maintain asset growth), one should expect that the asset growth anomaly should be stronger when the firm is in a low competition and high growth opportunities industry, because investors tend to raise the probability that such a firm can keep its high growth. And therefore investors are likely to overestimate the chance to have sustainable growth and we can observe a much stronger anomaly.

The results presented here offer two key findings. First, the asset growth anomaly is limited to 13 of 44 industries for the US for the period from 1963 to 2011. Second, I show that certain factors influence the asset growth anomaly at the industry level. After controlling for the major, existing explanations of the asset growth anomaly (Q-theory with investment frictions and mispricing with limits-to-arbitrage), I find the anomaly is a function of industry characteristics which proxy for industry competition and to a lesser degree the growth opportunities within an industry. The findings suggest that the asset growth anomaly can be at least partly explained by the reaction of investors to the growth opportunities within less competitive industries.

The rest of this paper proceeds as follows. The next section describes the data used and the research methodology building on the exiting literature. Section three presents the results. Section four offers conclusions.

## 3.2. Data, Variables and Methodology

### 3.2.1 The Asset Growth Anomaly in Each Industry

I use US data including NYSE, Nasdaq and Amex from 1963 to 2011 and identify 44 non-financial industries following the Fama and French (1997) classification. The return data is from CRSP and the accounting data is from Compustat. I do not include financial firms due to their different accounting practices (Durnev, Morck, Yeung and Zarowin, 2003). To test whether each industry displays an asset growth anomaly, following the standard approach in this literature (Fama and French, 2008), I run the following Fama-MacBeth regression for each industry in each month:

$$\boldsymbol{Ret_{i,t} = \alpha + \beta_1 \ln(1 + AG_{i,t-1}) + \beta_2 lnBM_{i,t-1} + \beta_3 lnMV_{i,t-1} + \varepsilon_{it}} \quad \text{(Eq. 3-1)}$$

where $Ret_{it}$ is return of stock i in time t, $AG_{i,t-1}$ is firm asset growth, $BM_{i,t-1}$ is book-to-market ratio and $MV_{i,t-1}$ is market value.

Specifically, asset growth, the book-to-market ratio and firm size are updated at the end of June in each year t. Asset growth is the logarithm of one plus the percentage change of firm total assets in year t-1 and year t-2. The book-to-market ratio is book equity in the previous fiscal year divided by market equity at the end of December in the previous year. Book equity is firm total assets minus total liabilities, plus balance sheet deferred taxes and investment tax credits; then if available, minus preferred stock liquidation value, redemption value, or carrying value. In addition, I take the natural log of the book-to-market value. Market value is the multiple of stock price and the number of shares outstanding at the end of December and I take the natural log of market value. Cross sectional returns are from July in year t to June in year t+1 and updated monthly. The time-series average of coefficients of asset growth from the cross sectional regressions is obtained with Newey-West (1987) standard errors that correct for heteroscedasticity and autocorrelation.

### 3.2.2 The Asset Growth Anomaly – Existing Explanations

The existing literature has focused on examining the mispricing with limits-to-arbitrage and Q-theory with investment frictions explanations of the asset growth anomaly at firm level. These literatures use idiosyncratic volatility, the number of analysts following a firm and closing price as proxies of limits-to-arbitrage and firm size as the proxy of investment frictions (see, for example, Li and Zhang, 2010; and Lam and Wei, 2011). For limits-to-arbitrage, the higher the limits-to-arbitrage the more costly it is to arbitrage and, therefore, the anomaly should be stronger for firms with high limits-to-arbitrage. Idiosyncratic volatility is positively related to arbitrage risk or costs (Wurgler and Zhuravskaya, 2002; Mashuwala, Rajgopal and Shevlin, 2006) and Lam and Wei (2011) show that idiosyncratic volatility is positively related to the asset growth anomaly. The number of analysts is the measure of information uncertainty. With high information uncertainty, the arbitrage risk is high. Hong, Lim and Stein (2000) find that there is high information uncertainty when the number of analysts following a firm is small. That is, the number of analysts is negatively associated with limits-to-arbitrage as well as the level of asset growth anomaly. The last limits-to-arbitrage proxy is stock price. It is documented that there is a negative relationship between the price of a stock and its bid-ask spread (Ball, Kothari and Shanken, 1995). As a high bid-ask spread means high arbitrage risk, a high stock price should indicate a low limits-to-arbitrage. I use firm size (as measured by market value) as the proxy of investment frictions. Li and Zhang (2010) and Lam and Wei (2011) suggest that the asset growth anomaly is stronger among firms with smaller firm size.

### 3.2.3 The Asset Growth Anomaly – Industry Characteristics

Given the myriad of industry characteristics that have been analyzed by industrial economists, I use Waring (1996) as a guide to the selection of a number of indicative factors. Waring (1996) reviewed the economics and management literatures to identify industry characteristics that might explain the persistence of firm specific returns. From his extensive list of variables I choose five characteristics that have the potential to explain asset growth and the response of investors. More specifically, in the context of asset growth, I expect two groups of industry characteristics to influence investors' valuation of a company; namely, growth opportunities and the level of competition within an industry.

In terms of growth opportunities, Anthony and Ramesh (1992) show that sales growth is a characteristic of the firm life cycle and firms in early stages have better growth prospects and higher sales growth. With better growth opportunities, investors may overreact more to future firm performance and then the price will be corrected in the long run. As a result, the asset growth anomaly should be stronger for industries with high sales growth rates. Indeed, Dong et al. (2012) show that mis-valuation is stronger in firms that have more growth opportunities. To proxy for growth opportunities, I use sales growth as well as research and development expenses (R&D). Lakonishok, Shleifer and Vishny (1994) suggest that past sales growth rate can be used as a measure of future expectations of firm growth. Cooper, Gullen and Schill (2008) also use sales growth as the growth measure. Furthermore, Abernathy and Utterback (1978) show that firm innovation activities are intensive in a new industry in order to achieve market share and market growth. Therefore, R&D expenditure is another proxy for firm growth opportunities. For example, Ho et al. (2006) provide evidence to show the positive impact of R&D investment on the growth opportunities of a firm. In summary, sales growth and R&D expenditure are proxies for growth opportunities.

In terms of industry competition, in highly competitive industries the gains from growth are likely to be short lived because of competitive pressures. In contrast, in less competitive (concentrated) industries, firms should be more able to reap the benefits of their investment in growth. Concentrated industries have higher barriers to entry and firms have more control over the market to ensure good performance. Waring (1996) shows that concentration leads to persistence of firm profitability. Investors are expected to be able to recognize these economic forces and react accordingly. I use three proxies for competition/concentration. The first proxy is the concentration ratio (CONCEN) which is the sales of the largest four firms within an industry divided by the sales of all firms in that industry. A high concentration ratio means that only a small number of firms accounts for a large proportion of sales in the industry. The second proxy is the number of firms in an industry (NUMFIRM). If a specific industry has no dominant power and is easy to enter, there should be many firms in that industry. The third proxy is advertising cost (AD/S). In a competitive industry, firms have to attract the attention of consumers to increase sales. As a result, firms in a competitive industry need to advertise more and consequently, have higher advertising costs. In summary, there is a range of literature which suggest that firms in different industries have different asset/performance relationships and different industries have different growth opportunities and competitive situations. Consequently, investors, at least partially, evaluate stocks conditional on industry characteristics. Table 3-1 shows the averages of the above variables for each of the industries in the sample. Healthcare, medical equipment and pharmaceutical products show high asset growth and the three industries are also the leaders in terms of research input; alcoholic beverages, candy and soda and consumer goods have higher advertisement costs; for concentration, defense and tobacco, no surprise, are controlled by a few firms; the business services industry has more firms than any other and there is a small number of firms in defense industry. Some of the industries have a low number of firms, for example, the defense industry has six firms and the coal industry has nine firms. Although the estimation with small sample size has larger standard errors, it is statistically feasible to run regressions because the number of observations is greater than the number of independent variables. In addition, I am interested with the industry asset growth anomaly and these firms represent the industry rather than the case that there are a small number of firms selected out of many firms in this industry.

**Table 3-1 Industry characteristics**

This table reports the time-series average of industry characteristic for each industry. Industry characteristics include natural log of sale growth (SALEG), R&D expense (RD/S) which is R&D expenditure dividend by sales, concentration ratio (CONCEN) which is the sum of sales of top four firms ranked by sales divided by total sales of all firms in that industry, number of firm (NFIRM) which is the number of firms at the end of June in each year in each industry, advertising costs (AD/S) which is the advertising expense divided by sales.

| | Industry | SALEG | AD/S | RD/S | CONCEN | NFIRM |
|---|---|---|---|---|---|---|
| 1 | Agriculture | 0.1187 | 0.0126 | 0.0315 | 0.8383 | 20 |
| 2 | Food Products | 0.0790 | 0.0320 | 0.0060 | 0.3898 | 84 |
| 3 | Candy and Soda | 0.0906 | 0.0597 | 0.0066 | 0.8506 | 16 |
| 4 | Alcoholic Beverages | 0.0740 | 0.0756 | 0.0055 | 0.6981 | 22 |
| 5 | Tobacco Products | 0.0708 | 0.0391 | 0.0053 | 0.9468 | 10 |
| 6 | Recreational Products | 0.0791 | 0.0436 | 0.0280 | 0.7411 | 55 |
| 7 | Entertainment | 0.0946 | 0.0465 | 0.0018 | 0.6874 | 69 |
| 8 | Printing and Publishing | 0.0772 | 0.0647 | 0.0079 | 0.4318 | 52 |
| 9 | Consumer Goods | 0.0749 | 0.0577 | 0.0225 | 0.5868 | 109 |
| 10 | Apparel | 0.0734 | 0.0335 | 0.0063 | 0.5073 | 68 |
| 11 | Healthcare | 0.2746 | 0.0116 | 0.0616 | 0.6055 | 92 |
| 12 | Medical Equipment | 0.1548 | 0.0198 | 0.0722 | 0.6998 | 116 |
| 13 | Pharmaceutical Products | 0.1351 | 0.0539 | 0.2560 | 0.3538 | 160 |
| 14 | Chemicals | 0.0850 | 0.0226 | 0.0284 | 0.4356 | 98 |
| 15 | Rubber and Plastic Products | 0.0885 | 0.0099 | 0.0184 | 0.6689 | 38 |
| 16 | Textiles | 0.0526 | 0.0120 | 0.0224 | 0.3993 | 49 |
| 17 | Construction Materials | 0.0757 | 0.0148 | 0.0124 | 0.2804 | 144 |
| 18 | Construction | 0.1034 | 0.0136 | 0.0187 | 0.4632 | 58 |
| 19 | Steel Works, Etc. | 0.0723 | 0.0165 | 0.0092 | 0.4426 | 81 |
| 20 | Fabricated Products | 0.0778 | 0.0153 | 0.0098 | 0.8363 | 20 |
| 21 | Machinery | 0.0879 | 0.0142 | 0.0231 | 0.3190 | 165 |
| 22 | Electrical Equipment | 0.0999 | 0.0322 | 0.0620 | 0.7333 | 106 |
| 23 | Miscellaneous | 0.0985 | 0.0193 | 0.0274 | 0.8251 | 65 |
| 24 | Automobiles and Trucks | 0.0806 | 0.0179 | 0.0176 | 0.6783 | 79 |
| 25 | Aircraft | 0.0842 | 0.0267 | 0.0239 | 0.7197 | 28 |
| 26 | Shipbuilding, Railroad Eq | 0.0762 | 0.0189 | 0.0123 | 0.8853 | 11 |
| 27 | Defense | 0.0911 | 0.0190 | 0.0195 | 0.9707 | 6 |
| 28 | Precious Metals | 0.1098 | 7.1929 | 0.0247 | 0.5609 | 57 |
| 29 | Nonmetallic Mining | 0.0952 | 0.0154 | 0.0105 | 0.6242 | 50 |
| 30 | Coal | 0.1093 | 0.0093 | 0.0106 | 0.8590 | 9 |
| 31 | Petroleum and Natural Gas | 0.1277 | 0.0184 | 0.0065 | 0.4810 | 238 |
| 32 | Utilities | 0.0845 | 0.0075 | 0.0063 | 0.1593 | 168 |
| 33 | Telecommunications | 0.1501 | 0.0248 | 0.0252 | 0.6787 | 123 |
| 34 | Personal Services | 0.1300 | 0.0436 | 0.0058 | 0.5936 | 51 |
| 35 | Business Services | 0.1527 | 0.0166 | 0.0877 | 0.2981 | 498 |
| 36 | Computers | 0.1345 | 0.0165 | 0.0818 | 0.6783 | 131 |
| 37 | Electronic Equipment | 0.1170 | 0.0180 | 0.0686 | 0.4852 | 250 |
| 38 | Measuring and Control Equip | 0.1112 | 0.0142 | 0.0742 | 0.6260 | 88 |
| 39 | Business Supplies | 0.0716 | 0.0179 | 0.0107 | 0.4088 | 50 |
| 40 | Shipping Containers | 0.0754 | 0.0141 | 0.0140 | 0.5706 | 33 |
| 41 | Transportation | 0.1062 | 0.0287 | 0.0100 | 0.3522 | 129 |
| 42 | Wholesale | 0.1090 | 0.0195 | 0.0013 | 0.5119 | 192 |
| 43 | Retail | 0.0968 | 0.0377 | 0.0000 | 0.3455 | 241 |
| 44 | Restaurants, Hotel, Motel | 0.1086 | 0.0288 | 0.0000 | 0.4245 | 93 |

### 3.2.4 Empirical Method

Empirically I use a two-stage generalized least square (GLS) method because this can address the problem of heteroscedasticity of the dependent variable (see Waring, 1996). In the first stage, for each month I run a cross sectional ordinary least square (OLS) regression of monthly returns on asset growth to estimate $\beta_1$ in equation (3-1) in each industry. In the second stage I use $-\beta_1$ as the dependent variable measuring the extent of the asset growth anomaly for each industry month. By multiplying the slope by minus 1, we can interpret the slope as the larger the value the stronger the asset growth effect. I use value-weighted industry characteristics as the independent variables. Value-weighed value is used because the results are not influenced by some small firms in an industry. In addition, I include the value-weighted average of four control variables: idiosyncratic volatility, number of analysts, stock price and the natural log of firm size in each industry (see Table 3-2 for detailed definitions)[3]. Li and Zhang (2010) and Lam and Wei (2011) show these variables have explanatory power in terms of the asset growth anomaly. To estimate efficient parameters, I use the standard errors of $\beta_1$ from the first stage as the weights in the second stage regression[4]. The reason is that the dependent variable (slope of asset growth in each industry) is from regression estimation and the slopes are not constant due to the standard error; in addition, it can solve the problem of heteroscedasticity (Saxonhouse, 1976; Waring, 1996).

[3] The advantage of value-weighted characteristics is that the result is not affected by small firms.
[4] See Saxonhouse (1976) for the details of the procedure.

**Table 3-2 Variable definition and construction**

| Variable | Definition | Computation | Reference |
|---|---|---|---|
| SALE | Sales (Net) | #12 (Compustat) | |
| AD | Advertising expense | #45 (Compustat) | |
| R&D | Research and development expense | #46 (Compustat) | |
| **Industry characteristics** | | | |
| SALEG | Sale growth | $(\mathrm{SALE}_t - \mathrm{SALE}_{t-1})/\mathrm{SALE}_{t-1}$ | Waring (1996) |
| AD/S | Advertising expense divided by Sales | AD/SALE | Waring (1996) |
| RD/S | Research and development expense divided by sales | R&D/SALE | Waring (1996) |
| CONCEN | Concentration: sales of largest four firms within an industry to total sales in the industry ratio | SALE(Largest 4)/SALE(total) | Waring (1996) |
| NFRIM | Number of firms | firm number in each industry per year | Waring (1996) |
| **Control variables** | | | |
| MV | Firm size: market value | price*outstanding shares | Lam and Wei (2011) |
| NANAL | Number of analysts for a firm | sum of analyst for a stock | Rajgopal and Venkatachalam (2011) |
| PRICE | Closing price | average of closing price over past 12 months | Lam and Wei (2011) |
| IVOL | Idiosyncratic volatility | variance of residual from CAPM | Lam and Wei (2011) |

## 3.3. Empirical Results

Table 3-3 shows that the asset growth anomaly exists for only 13 out of the 44 industries (agriculture, candy and soda, chemicals, rubber and plastic products, construction, steel works, automobiles and trucks, nonmetallic mining, petroleum and natural gas, electronic equipment, transportation, wholesale and restaurants, hotel and motels). Furthermore, the coefficients range from -0.0346 to -0.0084 for the industries displaying the growth anomaly. The results show, therefore, that the asset growth anomaly is not a universal phenomenon for all industries and it varies across different industries. Testing the asset growth effect in general (by pooling firms from all industries) gives a slope of -0.0101 with t value of -8.19. Taken together these results show that the asset growth effect is significant for the overall US market and this seemingly general result is driven by specific industries.

Table 3-4 shows how the asset growth anomaly responds to industry characteristics. The dependent variable is asset growth slope from equation 3-1 times minus one. By doing this, we can interpret the results that the larger the slope the stronger the anomaly (because of negative effect of asset growth on subsequent returns). The independent variables include natural log of sale growth (lnSALEG), R&D expense (RD/S), concentration ratio (CONCEN), number of firms (NFIRM), advertising costs (AD/S). Control variables include idiosyncratic volatility (IVOL), number of analysts following a firm (NANAL), stock closing price (PRICE) and natural log of market value (lnMV). The results presented in Model 1 (industry characteristics) and Model 3 (industry characteristics, Q-theory and limits-to-arbitrage) show that the asset growth anomaly is positively but weakly related to sales growth (Model 1) and R&D expenses (Model 3). Model 2 shows the relation between the asset growth anomaly and limits-to-arbitrage or investment frictions. It shows that the asset growth anomaly is stronger in industries with high limits-to-arbitrage and high frictions. This is consistent with Li and Zhang (2010) and Lam and Wei (2011). The results for competition are, however, of more importance with the asset growth anomaly being positively related to concentration and negatively related to the number of firms and advertising expenses. The adjusted R square values in Table 3-4 show 8%, 6% and 13% explanatory power for industry characteristics, the two existing explanations (investment frictions and limits-to-arbitrage) and the combination of industry characteristics and existing explanations, respectively. These results indicate that industry characteristics have explanatory power over and above the existing explanations of investment frictions and limits-to-arbitrage, and that the asset growth anomaly is related to industry characteristics.

**Table 3-3 Asset growth anomaly in each industry**

This table reports asset growth anomaly in each industry. I regress monthly return on lagged asset growth and two control variables (natural log of firm size and book-to-market ratio) in each month and summarize the time-series mean of the slope coefficient. The standard error is corrected by the Newey-West (1987) method. *, ** and *** indicate statistical significance at 10%, 5% and 1%.

| | Industry | Slope | t | | Industry | Slope | t |
|---|---|---|---|---|---|---|---|
| 1 | Agriculture | -0.0318** | -2.40 | 23 | Miscellaneous | -0.0309 | -0.41 |
| 2 | Food Products | -0.0074 | -1.20 | 24 | Automobiles and Trucks | -0.0104* | -1.75 |
| 3 | Candy and Soda | -0.0346*** | -2.78 | 25 | Aircraft | -0.0081 | -0.63 |
| 4 | Alcoholic Beverages | -0.0159 | -1.30 | 26 | Shipbuilding, Railroad Eq | -0.3892 | -1.01 |
| 5 | Tobacco Products | 0.0057 | 0.27 | 27 | Defense | 0.1479 | 0.15 |
| 6 | Recreational Products | -0.0439 | -0.88 | 28 | Precious Metals | -0.0016 | -0.25 |
| 7 | Entertainment | -0.0070 | -0.99 | 29 | Nonmetallic Mining | -0.0177*** | -2.57 |
| 8 | Printing and Publishing | 0.1391 | 1.52 | 30 | Coal | -0.0329 | -0.40 |
| 9 | Consumer Goods | -0.0134 | -1.27 | 31 | Petroleum and Natural Gas | -0.0084*** | -3.09 |
| 10 | Apparel | -0.0149 | -2.86 | 32 | Utilities | -0.0045 | -1.25 |
| 11 | Healthcare | -0.0109 | -1.22 | 33 | Telecommunications | -0.0041 | -0.65 |
| 12 | Medical Equipment | 0.0312 | 0.55 | 34 | Personal Services | 0.0043 | 0.33 |
| 13 | Pharmaceutical Products | -0.0094 | -1.56 | 35 | Business Services | 0.0597 | 0.65 |
| 14 | Chemicals | -0.0086** | -1.95 | 36 | Computers | -0.0033 | -0.26 |
| 15 | Rubber and Plastic Products | -0.0337* | -1.70 | 37 | Electronic Equipment | -0.0110*** | -2.68 |
| 16 | Textiles | -0.0056 | -0.50 | 38 | Measuring and Control Equip | -0.0142 | -1.21 |
| 17 | Construction Materials | -0.0093 | -1.46 | 39 | Business Supplies | 0.0094 | 0.30 |
| 18 | Construction | -0.0143*** | -2.56 | 40 | Shipping Containers | 0.0149 | 1.13 |
| 19 | Steel Works, Etc. | -0.0259*** | -2.75 | 41 | Transportation | -0.0136*** | -2.87 |
| 20 | Fabricated Products | -0.0120 | -0.74 | 42 | Wholesale | -0.0103** | -2.07 |
| 21 | Machinery | -0.0044 | -1.03 | 43 | Retail | -0.0078 | -1.59 |
| 22 | Electrical Equipment | -0.0052 | -0.61 | 44 | Restaurants, Hotel, Motel | -0.0120*** | -2.45 |

**Table 3-4 Effect of industry characteristics on the asset growth anomaly**
This table reports how the asset growth anomaly responds to industry characteristics and other control variables. The dependent variable is the asset growth slope from equation (3-1) times minus one. Industry characteristics include natural log of sale growth (lnSALEG), R&D expense (RD/S) which is R&D expenditure dividend by sales, concentration ratio (CONCEN) which is the largest four sales divided by total sales of all firms in that industry, number of firms (NFIRM) which is the number of firms at the end of June in each year in each industry, advertising costs (AD/S) which is the advertising expense divided by sales. Control variables include idiosyncratic volatility (IVOL), number of analysts following a firm (NANAL), stock closing price (PRICE) and natural log of market value (lnMV). Industry characteristics are past three-year average and control variables are measures at one period before the measurement period of the dependent variable. The regression uses the standard error of the asset growth slope in the first stage estimation as the weight. VIF is the variance inflation factor. *, ** and *** indicate statistical significant at 10%, 5% and 1%.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | slope (t) | VIF | slope (t) | VIF | slope (t) | VIF |
| Intercept | -0.0288*** | 0 | 0.1819*** | 0 | 0.1013*** | 0 |
| | (-8.33) | | (17.62) | | (9.81) | |
| lnSALEG | 0.0272*** | 1.54 | | | 0.0065 | 1.63 |
| | (5.81) | | | | (1.42) | |
| RD/S | 0.0000 | 1.03 | | | 0.0005* | 1.05 |
| | (0.12) | | | | (1.91) | |
| CONCEN | 0.1323*** | 1.59 | | | 0.1132*** | 1.69 |
| | (23.81) | | | | (20.80) | |
| NFIRM | -0.00001*** | 2.12 | | | -0.00002*** | 2.55 |
| | (-2.48) | | | | (-3.82) | |
| AD/S | -0.1830*** | 1.10 | | | -0.2015*** | 1.12 |
| | (-9.44) | | | | (-11.71) | |
| IVOL | | | 0.3143*** | 1.08 | 0.4466*** | 1.41 |
| | | | (11.67) | | (15.10) | |
| NANAL | | | -0.0000 | 1.85 | 0.0000 | 1.92 |
| | | | (-1.26) | | (0.00) | |
| PRICE | | | 0.0011*** | 2.13 | 0.0012*** | 2.28 |
| | | | (15.40) | | (16.28) | |
| lnMV | | | -0.0150*** | 3.23 | -0.0134*** | 3.35 |
| | | | (-18.44) | | (-16.83) | |
| Adj. $R^2$ | 8% | | 6% | | 13% | |

The additional explanatory power of the industry characteristics are further evidenced in Table 3-5 that presents the correlations across the industry characteristic proxies with those of the two existing explanations. Lam and Wei (2011) show a high correlation across investment frictions and limits-to-arbitrage proxies that make it difficult to identify the source of the explanatory power from the two explanations. The correlations shown in Table 3-5 confirm that there is high correlation among investment friction and limits-to-arbitrage proxies which range from 0.22 to 0.69 in absolute value. If industry characteristics are also highly correlated with investment frictions and limits-to-arbitrage proxies, it would be difficult to confirm that industry characteristics have additional information beyond the two explanations. I find, however, very low correlations across the industry characteristic proxies and existing explanations - with correlation coefficients ranging from -0.07 to 0.19.

Therefore, the results demonstrate that industry growth characteristics have additional explanatory power over and above the existing Q-theory with frictions and mispricing with limits-to-arbitrage explanations.

**Table 3-5 Correlation among the explanatory variables**
This table reports the correlation coefficients among the variables.

| | ln(SALEG) | RD/S | CONCEN | NFIRM | AD/S | IVOL | NANAL | PRICE | ln(MV) |
|---|---|---|---|---|---|---|---|---|---|
| ln(SALEG) | 1.00 | | | | | | | | |
| RD/S | 0.00 | 1.00 | | | | | | | |
| CONCEN | 0.01 | -0.05 | 1.00 | | | | | | |
| NFIRM | 0.00 | 0.04 | -0.51 | 1.00 | | | | | |
| AD/S | 0.02 | -0.02 | -0.02 | 0.08 | 1.00 | | | | |
| IVOL | 0.03 | 0.04 | 0.07 | 0.10 | -0.04 | 1.00 | | | |
| NANAL | 0.03 | 0.01 | -0.01 | 0.10 | -0.14 | -0.22 | 1.00 | | |
| PRICE | 0.00 | -0.01 | -0.07 | 0.14 | 0.02 | -0.33 | 0.33 | 1.00 | |
| ln(MV) | 0.02 | 0.03 | -0.07 | 0.19 | 0.02 | -0.33 | 0.61 | 0.69 | 1.00 |

## 3.4. Conclusions

The financial markets have been shown to feature a range of asset pricing anomalies, the latest being the asset growth anomaly. This paper demonstrates that the asset growth anomaly is not a general feature of the US market but is specific to 13 out of 44 industries. In addition, the asset growth anomaly is found to be a function of industry characteristics proxying for growth opportunities (sales growth and R&D costs) and competition (concentration, the number of firms and advertising costs). Therefore, this paper shows that the asset growth anomaly is not a feature of the whole market but is specific to a relatively small number of industries and industry characteristics. The finding is consistent with arguments that the asset growth anomaly is driven by investors' mispricing and such mispricing is especially acute in industries with higher growth opportunities and lower competition.

One of the main limitations of this chapter is the proxies used to measure growth opportunities and competition. I collect these proxies from one source and the source is relatively old so that the proxies may contain a lot of noise. For example, large number of firm is either the indicator of low barriers to entry or more competitors. Another limitation is that there are only a few observations in some industries, which make the regression results less conclusive. However, it needs to be recognised that the measures used are the best available.

The response to asset growth given industry characteristics show some evidence that overreaction to asset growth may the driver of the asset growth effect. However, this is not the direct test for overreaction explanation. Therefore, in the second chapter, I will explicitly design a test to examine the relation between degree of overreaction and the asset growth anomaly.

# Chapter 4

# Paying too Much for Growth!

# An Overreaction Explanation of the Asset Growth Anomaly

## 4.1. Introduction

Investment textbooks and financial newspapers often warn investors not to pay too much for growth (see, e.g., Penman 2012, pages 154-156). Even the most experienced of investors such as Warren Buffett can, however, make the mistake of paying too much for growth. Berkshire Hathaway's investment in the British supermarket Tesco is one of the few mistakes that Warren Buffett has admitted to making. When he invested in Tesco back in 2006, he cited the promising growth of Tesco[5].

Warren Buffet's Tesco debacle exemplifies the dangers of paying too much for growth for ordinary investors. Running parallel is a debate in the academic literature about the cause of the asset growth anomaly - the negative relationship between asset growth and subsequent stock returns (Cooper et al., 2008). What remains unclear is the driver behind this phenomenon. In this paper I study the common driver that provides a unified explanation for the industry and academic views on the growth and valuation relationship. I anchor the analysis in an accounting valuation model to understand investors' reactions to asset growth. In particular, I propose that the reason behind investors paying too much for growth (and, hence, the asset growth anomaly) is because of their expectation errors

[5] Berkshire Hathaway began building its Tesco holding in 2006 after the grocery chain announced plans for an expansion in the U.S and internationally. (http://www.warrenbuffett.com/warren-buffetts-investments-in-uk-companies/ Accessed April 2015). In the 2014 annual report, Buffet admits his mistake of investing in the company that cost Berkshire Hathaway $444 million. (http://www.berkshirehathaway.com/2014ar/2014ar.pdf accessed April 2015).

in the *trend* and *profitability* of asset growth where trend is captured by the *growth rate* and profitability by the asset turnover ratio and the net profit margin. When such expectations are not realized, there is a market correction and this induces the negative relationship between asset growth and subsequent returns.

The argument is developed as follows. Managers of a company are assumed to act to the benefit of shareholders and to only select positive NPV projects given the cash flows of the projects and the firm's discount rate. Every addition of assets to the company through these projects should add value to shareholders' wealth. Therefore, in general, asset growth increases firm value and, ceteris paribus, on the announcement of asset growth there will be an increase in the market value of the firm. This assumption is crucial for q theory or optimal investment. Otherwise, if there is an agency problem and firm managers do not make investment decisions according to net present value, there should be a weak or no relation between return and investment. As a result, one should not observe the asset growth effect. Watanabe, Xu, Yao and Yu (2013) and Titman, Wei and Xie (2013) show stronger asset growth effect in developed markets than less developed markets. This evidence may suggest that the assumption is reasonable in developed markets and therefore they have stronger effect. Importantly, the extent of this increase in the market value of the firm depends on the investors' expectations of the firm's future prospects given the additional assets and investors may overreact to asset growth in two ways.

First, in the context of accounting valuation models (such as residual income or abnormal earnings), estimating the growth rate (both in the short and long term) is an important, yet speculative, task in applying the models. This leads to the first hypothesis which I refer to as the "trend hypothesis": if investors' overestimation of the trend of asset growth is the driver of the asset growth anomaly, investors should overreact more when they expect that the current growth is more likely to continue. To test this hypothesis empirically, I need an approach to capture investors' expectation formation. It is documented that investors form expectations about growth based on their past experiences and there is a large amount of evidence that investors are prone to the representativeness bias after observing a sequence of the same signed signal[6]. In the current context investors are seen as estimating that future growth is more likely after observing a sequence of growth; the sequence of growth not only providing information regarding the future cash flows generated from the additional assets but also the future prospect of further growth in the assets. I expect, therefore, that investors will overreact more to asset growth and hence, there is a stronger asset growth anomaly in firms that experience a longer sequence of growth.

A second factor that would affect investors' assessment of the value of asset growth is the direct benefit of the asset growth on future cash flows. In other words, how much additional value can the new assets bring to the company? The accounting ratio that helps investors evaluate a company's profitability in combination with total assets is the return on assets (ROA) that can further be broken down into the asset turnover ratio (ATO) and the net profit margin (NPM). Importantly, investors do not focus on these two ratios equally given a firm's asset growth status. Aghion and Stein (2008) argue that the market places different weights on the two profitability drivers (ATO and NPM) conditional on the adopted strategy of a firm. Particularly, analysts focus more on growth related metrics when a company is in a growth phase and conversely more on per unit profitability measures in cost-cutting/efficiency phases. In this regard, for a high growth firm, the market will focus more on ATO and ignore the effect of NPM. For a firm that

[6] For example, according to Barberis et al. (1998), after a trend of good or bad news, representativeness causes investors to overreact to information and push a stock's price too high or too low. Hong and Stein (1999) argue that momentum traders make decisions conditional on past price changes; that is, momentum traders push stock prices higher (lower) when there is an up (down) trend.

has a high asset turnover ratio, the addition of new assets should have a strong effect on earnings and, therefore, residual earnings. I expect investors in firms with a higher ATO to overreact more to asset growth. In other words, as ATO increases I expect the asset growth anomaly to increase. By contrast, for a low growth firm, the market will focus more on the NPM and ignore the effect of ATO. Low asset growth and low NPM are both seen as bad news since they indicate that a firm has neither a growth nor an efficiency focus. Therefore, investors will overreact to low asset growth even more when the NPM is low. In other words, as the NPM increases I expect that the asset growth anomaly will decrease.

Using US data from 1963 to 2011, I test the above hypotheses in the following ways. First, by comparing the slope coefficients of asset growth in asset growth regressions (regressing asset growth on stock return with other control variables) for each growth sequence portfolio (from one to four years of consecutive high or low growth), I find that as the asset growth sequence lengthens the asset growth anomaly becomes stronger. This confirms that the representativeness bias is at work in predicting growth given prior sequences. Second, I show, by comparing the asset growth slope coefficients of the four portfolios of stocks sorted by their asset turnover ratio and net profit margin respectively, that stocks with a higher asset turnover ratio (low net profit margin) have a stronger asset growth anomaly in the high (low) asset growth companies. These findings support investors placing different weights on the two profitability drivers (ATO and NPM) conditional on the adopted strategy of a firm (Aghion and Stein, 2008).

I examine the robustness of the results in a number of ways. First, I study the explanatory power of growth sequences, the asset turnover ratio and the net profit margin after controlling for factors that proxy for three possible alternative explanations: limits to arbitrage, investment frictions (Q-theory - Li and Zhang, 2010) and a traditional risk explanation (Berk, et al., 1999). Following Lam and Wei (2011) I include 14 proxies. As they point out and I empirically demonstrate, these proxies are highly correlated – therefore, to maximize the information and reduce the effect of multicollinearity in the regressions, I abstract factors using principal component analysis. Furthermore, as some of the proxies are only available later on in the sample period, I abstract factors using the maximum number of available proxies in any given sample sub-period. In all of the cases, three factors are identified: a size factor, an idiosyncratic factor and an illiquidity factor. In the regressions including the three constructed factors, the growth sequence results are very robust in all the sub period analyses. The asset growth and its sequence interaction term is significant and negative, suggesting that the asset growth anomaly is stronger as the sequence lengthens. The coefficients of the asset turnover ratio and net profit margin, however, are not significant in the regressions, suggesting that their effect on the anomaly is weak and subsumed by other explanatory variables (particularly the size factor) in the regression analysis.

Second, I further test the overreaction explanation by examining the formation and correction phases around the asset growth. If the overreaction of investors to growth is the driver of the anomaly, i.e., the observed anomaly is a correction of mispricing, I should observe a price movement that leads to the formation of mispricing and such a price movement should be opposite to the post growth price movement. In other words, there should be a clear reversal pattern in the price around the portfolio formation point. To confirm this, I plot the market adjusted return for the growth deciles portfolio one year before and after the formation year. I show that the pair-up of the pre formation run-up and post formation decline are nearly perfectly ordered by asset growth deciles. For the highest asset growth portfolio, there is the largest cumulated price run-up from one year (highest return) before the portfolio formation point; this largest price run-up is associated with the largest decline in price in the post formation period (lowest return) and vice versa. This evidence provides strong support to the mispricing explanation of the anomaly.

Furthermore, for the correction phase, if the expectation error in the growth trend is the driver of the anomaly, the correction will be mainly concentrated on those firms that cannot maintain their growth trend expectations. I, therefore, examine the asset growth effect conditional on the following year's asset growth rate. I show in the post formation period that if the trend of growth, either high or low growth trend, cannot be maintained, there is a larger correction in price and a higher expectation error (the spread between the earnings announcement day [EAD] return and the non-EAD return).

This study contributes to the literature in the following ways. First, I dig deeper into the mispricing explanation of the asset growth anomaly. The importance of asset growth has been recognized formally as the investment factor in recently developed multi-factor asset pricing models such as the q-factor model by Hou, Xie and Zhang (2015) and 5-factor model by Fama and French (2015). While both mispricing and rational explanations of the asset growth factor have been proposed, much of the recent evidence in the literature has been focused on rational explanations via Q-theory and it is largely inconclusive, with mispricing as an explanation receiving a lot less attention. I identify the potential source of investors' expectation error in the use of accounting valuation models that helps to contextualize the links between valuation fundamentals and the pricing anomaly.

Second, the prior literature related to mispricing explanations mainly tests whether firms with different limits-to-arbitrage levels show different degrees of the asset growth anomaly (Lam and Wei, 2011; Watanabe et al., 2013). However, as Shleifer (2000) argues "Limited arbitrage … explains why markets may remain inefficient when perturbed by noise trader demands, but it does not tell us much about the exact form that inefficiency might take. For that, I need the second foundation of behavioural finance, namely investor sentiment: the theory of how real-world investors actually form their beliefs and valuations, and more generally their demands for securities." Ch 1, p24. The limits-to-arbitrage approach only studies the constraints to the correction of the initial mispricing, it does not explicitly analyze whether the mispricing is due to over- or under-reaction. I contribute to this line of literature by studying over-reaction to current growth as the source of the mispricing.

Third, while Cooper et al. (2008) provide some evidence on testing the over-reaction to past earnings, they do not identify the sources of the expectation errors explicitly – in contrast, I show that it is the over-reaction of investors to current growth that leads to them forming expectation errors on the trend of growth and this is the core of the asset growth anomaly. I extend the mispricing analyses of Cooper et al. (2008) with a direct investigation of the representative bias as the source of the asset growth anomaly. Importantly, I provide a direct test of the extrapolation hypothesis (Lakonishok et al., 1994) in the context of the asset growth anomaly. The mispricing analysis also takes into consideration the alternative rational explanation (Q-theory with investment frictions) that was not available to Cooper et al. (2008) at the time of their analyses.

The remainder of the chapter is organized as follows. I review the extant asset growth anomaly literature and construct the hypotheses in section 2. I describe the data and variables used in this study in section 3. In section 4 I show results for the growth sequence portfolios and asset turnover ratio, while in section 5 I present further evidence on expectation errors and corrections around asset growth. I provide conclusions in section 6.

## 4.2. Related Literatures and Hypothesis Development

### 4.2.1. Asset Growth Anomaly

The efficient market hypothesis has faced a long line of challenges from anomalies (see Schwert, 2003, for a survey). The asset growth anomaly (where subsequent returns are negatively related to asset growth) is one of the latest challenges to be investigated. Cooper, Gulen and Schill (2008) and Fama and French (2008) show that firms with high asset growth have lower future returns: that is, firms earn lower subsequent returns when they expand their assets; whereas firms earn higher subsequent returns when they experience a contraction of their assets[7]. Furthermore, as the Fama-French 3-factor model cannot explain the returns of portfolios sorted by asset growth, this negative relationship between asset growth and future stock returns at the cross sectional level is referred to as the asset growth anomaly.

Two branches of explanation are proposed in the literature: risk-based (rational) and mispricing (behavioural) explanations. Regarding the risk-based explanation, upon discovery of the asset growth anomaly, Cooper et al. (2008) test the risk based explanation and show that standard risk factors such as three factor models and the conditional CAPM model using a standard set of macroeconomic variables cannot explain the effect. More recent searches for a rational explanation shift from an investor to a firm point of view. Q-theory suggests that firms invest when the discount rate (expected return) is lower because a lower discount rate leads to a higher net present value and consequently, a negative investment-return relation is observed (e.g., Cochrane, 1991; 1996). However, such a prediction is difficult to test empirically since managerial expectations of a discount rate are unobservable and it requires the strong assumption of market efficiency to make

[7] For events associated with expansion, Loughran and Ritter (1995) show that firms with equity issuance earn lower stock returns. For events associated with contraction, Lakonishok and Vermaelen (1990) show firms with share repurchases earn higher returns.

connections between managerial expected discount rates and subsequent realized stock returns. As a way forward, Li and Zhang (2010) construct an optimal investment model by incorporating investment frictions within Q-theory. Firms with high investment frictions produce higher investment costs and are, therefore, not as sensitive to changes in the discount rate; that is, only large decreases in the discount rate can induce firms with high frictions to invest. If Q-theory is the reason behind the asset growth anomaly, it predicts that firms with higher investment frictions should show a stronger asset growth anomaly. Q-theory with investment frictions has received support in the literature; for example, Chen and Zhang (2010) develop a 3-factor model based on Q-theory and find supportive evidence[8].

A parallel development in the literature is the mispricing explanation of the asset growth anomaly. Cooper et al. (2008) argue that the asset growth anomaly reflects investor overreaction to firm growth (contraction). They find that firms that grow (contract) tend to be firms with future negative (positive) profitability shocks with respect to performance in the sorting year. Furthermore, they show that subsequent earnings announcements for low growth firms are associated with positive abnormal returns and vice versa. While the results are consistent with the La Porta, Lakonishok, Shleifer, and Vishny (1997) expectation errors mispricing story, there has been no development of this line of enquiry.

Further developments in the study of the mispricing explanation of the asset growth anomaly focus instead more on why it persists after it occurs rather than why it occurs in the first place. For example, both Li and Zhang (2010) and Lam and Wei (2011) propose that if mispricing leads to the asset growth anomaly, firms with high limits-to-arbitrage should show a stronger asset growth anomaly than firms with low limits-to-

[8] Titman, Wei and Xei (2013) and Watanabe et al. (2013) undertake cross country studies and find a stronger asset growth anomaly in more developed stock markets, this is consistent with dynamically optimal investment; that is, they find support for Q-theory.

arbitrage. The reason is that the anomaly cannot be traded away quickly and should last for longer periods when there are high limits-to-arbitrage such as high transaction costs, high stock volatility and/or little information about the firm. It is important to note that these studies do not directly study the underlining cause of the mispricing. There is an implicit assumption that mispricing occurs in the market and arbitrage fails to fully correct the mispricing.

In summary, while the literature finds support for both Q-theory with investment frictions and mispricing with limits-to arbitrage to explain the asset growth anomaly, recent studies have focused more towards the Q-theory explanation. Mispricing as an explanation of the phenomenon has received less attention since Cooper et al.'s early analysis. Importantly, recent studies on the mispricing explanation only focus on the condition of the subsequent persistence of mispricing rather than the cause of the initial pricing. This study aims to fill this void.

### 4.2.2. Investors' Expectation of Firm Growth

Concerns about investors paying too much for "growth" prospects can be dated back to the 1960s. Little (1962) and Rayner and Little (1966) argue that the implicit assumption in the growth investment philosophy is that "past growth is repeated in the future". Challenging this assumption, they empirically show that the past earnings growth has little explanatory power in terms of future growth in the UK; similar evidence is documented in the US by Lintner and Glauber (1967). This evidence concludes that 'growth' investment – investing in stocks with high historic growth is speculative. Haugen (1995) argues that good and bad quickly converge to the average; in other words, growth rates are mean reverting. This characteristic of firm growth is robust over different periods. For example, I examine the migration of firms from one asset growth group to another using

US stocks from 1963 to 2011 in Figure 4-1. I plot the average asset growth rank for stocks starting from their ranks in the formation year and for the coming ten years. I do this analysis for every year and report the average pattern in Figure 4-1. A clear mean reverting pattern is observed. Importantly, the reversion is very quick. This finding suggests that firms struggle to maintain relative growth – evidence points towards competition, economic cycles and technological shocks being the key drivers of firm growth (Klepper, 1996; Agarwal and Gort, 2002).

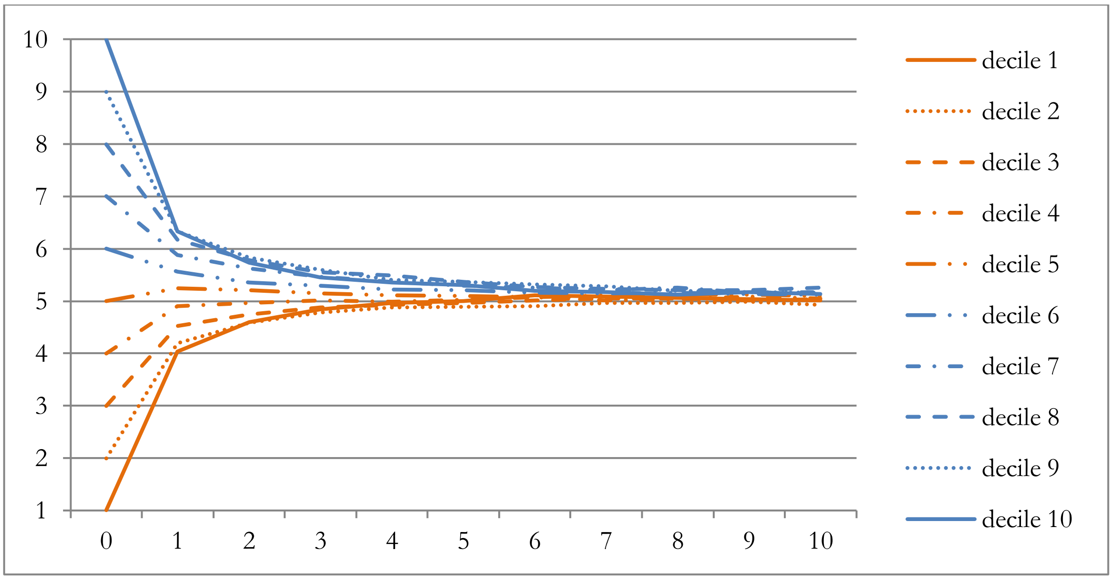
Given that firms face difficulties in maintaining their growth trend, investors are warned not to pay too much for current and historic growth (Penman, 2013)[9]. However, there is evidence that investors are excited by growth news and make investment decisions citing the further growth opportunities[10]. In forming expectations about the future, investors often rely on the historical data and are prone to the representative bias and extrapolate the current trend too far ahead into the future (Lakonishok et al., 1994; Barberis et al., 1998). Chan et al. (2003) test for persistence and predictability in earnings growth and show that while some firms have grown at high rates historically, there is no persistence in long-term earnings growth beyond chance. Yet, even the professionals are overly optimistic in their forecasts and add little predictive power - Lipson et al. (2012) find that analyst forecasts are systematically higher than realized earnings for faster growing firms.

[9] See also the example of such a warning in the industry: https://prudena.com/Risks/paying-too-much-for-growth

[10] For example, growth opportunity is the reason behind Buffet's buying and selling of Tesco's shares. (http://www.iii.co.uk/articles/124653/why-warren-buffett-sold-tesco-plc Access Jan 2014).

**Figure 4-1 Firm growth evolution**

This figure plots the average ranking of the growth deciles up to ten years after the formation year. At the end of June of each year t from 1965 to 2001, stocks are allocated into deciles based on their asset growth rates defined as the percentage change in total assets over the previous fiscal year. For each of the deciles in each formation year, the following ten years average ranking is computed. The Figure reports the average of all the formation years from 1965 to 2001.



### 4.2.3. Expectation error in the context of an accounting valuation model

In this section I borrow the residual income model from Penman (2012) and develop hypotheses concerning how investors use information about the current asset growth of a firm to form expectations about its future in the context of the residual income valuation model. Such a model provides a useful benchmark to conceptualize how market value relates to accounting data and other information (Olson, 1995). Applying it to analyze asset pricing anomalies will allow us to identify the potential source of investors' valuation errors.

I start with a simple one period perpetual growth residual income model:

$$\boldsymbol{V_0 = B_0 + \frac{RE_1}{r-g}} \quad \text{(Eq. 4-1)}$$

where $V_0$ is the equity value at time 0; $B_0$ is the book value of equity; $r$ is the required rate of return; $g$ is the growth rate; and $RE_1$ is the residual earnings in time 1 which is further defined as:

$$\boldsymbol{RE_1 = Earnings_1 - r \times B_0} \quad \text{(Eq. 4-2)}$$

where $Earnings_1$ is the comprehensive earnings at time 1. In other words, residual earnings are the earnings after charging the equity employed at the required rate of return. Equation (4-1) shows that the value of equity is equal to its book value and the present value of the future value added from the residual earnings. In order to understand how total asset growth will affect valuations I can rewrite equation (4-2) to include total assets in the following equation:

$$\boldsymbol{RE_1 = ROA_1 \times TA_0 - r \times B_0} \quad \text{(Eq. 4-3)}$$

Where $ROA_1$ is the return on assets at time 1 and $TA_0$ is total assets at time 0. And this can be further extended to

$$\boldsymbol{RE_1 = (ATO_1 \times NPM_1) \times TA_0 - r \times B_0} \quad \text{(Eq. 4-4)}$$

Where $ATO_1$ and $NPM_1$ are the asset turnover ratio and net profit margin at time 1. If I substitute equation (4-4) into equation (4-1) I have

$$\boldsymbol{V_0 = B_0 + \frac{(ATO_1 \times NPM_1) \times TA_0 - r \times B_0}{r - g}} \quad \text{(Eq. 4-5)}$$

Given this valuation model, I can pinpoint the key parameters that require investors' input for generating their valuations: $ATO_1$, $NPM_1$, $r$ and $g$. Asset growth will affect firm valuation through three types of expectations: the direct benefit of asset growth on future earnings ($ATO_1$ and $NPM_1$), the trend growth rate ($g$) and the required rate of return ($r$). I discuss these three aspects in the following paragraphs.

First, the most important (and speculative) element of the valuation model is the future growth rate (Penman 2012, chapter 5). In observing asset growth, even if investors are able to accurately estimate its immediate economic impact on firm value, their speculations on future growth, given current growth, may induce large mis-valuations. If investors wrongly believe that the high level of growth will be maintained in the future, they will overvalue the stock. In an earnings research context, Lakonishok et al. (1994) show that investors extrapolate firm performance too far into the future and, therefore, push price too high or too low causing a subsequent reversal.

Furthermore, Barberis et al. (1998) argue that investors tend to confirm a trend when they witness a growth surprise followed by another surprise and this is consistent with representativeness[11]. Therefore, the representativeness bias will induce investors to extrapolate firm level information. This suggests that the longer is the asset growth trend the stronger should be the asset growth anomaly. Specifically, when investors see a series of high (low) asset growth they believe the trend will continue and push the price to a high (low) level; and they push the price to an even higher (lower) level when the series is longer. Afterwards, when investors recognize reality and correct their valuations, the stock price reverses. As a result, a negative relation between asset growth and subsequent returns should be observed. If this is the case, the findings will tend to support overreaction as the explanation of the asset growth anomaly and, furthermore, the representativeness heuristic will be the underlying driver of the overreaction. Hence, I develop the first hypothesis.

**H1.** Firms with longer asset growth sequences should display a stronger asset growth anomaly (a negative relationship between asset growth and stock returns), ceteris paribus, than firms with shorter asset growth sequences because of the representativeness bias.

Second, regarding the estimation of the direct benefit of asset growth, Aghion and Stein (2008) argue that market valuation will place different weights on the two profitability drivers (ATO and NPM) conditional on the adopted strategy of the firm. For example, Hong and Stein (2003) demonstrate this in a case study of Amazon. They show that during the period of "… the growth phase (roughly through the end of 1999), analysts were almost uniformly focused on growth-related metrics in valuing Amazon stock, to the virtual exclusion of profitability or cost-related metrics. Conversely, during the cost-cutting phase that followed, analysts began to pay much more attention to per-unit measures of costs and profits" p. 1026, Aghion and Stein (2008). In this regard, for high growth firms,

[11] Tversky and Kahneman (1974) show representativeness as a behavioural heuristic; that is, people determine probability by using a sample that they think reflects the distribution of the population. Such a process results in the bias of over-generalizing recent observations.

the market will focus more on ATO and ignore the effect of NPM. For the firms that have a high asset turnover ratio, the addition of new assets should have a strong effect on earnings and, therefore, residual earnings. Therefore, I expect investors to react more to asset growth when firms also have a higher ATO ratio.

By contrast, according to Aghion and Stein's (2008) arguments discussed above for low growth firms, investors will focus more on the NPM and ignore the effect of ATO. Low asset growth and low NPM are both seen as bad news since they indicate that the firm is focused on neither growth nor efficiency and, therefore, investors overreact to low asset growth even more. Whereas, low asset growth with a high NPM would suggest that the firm is focusing on a cost cutting strategy. I expect that a high NPM will lead to less overreaction to the low asset growth and hence a lower AG anomaly. Overall I have the following two hypotheses:

**H2.** Firms with a higher asset turnover ratio should show a stronger asset growth anomaly (negative relation between asset growth and stock returns) than those with a lower asset turnover ratio.

**H3.** Firms with a higher net profit margin should show a weaker asset growth anomaly (negative relation between asset growth and stock returns) than those with a lower net profit margin.

Third, asset growth may affect (for the traditional risk explanation see Berk, Green and Naik, 1999) or have been conditioned (Q-theory) on the future required rate of return. Berk, Green and Naik (1999) argue that low systematic risk investment opportunities are more attractive to firms, and risk will be reduced after low risk investment because the cash flows from the investment in the future are less risky. Therefore, firms with higher investments should have lower risk of future cash flow and, therefore, lower expected returns. Their argument suggests that there is a negative relationship between asset growth and expected return.

There is another rational explanation of the asset growth anomaly which relies on the Q-theory model that studies the investment-return relationship from a production-based asset pricing or firm optimal investment standpoint (e.g., Cochrane, 1991, 1996; Chen and Zhang, 2010; Li, Livdan and Zhang, 2009; Li and Zhang, 2010). The basic argument is that firms with low discount rates (expected returns) have high net present values and high investment, whereas firms with high discount rates have low net present values and low investment. Li and Zhang (2010) show that limits-to-arbitrage dominates Q-theory in explaining the asset growth anomaly. Watanabe, Xu, Yao and Yu (2013) favour the optimal investment explanation by using global stock markets; they find that the asset growth anomaly is stronger in more advanced markets where stocks are more efficiently priced. Finally, Lam and Wei (2011) present evidence to support both limits-to-arbitrage and Q-theory. Therefore, in testing the behavioural Hypotheses 1 to 3, I have to control for the factors that are relevant to these rational explanations. I detail the discussion of the variables in the analysis section.

## 4.3. Sample and measurement

I use US data including NYSE, Amex and NASDAQ from 1963 to 2011 based on the CRSP and Compustat datasets. Monthly and daily stock returns are from CRSP and yearly or quarterly financial reporting variables are from Compustat. Also, I exclude financial firms with four-digit SIC codes between 6000 and 6999[12]. High leverage has different meaning for financial firms and non-financial firms. For financial firms, high leverage is their nature, for example, banks have large number of savings from clients. High leverage, however, is likely to indicate distress for other firms (See Fama and French, 1992). To avoid the problems of survivorship or selection biases, I follow Fama and French (1993) and Cooper et al. (2008) to retain firms with at least two years of Compustat data[13]. For some portfolio formations, I require four-years of data availability prior to the formation date. There are 134,879 firm-year observations after following the sample selection procedure. For the Fama-MacBeth regressions, I update returns monthly and asset growth or other financial variables on a yearly basis.

Following Cooper et al. (2008) I use the percentage change of a firm's assets between the current and previous year as the measure of firm asset growth. That is, firm asset growth, AG = $Asset_{t-1}/Asset_{t-2}-1$. Lipson et al. (2011) compare different definitions of asset growth and show that there is little effect on the asset growth anomaly. I discuss the construction of the other control variables in a later section.

[12] Fama and French (2008), Cooper et al. (2008) and Lam and Wei (2011) do not include financial firms in their samples when investigating the asset growth anomaly.
[13] Banz and Breen (1986) and Lam and Wei (2011) also set this requirement to select their samples in order to minimize the selection bias.

## 4.4. Analyses

### 4.4.1. The Asset Growth Anomaly Sorted by Conditional Variables

The hypothesis posits that if the asset growth anomaly is driven by overreaction, I expect the sequence of asset growth to affect the asset growth anomaly. More specifically, investors overreact to firm asset growth when they see a growth trend and as the trend becomes longer, investors overreact more.

To construct asset growth sequence portfolios I first divide firms into deciles in the June of each year based on asset growth. Then I look back to find which asset growth decile the firm is allocated to in previous years. The top two asset growth deciles are considered as the high asset growth group, while the bottom two asset growth deciles are viewed as the low asset growth group. Decile 10 is the firms with highest growth. However, maintaining high growth is difficult. I need to look back to the past five years to construct sequence portfolio. If only firms in decile 10 is considered as high asset growth, there are less observations. Therefore, I consider the top two deciles as high asset growth group. I then trace back firm asset growth to count how many consecutive years that a firm stays in the high (low) two deciles. Trends 1 to 4 denote the portfolios of firms that have 1 to 4 consecutive years of high (low) growth. Panel A of Table 4-1 demonstrates the process of eight portfolios. They are [+], [++], [+++], [++++], [-], [--], [---] and [----] (x indicates that the asset growth trend has stopped; for high (low) asset growth, either medium asset growth or low (high) asset growth will interrupt the trend).

To examine whether the anomaly increases with an increase in the length of the asset growth trend, I examine the difference between the high and low asset growth portfolios' equal weighted average monthly returns in the next 12 months. Further, I examine the slope of the asset growth regression in each portfolio. I only report equal weighted return in Table 4-1 because the regression analysis in Table 4-1 considers firm size as one of the control variables. The results of equal weighted return and slope from the regression are consistent. Therefore, firm size cannot change the conclusion.

Panel B of Table 4-1 shows the return pattern of the growth trend portfolios. The evidence is consistent with investors behaving according to the representativeness heuristic. The anomaly measured by the differences between the low and high growth portfolios (Return Spread) are statistically significant and positive. Importantly, the return spreads, hence the anomaly, are monotonically increasing as the length of the asset growth sequence increases. The difference between Trends 4 and 1 is highly significant and economically important. It suggests that investing in the high-low growth hedge return in stocks with 4 consecutive high/low growth sequences will earn an annualized 9.5% more than investing in the hedge portfolios with only 1 growth sequence.

For the second test reported in Panel B of Table 4-1, I study the effect of asset growth in a Fama-MacBeth regression. Within each asset growth sequence portfolio, I employ a Fama-MacBeth regression that controls for the natural logarithm of market value, the natural logarithm of the book-to-market ratio and the previous six months of returns[14]. The mean slope coefficient is reported in the 'Asset growth Slope Coefficient' column in Table 4-1. The asset growth coefficients are negative and significant confirming the asset growth anomaly in each sub-Trend portfolio. Consistent with the return analysis, the magnitudes of the slope coefficient are monotonically increasing - suggesting an increase in the anomaly as the length of the trend increases. Overall, the analyses in Table 4-1 show

[14] The sample with total asset data is from the fiscal year 1963. This enables us to calculate asset growth from the fiscal year 1964. When I analyze growth sequence data, I require at least five years of data; therefore, I start the analysis from the fiscal year 1968. Furthermore, because I need the return data in the subsequent year, I conduct the regression from the calendar year 1969.

evidence to support the first hypothesis that the asset growth anomaly is stronger for firms with a longer sequence of asset growth.

### 4.4.2 The Asset Turnover Ratio, the Net Profit Margin and the Asset Growth Anomaly

I have four groups of sequence portfolios in Table 4-1 and to make it consistent I also divide firms into four groups in Table 4-2. Table 4-2 reports the asset growth anomaly conditional on the asset turnover ratio and net profit margin ranked in quartiles. The ATOs are calculated as sales divided by average total assets. The NPMs are calculated as income before extraordinary items divided by sales[15]. The Hypotheses 2 and 3 posit that there is an asymmetric focus on the two profitability drivers conditional on the firm's growth status. I, therefore, report the slopes of the asset growth anomaly for both low and high asset growth firms. Table 4-2 presents strong support for the hypotheses. Particularly, Panel A shows that the asset growth anomaly is affected by the ATO sorting in the high asset growth portfolios but not in the low asset growth portfolios. The difference between the highest and lowest ATO portfolios is negative and only significant for the high asset growth portfolios. This confirms that the anomaly increases (the slopes become more negative) with ATO in high growth firms. When observing high growth, investors turn their focus to the growth metric of ATO. A higher ATO amplifies the good news of high growth and there is, therefore, more overreaction that leads to subsequent market corrections when a firm's performance cannot live up to these expectations.

[15] In this regard, I start the analysis on the 2nd year of the sample (1964) since I need two years of accounting data and the availability of accounting data has a one year lag. Furthermore, because I need the return data in the subsequent year, I run the regression from the calendar year 1965.

**Table 4-1 Asset growth trends and the asset growth anomaly**
This table presents returns and the asset growth anomaly for growth trend portfolios. The sample period is 1963 to 2011.To identify growth trends, I require firms with at least five years of asset growth and I first sort firms into deciles based on their asset growth rate at the end of June in each year; and define the top two deciles as high asset growth and the bottom two deciles as low asset growth. I then trace back firm asset growth to count how many consecutive years that a firm stays in the high (low) two deciles. Trends 1 to 4 denote the portfolios of firms that have consecutive 1 to 4 years of high (low) growth. Return Spread is the mean monthly return difference between the low and high growth portfolio. The asset growth slope coefficient reports the average of monthly coefficients from cross sectional regressions from July 1969 to December 2011 with 510 months. The cross sectional regression is the regression of monthly return between July of year t and June of year t+1 on the natural log of gross asset growth with control variables of the natural log of book-to-market ratio, the natural log of market value and the past six month returns in year t-1. Diff(4-1) reports the difference between the portfolios of Trend 4 and Trend 1. The t-values are in parentheses; *, **, and *** indicate the significance level at 0.10, 0.05 and 0.01.

**Panel A. Formation of growth trend portfolio**

| Trend | t | t-1 | t-2 | t-3 | t-4 |
|---|---|---|---|---|---|
| 1 | + | x | | | |
| 2 | + | + | x | | |
| 3 | + | + | + | x | |
| 4 | + | + | + | + | x |
| | | | | | |
| 1 | - | x | | | |
| 2 | - | - | x | | |
| 3 | - | - | - | x | |
| 4 | - | - | - | - | x |

**Panel B. Asset growth effect in different trend portfolios**

| Trend | Return Spread (Low - High) | Asset Growth Slope Coefficient |
|---|---|---|
| 1 | 0.0086*** | -0.0089*** |
| | (6.53) | (-6.12) |
| 2 | 0.0136*** | -0.0104*** |
| | (6.59) | (-4.47) |
| 3 | 0.0166*** | -0.0118*** |
| | (5.36) | (-2.75) |
| 4 | 0.0227*** | -0.0190*** |
| | (6.73) | (-3.25) |
| Diff(4-1) | 0.0141*** | -0.0101* |
| | (4.76) | (-1.69) |

In contrast, Panel B in Table 4-2 shows that the asset growth anomaly decreases (the slope become less negative) with the NPM rank (although they are not monotonic, the trend is that the asset growth effect is weaker) and such an effect is only found to be significant in the low asset growth portfolios. This suggests that when observing companies with low growth, investors turn their focus to a per-unit profit measure such as NPM. Low asset growth (seen as bad news) is amplified by low NPM (less profitable or efficient in cost cutting) and, therefore, investors overreact more to the low asset growth news. This leads to the largest price reversal (most negative slope) in the low asset growth and low NPM portfolios.

Finally, for the full sample result, the sequences in the ATO and NPM ranks are consistent with the high and low asset growth sequences, respectively, as discussed above. Specifically, the asset growth slopes become more (less) negative as ATO (NPM) increases. Overall, these results support Hypotheses 2 and 3 that investors place different weights on the two profitability drivers – such that the asset growth anomaly increases with ATO and decreases with NPM.

**Table 4-2 The asset turnover ratio, the net profit margin and the asset growth anomaly**
This table reports the asset growth anomaly conditional on the asset turnover ratio (Panel A) and net profit margin (Panel B). At the end of June in each year, firms are divided into quartiles based on their asset turnover ratio and net profit margin and also divided into deciles based on their asset growth rate. The asset turnover ratio (ATO) is sales scaled by the average of total assets. Net profit margin (NPM) is income before extraordinary items divided by sales. For each asset turnover ratio quartile, the asset growth anomaly is measured by slope. The ATO (NPM) column reports the average ATO (NPM). The slope is the average of coefficients from cross sectional regressions from July 1965 to December 2011 (558 months). The cross sectional regression is the regression of monthly return between July of year t and June of year t+1 on the natural log of gross asset growth with control variables of the natural log of book-to-market ratio, the natural log of market value and the past six month returns in year t-1. The slope differences between the high and low ATO (NPM) groups are tested [diff(4-1)]. The t-values are in parentheses; *, **, and *** indicate the significance level at 0.10, 0.05 and 0.01. N is the firm-year observations.

**Panel A. Asset growth slope conditional on asset turnover**

| ATO rank | Low asset growth slope | High asset growth slope | Full sample slope | N |
|---|---|---|---|---|
| 1 (lowest) | -0.0077* | -0.0045** | -0.0065*** | 40915 |
| | (-1.80) | (-2.55) | (-4.87) | |
| 2 | -0.0112** | -0.0095*** | -0.0120*** | 40936 |
| | (-2.41) | (-4.66) | (-7.26) | |
| 3 | -0.0117** | -0.0088*** | -0.0113*** | 40948 |
| | (-2.24) | (-4.26) | (-6.59) | |
| 4 (highest) | -0.0084 | -0.0124*** | -0.0128*** | 40930 |
| | (-1.49) | (-6.46) | (-8.29) | |
| diff(4-1) | -0.0006 | -0.0079*** | -0.0063*** | |
| | (-0.09) | (-3.04) | (-3.06) | |

**Panel B. Asset growth slope conditional on net profit margin**

| NPM rank | Low asset growth slope | High asset growth slope | Full sample slope | N |
|---|---|---|---|---|
| 1 (lowest) | -0.0128*** | -0.0080*** | -0.0125*** | 40773 |
| | (-3.73) | (-3.29) | (-8.45) | |
| 2 | -0.0050 | -0.0116*** | -0.0135*** | 40796 |
| | (-1.13) | (-5.74) | (-9.09) | |
| 3 | -0.0054 | -0.0131*** | -0.0113*** | 40811 |
| | (-1.09) | (-6.72) | (-6.73) | |
| 4 (highest) | 0.0005 | -0.0047** | -0.0043** | 40782 |
| | (0.11) | (-2.32) | (-2.17) | |
| diff(4-1) | 0.0133** | 0.0033 | 0.0082*** | |
| | (2.24) | (1.44) | (3.30) | |

### 4.4.3. Regression Analyses

The analyses in the previous two sub-sections provide supporting evidence to the three hypotheses in a univariate framework through sorting. In this sub-section, I test the hypotheses via regression analysis in order to control for existing risk and limits-to-arbitrage measures. To this end, I perform Fama-MacBeth regressions of monthly returns on asset growth, interacting between the asset growth sequence, asset turnover, limits-to-arbitrage and investment friction proxies. In addition, the regular control for cross-sectional variations of return such as firm size, the book-to-market ratio, beta and prior six-month returns are included in the regression.

Two important considerations in the empirical setup are worth noting. First, in selecting the proxy it is a challenging task to identify proxies that are unique in capturing either limits-to-arbitrage or investment frictions (for testing Q-theory). For example, Watanabe et al. (2013) note that these two groups of variables are closely related. Lam and Wei (2011) present a comprehensive list of 14 proxy variables. The definition and source of the proxy variable construction used in this study is given in Table 4-3. To address the potential multicollinearity issue, the prior literature controls for limits-to-arbitrage and investment friction proxies separately (see, e.g., Watanabe et al. 2013) or uses each proxy variable separately to sort the data into portfolios and compare the asset growth slope among the portfolios (Li and Zhang, 2010; Lam and Wei, 2011). However, these approaches suffer from an omitted variable problem and ignore factors that are known to be important in this research domain. In order to maximize the information content while reducing multicollinearity in the analysis, I use principal components to extract common factors among the proxies (see, e.g., Zhang, Cai and Keasey, 2013) and examine the interactive effect of these factors on the asset growth slope coefficients in the Fama-

MacBeth regressions[16]. Second, the inclusion of some of the proxy variables would dramatically reduce the sample size (for example, analyst coverage [COV] and analyst dispersion [DISP] are available from 1976; institutional ownership [INSTOWN] and the number of institutional shareholders [INSTN] are available from 1980, and Bid-ask spread [BAS] is available from 1993) and, therefore, the use of the full list of control variables would mean a large reduction in the sample. In order to examine the robustness of the result for the whole period, I conduct analysis in sub periods that include different numbers of control variables while maximizing the sample period length.

Table 4-4 reports the descriptive statistics and correlations for the proxies. The descriptive statistics are comparable to those in the existing literature (Zhang, 2006; Lam and Wei, 2011). Panel B confirms that there are many high correlations among the variables especially when the nonparametric correlation (Spearman Rank correlations above the diagonal of the table) is considered. Table 4-5 reports the factor analysis for two sub periods. Panel A reports the analysis for the full sample from 1968 for which nine proxies are available. The eigenvalues of the correlation matrix suggests that three factors, having an eigenvalue larger than 1, are sufficient to capture the variation of the data. The rotated pattern in Panel A2 provides a clear economic grouping of the variables. Factor1, which captures the largest contribution to the variance, is a size factor including characteristics that are highly correlated with total assets, trading volume, the likelihood of having a credit rating, price level and the age of the firm. These include both investment frictions and transaction cost proxies classified in previous literature.

[16] Fama and French (2008) argue that sorts can capture stock return patterns based on an anomaly variable but sorts cannot show the marginal effect and the unique information of an anomaly variable. Regression is one solution to this shortcoming of sorts.

**Table 4-3 Summary of limits-to-arbitrage and investment friction proxies**
This table reports the definition of investment and limits-to-arbitrage proxies, the data sources and references. The proxies of limits-to-arbitrage are also grouped into different categories: arbitrage risk, information uncertainty and transaction cost.

| Category | Proxy | Definition | Periods | Data source | Studies |
|---|---|---|---|---|---|
| Panel A: Limits-to-arbitrage | | | | | |
| Arbitrage risk | IVOL | **Idiosyncratic volatility** is the standard deviation of the error term from regressions of monthly stock return on the market index return in a 36-month window at the end of June in each year | 1963-2011 | CRSP | Mashruwala et al.(2006)<br>Li and Zhang(2010)<br>Lam and Wei(2011) |
| | INSTN | **Number of institutional shareholders** is the number of institutional investors of a firm at the end of June in each year | 1980-2011 | Institutional Holdings (13F) | Ali et al.(2003)<br>Lam and Wei(2011) |
| Information uncertainty | COV | **Analyst coverage** is the number of analysts of a firm making annual earnings forecasts at June in each year | 1976-2011 | I/B/E/S | Zhang(2006)<br>Lam and Wei(2011)<br>Zhang et al.(2013) |
| | DISP | **Dispersion** is the standard deviation of annual earnings per share forecast scaled by stock price at the end of June in each year | 1976-2011 | I/B/E/S | Zhang(2006)<br>Lam and Wei(2011)<br>Zhang et al.(2013) |
| | CVOL | **Cash flow volatility** is the standard deviation of cash flow in the past 5 years window (at least three years if five years of data are not available). Cash flow is earnings before extraordinary items minus total accruals, scaled by average total assets. Total accruals is the change in current assets less the change in cash, the change in current liabilities, and depreciation plus the change in short-term debt | 1963-2011 | Compustat | Zhang(2006)<br>Lam and Wei(2011) |
| Transaction cost | lnDVOL | **Dollar trading volume** is the average of monthly dollar trading volume in the past 12 months before the end of June in each year. Monthly dollar trading volume is the monthly volume multiplied by monthly closing price | 1963-2011 | CRSP | Li and Zhang(2010)<br>Lam and Wei(2011) |
| | ILLIQ | **Illiquidity** is the average of absolute daily returns divided by daily dollar trading volume in the past one year before the end of | 1963-2011 | CRSP | Amihud(2002)<br>Lam and Wei(2011) |

| | | | | |
|---|---|---|---|---|
| | June in each year. Daily dollar trading volume is the daily volume multiplied by daily closing price | | | |
| PRICE | **Price** is the closing share price at the end of June in each year | 1963-2011 | CRSP | Stoll(2000)<br>Lam and Wei(2011) |
| INSTOWN | **Institutional ownership** is the shares held by institutional investors divided by outstanding shares at the end of June in each year | 1980-2011 | Institutional Holdings (13F) | Nagel(2005)<br>Lam and Wei(2011) |
| BAS | **Bid-ask spread** is the average of monthly bid-ask spread in the past 12 months at the end of June in each year. Monthly bid-ask spread is computed as $2\times\left\lvert\frac{price(ask+bid)}{2}\right\rvert/price$ | 1993-2011 | CRSP | Saffi and Sigurdsson(2010)<br>Lam and Wei(2011) |
| Panel B: Investment frictions | | | | |
| lnASSET | **Total asset** is a firm's total assets in the previous fiscal year | 1963-2011 | Compustat | Li and Zhang(2010)<br>Lam and Wei(2011) |
| AGE | **Age** is the number of years a firm exists in CRSP at the end of June in each year | 1963-2011 | CRSP | Zhang(2006)<br>Lam and Wei(2011)<br>Zhang et al.(2013) |
| RATING | **Credit rating** is a dummy variable. It equals one if a firm has a Standard & Poor's long-term credit rating in Compustat in the sample period and zero if a firm never has a rating | 1963-2011 | Compustat | Lam and Wei(2011) |
| PAYOUT | **Payout rank** is the tercile ranking of the payout ratio. The payout ratio is a firm's payout divided by operating income before depreciation. Payout includes share repurchases, dividends to preferred stock, and dividends to common stock. Firms with earnings less than or equal to zero but positive distributions are in the high payout ratio tercile, while firms with earnings less than or equal to zero but zero distributions are in the low payout ratio tercile. | 1963-2011 | Compustat | Li and Zhang(2010)<br>Lam and Wei(2011) |

**Table 4-4 Descriptive statistics and correlations**
This table reports descriptive statistics and correlations of the ten limits-to-arbitrage proxies and four investment friction proxies (see definition of proxies in Table 4-3). Analyst coverage (COV) and analyst dispersion (DISP) are included from 1976. Institutional ownership (INSTOWN) and the number of institutional shareholders (INSTN) are included from 1980. Bid-ask spread (BAS) is included from 1993. Panel A reports descriptive statistics and Panel B reports the correlation matrix, below the diagonal are Pearson correlations and above the diagonal are Spearman Rank correlations.

**Panel A. Descriptive statistics**

| | | Mean | Min | Median | Max | Std | N |
|---|---|---|---|---|---|---|---|
| Arbitrage risk | IVOL | 0.129 | 0.013 | 0.110 | 2.232 | 0.083 | 85670 |
| | INSTN | 138.708 | 1 | 92 | 1651 | 160.616 | 37726 |
| Information uncertainty | DISP | 0.008 | 0 | 0.002 | 2.523 | 0.037 | 39178 |
| | COV | 8.947 | 2 | 7 | 54 | 7.202 | 39178 |
| | CVOL | 0.092 | 0.001 | 0.063 | 12.451 | 0.146 | 85670 |
| Transaction cost | lnDVOL | 11.329 | 0.616 | 11.221 | 20.988 | 2.862 | 85670 |
| | BAS | 0.007 | 0 | 0.004 | 0.273 | 0.009 | 26875 |
| | ILLIQ | $7.04\times10^{-6}$ | $1.85\times10^{-12}$ | $1.01\times10^{-7}$ | $2.29\times10^{-2}$ | $1.26\times10^{-4}$ | 85670 |
| | INSTOWN | 0.545 | 5.7E-06 | 0.554 | 4.932 | 0.273 | 37726 |
| | PRICE | 20.606 | 0.031 | 14.750 | 2418.000 | 27.314 | 85670 |
| Investment frictions | lnASSET | 5.438 | -2.071 | 5.281 | 12.795 | 2.102 | 85670 |
| | AGE | 19.507 | 5 | 14 | 86 | 15.019 | 85670 |
| | RATING | 0.419 | 0 | 0 | 1 | 0.493 | 85670 |
| | PAYOUT | 1.073 | 0 | 1 | 2 | 0.851 | 85670 |

**Table 4-4 (continued)**

**Panel B. Correlation matrix**

| | IVOL | INSTN | DISP | COV | CVOL | lnDVOL | BAS | ILLIQ | INSTOWN | PRICE | lnASSET | AGE | RATING | PAYOUT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IVOL | 1.00 | -0.28 | 0.29 | -0.30 | 0.55 | -0.26 | 0.50 | 0.39 | -0.24 | -0.63 | -0.51 | -0.40 | -0.38 | -0.49 |
| INSTN | -0.23 | 1.00 | -0.29 | 0.73 | -0.24 | 0.70 | -0.67 | -0.69 | 0.81 | 0.52 | 0.59 | 0.24 | 0.32 | 0.16 |
| DISP | 0.09 | -0.05 | 1.00 | -0.18 | 0.21 | -0.20 | 0.21 | 0.23 | -0.19 | -0.51 | -0.09 | -0.09 | -0.10 | -0.12 |
| COV | -0.25 | 0.66 | -0.05 | 1.00 | -0.23 | 0.71 | -0.55 | -0.72 | 0.47 | 0.50 | 0.62 | 0.23 | 0.42 | 0.17 |
| CVOL | 0.30 | -0.09 | 0.07 | -0.07 | 1.00 | -0.23 | 0.36 | 0.30 | -0.21 | -0.45 | -0.45 | -0.29 | -0.32 | -0.29 |
| lnDVOL | -0.21 | 0.66 | -0.06 | 0.66 | -0.07 | 1.00 | -0.78 | -0.97 | 0.73 | 0.63 | 0.78 | 0.23 | 0.46 | 0.17 |
| BAS | 0.35 | -0.29 | 0.16 | -0.35 | 0.08 | -0.53 | 1.00 | 0.83 | -0.61 | -0.71 | -0.71 | -0.27 | -0.42 | -0.25 |
| ILLIQ | 0.08 | -0.03 | 0.05 | -0.07 | 0.03 | -0.12 | 0.15 | 1.00 | -0.72 | -0.70 | -0.82 | -0.29 | -0.50 | -0.24 |
| INSTOWN | -0.14 | 0.33 | -0.06 | 0.34 | -0.06 | 0.47 | -0.25 | -0.05 | 1.00 | 0.50 | 0.57 | 0.20 | 0.33 | 0.12 |
| PRICE | -0.29 | 0.35 | -0.08 | 0.39 | -0.11 | 0.42 | -0.24 | -0.04 | 0.17 | 1.00 | 0.66 | 0.34 | 0.45 | 0.36 |
| lnASSET | -0.43 | 0.60 | -0.02 | 0.58 | -0.18 | 0.78 | -0.47 | -0.08 | 0.35 | 0.44 | 1.00 | 0.39 | 0.64 | 0.32 |
| AGE | -0.30 | 0.39 | -0.02 | 0.30 | -0.09 | 0.31 | -0.19 | -0.02 | 0.13 | 0.26 | 0.45 | 1.00 | 0.29 | 0.29 |
| RATING | -0.31 | 0.37 | -0.01 | 0.39 | -0.12 | 0.46 | -0.28 | -0.04 | 0.21 | 0.29 | 0.63 | 0.33 | 1.00 | 0.23 |
| PAYOUT | -0.38 | 0.20 | -0.02 | 0.18 | -0.11 | 0.18 | -0.17 | -0.04 | 0.07 | 0.21 | 0.32 | 0.28 | 0.23 | 1.00 |

**Table 4-5 Factor analysis**

This table reports the summary of the factor analysis on the ten limits-to-arbitrage proxies and the four investment friction proxies (see the definition of proxies in Table 4-3). Analyst coverage (COV) and analyst dispersion (DISP) are included from 1976. Institutional ownership (INSTOWN) and the number of institutional shareholders (INSTN) are included from 1980. Bid-ask spread (BAS) is included from 1993. Panels A and B report the factor analysis for 9 and 14 proxies, respectively. For each factor analysis, eigenvalues and rotated factor patterns are reported.

**Panel A. 9 proxies from 1968**

Panel A1. Eigenvalues of the correlation matrix

| Factors | Eigenvalue | Difference | Proportion |
|---|---|---|---|
| 1 | 3.318 | 2.190 | 0.369 |
| 2 | 1.128 | 0.127 | 0.125 |
| 3 | 1.001 | 0.117 | 0.111 |
| 4 | 0.884 | 0.129 | 0.098 |
| 5 | 0.755 | 0.082 | 0.084 |
| 6 | 0.672 | 0.088 | 0.075 |
| 7 | 0.584 | 0.075 | 0.065 |
| 8 | 0.509 | 0.360 | 0.057 |
| 9 | 0.149 | 0.000 | 0.017 |

Panel A2. Rotated factor pattern

| Variables | Factor1 | Factor2 | Factor3 | Final Communality Estimates |
|---|---|---|---|---|
| lnASSET | 0.886 | -0.255 | -0.044 | 0.852 |
| lnDVOL | 0.877 | 0.037 | -0.120 | 0.785 |
| RATING | 0.712 | -0.187 | 0.020 | 0.542 |
| PRICE | 0.581 | -0.193 | -0.002 | 0.374 |
| AGE | 0.469 | -0.393 | 0.142 | 0.395 |
| IVOL | -0.276 | 0.736 | 0.045 | 0.619 |
| CVOL | -0.011 | 0.660 | 0.107 | 0.448 |
| PAYOUT | 0.195 | -0.656 | 0.073 | 0.474 |
| ILLIQ | -0.051 | 0.052 | 0.976 | 0.958 |
| | | | | |
| Variance explained | 2.735 | 1.704 | 1.009 | 5.447 |

**Table 4-5 (continued)**

**Panel B. 14 proxies from 1993**

Panel B1. Eigenvalues of the correlation matrix

| Factors | Eigenvalue | Difference | Proportion |
|---|---|---|---|
| 1 | 4.825 | 3.320 | 0.345 |
| 2 | 1.505 | 0.299 | 0.108 |
| 3 | 1.206 | 0.224 | 0.086 |
| 4 | 0.981 | 0.098 | 0.070 |
| 5 | 0.884 | 0.058 | 0.063 |
| 6 | 0.826 | 0.071 | 0.059 |
| 7 | 0.755 | 0.091 | 0.054 |
| 8 | 0.664 | 0.020 | 0.047 |
| 9 | 0.644 | 0.094 | 0.046 |
| 10 | 0.549 | 0.024 | 0.039 |
| 11 | 0.525 | 0.212 | 0.038 |
| 12 | 0.313 | 0.115 | 0.022 |
| 13 | 0.198 | 0.072 | 0.014 |
| 14 | 0.126 | 0.000 | 0.009 |

Panel B2. Rotated factor pattern

| Variables | Factor1 | Factor2 | Factor3 | Final Communality Estimates |
|---|---|---|---|---|
| lnDVOL | 0.862 | 0.016 | -0.371 | 0.881 |
| INSTN | 0.848 | -0.164 | -0.099 | 0.756 |
| lnASSET | 0.804 | -0.372 | -0.049 | 0.788 |
| COV | 0.785 | 0.007 | -0.146 | 0.638 |
| RATING | 0.585 | -0.297 | 0.129 | 0.447 |
| PRICE | 0.509 | -0.294 | -0.267 | 0.417 |
| AGE | 0.460 | -0.457 | 0.090 | 0.428 |
| IVOL | -0.196 | 0.757 | 0.148 | 0.633 |
| CVOL | -0.014 | 0.640 | 0.125 | 0.425 |
| PAYOUT | 0.198 | -0.615 | 0.070 | 0.422 |
| BAS | -0.429 | 0.120 | 0.633 | 0.600 |
| DISP | 0.116 | 0.244 | 0.577 | 0.406 |
| ILLIQ | -0.014 | -0.008 | 0.470 | 0.221 |
| INSTOWN | 0.296 | 0.122 | -0.609 | 0.473 |
| Variance explained | 3.902 | 1.997 | 1.637 | 7.535 |

The second factor captures firm specific risk including idiosyncratic volatility, cash flow volatility and the payout ratio. The last factor is the illiquidity factor of the stock.

Panel B reports the analyses for 14 proxies from 1993. The factors and loading factors are relatively stable when additional proxies are added and a shorter sample period is used. The three factors mentioned above are identified by this factor analyses and the additional proxies are absorbed by factor1 (the size factor) and factor3 (the illiquidity factor).

With the newly constructed factors, I run the following cross sectional regression for each month:

$$\boldsymbol{Ret_{i,t} = \alpha + \beta \ln(1 + AG)_{i,t-1} + \varphi_1 \ln(1 + AG)_{i,t-1} \times SEQ_{i,t-1} + \varphi_2 \ln(1 + AG)_{i,t-1} \times ATO\ rank_{i,t-1} + \varphi_3 \ln(1 + AG)_{i,t-1} \times NPM\ rank_{i,t-1} + \sum_{j=1}^{3} \gamma_j \ln(1 + AG)_{i,t-1} \times Factor_{i,j,t-1} + \sum_{k=1}^{3} \theta_k Control_{i,k,t-1} + \varepsilon_{i,t}} \quad \text{(Eq. 4-6)}$$

Where $Ret$ is the monthly return between July of year t and June of year t+1; AG is asset growth ($Asset_{t-1}/Asset_{t-2}$-1) that updates on an annual basis; Sequence (SEQ) is the length of consecutive years of high (top two growth deciles) or low (bottom two growth deciles) growth, and zero otherwise; ATO rank is the asset turnover ratio rank (from 0-lowest to 3-highest); NPM rank is the net profit margin rank (from 0-lowest to 3-highest); and $Factor_i$ are the three factors constructed in Table 4-5; control variables include all the variables that are interactive with the asset growth, the natural logarithm of market value (lnMV), the natural logarithm of the book-to-market ratio (lnBM), systematic risk (Beta) and the prior six month returns (Pre6ret) – all of which are widely used predictors of cross sectional returns. I estimate the above model for different subsamples and the full sample where the maximum amount of proxy data is available.

Table 4-6 reports the regression results. In the baseline models 1 and 2 I do not add controls for the limits-to-arbitrage and investment friction proxies. The results confirm that there is a significant negative relationship between asset growth and subsequent returns. Such a negative relationship is deepened when a longer sequence of a consecutive growth pattern is observed. The coefficient for the asset growth and sequence interactive term is negative and highly significant in Model 2. Furthermore, consistent with the sorting results, increases in asset turnover deepen the negative relationship between asset growth and return, while increases in the net profit margin have an opposite effect on the anomaly. These result provide further support to the three hypotheses.

When proxies of investment friction and limits-to-arbitrage are taken into consideration, the results in Models 3 to 6 demonstrate consistent evidence that the length of the sequence of the growth pattern is important in terms of the growth anomaly. The coefficients are significant and negative. For the asset turnover ratio and the net profit margin variables, the coefficients for their interaction with asset growth are with the same signs as in the baseline model. However, only the coefficient for the net profit margin interactive term is statistically significant in Model 4 where 9 proxies are used. These results suggest that the effect of asset turnover and net profit margin play a less important role in affecting the anomaly after controlling for other factors.

**Table 4-6 Fama-MacBeth regression: growth sequence, asset turnover ratio, net profit margin, limits-to-arbitrage and investment frictions**

This table reports the time-series average of estimated coefficients of monthly regressions. In each month I run the following regression:

$$Ret_{i,t} = \alpha + \beta \ln(1+AG)_{i,t-1} + \varphi_1 \ln(1+AG)_{i,t-1} \times SEQ_{i,t-1} + \varphi_2 \ln(1+AG)_{i,t-1} \times ATO\ rank_{i,t-1} + \varphi_3 \ln(1+AG)_{i,t-1} \times NPM\ rank_{i,t-1} + \sum_{j=1}^{3} \gamma_j \ln(1+AG)_{i,t-1} \times Factor_{i,j,t-1} + \sum_{k=1}^{3} \theta_k Control_{i,k,t-1} + \varepsilon_{i,t}$$

Where $Ret$ is the monthly return between July of year t and June of year t+1; AG is firm asset growth; sequence (SEQ) indicates the length of asset growth sequence (from 1-shortest to 4-longest); asset turnover ratio ranking (ATOrank) is measured by ranking firms into quartiles in each year (from 0-lowest to 3-highest) based on asset turnover ratio. Asset turnover ratio is sales scaled by average total assets; net profit margin ranking (NPMrank) is measured by ranking firms into quartiles in each year (from 0-lowest to 3-highest) based on net profit margin. Net profit margin is income before extraordinary items scaled by sales. Model 1 to Model 4 are the baseline regressions without controlling for limits-to-arbitrage and investment frictions factors. Models 5 to 6 report the interactive effect of both the growth sequence and the asset turnover rank with asset growth by controlling for limits-to-arbitrage and investment friction proxies. The three factors--Factor 1, Factor 2 and Factor 3 are extracted from limits-to-arbitrage and investment friction proxies. There are two versions of factors based on the number of proxies used in different models. Model 3(4) and Model 5(6) use 9 and 14 proxies, respectively (see Table 4-5 for detailed factor analysis). Control variables include all the variables that are interactive with the asset growth, the natural logarithm of market capitalization (lnMV), the natural logarithm of the book-to-market ratio (lnBM), rolling beta based on past 36-month ending at the end of June (Beta) and the previous 6-month returns at the end of June (Pre6ret). The t-values are reported in parentheses; *, **, and *** indicate the significance level at 0.10, 0.05 and 0.01.

**Table 4-6 (continued)**

| | Baseline | | 9 proxies | | 14 proxies | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| Intercept | 0.0182*** | 0.0156*** | 0.0129*** | 0.0110*** | 0.0126*** | 0.0117*** |
| | (5.84) | (4.53) | (5.93) | (4.24) | (3.74) | (2.92) |
| ln(1+AG) | -0.0106*** | -0.0070*** | -0.0074*** | -0.0060* | -0.0067*** | -0.0036 |
| | (-7.88) | (-2.78) | (-4.55) | (-1.83) | (-3.62) | (-1.01) |
| ln(1+AG)×SEQ | | -0.0027*** | | -0.0026** | | -0.0030** |
| | | (-2.89) | | (-2.13) | | (-1.99) |
| ln(1+AG)×ATOrank | | -0.0022*** | | -0.0015 | | -0.0013 |
| | | (-2.82) | | (-1.44) | | (-1.09) |
| ln(1+AG)×NPMrank | | 0.0018* | | 0.0023** | | 0.0016 |
| | | (1.79) | | (2.08) | | (1.30) |
| SEQ | | 0.0001 | | -0.0001 | | -0.0001 |
| | | (0.38) | | (-0.40) | | (-0.15) |
| ATOrank | | 0.0009*** | | 0.0009** | | 0.0005 |
| | | (2.64) | | (2.30) | | (0.62) |
| NPMrank | | 0.0008* | | 0.0004 | | -0.0001 |
| | | (1.79) | | (1.06) | | (-0.15) |
| ln(1+AG)×Factor 1 | | | 0.0044*** | 0.0036*** | 0.0034** | 0.0036*** |
| | | | (3.35) | (2.58) | (2.45) | (2.59) |
| ln(1+AG)×Factor 2 | | | -0.0010 | -0.0001 | -0.0018 | -0.0010 |
| | | | (-0.63) | (-0.06) | (-1.37) | (-0.69) |
| ln(1+AG)×Factor 3 | | | 0.0005 | 0.0011 | -0.0006 | -0.0006 |
| | | | (0.10) | (0.18) | (-0.31) | (-0.32) |
| Factor 1 | | | -0.0018** | -0.0018*** | -0.0013* | -0.0013* |
| | | | (-2.48) | (-2.58) | (-1.64) | (-1.69) |
| Factor 2 | | | 0.0003 | 0.0008 | 0.0019 | 0.0018 |
| | | | (0.30) | (0.83) | (1.35) | (1.37) |
| Factor 3 | | | 0.0042** | 0.0051*** | 0.0014 | 0.0014 |
| | | | (2.25) | (2.80) | (1.50) | (1.49) |
| lnBM | 0.0014*** | 0.0015*** | 0.0014*** | 0.0016*** | 0.0000 | -0.0000 |
| | (3.20) | (3.54) | (4.05) | (4.58) | (0.06) | (-0.06) |
| Beta | 0.0005 | 0.0007 | 0.0006 | 0.0006 | 0.0012 | 0.0011 |
| | (0.50) | (0.79) | (0.78) | (0.79) | (0.84) | (0.81) |
| Pre6ret | 0.0010 | 0.0008 | 0.0014 | 0.0010 | -0.0008 | -0.0007 |
| | (0.72) | (0.60) | (0.87) | (0.66) | (-0.34) | (-0.32) |
| lnMV | -0.0009** | -0.0010*** | | | | |
| | (-2.14) | (-2.79) | | | | |
| N | 1143466 | 1138256 | 944628 | 941178 | 293687 | 292928 |

Among the three factors, only the size factor (Factor 1) demonstrates a consistent influence on the anomaly. The coefficient of the size factor and asset growth interaction term is significant and positive. It suggests that as size increases, the negative effect on the asset growth coefficient become less negative. This finding is consistent with both limits-to-arbitrage arguments that larger firms have less limits-to-arbitrage (Wurgler and Zhuravskaya, 2002; Baker and Wurgler, 2006) and Q-theory with investment frictions that larger firms have lower investment frictions (Almeida and Campello, 2007; Li and Zhang, 2010). These findings are consistent in different model specifications across different sample lengths. Importantly, in the fully controlled model (Model 6) that includes the sequence variables, the asset growth anomaly is fully explained by the interactive factors and the sequence variable. The coefficient for asset growth (ln(1+AG)) is not significant.

To summarize, the results support the prediction that there is a stronger asset growth anomaly when the asset growth trend is longer after controlling for a large number of firms and stock specific characteristics that are related to limits-of-arbitrage and Q investment frictions. Finally, the effect of asset turnover and net profit margin are subsumed by other firm specific factors (particularly the size factor).

## 4.5. Expectation Error and Correction

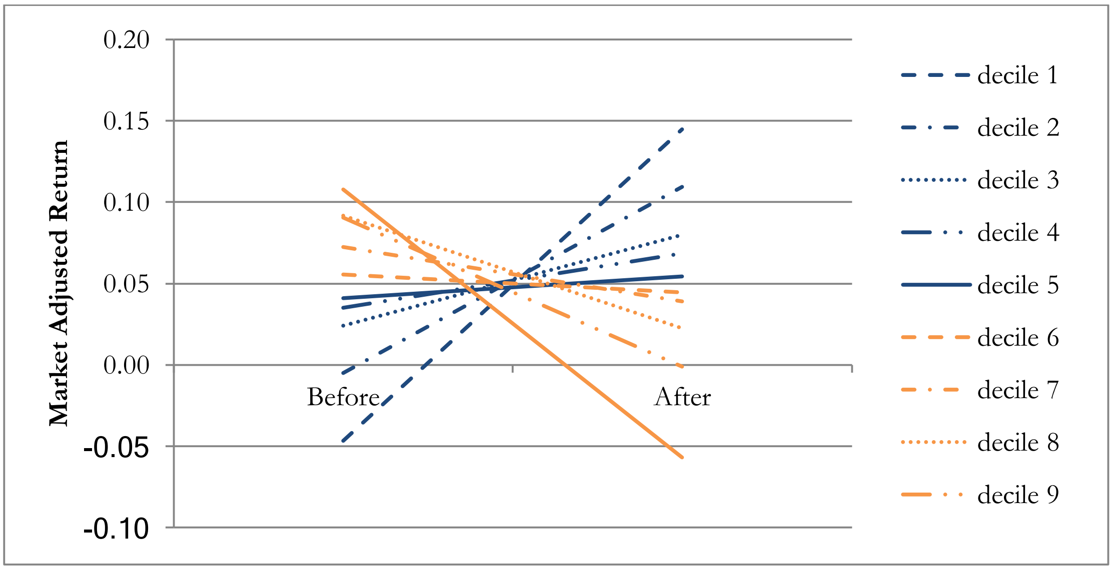
Previous sections provide strong support to the first hypothesis that the length of the growth sequence affects the asset growth anomaly. This evidence is consistent with the argument that overreaction is the mechanism that drives the asset growth anomaly and representativeness is the heuristic that strengthens the relationship. In this section I provide further tests for the expectation error of growth sustainability being the source of the overreaction. First, if the observed predictability of the return after the asset growth formation is due to the correction of the overreaction to previous growth, I should see a run up (down) of the price for high (low) asset growth firms. I examine this prediction.

Second, if the expectation error is the driver, the anomaly will be mainly concentrated on those firms that cannot maintain the growth rates. I, therefore, examine the asset growth effect conditional on the following year's asset growth rate.

### 4.5.1. Return Patterns around Asset Growth

The main analysis in Section 4.4 demonstrates the predictability of returns according to their asset growth sorting. If this predictability is due to the correction of the overreaction to growth, I should observe a reversal in the return. In other words, before the formation day, the return for the high asset growth portfolio should be greater than those of the low asset growth portfolio. To verify this, I examine the return pattern around the asset growth formation year. Figure 4-2 reports the average annual return up to and after the formation day. It shows a clear cross over pattern that confirms the predictability in the return can be attributed to a reversal in the return. The pattern is strikingly strong with the lowest asset growth group having the lowest pre-formation return and highest post-formation return and vice versa. Accordingly, the portfolios with a middle level of growth show the least reversal. This is consistent with Cooper, Gullen Schill (2008) that there is a stronger reversal of net profit margin for extreme high and low asset growth portfolios.

**Figure 4-2 Market-adjusted returns one year before and after the formation year**
This figure reports the market adjusted return one year before and after the formation year. At the end of June of each year t over 1965 to 2010, stocks are allocated into deciles based on asset growth rates defined as the percentage change in total assets over the previous fiscal year. Decile 1 is the lowest growth decile and Decile 10 is the highest growth decile. For each of the deciles in each formation year, one year average market-adjusted returns before and after formation day are computed. Market-adjusted return is the yearly return minus the CRSP value-weighted market return.



### 4.5.2. The Asset Growth Effect Conditional on the Subsequent Asset Growth

If the asset growth anomaly is driven by investors' error of expectations regarding the sustainability of the growth trend, I expect investors will be more likely to realize that they have made an error in their expectations of the growth trend when they find out that firms with a high (low) asset growth sequence at the formation year actually have low (high) asset growth in the subsequent year. Table 4-7 reports the analysis. I construct four portfolios including LH, LL, HH and HL, where the first letter refers to the group the firm belongs to at the formation year and the second letter refers to the group the firm belongs to after the formation year according to their relative asset growth. All firms are ranked into deciles and similar to the analysis in Section 4.4 I define the top two deciles as high asset growth (H) and the bottom two deciles as low asset growth (L). For example, LH indicates a portfolio consisting of stocks that have low growth at the formation year end and high growth one year after the formation. I report two test statistics. First, I report the subsequent monthly average return of the stocks in the one year post formation. Second, another potential sign of unsustainable growth is when the growth does not produce the expected earnings. Therefore, I adopt the expectation error test of La Porta et al. (1997) to examine if the reversal in the price of the asset growth portfolios is due to a correction in the market given the additional earnings information.

For return measurement, Table 4-7 shows that the portfolio of stocks that cannot sustain the high growth expectation (HL) has a lower return than those that can (HH). The negative difference (annualized at 13.7%) is statistically significant[17]. Furthermore,

[17] $-0.00114 \times 12 = -0.1368$.

when low growth firms break their low growth trend, there is evidence that the market makes corrections here as well.

When the earnings announcement day (EAD) and non-EAD returns are studied, similar conclusions to the above can be reached[18]. There is a large negative correction in the portfolio of stocks that cannot sustain their growth. The expectation error measure (the difference between returns on the EADs and non-EADs) for the HL portfolio is negative and significant. By contrast, for stocks that continued to grow as expected (the HH portfolio) there is no significant error correction within the earnings announcement dates. Furthermore, the difference of error between these two sub-portfolios of high growth firms is significant (see the Error row of the diff (HL-HH) column). When the low growth portfolios are examined, there is evidence of error correction on the earnings day when low growth firms present high growth rates subsequently; the LH portfolio earns significantly higher returns on EAD than on non-EAD. The difference between the LH and LL portfolios, however, is not statistically significant. This suggests that the expectation error is less prominent for low growth firms.

Overall, in this section I show that the return predictability subsequent to asset growth is consistent with an overreaction and subsequent reversal pattern. In addition, this reversal can be explained by the correction of expectation errors subsequent to the formation day. Furthermore, the evidence for the high growth deciles is stronger than for the low growth deciles in both magnitude and statistical significance.

[18] EAD return is the mean daily return for the 3 days around the four quarterly EADs. Non-EAD return is the mean daily return for all non-EADs. For a firm to be included in the tests it is required to have at least three daily EAD returns.

**Table 4-7 The asset growth effect conditional on subsequent asset growth**

This table reports the asset growth effect conditional on subsequent asset growth. At the end of June of each year *t* from 1965 to 2011, stocks are allocated into deciles based on their asset growth rates defined as the percentage change in total assets over the previous fiscal year. The top two deciles are defined as high asset growth (H) and the bottom two deciles as low asset growth (L). Using similar methods, the stocks' growth deciles at time t+1 are obtained. Based on the combination of the asset growth deciles at time t and t+1 I form four portfolios that are denoted by HL, HH, LH and LL where the first and second letters represent the growth deciles the stock was allocated at time t and t+1, respectively. *Return* is the average monthly return in the 1 year period post formation (from the portfolio formation day to the end of June of year t+1). *EAD[-1,1]* is the mean daily return for the 3 days around the four quarterly earnings announcement days (Day –1 to Day +1) in the 1 year period post formation. *non-EAD* is the mean daily return for all non-EADs in the 1 year period post formation. *Error(EAD-nonEAD)* is the mean difference between the *EAD[-1,1]* and *non-EAD*. t-values are reported in parentheses, where t-tests for statistical difference from zero are performed. *, **, and *** indicate the significance level at 0.10, 0.05 and 0.01.

| | **High Growth Portfolios** | | | **Low Growth Portfolios** | | |
|---|---|---|---|---|---|---|
| **Asset growth(t,t+1)** | **HL** | **HH** | **diff(HL-HH)** | **LH** | **LL** | **diff(LH-LL)** |
| Return | -0.0009 | 0.0105 | -0.0114*** | 0.0240 | 0.0165 | 0.0075*** |
| | | | (-5.93) | | | (4.74) |
| EAD[-1,1] | -0.0025 | 0.0011 | -0.0035*** | 0.0031 | 0.0022 | 0.0009 |
| | | | (-4.33) | | | (1.36) |
| nonEAD | 0.0007 | 0.0006 | 0.00004 | 0.0014 | 0.0015 | -0.0002 |
| | | | (0.34) | | | (-1.08) |
| Error(EAD-nonEAD) | -0.0031*** | 0.0004 | -0.0036*** | 0.0017*** | 0.0007 | 0.0011 |
| | (-5.04) | (1.01) | (-4.30) | (2.76) | (1.26) | (1.59) |
| N | 6585 | 13246 | | 4552 | 15237 | |

## 4.6. Conclusions

This chapter unites the industry and academic debate on the valuation of growth by examining the drivers of investors paying too much for growth. Building on the literature of firm growth and behavioural biases in investors' formation of expectations, I identify that investors' expectation errors of the trend and benefit of growth is the core driver of the phenomenon of paying too much for growth in the context of an accounting valuation model. When such errors in expectation are corrected because of subsequent realized information, it induces a reversal in the stock price and hence produces the asset growth anomaly – a negative relationship between the growth rate and the subsequent return.

I offer many tests of the above conjecture. I develop three hypotheses concerning investors' expectation errors. First, when forming expectations regarding a company's growth rate, the current growth trend is seen as influencing investors' expectations. I hypothesize and document that investors extrapolate a past growth trend that induces a stronger asset growth anomaly when there is a longer consecutive sequence of a growth trend. Second, when forming expectations regarding future cash flows, investors may make errors in how much value the current growth will generate. In this regard, Aghion and Stein's (2008) work provides further guidance on how the market may place different weights on the two profitability drivers (ATO and NPM) conditional on the adopted strategy of a firm. I hypothesize and show in the univariate analysis that firms with a higher asset turnover ratio (the ability to generate sales per unit of asset)/lower net profit margin are associated with a greater asset growth anomaly.

I examine the two hypotheses in a regression framework controlling for an extensive list of control variables for three possible alternative explanations: limits to arbitrage, investment frictions (Q-theory Li and Zhang (2010)) and a traditional risk explanation (Berk, et al., 1999). Importantly I improve the empirical design by using factor analysis that maximizes the information of the proxy variables while minimizing the multicollinearity issue. After controlling for existing explanations, the first hypothesis regarding the growth sequence is consistently supported by the evidence while the effect of the asset turnover ratio and the net profit margin is subsumed by the size factor.

Therefore, the empirical analysis provides strong support to the first hypothesis suggesting that the asset growth anomaly is driven by investors' overreaction to the growth trend. This is further confirmed in a series of robustness checks. I further demonstrate that the asset growth anomaly is consistent with the mispricing explanation by showing a clear reversal return pattern around the asset growth portfolio formation day. The reversal can be attributed to corrections of expectation errors; those stocks that do not maintain their growth trend show a significant reversal in their return and significant error corrections on the earnings announcement days.

The study provides new insights into the drivers of the asset growth anomaly and therefore provides theoretical supports to the investment factor in the newly developed multi-factor asset pricing models (Hou, Xie and Zhang,2015 and Fama and French 2015). It identifies the potential sources of investors' valuation errors via an accounting valuation model. This provides a unified framework for analyzing the anomaly that connects fundamentals with valuations. I present strong evidence that the asset growth anomaly is due to mispricing and that overreaction to growth, underpinned by the representativeness heuristic, is the source of the mispricing.

There are two limitations of this chapter. First, the study does not distinguish between mispricing and q theory, because the growth sequence cannot rule out the explanatory power of investment frictions. Therefore, how to distinguish the two explanations needs further investigation. Second, the evidence for the second and third hypotheses is relatively weak in regression of full set of variables although the results are significant in univariate tests.

To decide the dominant explanation, Watanabe et al (2013) compare mispricing and q theory in a global context and support q theory. They argue that managers are likely to focus on the investment-return relation and therefore the asset growth anomaly is stronger in developed markets than emerging markets. However, this can only apply to investment-related anomalies. And it raises the question whether there are more anomalies in developed markets than emerging markets and why. I will address the two questions in the next chapter.

Chapter 5

# Understanding Asset Pricing Anomalies across the Globe: The Role of News Watchers

## 5.1. Introduction

The presence of an asset pricing anomaly in a given market is often seen as a sign of market inefficiency since there are excess returns to be earned that cannot be explained by traditional risk metrics. Some recent studies post a challenge to this argument by showing that developed markets are more prone to some anomalies than emerging markets. For example, McLean, Pontiff and Watanabe (2009) show a stronger stock issuance effect in developed countries, while Watanabe, Xu, Yao and Yu (2013) and Titman, Wei and Xie (2013) show a stronger asset growth anomaly in developed countries. These papers, however, only focus on a single anomaly. In order to offer a more general explanation of the variation in the presence of anomalies in different markets, I provide a unified study of multiple anomalies around the world.

I have two objectives. First, it is to establish whether there is a clear difference, after adjusting for risk with the latest asset pricing models, between the number of anomalies in developed and emerging markets. In particular, there are two new developments in empirical asset pricing by Hou, Xie and Zhang (2015) and Fama and French (2015). If the additional investment and profitability factors, noted by these authors, are relevant to capturing the appropriate hidden state variables, they should help to explain anomalies in different country settings. Second, it is to explore a possible theoretical framework that may improve the understanding of the relationship between market development and anomalies.

Empirically I study 16 well documented accounting and market based asset pricing anomalies for 45 markets for the period between 1980 and 2013[19]. Regarding the first objective, I show that developed markets have significantly more anomalies than emerging markets when both equal- and value- weighted anomaly returns are considered. Applying the q- and 5- factor models gives two main observations. First, the recent multi-factor models reduce the number of significant anomalies in both emerging and developed markets, with the reduction being more pronounced in the latter. If risk factors are the main driver of the difference, it suggests that investing in the anomaly portfolio in developed markets will bear higher risk than is the case in emerging markets. I show that the newly added investment and profitability factors do play a more important role in explaining anomaly returns in developed markets (a greater number of significant loading coefficients are observed for these markets). Second, while the gap between the developed and emerging markets narrows in terms of the number of significant anomalies, the difference still persists after controlling for the factor models. For example, on average, a significant alpha is documented in 37% of the developed markets compared to 22% in the emerging markets when equal weighted returns are studied with the q-factor model. When valued weighted returns are studied, the percentage reduces to 18% (9%) for the developed (emerging) markets.

This new evidence presents two challenges to the existing understanding. First, the puzzle that developed markets have more anomalies is still unresolved after taking into account the latest empirical asset pricing factors. Rational theories suggest that developed

[19] The 16 anomalies include asset growth, investment growth, accrual, working capital accrual, gross profits, book-to-market, distress risk, momentum, beta, idiosyncratic volatility, illiquidity, long term reversal, maximum daily return, trading volume and short term reversal. See Table 5-1 for detail.

markets are more efficient and, therefore, they should have less pricing anomalies. While q- theory helps to reconcile the difference between developed and emerging markets in some investment related accounting anomalies (Watanabe, Xu, Yao and Yu, 2013; Titman, Wei and Xie, 2013), it is less effective for other types. Furthermore, this puzzle also challenges existing behavioural mispricing theories. Emerging markets are expected to have more limits to arbitrage and their investors to suffer more behavioural bias given that their education, especially financial education, is lower and this should lead to more rather than less anomalies. Second, an additional question that arises from the analysis is why the difference between developed and emerging markets is strongest when using equal-weighted hedged returns. I find that the difference between the two types of market is reduced significantly by the value-weighted method. Since a value weighted portfolio will place more weight on large stocks, while an equal weighted portfolio places more weight on small stocks, the finding suggests that the difference between the emerging and developed markets is most pronounced for smaller firms. Fama and French (2015) suggest that "…one of the main messages here and in Fama and French (1993, 2012, 2014) is that the most serious problems of asset pricing models are in small stocks." (p.19). In other words, factor models fail to account for the small size effect (i.e., anomalies are more pronounced in smaller than larger size firms). It is a further puzzle to see that the small firm effect is stronger in developed markets. Existing limits to arbitrage or behavioural bias explanations of the small firm effect would seem to suggest that the small size effect should be stronger in emerging as compared to developed markets.

Another concern is investor's learning. Theoretically, an anomaly should become weaker or disappear after the publication of evidence of the anomaly, because investors know the anomaly and they can take the arbitrage opportunities to trade away the anomaly. McLean and Pontiff (2016) show lower anomaly return post publication which indicates that investors learn about the anomaly from publication. However, this cannot explain the puzzle that there are more anomalies in developed markets than emerging markets. The awareness of an anomaly and limits-to-arbitrage play an important role in this argument. All of the 16 anomalies in my study are initially examined in the US market and developed markets should be aware of these anomalies more than emerging markets. Further, knowing the anomaly does not necessarily mean that investors can arbitrage for profits. Many anomalies are weaker in large firms which suggests that anomalies may exist in less liquid stocks (see Fama and French, 2015). This would limit the arbitrage activities. In addition, there are higher limits-to-arbitrage in emerging markets than developed markets, for example, stocks are considered as less liquid, high transaction cost, and small size. Therefore, we should expect that emerging markets have more anomalies than developed markets.

Given the two challenges noted above (after taking into consideration the latest rational risk models), the second objective of this study is to explore a possible theoretical framework that may improve the understanding of the relationship between market development and anomalies from a behavioural perspective. There are three unified behavioural models that offer insight into the formation of pricing anomalies. The models by Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) assume prices are driven by a single representative agent prone to a small number of cognitive biases (conservatism, representativeness, or overconfidence). Whereas, Hong and Stein (1999) propose a more general model that focuses on the interaction between heterogeneous agents and avoids a direct reference to any specific behavioural bias. They model a market populated by two groups of boundedly rational agents: "news watchers" and "momentum traders." One of the key insights of their model is that the presence of news watchers is a necessary condition for the existence of a pricing anomaly; with the seeds of momentum trading being sown by information diffusing gradually across the population and prices under-reacting in the short run.

Hong and Stein (1999) build their model with a focus on explaining anomalies in developed markets. Their original model predicts that as the efficiency of news watchers (measured by the speed of information diffusion) increases, the number of anomalies decreases. Applying their model to studying cross-country differences, I reveal an important insight regarding the role of news watchers and the presence of anomalies. Particularly, the efficiency of news watchers has two distinct phases of impact on price discovery and, therefore, the formation of anomalies - with Hong and Stein's (1999) predictions being observed in the second phases.

In Phase I, in markets where news watchers are very low in number and efficiency (and hence news diffusion is very slow), pricing anomalies are less likely to be observed in the short run because of two reasons. First, price converges to its fundamental value in the long run very slowly. Therefore, under-reaction will be difficult to quantify in the short-run since the small and gradually informed price movement is difficult to distinguish from noise in the market between the time of the new information and when it is fully reflected in price. Second, without the leads from news watchers to follow, momentum traders have no trend (respective to that particular piece of news) to chase. The central prediction is that the absence of some anomalies in emerging markets can be attributed to the general absence of news watchers who would have paid attention to that particular type of news.

As the market develops, there are more efficient news watchers who pay attention to fundamental news and reveal this information in price in a more timely fashion. However, the diffusion of information among news watchers is still relatively slow. The combined actions of news watchers and momentum traders will produce short run under-reaction, subsequent over-reaction and long run reversal around that type of information. Overall, this Phase applies to countries ranging from very low to medium news watcher efficiency. The increases of news watcher efficiency from a relatively low level will lead to more clear underreaction patterns and induce more momentum trading. Therefore, the number of anomalies observed in a given country is positively correlated with the overall efficiency of news watchers in that market.

In Phase II as a market develops further and the number/efficiency of news watchers continues to increase/improve, the speed of information diffusion increases. At this high level of news watcher efficiency, an increase of news watcher efficiency would further squeeze the profit for momentum traders and hence, there will be less subsequent over-reaction. For countries that are in this phase, the cross-sectional prediction on the marginal effect of news watcher efficiency on the number of anomalies is expected to be negative as Hong and Stein's (1999) original analysis shows.

The above two phases suggest that a nonlinear relationship is to be expected between the efficiency of news watchers and the number of anomalies. The number of anomalies will be increasing (decreasing) with news watcher efficiency in Phase I (II). Empirically I test the relationship between the efficiency of news watchers and the number of significant anomalies by using three proxies to capture cross-country difference in news watcher efficiency - education, sophistication of buying behaviour and accounting quality. Sorting the countries by the three proxies into quintiles from low to high news watcher efficiency, I show, as expected, that emerging countries are concentrated in the low and median groups while developed countries are in the median and high groups.

I show that the number of anomalies measured by hedged returns and alphas demonstrates a nonlinear pattern (the only exception being the results for the sophistication of buying behaviour variable). The number of anomalies normally peak at the fourth quintile suggesting that the majority of the countries are still in Phase I (the increasing phase). In other words, only very few developed countries have entered Phase II (the declining phase). These findings provide an important insight for solving the puzzle. Combining these findings with the fact that emerging countries are concentrated in the low and median groups while developed countries are in the median and high groups it provides a new explanation for the difference in anomalies between developed and emerging markets. Emerging markets are concentrated in the early part of Phase I, where a lower average number of anomalies are observed, while the majority of the developed markets are concentrated in the latter part of Phase I, where a higher average number of anomalies are observed.

The predicted nonlinear relationship between the efficiency of news watchers and the number of anomalies also provides insight into why the small size effect is more observable in developed markets. If size is used as a proxy for news watcher efficiency, then there will be a nonlinear relationship between size and the number of observed anomalies[20]. Such a prediction is supported by Hong, Lim, and Stein (2000) who document that the smallest size firms (in the smallest two deciles; I refer to them as micro firms) have less anomalies than small size firms (in the third and fourth smallest deciles). In other words, there is an inverted U shape relationship between size and anomaly returns that is similar to the theoretical prediction of a two-phase effect[21]. I replicate their analyses on all 16 anomalies for emerging and developed markets separately. Examining the plots of hedged anomaly returns against firm size deciles, I document an inverted U shape relationship in both markets. When comparing between the two types of market, the anomalies in developed markets are stronger than is the case in emerging markets as the puzzle suggests. Importantly, this difference is much stronger in the small size deciles part of the plot and weaker in the larger size deciles part. This explains why for equal weighted hedged returns the difference between emerging and developed markets is larger than is the case of value-weighted hedged returns. It suggests that more of the small stocks in

[20] Hong, Lim, and Stein (2000) use size as a sorting variable to capture variations of information diffusion speed.
[21] A clear inverted U shaped relationship between size and the hedged return of the momentum anomaly is presented in Figure 1 of Hong, Lim, and Stein (2000).

emerging market would have behaved like the US micro stocks that have close to zero anomalies. Therefore, I observe fewer anomalies in small firms in emerging markets. In other words, the evidence supports that the very low efficiency of news watchers for small size firms in emerging markets helps to explain why there are less anomalies in emerging market small size firms than in developed market small size firms.

I contribute to the debate on asset pricing anomalies by presenting a comprehensive and unifying study of multiple anomalies around the world. Prior cross-country studies have limited themselves to analyzing a single anomaly. While explanations have been proposed for specific individual anomalies (see for example, Watanabe, Xu, Yao and Yu, 2013; Titman, Wei and Xie, 2013), there is a lack of a more general and cohesive explanation for the cross-country differences in anomalies; such an explanation can only be developed and tested by studying anomalies with different characteristics. I, therefore, contribute to the literature on asset pricing anomalies by providing a more comprehensive analysis with consideration being given to rational risk and investment based models, and an extension of behavioural theories.

Regarding the risk and investment based analyses, the global markets provide an out of sample test for these models that are normally developed and tested in the US market (arguably the most advanced financial market). On the one hand, factors that are important in developed markets may not be readily relevant to emerging markets. On the other hand, if a factor is indeed capturing fundamental risk it should have good explanatory power in different market set-ups. I offer important insights on how rational factors can improve the understanding of the difference in anomalies between emerging and developed markets.

In terms of the extension of behavioural theory, building on Hong and Stein (1999), I offer a new angle for studying international anomalies: news watcher efficiency.

This concept helps solve two aspects of the current puzzle: why market development and the number of significant anomalies are not found to be negatively associated in prior studies and why there is a difference in the size effect in the two types of market documented in the current study. Hong and Stein (1999) develop their model with the aim of explaining short-term under-reaction and long-term reversal in a relatively developed market where there is a reasonable efficiency of news watchers in the market. I apply its prediction to a cross-market setting with a wider range of news watcher efficiency which provide a good 'out of sample' test of the theory. Such an analysis does not rely on the argument that investors in different countries possess different levels of behavioural bias. It emphasizes that it is the mix of the investors (news watchers and momentum traders) and the relative efficiency of the news watchers that play important roles in affecting price discovery. This finding has a strong implication for the relationship between pricing anomalies and market efficiency. Market efficiency cannot be associated with the absence or otherwise of anomalies; a market with less anomalies could be a reflection of low information asymmetry, less market frictions and biased investors or it could simply be the case that there are insufficient sophisticated investors to obtain and process price related information. The analyses provide a consistent framework that helps us to understand the links between market development, anomalies and market efficiency.

The remainder of the paper is organized as follows. Section 2 provides the analysis of anomalies around the world with q- and 5- factor models. Section 3 presents the search for a behavioural explanation and an extended numerical analysis of Hong and Stein (1999). Section 4 presents the analyses. I provide conclusions in section 5.

## 5.2. Anomalies around the World and Recent Multi-Factor Models

In this study I examine a wide range of 16 anomalies that include investment related anomalies, accrual anomalies, financial distress anomaly, value premium, price momentum, return reversal, trading friction and profitability anomalies[22]. I further classify these anomalies into accounting and market based anomalies given the key information type used to construct the anomaly portfolios. The definitions of these anomalies are given in Table 5-1. The details of the construction of these anomaly variables are given as follows.

For accounting based anomalies, for each market all firms are divided into quintiles based on the *anomaly variable* at the end of June in each year t. The average return for each quintile is computed monthly from July in year t to June in year t+1. The definitions of the accounting based anomalies are shown below.

*Accrual (AC).* Following Sloan (1996), accrual is computed via the following formula:

$$\boldsymbol{Accruals} = (\Delta \boldsymbol{CA} - \Delta \boldsymbol{Cash}) - (\Delta \boldsymbol{CL} - \Delta \boldsymbol{STD} - \Delta \boldsymbol{TP}) - \boldsymbol{Dep} \quad \text{(Eq. 5-1)}$$

Where $\Delta CA$ is the change in current assets; $\Delta Cash$ is the change in cash and short-term investments; $\Delta CL$ is the change in current liabilities; $\Delta STD$ is the change in debt included in current liabilities; $\Delta TP$ is the change in income tax payable; and Dep is the depreciation

[22] There are studies of single anomalies in a global context. For example, Ang, Hodrick, Xing and Zhang (2009) document a high idiosyncratic volatility-low return relationship in developed countries (the G7). After a comprehensive test of different explanations, they rule out the risk factor explanation. Griffin, Kelly and Nardari (2010) show the return of the momentum strategy is, on average, 14% per year in developed markets while it is 8.5% per year in emerging markets. Chui, Titman, and Wei (2010) show that the momentum magnitude is larger in markets with a higher individualism index. Kaniel, Ozoguz and Starks (2012) show the phenomenon that most developed countries have a stronger extreme volume effect than less developed countries. Watanabe, Xu, Yao and Yu (2013) and Titman, Wei and Xie (2013) report a stronger asset growth anomaly in developed markets than emerging markets.

and amortization expense. Accruals are then scaled by average total assets in the previous two years.

*Asset growth (AG).* Asset growth is defined as the yearly percentage change between previous and current fiscal years.

*Asset-to-market (AM).* Asset-to-market is the ratio of total assets in the previous fiscal year over the market value of equity at the end of the previous year.

*Book-to-market (BM).* Following Fama and French (1993), the book-to-market ratio is the book value of equity in the previous fiscal year over the market value of equity at the end of the previous year. Book value is total assets minus liabilities, plus balance sheet deferred taxes and investment tax credits, and minus preferred stock liquidation or carrying value if available.

*Gross profits (GP).* According to Novy-Marx (2013), I construct gross profits as firm gross profits scaled by firm total assets. Firm gross profits are the difference between total revenue and cost of goods.

*Investment growth (IG).* Investment growth is the percentage change of capital expenditures in the previous fiscal year.

**Table 5-1 Summary of anomalies**

| Type | Anomaly | Abbreviation | Key papers | Short description |
|---|---|---|---|---|
| accounting | Accrual | AC | Richardson et al (2005) | Negative association of accruals and stock returns |
| accounting | Asset growth anomaly | AG | Cooper, Gullen and Schill (2008) | Negative relationship between the asset growth rate and subsequent one year return |
| accounting | Asset-to-market anomaly | AM | Bhandari (1988) | Firms with a higher asset-to-market ratio have higher returns |
| accounting | Book-to-market anomaly | BM | Rosenberg, Reid, and Lanstein (1985), DeBondt and Thaler (1987) | High book-to-market ratio stocks will earn higher returns |
| accounting | Gross profits | GP | Novy-Marx (2013) | Higher stock return for profitable firms than unprofitable firms |
| accounting | Investment growth anomaly | IG | Xing (2008) | Negative relationship between investment growth and future returns |
| accounting | Financial distress | OS | Dichev (1998) | Firms with a high probability of bankruptcy have lower stock returns |
| accounting | Working capital accrual | WAC | Sloan (1996) | Negative correlation of stock returns and operating accruals |
| market | Beta | BETA | Frazzini and Pedersen (2014) | Negative relation between stock returns and beta |
| market | Trading volume | DVOL | Brennan, Chordia, and Subrahmanyam (1998) | Negative dollar trading volume return relation |
| market | Illiquidity | ILLIQ | Amihud (2002) | Positive return illiquidity correlation |
| market | Idiosyncratic volatility | IVOL | Ang, Hodrick, Xing and Zhang (2006, 2009) | Stock return and idiosyncratic volatility is negatively associated |
| market | Long-term reversal | LREV | De Bondt and Thaler (1985) | Stock return reversal, that is, winner stocks in the past 5 years will become loser stocks |
| market | Maximum daily return | MDR | Bali, Cakici, and Whitelaw (2011) | Negative relationship between a firm's extreme daily return in the last month and stock returns in the next month |
| market | Momentum | MOM | Jegadeesh and Titman (1993) | Firms with a higher return in the past 6 months continue to have higher returns in the following 6 months |
| market | Short-term reversal | SREV | Jegadeesh (1990) | Firms with a higher return in the past month tend to have lower stock return in the following month |

*Distress risk (OS).* Distress risk or O score is formed by following Ohlson (1980). O score is calculated as follows:

$$-1.32 - 0.407*\log(TA) + 6.03*TLTA - 1.43*WCTA + 0.076*CLCA - 1.72*OENEG - 2.37*NITA - 1.83*FUTL + 0.285*INTWO - 0.521*CHIN \quad \text{(Eq. 5-2)}$$

Where TA is a firm's total assets, TLTA is total liabilities divided by total assets, WCTA is working capital divided by total assets, CLCA is current liabilities divided by current assets, OENEG is a dummy variable of 1 if total liabilities are greater than total assets and 0 otherwise, NITA is net income divided by total assets, FUTL is funds provided by operations plus depreciation and then divided by total liabilities, INTWO is a dummy variable that equals 1 if net income is negative in the last two years and 0 otherwise, CHIN is a ratio where the numerator is net income change and the denominator is the sum of the absolute value of net income in year t and the absolute value of net income in year t-1.

*Working capital accrual (WAC).* Working capital accrual is defined as the sum of accruals (see AC) and depreciation divided by the average total assets of the previous two years.

For market based anomalies, portfolios are formed and updated monthly. The definitions of the market based anomalies are as follows.

*Beta (Beta).* Beta is estimated via the following formula:

$$\boldsymbol{\beta_i = \rho \frac{\sigma_i}{\sigma_m}} \quad \text{(Eq. 5-3)}$$

$\rho$ is the correlation between stock return and market return. Correlation is calculated in each month by using the past five years' daily return. A longer horizon for calculation of correlation is required because correlations tend to move slowly (see Frazzini and Pedersen, 2015) and at least 750 daily returns are required. $\sigma_i$ and $\sigma_m$ are the standard deviations of stock returns and market returns respectively. The standard deviation is estimated in each month by using the past two years' daily return and at least 120 daily returns are required. All firms are then divided into quintiles based on beta in the last month. The current month return is computed for each quintile.

*Trading volume (DVOL).* I separate firms into quintiles according to the average daily value trading volume in the past six months and compute the decile returns in the current month.

*Idiosyncratic volatility (IVOL).* It is the standard deviation of residuals from regressions of daily stock returns on market returns in each month. Quintiles are constructed at the end of each month based on previous idiosyncratic volatility. The current month return is computed for each quintile.

*Illiquidity (ILLIQ).* Illiquidity is the average of daily returns divided by daily trading volume over the past six months. Daily trading volume is the price multiplied by the number of shares traded. All the firms are ranked into quintiles in each month t based on illiquidity in month t-1. The current month return is computed for each quintile.

*Long-term reversal (LREV).* Firms are ranked into quintiles based on returns from t-60 to t-13 in each month and I compute the average quintile returns on the current month.

*Maximum daily return (MDR).* Following Hou et al (2014), I rank firms into quintiles according to the maximum daily return in the past month, and calculate returns on the current month. The anomaly is first documented by Bali, Cakaci and Whitelaw (2011) where they find that the maximum daily return in the previous month is negatively related to return in the next month due to overreaction to assets with a small chance to have high profits.

*Momentum (MOM).* Momentum is about price continuation, i.e. stocks with higher returns in the past 6 to 12 months perform better in the future 6 to 12 months (Jegadeesh and Titman, 1993). I form momentum portfolios based on the previous 6 months' returns. All firms are divided into quintiles based on the buy-and-hold return in the past six months in each month. And the subsequent six months return is computed for each quintile in each month.

*Short-term reversal (SREV).* Firms are divided into quintiles based on past month returns and I compute the average decile returns on the current month.

For the coverage of markets I include 23 developed and 22 emerging markets. The classification of market development is based on the MSCI classification. All data are obtained from Worldscope and Compustat. Table 5-2 presents a list of the countries and the data availability for each country. Most of the developed markets have data from the early 1980's, while emerging markets have valid data from 1990 or even later. In summary, developed markets, on average, have stock markets data earlier than emerging markets.

**Table 5-2 Market summary**
The table summarizes the markets included in this study, the time periods for data availability and the development classification. The market development classification is according to the MSCI market classification.

| Market | Start | End | Development Status |
|---|---|---|---|
| Australia | 1980 | 2013 | Developed |
| Austria | 1980 | 2013 | Developed |
| Belgium | 1980 | 2013 | Developed |
| Canada | 1980 | 2013 | Developed |
| Denmark | 1980 | 2013 | Developed |
| Finland | 1987 | 2013 | Developed |
| France | 1980 | 2013 | Developed |
| Germany | 1980 | 2013 | Developed |
| Hong Kong | 1980 | 2013 | Developed |
| Israel | 1986 | 2013 | Developed |
| Italy | 1980 | 2013 | Developed |
| Japan | 1980 | 2013 | Developed |
| Netherlands | 1980 | 2013 | Developed |
| New Zealand | 1986 | 2013 | Developed |
| Norway | 1980 | 2013 | Developed |
| Singapore | 1980 | 2013 | Developed |
| South Korea | 1980 | 2013 | Developed |
| Spain | 1980 | 2013 | Developed |
| Sweden | 1980 | 2013 | Developed |
| Switzerland | 1980 | 2013 | Developed |
| Taiwan | 1988 | 2013 | Developed |
| United Kingdom | 1980 | 2013 | Developed |
| United States | 1980 | 2013 | Developed |
| Brazil | 1991 | 2013 | Emerging |
| Bulgaria | 1998 | 2013 | Emerging |
| Chile | 1990 | 2013 | Emerging |
| China | 1991 | 2013 | Emerging |
| Cyprus | 1993 | 2013 | Emerging |
| Egypt | 1995 | 2013 | Emerging |
| Greece | 1988 | 2013 | Emerging |
| India | 1981 | 2013 | Emerging |
| Indonesia | 1990 | 2013 | Emerging |
| Malaysia | 1980 | 2013 | Emerging |
| Mexico | 1988 | 2013 | Emerging |
| Pakistan | 1988 | 2013 | Emerging |
| Peru | 1991 | 2013 | Emerging |
| Philippines | 1980 | 2013 | Emerging |
| Poland | 1991 | 2013 | Emerging |
| Romania | 1996 | 2013 | Emerging |
| Saudi Arabia | 1996 | 2013 | Emerging |
| South Africa | 1980 | 2013 | Emerging |
| Sri Lanka | 1987 | 2013 | Emerging |
| Thailand | 1987 | 2013 | Emerging |
| Turkey | 1988 | 2013 | Emerging |
| Vietnam | 2007 | 2013 | Emerging |

### 5.2.1. Anomaly Variables Sorted Hedged Returns

To measure the degree of an anomaly, both economic scale and significance are important. In this chapter, I focus on the significance rather than the scale for two reasons. First, persistence is important to confirm an anomaly. An anomaly is robust only if the anomaly can persist in the market for a longer period, otherwise it may be by chance. Further, another consideration about the existence of an anomaly is whether the anomaly return is volatile. If there is high volatility of anomaly return, the large magnitude may be driven by some large returns in certain time periods. The significance of an anomaly is emphasized in Harvey, Liu and Zhu (2015) that higher t value should be employed to determine the existence of an anomaly. The two effects should be stronger in emerging markets due to the highly volatile stock markets. Using significance (determined by t value) rather than raw return can overcome the two problems. If the anomaly is just by chance or the anomaly returns are too volatile, even if there is a large magnitude, the t test cannot confirm the significance. And therefore, I do not consider it as an anomaly. Second, the number of significant anomalies is more reasonable for the cross markets regression in section 5.4.2. There are 16 anomalies in my study, if I aggregate an anomaly measurement for a market by using the average return of the 16 anomalies, the scale suffers a problem that it is driven by some particular anomaly. Therefore, the scale is not a proper proxy for anomalies for the entire market. Scale is more important for a single anomaly and in time series or panel regression specification which can avoid the two concerns.

To study the overall distribution of anomalies I summarize the number of countries having significant anomalies in Table 5-3. All stocks in each market are ranked into quintiles based on the anomaly variables. To facilitate the discussion, I sort the five quintile portfolios by the anomaly variable into either ascending or descending order so that the first quintile always contains stocks that are expected to earn higher returns according to the anomaly.

The significance of an anomaly is determined by examining the post-formation return spread (hedged return) between the first and fifth quintiles. Following Hou, Xue and Zhang (2015) I apply a stronger hurdle rate of a 5% significance level. Num of sig. is the number of significant hedged returns. % of sig. is the number of significant anomalies divided by the number of countries.

When equal weighted hedged returns are considered, Panel A in Table 5-3 shows that, on average, 10 out of the 23 developed markets produced significant anomalies, while this was the case for only 4 out of the 22 emerging markets. The difference between the two market types is statistically significant in most anomalies. Among the anomalies the most commonly documented is the momentum anomaly - found in 87% and 59% of the developed and emerging markets, respectively (Japan has no momentum effect). Another widely observed anomaly is value premium especially for equal-weighted hedge return, i.e. 19 out of 45 markets exhibit significant value premium. This is consistent with existing evidence, for example, Asness, Moskowitz and Pedersen (2013). At the other end of the spectrum, the asset growth anomaly is among the least documented in both developed and emerging markets which is consistent with Watanabe, Xu, Yao and Yu (2013).

**Table 5-3 Anomalies across the world**

This table reports the number of significant anomalies and the percentage of significant anomalies for developed and emerging markets. 16 anomalies are computed by using available data from 1980 to 2013 in 45 markets (23 developed and 22 emerging markets according to the MSCI classification). The anomalies include accrual, asset growth, asset-to-market, beta, book-to-market, distress risk, gross profit, idiosyncratic volatility, illiquidity, investment growth, long term reversal, maximum daily return, momentum, short term reversal, trading volume and working capital accrual. Accrual, asset growth, asset-to-market, book-to-market, distress risk, gross profit, investment growth and working capital accrual are constructed and updated yearly; while beta, idiosyncratic volatility, illiquidity, long term reversal, maximum daily return, momentum, short term reversal, trading volume are constructed and rebalanced monthly (see Section 5.2 for the detailed definition of variables and their construction). All firms in each market are then ranked into quintiles based on the anomaly variables. The significance of an anomaly is determined by examining the subsequent return spread between high and low quintiles. Num of sig. is the number of significant spreads at least at the 5% significance level. % of sig. is the number of significant anomalies divided by the number of markets. Diff(developed-emerging) is the percentage difference between developed and emerging markets. A Chi-square test is conducted to indicate the significance of the difference with the null hypothesis being that the proportion having significant anomalies is the same. The average is also reported in the last row. For the US market, the financial data are from Compustat and the return data are from CRSP; for other markets, both financial and return data are from Datastream. Only common stocks are included and financial firms are excluded. Following Watanabe et al. (2012), to avoid price error in Datastream, $R_t$ and $R_{t-1}$ are treated as missing if $R_t$ or $R_{t-1}$ is greater than 300% and $(1+R_{t-1})(1+R_t)<50\%$. In addition, the returns are trimmed at 1% and 99% (after the above screening, there are still some extreme values; in order to avoid the influence of outliers, I trim the data).

**Table 5-3 (continued)**

**Panel A. Equal-weighted hedged return**

| | | Num of sig. | | Percent of sig. | | |
|---|---|---|---|---|---|---|
| Type | Anomaly | Developed | Emerging | Developed | Emerging | Diff(D-E) |
| Accounting | AC | 6 | 2 | 26.10% | 9.10% | 17.00% |
| Accounting | AG | 5 | 0 | 21.70% | 0.00% | 21.70%** |
| Accounting | AM | 11 | 5 | 47.80% | 22.70% | 25.10%* |
| Accounting | BM | 14 | 5 | 60.90% | 22.70% | 38.10%*** |
| Accounting | GP | 13 | 3 | 56.50% | 13.60% | 42.90%*** |
| Accounting | IG | 4 | 1 | 17.40% | 4.50% | 12.85% |
| Accounting | OS | 14 | 3 | 60.90% | 13.60% | 47.20%*** |
| Accounting | WAC | 7 | 2 | 30.40% | 9.10% | 21.30%* |
| Average | | 9 | 3 | 40% | 12% | 28% |
| | | | | | | |
| Market | BETA | 3 | 0 | 13.00% | 0.00% | 13.00%* |
| Market | DVOL | 3 | 7 | 13.00% | 31.80% | -18.78% |
| Market | ILLIQ | 13 | 0 | 56.50% | 0.00% | 56.50%*** |
| Market | IVOL | 19 | 5 | 82.60% | 22.70% | 59.90%*** |
| Market | LREV | 5 | 4 | 21.70% | 18.20% | 3.56% |
| Market | MDR | 11 | 9 | 47.80% | 40.90% | 6.92% |
| Market | MOM | 20 | 13 | 87.00% | 59.10% | 27.90%** |
| Market | SREV | 14 | 11 | 60.90% | 50.00% | 10.87% |
| Average | | 11 | 6 | 48% | 28% | 20% |
| | | | | | | |
| All | | 10 | 4 | 44% | 20% | 24% |

**Table 5-3 (continued)**

**Panel B. Value-weighted hedged return**

| | | Num of sig. | | Percent of sig. | | |
|---|---|---|---|---|---|---|
| Type | Anomaly | Developed | Emerging | Developed | Emerging | Diff(D-E) |
| Accounting | AC | 5 | 0 | 21.70% | 0.00% | 21.70%** |
| Accounting | AG | 5 | 0 | 21.70% | 0.00% | 21.70%** |
| Accounting | AM | 5 | 4 | 21.70% | 18.20% | 3.56% |
| Accounting | BM | 5 | 2 | 21.70% | 9.10% | 12.65% |
| Accounting | GP | 6 | 2 | 26.10% | 9.10% | 17.00% |
| Accounting | IG | 2 | 2 | 8.70% | 9.10% | -0.40% |
| Accounting | OS | 8 | 4 | 34.80% | 18.20% | 16.60% |
| Accounting | WAC | 6 | 0 | 26.10% | 0.00% | 26.10%** |
| Average | | 5 | 2 | 23% | 8% | 15% |
| | | | | | | |
| Market | BETA | 1 | 0 | 4.30% | 0.00% | 4.35% |
| Market | DVOL | 6 | 6 | 26.10% | 27.30% | -1.19% |
| Market | ILLIQ | 9 | 2 | 39.10% | 9.10% | 30.0%** |
| Market | IVOL | 0 | 0 | 0.00% | 0.00% | 0.00% |
| Market | LREV | 7 | 5 | 30.40% | 22.70% | 7.71% |
| Market | MDR | 0 | 3 | 0.00% | 13.60% | -13.60%* |
| Market | MOM | 20 | 15 | 87.00% | 68.20% | 18.78% |
| Market | SREV | 3 | 3 | 13.00% | 13.60% | -0.59% |
| Average | | 6 | 4 | 25% | 19% | 6% |
| | | | | | | |
| All | | 6 | 3 | 24% | 14% | 10% |

When value-weighted returns are considered in Panel B of Table 5-3, the number of significant anomalies decreases. This difference between equal and value weighted returns confirms that anomalies are more common in small companies. Furthermore, Table 5-3 shows that this is especially the case for developed markets. The difference in the number of anomalies between developed and emerging markets becomes smaller when value weighted returns are considered. Furthermore, the main difference between developed and emerging markets is observed in the accounting anomalies.

### 5.2.2. Rational Explanations: Multi-Factor Asset Pricing Model Analyses

The asset pricing anomalies are normally established by passing a series of tests with a traditional asset pricing model, such as CAPM, acting as the 'control'. The search for the drivers of anomalies has led to the incremental development of multi-factor models. For example, in the latest development of Fama and French (2015) and Hou, Xue, and Zhang (2015), profitability and investment/asset growth have been introduced as new pricing factors.

For the construction of the factors in the q factor model I follow Hou, Xue and Zhang (2015) and form 2 by 3 by 3 portfolios on firm size, asset growth and the return on equity (ROE). To form the two firm size groups, at the end of June in each year, all the firms are grouped into two size groups according to the median of market value. Firms are divided into three asset growth groups and three ROE groups based on 30, 40 and 70 percentile cutoffs[23]. With the intersection of 2 size, 3 asset growth and 3 ROE portfolios, there are 18 portfolios in total. I calculate 12 monthly returns for the 18 portfolios post formation. The size factor is the difference between the 9 small size groups and the 9 large

[23] The cut-offs are calculated based on all sample firms in a given market. One exception is for the US market. I follow previous studies and use NYSE stocks to calculate cut-offs for sorting all US stocks.

size groups; the investment factor is the difference between the 6 low asset growth groups and the 6 high asset growth groups; the profitability factor is the difference between the 6 low ROE groups and the 6 high ROE groups.

Similarly, for the construction of the 5-factor model I follow Fama and French (2015) to form 2 by 2 by 2 by 2 portfolios on size, the book-to-market ratio (BM), asset growth and ROE[24]. There are 16 portfolios by taking the intersection of 2 size groups, 2 book-to-market groups, 2 asset growth groups and 2 ROE groups. The size factor is the difference between the 8 small groups and the 8 large groups; the BM factor is the difference between the 8 high BM groups and the 8 low book-to-market groups; the investment factor is the difference between the 8 low asset growth groups and the 8 high asset growth groups; and the profitability factor is the difference between the 8 high ROE groups and the 8 low ROE groups.

For each anomaly in each country, the monthly hedged returns are regressed against the factor-returns constructed above[25]. Before I look at a summary of the alphas from the regressions, it is beneficial to examine the loading of the risk factor in the anomaly returns. This will provide some insights into what systematic risk factors may have been driving the returns of the anomaly portfolios.

[24] I follow the 2 by 2 by 2 by 2 portfolios set up rather than the 2 by 3 by 3 by 3 so that there are more observations in each portfolio group for countries with fewer listed companies in the sample. And the definition of ROE is different from Hou, Xue and Zhang (2015). The ROE represents profitability factor which is the RMW factor in Fama and French (2015) constructed by operating profits. The operating profits is measured by revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense and then divided by book equity. Due to data availability of the accounting data in constructing operating profits in other markets but US, I use ROE factor to approximate the RMW factor to capture the profitability factor. The investment factor (I/A) in Hou, Xue and Zhang (2015) is the same with Fama and French (2015) where they use the name of CMA rather than I/A.

[25] See section 5.2 for details of the anomaly return constructions.

Table 5-4 reports the total number of significant factor loading coefficients for each anomaly type, market type and factor. It reports the number of factor loading coefficients that are significant at 5% in the country level regressions. The loading pattern is very similar for equal and value weighted returns. Therefore, I report only the results of the value return here[26].

For the q-factor model, Table 5-4 Panel A reveals several important findings. First, for the overall summary I can see that the factor model provides much better explanatory power for accounting as compared to market based anomalies. The R-square is 17% (20%) for the accounting based anomalies and 8% (7%) for the market based anomalies in developed (emerging) markets. This is also reflected in the total number of significant coefficients for the two types of anomaly. Second, when examining the explanatory power of each individual factor, the investment and profitability factors provide better explanatory power than the market and size factors in terms of the accounting anomalies. By contrast, this trend reverses for market-based anomalies with the market and size factors having higher explanatory power. Third, comparing emerging with developed markets, the multi-factor models, in general, have similar explanatory power in terms of the anomalies' returns in both markets. The average R-square is 12 and 13 percent for developed and emerging markets, respectively. This evidence suggests that the factor model is general enough to cover factors that are important for both developed and emerging markets. For individual factors, it shows that q-related factors (INV and ROE) provide stronger explanatory power for developed than emerging markets – and this is especially the case for accounting anomalies. This suggests that the hedged returns of accounting based anomalies in developed markets are more likely to be due to the q-related risk factors. This is less true in emerging markets. Fourth, when the individual anomalies

[26] The equal weighted results are available on request from the author.

are examined, the multi-factor model performs best in explaining the asset growth anomaly with a 34% adjusted R-square[27]. Although the momentum factor has been dismissed from the q factor model, the study shows that the factor model performs poorly in explaining the momentum strategy return.

When the Fama and French (2015) 5-factor model is considered in Panel B of Table 5-4, the added BM factor increases the adjusted R-square and this is especially the case in developed markets. The BM factor behaves more in line with the other two q-factors than the size and market factors. In fact, it seems to be taking some of the explanatory power of the investment factor (INV).

I show a summary of the anomalies by alpha of the two factor models in Table 5-5. Table 5-5 shows that the average number of anomalies is reduced in general after considering the loading of risk factors. This suggests that risk factors help to explain cross-sectional differences in returns. However, the difference between the two types of market still exists. There are 15% (13%) and 9% (7%) differences in the equal and value weighed returns for the q- (ff5-) factor models. Although these differences are smaller when compared to the hedged return results, using the multi-factor model does not help to reconcile fully the difference between emerging and developed markets.

[27] This is not surprising, as attempting to explain the asset growth anomaly was the original start of the investment based asset pricing research (Li, Livdan and Zhang, 2009; Li and Zhang, 2010; Hou, Xue and Zhang, 2015).

**Table 5-4 Factor loadings with value weighted returns**

Panel A covers the q factor model. The four factors are MKT, SIZE, INV and ROE. MKT is the market return premium. For the construction of SIZE, INV and ROE factors I follow Hou, Xue and Zhang (2015) and form 2 by 3 by 3 portfolios on firm size, asset growth and return on equity (ROE). To form the two firm size groups, at the end of June in each year, all the firms are grouped into two size groups according to the median of market value. Firms are divided into three asset growth groups and three ROE groups based on 30, 40 and 70 percentile cutoffs. With the intersection of 2 size, 3 asset growth and 3 ROE portfolios, there are 18 portfolios. I calculate 12 monthly returns for the 18 portfolios post formation. The size factor is the difference between the 9 small size groups and the 9 large size groups; the investment factor is the difference between the 6 low asset growth groups and the 6 high asset growth groups; the profitability factor is the difference between the 6 low ROE groups and the 6 high ROE groups. Similarly, for the construction of the 5-factor model I follow Fama and French (2015) to form 2 by 2 by 2 by 2 portfolios on size (SIZE), the book-to-market ratio (BM), asset growth (INV) and ROE. There are 16 portfolios by taking the intersection of 2 size groups, 2 book-to-market groups, 2 asset growth groups and 2 ROE groups. The size factor is the difference between the 8 small groups and the 8 big groups; the BM factor is the difference between the 8 high BM groups and the 8 low book-to-market groups; the investment factor is the difference between the 8 low asset growth groups and the 8 high asset growth groups; and the profitability factor is the difference between the 8 high ROE groups and the 8 low ROE groups. When generating the cutoff point, for the US market the NYSE sample is used, while for other markets the full sample of the market is used. I run regressions of the hedged return of each anomaly on the factors. For each anomaly, I count the number of significant factor loadings at 5% in developed, emerging and all markets respectively. The average adjusted R square is also reported.

**Table 5-4 (continued)**

**Panel A. q-factor model**

| | All significant | | | | | | | | | | | | Adj. R-square | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Developed | | | | Emerging | | | | All markets | | | | Developed | Emerging |
| **Anomaly** | **MKT** | **SIZE** | **INV** | **ROE** | **MKT** | **SIZE** | **INV** | **ROE** | **MKT** | **SIZE** | **INV** | **ROE** | **Mean** | **Mean** |
| Accounting anomalies | | | | | | | | | | | | | | |
| AC | 8 | 7 | 3 | 6 | 7 | 7 | 3 | 3 | 15 | 14 | 6 | 9 | 0.06 | 0.12 |
| AG | 6 | 4 | 23 | 12 | 6 | 6 | 19 | 12 | 12 | 10 | 42 | 24 | 0.34 | 0.33 |
| AM | 11 | 10 | 14 | 12 | 11 | 11 | 6 | 12 | 22 | 21 | 20 | 24 | 0.18 | 0.23 |
| BM | 6 | 12 | 11 | 12 | 9 | 11 | 6 | 10 | 15 | 23 | 17 | 22 | 0.15 | 0.21 |
| GP | 11 | 9 | 5 | 16 | 8 | 5 | 5 | 16 | 19 | 14 | 10 | 32 | 0.18 | 0.24 |
| IG | 3 | 8 | 10 | 1 | 3 | 6 | 7 | 6 | 6 | 14 | 17 | 7 | 0.08 | 0.09 |
| OS | 7 | 17 | 6 | 19 | 6 | 13 | 8 | 15 | 13 | 30 | 14 | 34 | 0.31 | 0.29 |
| WAC | 4 | 3 | 6 | 3 | 9 | 2 | 2 | 3 | 13 | 5 | 8 | 6 | 0.03 | 0.08 |
| Sub-sum | 56 | 70 | 78 | 81 | 59 | 61 | 56 | 77 | 115 | 131 | 134 | 158 | 0.17 | 0.20 |
| Market anomalies | | | | | | | | | | | | | | |
| BETA | 18 | 9 | 3 | 2 | 15 | 4 | 5 | 6 | 33 | 13 | 8 | 8 | 0.16 | 0.14 |
| DVOL | 10 | 17 | 4 | 4 | 7 | 7 | 3 | 4 | 17 | 24 | 7 | 8 | 0.17 | 0.12 |
| ILLIQ | 5 | 7 | 2 | 3 | 1 | 4 | 4 | 2 | 6 | 11 | 6 | 5 | 0.05 | 0.04 |
| IVOL | 6 | 6 | 0 | 10 | 5 | 9 | 3 | 3 | 11 | 15 | 3 | 13 | 0.06 | 0.06 |
| LREV | 2 | 6 | 9 | 10 | 4 | 5 | 4 | 7 | 6 | 11 | 13 | 17 | 0.05 | 0.07 |
| MDR | 15 | 3 | 1 | 4 | 6 | 2 | 2 | 4 | 21 | 5 | 3 | 8 | 0.09 | 0.04 |
| MOM | 1 | 0 | 2 | 1 | 3 | 2 | 0 | 2 | 4 | 2 | 2 | 3 | 0.00 | 0.01 |
| SREV | 6 | 2 | 5 | 4 | 2 | 8 | 3 | 1 | 8 | 10 | 8 | 5 | 0.02 | 0.04 |
| Sub-sum | 63 | 50 | 26 | 38 | 43 | 41 | 24 | 29 | 106 | 91 | 50 | 67 | 0.08 | 0.07 |
| Total | 119 | 120 | 104 | 119 | 102 | 102 | 80 | 106 | 221 | 222 | 184 | 225 | 0.12 | 0.13 |

**Table 5-4 (continued)**

**Panel B. 5-factor model**

| | All significant | | | | | | | | | | | | | | | Adj. R-square | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Developed | | | | | Emerging | | | | | All markets | | | | | Developed | Emerging |
| Anomaly | MKT | SIZE | BM | INV | ROE | MKT | SIZE | BM | INV | ROE | MKT | SIZE | BM | INV | ROE | Mean | Mean |
| | Accounting anomalies | | | | | | | | | | | | | | | | |
| AC | 5 | 5 | 8 | 2 | 3 | 7 | 6 | 3 | 4 | 4 | 12 | 11 | 11 | 6 | 7 | 0.07 | 0.10 |
| AG | 6 | 5 | 7 | 22 | 13 | 8 | 0 | 3 | 15 | 10 | 14 | 5 | 10 | 37 | 23 | 0.26 | 0.20 |
| AM | 14 | 13 | 22 | 9 | 13 | 10 | 12 | 16 | 4 | 13 | 24 | 25 | 38 | 13 | 26 | 0.26 | 0.30 |
| BM | 7 | 11 | 22 | 5 | 14 | 5 | 9 | 20 | 6 | 8 | 12 | 20 | 42 | 11 | 22 | 0.29 | 0.32 |
| GP | 8 | 8 | 16 | 6 | 17 | 10 | 6 | 10 | 4 | 16 | 18 | 14 | 26 | 10 | 33 | 0.21 | 0.25 |
| IG | 4 | 8 | 4 | 12 | 2 | 3 | 8 | 4 | 6 | 8 | 7 | 16 | 8 | 18 | 10 | 0.09 | 0.10 |
| OS | 8 | 20 | 8 | 9 | 21 | 4 | 12 | 6 | 10 | 15 | 12 | 32 | 14 | 19 | 36 | 0.30 | 0.32 |
| WAC | 7 | 3 | 5 | 6 | 5 | 5 | 3 | 3 | 2 | 5 | 12 | 6 | 8 | 8 | 10 | 0.04 | 0.08 |
| Sub-sum | 59 | 73 | 92 | 71 | 88 | 52 | 56 | 65 | 51 | 79 | 111 | 129 | 157 | 122 | 167 | 0.19 | 0.21 |
| | Market anomalies | | | | | | | | | | | | | | | | |
| BETA | 18 | 16 | 5 | 2 | 2 | 14 | 3 | 5 | 3 | 3 | 32 | 19 | 10 | 5 | 5 | 0.17 | 0.13 |
| DVOL | 11 | 22 | 6 | 1 | 7 | 8 | 7 | 4 | 1 | 1 | 19 | 29 | 10 | 2 | 8 | 0.18 | 0.10 |
| ILLIQ | 2 | 9 | 1 | 4 | 3 | 1 | 3 | 2 | 2 | 2 | 3 | 12 | 3 | 6 | 5 | 0.04 | 0.03 |
| IVOL | 8 | 11 | 2 | 1 | 9 | 4 | 6 | 3 | 1 | 4 | 12 | 17 | 5 | 2 | 13 | 0.07 | 0.06 |
| LREV | 1 | 7 | 7 | 8 | 8 | 1 | 2 | 0 | 4 | 4 | 2 | 9 | 7 | 12 | 12 | 0.07 | 0.06 |
| MDR | 18 | 4 | 2 | 3 | 5 | 7 | 3 | 1 | 2 | 1 | 25 | 7 | 3 | 5 | 6 | 0.10 | 0.05 |
| MOM | 4 | 2 | 0 | 3 | 2 | 4 | 3 | 2 | 3 | 1 | 8 | 5 | 2 | 6 | 3 | 0.01 | 0.01 |
| SREV | 6 | 3 | 1 | 0 | 2 | 4 | 7 | 4 | 3 | 1 | 10 | 10 | 5 | 3 | 3 | 0.02 | 0.04 |
| Sub-sum | 68 | 74 | 24 | 22 | 38 | 43 | 34 | 21 | 19 | 17 | 111 | 108 | 45 | 41 | 55 | 0.08 | 0.06 |
| Total | 127 | 147 | 116 | 93 | 126 | 95 | 90 | 86 | 70 | 96 | 222 | 237 | 202 | 163 | 222 | 0.14 | 0.13 |

**Table 5-5 Anomalies - summary by Alpha**

This table reports summaries of alphas that are estimated from the multi-factor regressions reported in Table 5-4. Num of sig. is the number of significant spreads at least at the 5% significance level. % of sig. is the percentage of significant anomalies divided by the number of markets. Diff(developed-emerging) is the percentage difference between developed and emerging markets. A Chi-square test is conducted to indicate the significance of the difference - with the null hypothesis being that the proportion having significant anomalies is the same. The average is also reported in the last row.

**Panel A. Equal-weighted alpha (q-factor model)**

| | | Num of sig. | | Percent of sig. | | |
|---|---|---|---|---|---|---|
| **Type** | **Anomaly** | **Developed** | **Emerging** | **Developed** | **Emerging** | **Diff(D-E)** |
| Accounting | AC | 7 | 1 | 30.40% | 4.50% | 25.90%** |
| Accounting | AG | 2 | 0 | 8.70% | 0.00% | 8.70% |
| Accounting | AM | 10 | 8 | 43.50% | 36.40% | 7.12% |
| Accounting | BM | 15 | 9 | 65.20% | 40.90% | 24.31% |
| Accounting | GP | 10 | 6 | 43.50% | 27.30% | 16.21% |
| Accounting | IG | 2 | 0 | 8.70% | 0.00% | 8.70% |
| Accounting | OS | 11 | 2 | 47.80% | 9.10% | 38.7%*** |
| Accounting | WAC | 10 | 3 | 43.50% | 13.60% | 29.8%** |
| Average | | 8 | 4 | 36% | 16% | 20% |
| Market | BETA | 2 | 0 | 8.70% | 0.00% | 8.70% |
| Market | DVOL | 2 | 8 | 8.70% | 36.40% | -27.70%** |
| Market | ILLIQ | 6 | 1 | 26.10% | 4.50% | 21.50%** |
| Market | IVOL | 14 | 5 | 60.90% | 22.70% | 38.10%*** |
| Market | LREV | 2 | 5 | 8.70% | 22.70% | -14.03% |
| Market | MDR | 9 | 6 | 39.10% | 27.30% | 11.86% |
| Market | MOM | 21 | 11 | 91.30% | 50.00% | 41.3%*** |
| Market | SREV | 13 | 12 | 56.50% | 54.50% | 1.98% |
| Average | | 9 | 6 | 38% | 27% | 10% |
| All | | 9 | 5 | 37% | 22% | 15% |

**Table 5-5 (continued)**

**Panel B. Value-weighted alpha (q-factor model)**

| | | Num of sig. | | Percent of sig. | | |
|---|---|---|---|---|---|---|
| **Type** | **Anomaly** | **Developed** | **Emerging** | **Developed** | **Emerging** | **Diff(D-E)** |
| Accounting | AC | 4 | 0 | 17.40% | 0.00% | 17.4%** |
| Accounting | AG | 3 | 1 | 13.00% | 4.50% | 8.50% |
| Accounting | AM | 5 | 2 | 21.70% | 9.10% | 12.65% |
| Accounting | BM | 6 | 2 | 26.10% | 9.10% | 17.00% |
| Accounting | GP | 3 | 3 | 13.00% | 13.60% | -0.59% |
| Accounting | IG | 0 | 1 | 0.00% | 4.50% | -4.55% |
| Accounting | OS | 1 | 0 | 4.30% | 0.00% | 4.35% |
| Accounting | WAC | 6 | 1 | 26.10% | 4.50% | 21.50%** |
| Average | | 4 | 1 | 15% | 6% | 10% |
| Market | BETA | 1 | 2 | 4.30% | 9.10% | -4.74% |
| Market | DVOL | 4 | 4 | 17.40% | 18.20% | -0.79% |
| Market | ILLIQ | 3 | 0 | 13.00% | 0.00% | 13.00%* |
| Market | IVOL | 0 | 1 | 0.00% | 4.50% | -4.55% |
| Market | LREV | 5 | 2 | 21.70% | 9.10% | 12.65% |
| Market | MDR | 0 | 0 | 0.00% | 0.00% | 0.00% |
| Market | MOM | 20 | 12 | 87.00% | 54.50% | 32.4%** |
| Market | SREV | 4 | 1 | 17.40% | 4.50% | 12.85% |
| Average | | 5 | 3 | 20% | 12% | 8% |
| All | | 4 | 2 | 18% | 9% | 9% |

**Table 5-5 (continued)**

**Panel C. Equal-weighted alpha (5-factor model)**

| | | Num of sig. | | Percent of sig. | | |
|---|---|---|---|---|---|---|
| **Type** | **Anomaly** | **Developed** | **Emerging** | **Developed** | **Emerging** | **Diff(D-E)** |
| Accounting | AC | 8 | 3 | 34.80% | 13.60% | 21.10%* |
| Accounting | AG | 2 | 1 | 8.70% | 4.50% | 4.15% |
| Accounting | AM | 5 | 5 | 21.70% | 22.70% | -0.99% |
| Accounting | BM | 7 | 5 | 30.40% | 22.70% | 7.71% |
| Accounting | GP | 12 | 4 | 52.20% | 18.20% | 34.0%** |
| Accounting | IG | 2 | 1 | 8.70% | 4.50% | 4.15% |
| Accounting | OS | 7 | 2 | 30.40% | 9.10% | 21.3%* |
| Accounting | WAC | 9 | 2 | 39.10% | 9.10% | 30.0%** |
| Average | | 7 | 3 | 28% | 13% | 15% |
| Market | BETA | 3 | 3 | 13.00% | 13.60% | -0.59% |
| Market | DVOL | 2 | 6 | 8.70% | 27.30% | -18.58% |
| Market | ILLIQ | 6 | 1 | 26.10% | 4.50% | 21.5%** |
| Market | IVOL | 15 | 6 | 65.20% | 27.30% | 37.90%** |
| Market | LREV | 0 | 5 | 0.00% | 22.70% | -22.73%** |
| Market | MDR | 10 | 8 | 43.50% | 36.40% | 7.12% |
| Market | MOM | 21 | 8 | 91.30% | 36.40% | 54.9%*** |
| Market | SREV | 15 | 14 | 65.20% | 63.60% | 1.58% |
| Average | | 9 | 6 | 39% | 29% | 10% |
| All | | 8 | 5 | 34% | 21% | 13% |

**Table 5-5 (continued)**

**Panel D. Value-weighted alpha (5-factor model)**

| Type | Anomaly | Num of sig. Developed | Num of sig. Emerging | Percent of sig. Developed | Percent of sig. Emerging | Diff(D-E) |
|---|---|---|---|---|---|---|
| Accounting | AC | 3 | 1 | 13.00% | 4.50% | 8.50% |
| Accounting | AG | 2 | 3 | 8.70% | 13.60% | -4.94% |
| Accounting | AM | 1 | 0 | 4.30% | 0.00% | 4.35% |
| Accounting | BM | 1 | 0 | 4.30% | 0.00% | 4.35% |
| Accounting | GP | 6 | 4 | 26.10% | 18.20% | 7.91% |
| Accounting | IG | 0 | 1 | 0.00% | 4.50% | -4.55% |
| Accounting | OS | 5 | 1 | 21.70% | 4.50% | 17.20%* |
| Accounting | WAC | 5 | 0 | 21.70% | 0.00% | 21.70%** |
| Average | | 3 | 1 | 12% | 6% | 7% |
| Market | BETA | 0 | 1 | 0.00% | 4.50% | -4.55% |
| Market | DVOL | 5 | 5 | 21.70% | 22.70% | -0.99% |
| Market | ILLIQ | 3 | 0 | 13.00% | 0.00% | 13.04%* |
| Market | IVOL | 0 | 1 | 0.00% | 4.50% | -4.55% |
| Market | LREV | 3 | 1 | 13.00% | 4.50% | 8.50% |
| Market | MDR | 0 | 0 | 0.00% | 0.00% | 0.00% |
| Market | MOM | 21 | 11 | 91.30% | 50.00% | 41.30%*** |
| Market | SREV | 4 | 2 | 17.40% | 9.10% | 8.30% |
| Average | | 5 | 3 | 20% | 12% | 8% |
| All | | 4 | 2 | 16% | 9% | 7% |

Overall, the analyses so far reveal three new findings. First, multi-factor models help to explain some of the anomalies with the numbers of significant anomalies reducing after considering the risk loading of the hedged return. The reduction in anomalies is more profound in developed than in emerging markets, hence the gap is narrowed between the two market types. Second, the factor models only provide a partial explanation to the puzzle regarding the developed and emerging market differences, with the empirical fact of developed markets having more anomalies still being consistently observed. Finally, this puzzle is especially pronounced when the anomaly returns are equally weighted as compared to when they are value weighted. This suggests that the small size effect on anomalies is more pronounced in developed markets - this is a new puzzle.

## 5.3. Review of Theoretical Explanations and Predictions

### 5.3.1. The Hong and Stein Model Revisited in an International Context

As discussed in the introduction, the search for explanations of anomalies leads us to explore potential variations in countries' investor mix as an explanation of cross country differences. The root of this explanation is that pricing anomalies are driven by bounded rationality.

In the Hong and Stein (1999, hereafter HS) model, there are two types of boundedly rational agents: news watchers and momentum traders. Specifically each type of agent is only able to process some subset of the available public information. Each news watcher observes some private information, but they fail to extract other news watchers' information from prices. The consequent under-reaction means that the momentum traders can profit by trend chasing. Momentum traders base their forecast of price on simple (i.e. univariate) functions of the history of past prices. The key prediction of the HS model is that if information diffuses gradually across the population, prices underreact in the short run. Momentum traders' attempts at arbitrage must inevitably lead to overreaction at longer horizons.

In an international context, a direct application of the HS model implies that more efficient prices and less anomalies are observed in markets with faster information diffusion across news watchers. In other words, the marginal effect of improved information diffusion on the number of anomalies is negative.

The above discussion, however, misses one important point – namely, that the existence of news watchers to set the trend is a necessary condition. Investors paying attention to and having the ability to process the appropriate type of information is a necessary condition for an anomaly to exist. Information is price relevant only if investors use it systematically in trading decisions. As HS point out, the very existence of under-reaction by news watchers sows the seeds for overreaction, by making it profitable for momentum traders to enter the market. In markets where there is a general lack of news watchers, there is insufficient critical mass to create the price trend for momentum traders to follow.

The above intuition can be summarized by an extended numerical analysis of the HS model. In the HS model the main parameter that captures the inverse of the information diffusion speed is z. z can be interpreted as the number of days for a piece of information to be fully diffused across the news watchers. The smaller is z the faster is the information diffusion. In addition, there are two parameters: the standard deviation of news shocks e, and the momentum traders' holding period j. Given a set of parameters for z, e, and j, the model can be solved numerically for the momentum traders' prediction coefficient *phi* that is similar to a positive feedback coefficient. In this framework, I can define an anomaly as an observation of a price process that exhibits short-term under-reaction and subsequent over-reaction. The parameter that captures under-reaction is z while the parameter that captures over-reaction is the parameter *phi*. I are interested in how the efficiency of news watchers, measured as the information diffusion speed (i.e. 1/z), affects momentum traders' behavior (i.e., *phi*). And the momentum intensity ($\boldsymbol{\phi}$) follows the equation below (see equation (7) of Hong and Stein ,1999):

$$\boldsymbol{\phi} = \frac{\gamma cov(P_{t+j}-P_t, \Delta P_{t-1})}{\{var(\Delta P) var_M(P_{t+j}-P_t)\}} \qquad \text{(Eq. 5-4)}$$

where P is the price and $\gamma$ is risk tolerance of momentum trader.

I extend HS's original numerical analysis by considering a wider range of information diffusion speeds 1/z; especially when z goes very large. Different z value will be used to simulate the price path then each z value will generate a $\boldsymbol{\phi}$ value from equation (5-4). Figure 5-1 presents a plot of the numerical analysis of phi and 1/z using a set of parameters similar to HS's analysis in their table A3, except that I use more variations of z. The phi values from simulated price are consistent and comparable with HS's results (detailed phi values can be found in Table 5-6). The reason why the simulation results are not exactly the same is the input of an error term following a normal distribution. The price path depends on the initial setting of the error term matrix which is a random number generation process. Figure 5-1 shows that when the speed of information diffusion (1/z) is low (between 0 and 0.01 that corresponds to z between 100 and infinity) the momentum intensity is also low. This demonstrates the effect of news watchers efficiency at the start of Phase I. With very slow information diffusion, it is less likely that short-term under-reaction (price hardly reflects information in the market) and subsequent over-reaction will be observed (momentum traders have no clear price change to chase the trend). As the speed of diffusion increases (up to 0.033 that corresponds to z equaling 30), the improved efficiency of news watchers leads to a general increase in the momentum intensity, although the changes are not monotonic. In this later stage of Phase I, anomalies are most likely to be observed since there is significant short-term under-reaction (it can be interpreted as within 30 days given the z parameter) and there is significantly high momentum intensity (because momentum traders can follow the price change). When the speed of information diffusion further increases (for z less than 30), the momentum intensity starts to decrease as the profit of momentum trading is reduced (i.e. information is incorporated into price very quickly and therefore there is no room for momentum traders to do momentum trading). Therefore, news watcher efficiency is negatively correlated with momentum activities in this Phase II. Overall, as the news watcher efficiency improved, the speed of information is becoming faster, but the degree of momentum activities is nonlinear instead of linear during this process.

To justify how price experience underreaction and overreaction after new information comes to the market. I also calculate the cumulative impulse response and plot them. Following HS's model, the cumulative impulse response function is as the following equation:

$$\boldsymbol{\Delta P_t = \frac{\sum_{i=0}^{z-1} \epsilon_{t+i}}{z} + \phi \Delta P_{t-1} - \phi \Delta P_{t-(j+1)}} \qquad \text{(Eq. 5-5)}$$

where P is price, z is measurement of information diffusion speed, $\epsilon$ is news shock, $\phi$ is momentum intensity and j is holding period of momentum traders.

**Figure 5-1 Information diffusion speed and momentum intensity**

This figure plots the relationship between information diffusion and momentum intensity. The solution to momentum intensity is based on equation (7) from Hong and Stein (1999). The predetermined parameters are as follows: the momentum traders' horizon is 12, the volatility of news shocks is 0.5, and the momentum traders' risk tolerance is 1/3. $\phi = \frac{\gamma cov(P_{t+j} - P_t, \Delta P_{t-1})}{\{var(\Delta P) var_M(P_{t+j} - P_t)\}}$.

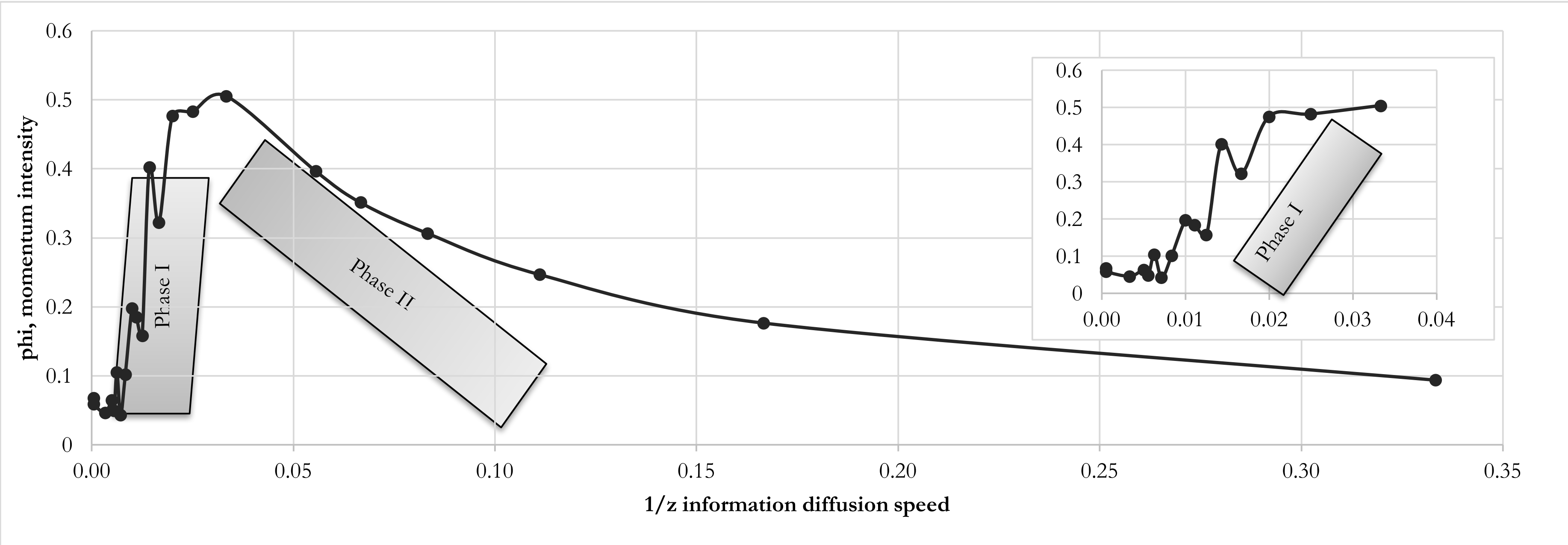
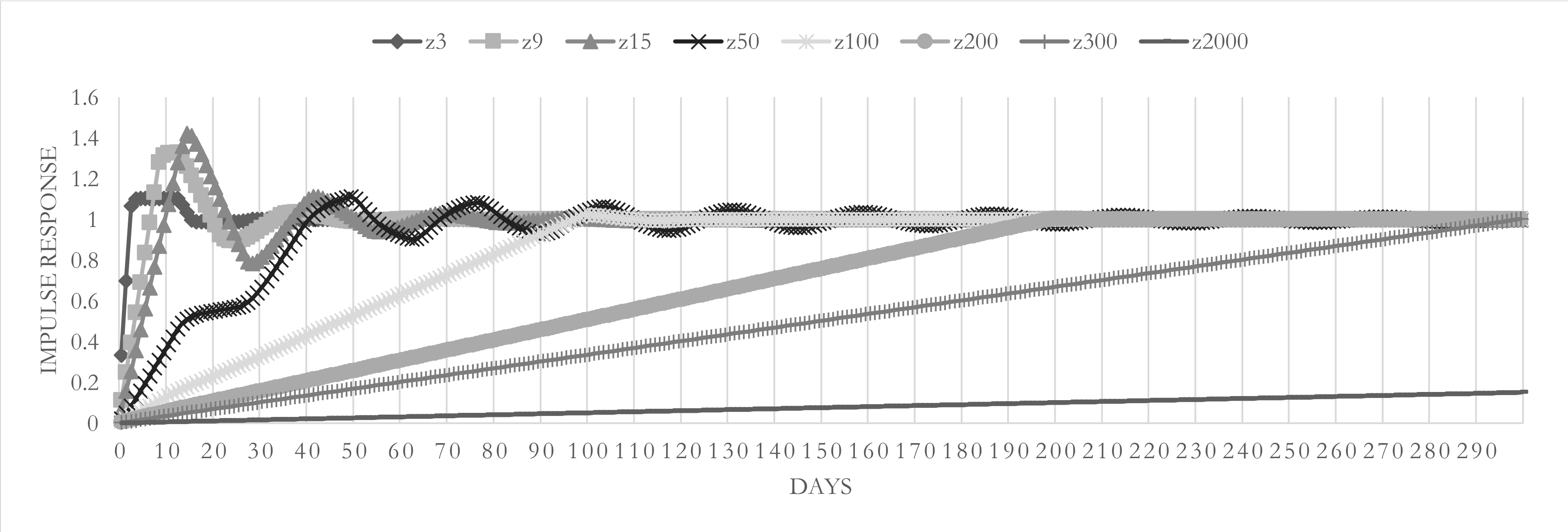


Figure 5-2 presents the impulse response functions given z. It shows that for those z that are large (larger than 100) news watchers are very ineffective and, therefore, information diffuses very slowly. In the short term (consider the short term window of 30 days), there is substantial under-reaction to a given news shock. However, such under-reaction is less likely to be observed empirically as the magnitude of the price discovery driven by this new information is too small and it will take a very long window to reach the equilibrium (fully informed) pricing benchmark to identify such an under-reaction. Therefore, the short-run under-reaction will not be clearly identified ex ante in the short term window. In absence of an identifiable under-reaction, as I show in Figure 5-1, the momentum parameters are very low in this phase. In other words, a lower number of anomalies (short-term momentum and long-term reversal) will be observed at this stage. As information diffusion speed increases (z reduced from 100 to 15), anomalies are more readily observable since news watchers, though still under-reacting to news, reveal substantial information in the price that gives momentum traders an opportunity to follow. The price converges to its fundamental value in a relatively shorter window as compared to those with (z greater than 100). Therefore, I clearly observe short-run under-reaction, and a subsequent over-reaction and reversal in price. Overall, when z decreases from 2000 to 15, I can see that the overreaction increases. This is corresponding to the Phase I in which news watcher efficiency and anomalies are positively correlated.

**Figure 5-2 Information diffusion speed and impulse response functions**

This figure plots cumulative impulse responses with respect to different information diffusion values (z). The cumulative impulse response function follows the equation (A2) from Hong and Stein (1999). The predetermined parameters are as follows: the momentum traders' horizon is 12, the volatility of news shocks is 0.5, and the momentum traders' risk tolerance is 1/3. Cumualtive impulse response function is $\Delta P_t = \frac{\sum_{i=0}^{z-1} \epsilon_{t+i}}{z} + \phi \Delta P_{t-1} - \phi \Delta P_{t-(j+1)}$.



In Phase II, as information diffusion speed increases (z decreases), anomalies are short-lived and with lower magnitude. This can be seen by comparing the lines for z=15 and z=3. The magnitude of the anomaly measured by the level of overshooting is smaller and the time length of mispricing (measured by the point of full adjustment to 1) is shorter when z=3 than when z=15. This suggests the increase of information diffusion speed (e.g., z decreases from 15 to 3) reduces anomalies.

Following Hong and Stein (1999), I further show the standard deviation of price error and return autocorrelations. The price error is the difference between stock price at time t and rational expectation price at time t. The equations for price path and rational price are as below:

Price path:

$$\boldsymbol{P_t = D_t + \frac{\{(z-1)\epsilon_{t+1} + (z-2)\epsilon_{t+2} + \cdots + \epsilon_{t+z-1}\}}{z} - Q + jA + \sum_{i=1}^{j} \phi \Delta P_{t-i}} \quad \text{(Eq. 5-6)}$$

Rational price:

$$\boldsymbol{P_t^* = D_{t+z-1} - Q} \quad \text{(Eq. 5-7)}$$

where P is price, D is value of dividend, z is information diffusion speed, $\epsilon$ is a random variable from a normal distribution, Q is asset supply, j is the holding period of momentum traders, A is a constant and $\boldsymbol{\phi}$ is momentum intensity.

Table 5-6 shows the simulated results and both of them can also confirm the above two-stage argument. Panel A in Table 5-6 shows that the standard deviation of price error that represents the distance from fundamental or the degree of mispricing. The standard deviation of price error increases as z varies until 28, while the standard deviation of price error decreases when the z value continues to grow. It means that mispricing is trivial when information diffusion at extremely fast or slow and therefore the observed anomalies are fewer. Panel B shows return autocorrelations given different information diffusion speed. Return autocorrelation indicates that there is some degree of predictability. Positive autocorrelation implies price continuation and negative autocorrelation implies reversal. With smaller z value (fast information diffusion), there should be short periods of momentum and return starts to reverse quickly. As information diffusion is getting slower, momentum trading activities should be stronger and the positive sign should appear in longer lag. In Panel B, we can observe that when the information diffusion is slow, the positive autocorrelation continues until the lag is long enough, in contrast, negative autocorrelation starts from very early when information diffusion is fast.

**Table 5-6 Simulation of Hong and Stein (1999) model: standard deviation of price error and autocorrelation**

This table shows detailed simulation results. Panel A reports the momentum intensity (phi) and standard deviation of price error (std of price error) with respect to different z values. The price error is $p_t - p_t^*$, where $p_t$ is the stock price at time t and $p_t^*$ is the rational expectation price at time t. Panel B reports the return autocorrelations based on the simulated price from different z values. Other parameters are fixed as follows: holding horizon of momentum trader is 12, volatility of news shock is 0.5 and the risk tolerance of momentum traders is 1/3.

**Panel A. Momentum intensity and standard deviation of price error**

| z | phi | std of price error |
|---|---|---|
| 3 | 0.0936 | 0.4428 |
| 6 | 0.1763 | 0.6160 |
| 9 | 0.2465 | 0.6429 |
| 10 | 0.2564 | 0.8614 |
| 11 | 0.2705 | 0.6723 |
| 12 | 0.3061 | 0.8325 |
| 13 | 0.3092 | 0.9379 |
| 14 | 0.3319 | 1.0878 |
| 15 | 0.3508 | 0.9922 |
| 16 | 0.3676 | 1.3476 |
| 17 | 0.3862 | 1.2929 |
| 18 | 0.3963 | 1.7441 |
| 19 | 0.4103 | 1.6883 |
| 20 | 0.4308 | 1.2208 |
| 21 | 0.4427 | 2.1110 |
| 22 | 0.4600 | 1.7595 |
| 23 | 0.4731 | 2.0224 |
| 24 | 0.4879 | 2.7175 |
| 25 | 0.4984 | 3.3021 |
| 26 | 0.5107 | 6.1131 |
| 27 | 0.5128 | 7.1801 |
| 28 | 0.4977 | 9.9490 |
| 29 | 0.4960 | 3.7372 |
| 30 | 0.5053 | 4.6072 |
| 40 | 0.4825 | 3.6999 |
| 50 | 0.4760 | 2.6225 |
| 60 | 0.3219 | 1.4269 |
| 70 | 0.4017 | 1.8953 |
| 80 | 0.1575 | 0.6962 |
| 90 | 0.1849 | 0.6611 |
| 100 | 0.1973 | 0.9044 |
| 120 | 0.1016 | 0.5738 |
| 140 | 0.0429 | 0.5691 |
| 160 | 0.1050 | 0.8273 |
| 180 | 0.0493 | 0.6388 |
| 200 | 0.0642 | 0.6037 |
| 300 | 0.0463 | 0.6185 |
| 1900 | 0.0588 | 0.8357 |
| 2000 | 0.0679 | 0.4824 |

**Panel B. Autocorrelations**

| lag | z3 | z6 | z10 | z20 | z50 | z100 | z200 | z300 | z2000 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.4531 | 0.7519 | 0.8477 | 0.9063 | 0.9617 | 0.9873 | 0.9949 | 0.9933 | 0.9932 |
| 2 | 0.0462 | 0.4918 | 0.6759 | 0.7955 | 0.9203 | 0.9744 | 0.9897 | 0.9865 | 0.9865 |
| 3 | -0.0088 | 0.2455 | 0.4925 | 0.6715 | 0.8768 | 0.9615 | 0.9845 | 0.9797 | 0.9796 |
| 4 | -0.0309 | 0.0377 | 0.3046 | 0.5375 | 0.8316 | 0.9486 | 0.9791 | 0.9728 | 0.9728 |
| 5 | -0.0500 | -0.1065 | 0.1205 | 0.3971 | 0.7855 | 0.9356 | 0.9737 | 0.9659 | 0.9659 |
| 6 | -0.0690 | -0.1629 | -0.0511 | 0.2540 | 0.7391 | 0.9226 | 0.9682 | 0.9590 | 0.9589 |
| 7 | -0.0880 | -0.2032 | -0.2011 | 0.1121 | 0.6932 | 0.9096 | 0.9626 | 0.9520 | 0.9519 |
| 8 | -0.1072 | -0.2400 | -0.3203 | -0.0244 | 0.6483 | 0.8966 | 0.9570 | 0.9450 | 0.9449 |
| 9 | -0.1265 | -0.2717 | -0.3994 | -0.1512 | 0.6054 | 0.8836 | 0.9512 | 0.9379 | 0.9378 |
| 10 | -0.1457 | -0.2934 | -0.4292 | -0.2639 | 0.5650 | 0.8706 | 0.9454 | 0.9308 | 0.9307 |
| 11 | -0.1631 | -0.2997 | -0.4340 | -0.3581 | 0.5279 | 0.8576 | 0.9395 | 0.9237 | 0.9236 |
| 12 | -0.1597 | -0.2849 | -0.4181 | -0.4297 | 0.4947 | 0.8447 | 0.9335 | 0.9165 | 0.9164 |
| 13 | -0.1136 | -0.2434 | -0.3811 | -0.4750 | 0.4662 | 0.8318 | 0.9275 | 0.9093 | 0.9092 |
| 14 | -0.0554 | -0.1884 | -0.3301 | -0.4950 | 0.4418 | 0.8188 | 0.9213 | 0.9020 | 0.9019 |
| 15 | -0.0098 | -0.1286 | -0.2701 | -0.4914 | 0.4209 | 0.8058 | 0.9151 | 0.8947 | 0.8946 |
| 16 | -0.0001 | -0.0705 | -0.2046 | -0.4659 | 0.4030 | 0.7926 | 0.9088 | 0.8874 | 0.8873 |
| 17 | 0.0030 | -0.0202 | -0.1364 | -0.4195 | 0.3874 | 0.7794 | 0.9024 | 0.8800 | 0.8799 |
| 18 | 0.0052 | 0.0167 | -0.0685 | -0.3536 | 0.3736 | 0.7660 | 0.8959 | 0.8725 | 0.8725 |
| 19 | 0.0073 | 0.0342 | -0.0041 | -0.2695 | 0.3612 | 0.7524 | 0.8893 | 0.8650 | 0.8650 |
| 20 | 0.0094 | 0.0451 | 0.0535 | -0.1686 | 0.3495 | 0.7388 | 0.8827 | 0.8575 | 0.8574 |
| 21 | 0.0114 | 0.0542 | 0.1010 | -0.0629 | 0.3379 | 0.7250 | 0.8759 | 0.8499 | 0.8499 |
| 22 | 0.0135 | 0.0619 | 0.1350 | 0.0405 | 0.3260 | 0.7111 | 0.8691 | 0.8423 | 0.8423 |
| 23 | 0.0156 | 0.0675 | 0.1520 | 0.1366 | 0.3130 | 0.6971 | 0.8622 | 0.8347 | 0.8346 |
| 24 | 0.0176 | 0.0697 | 0.1577 | 0.2211 | 0.2984 | 0.6829 | 0.8552 | 0.8269 | 0.8269 |
| 25 | 0.0174 | 0.0673 | 0.1549 | 0.2903 | 0.2814 | 0.6687 | 0.8481 | 0.8192 | 0.8191 |
| 26 | 0.0128 | 0.0589 | 0.1441 | 0.3409 | 0.2617 | 0.6543 | 0.8409 | 0.8114 | 0.8113 |
| 27 | 0.0067 | 0.0469 | 0.1274 | 0.3720 | 0.2389 | 0.6399 | 0.8337 | 0.8036 | 0.8035 |
| 28 | 0.0016 | 0.0332 | 0.1067 | 0.3839 | 0.2135 | 0.6254 | 0.8263 | 0.7957 | 0.7956 |
| 29 | 0.0001 | 0.0196 | 0.0834 | 0.3774 | 0.1859 | 0.6108 | 0.8189 | 0.7877 | 0.7877 |
| 30 | -0.0003 | 0.0074 | 0.0588 | 0.3536 | 0.1567 | 0.5962 | 0.8114 | 0.7798 | 0.7797 |

The above discussion demonstrates that there are two phases of the effect of news watchers on anomalies. The empirical prediction is that if the information diffusion speed in the world covers the whole spectrum from very slow (very inefficient market) to very fast (very efficient market) I should observe a nonlinear relationship between information diffusion speed and the number of observed anomalies.

How can this theoretical insight help us to explain there are more anomalies in developed than in emerging markets? A further empirical prediction to help solve this puzzle is that developed markets are more likely to be in the later stage of Phase I and beginning of Phase II, while emerging markets are more likely to be in the early stage Phase I.

### 5.3.2. Alternative Explanations

One of the rational explanations of anomalies is the Q-theory approach, which studies the investment-return relationship from a production-based asset pricing or a firm's optimal investment standpoint (e.g., Cochrane, 1991, 1996; Chen and Zhang, 2010; Li, Livdan and Zhang, 2009; Li and Zhang, 2010). The basic argument is that firms with low discount rates (expected returns) have high net present values and high investment, whereas firms with high discount rates have low net present values and low investment.

Watanabe, Xu, Yao and Yu (2013) and Titman, Wei and Xie (2013) assert q- theory is responsible for the difference in the asset growth effect across markets. The former suggest that the increase or decrease in assets depends on stock price efficiency, that is, firm managers rely on an efficient price to make decisions on asset expansion or reduction. As a result, developed markets show a stronger asset growth anomaly. The latter considers that managers in less developed markets put less weight on the maximization of shareholder value when they make investment decisions and, therefore, there is a weaker link between investment and expected returns in these markets.

Following the above argument, Q-theory can be put forward to explain the difference between emerging and developed markets in most of the investment based anomalies. However, it cannot be used to explain non-investment based anomalies such as market-based anomalies.

## 5.4. Analyses of News Watchers and Anomalies

To test the central prediction regarding news watcher efficiency and the number of anomalies, I capture the cross-sectional difference of news watcher efficiency by three proxies: higher education, consumer buying sophistication and accounting standard. I choose these proxies with a number of considerations.

The speed of information diffusion depends on two components: information quality and investors' ability to process the information. For example, You and Zhang (2009) find that information travels slower across the market when information readability is lower. They show that the under-reaction to 10-K reports is stronger when they are more complex. In this regard, information diffusion speed can be increased by an improvement in two aspects: better disclosure practice (such as improved accounting standards) and improved investment analysis skills through investor education. Therefore, to capture cross-country differences in news watcher efficiency, I use accounting standards, higher education and consumer buying sophistication to proxy for information quality, investor education and sophistication. Higher accounting standards should increase the readability of accounting reports and Kaniel, Ozoguz and Starks (2012) argue that higher accounting quality can increase investor confidence. Investors with more confidence may lead to quicker reaction and faster information diffusion as a result.

Investor sophistication and education will help measure the cross sectional difference in the ability of investors to process information. Chang, Hsieh and Wang (2015) show that less sophisticated investors tend to mis-react to information. The definitions and data sources of the variables are given in Table 5-7. Investor sophistication is measured based on whether buyers make decision by their analysis rather than only by price. So this variable can reflect investors' sophistication when they make investment decisions. The ability to access financial information depends on the degree of financial analytical knowledge, hence I use higher education because financial theory is more likely to be delivered in higher education. The accounting standard is used to measure the transparency and reliability of accounting reports which can indicate the quality of accounting or financial information in a market. The disadvantage of the three news watcher proxies is that the time period is relatively short compared with the sample used to construct anomalies. Therefore, they may be not be representative in a longer period. This should be addressed when there are better proxies with longer time-series data.

Table 5-8 provides summary statistics of the country characteristic variables. Panel A shows that developed countries have higher measures in all the variables, and this is in line with expectations for more mature and developed economies. Specifically, there are significantly higher values of the three news watcher efficiency proxies in developed markets. Given that all of the measures capture dimensions of market development, one concern is the potentially high correlation among the variables. Panel B presents a correlation matrix. The three news watcher efficiency measures have the highest correlations (ranging from 0.67 to 0.79). Given these concerns over potential multicollinearity, I run analysis for each news watcher efficiency proxy separately with control variables[28].

### 5.4.1. Univariate Sort

To explore how news watcher efficiency might help to explain the difference in anomalies between emerging and developed markets, I study the anomaly distribution by univariate sort using the three news watcher efficiency proxies. Table 5-9 reports the results. I sort countries by the three proxies into quintiles from low to high news watcher efficiency. Table 5-9 shows, as expected, that emerging countries are concentrated in the low and median (1 to 3) groups while developed countries are in the median and high (3 to 5) groups as indicated in the number of country columns. It further shows that the average number of anomalies measured by hedged return and alphas demonstrate a nonlinear pattern (the results for the sophistication of buying behaviour variable being the exception).

[28] The other notably high correlations are the CAP and REGU variables with the news watcher efficiency proxies. To make sure potential multicollinearity among the explanatory variables doesn't affect the conclusion, I also experiment creating uncorrelated variables using factor analyses on each of the news watcher efficiency variables and the rest of the control variable. I am able to identify three (two) factors for the analyses with the EDU and SOPHI (ACCT) variables. When using the factors instead of the variable in the regressions the results for the documented nonlinear effect of news watcher efficiency still holds.

**Table 5-7 Information environment, investor sophistication and control variables**

| Variable | Definition | Data source |
|---|---|---|
| ACCT | Accounting standard index. The index is computed based on 90 items of 1990 annual reports including general information, income statements, balance sheets, funds flow statement, accounting standards, stock data and special items. | La Porta, Lopez-de-Silanes, Shleifer and Vishny(1998) |
| SOPHI | Average of buyer sophistication from 2006 to 2014. 'In your country, how do buyers make purchasing decisions? [1 = based solely on the lowest price; 7 = based on a sophisticated analysis of performance attributes]' | World Economics Form |
| EDU | Average of higher education and training from 2006 to 2014 | World Economics Form |
| CAP | Average of market capitalization from 1980 to 2013. Market capitalization is the value of shares traded over GDP. | World Bank |
| TURN | Average of the stock market turnover ratio from 1980 to 2013. Turnover ratio is the total value of shares traded divided by the average market capitalization. | World Bank |
| AD | Anti-director rights index. The index is created by aggregating: vote by mail, shares not blocked or deposited, cumulative voting, oppressed minority, pre-emptive rights and capital. | Djankov, La Porta, Lopez-de-Silanes and Shleifer(2005) |
| LAW | Dummy variable of legal system, 1 indicates common law, 0 indicates civil law. | La Porta, Lopez-de-Silanes, Shleifer and Vishny(2000) |
| REGU | Average of regulation of securities exchanges from 2006 to 2014. 'In your country, how effective are the regulation and supervision of securities exchanges? [1 = not at all effective; 7 = extremely effective]' | World Economics Form |
| ITEXE | Dummy variable of insider trading law enforcement. 1 indicates insider trading laws are enforced and 0 indicates no enforcement as of March 1999. | Bhattacharya and Daouk (2002) |

**Table 5-8 Summary statistics of market characteristics**

Panel A reports the descriptive statistics for the proxies of news watcher and control variables in developed and emerging markets and the difference between these markets. For the definition of these variables, see Table 5-7 for the detail. The number of observations, mean, minimum and maximum are reported for each variable. Diff(developed-emerging) is the difference between the developed and emerging markets, and the two sample t-test shows the significance of the difference. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Panel B reports the correlation matrix for these variables.

**Panel A. Summary statistics**

| | Developed | | | | Emerging | | | | Diff (developed-emerging) |
|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Min | Max | N | Mean | Min | Max | |
| EDU | 23 | 5.478 | 4.613 | 6.110 | 22 | 4.156 | 2.837 | 4.843 | 1.323*** |
| SOPHI | 23 | 4.712 | 4.040 | 5.417 | 22 | 3.831 | 2.605 | 4.655 | 0.881*** |
| ACCT | 23 | 68.304 | 54.000 | 83.000 | 12 | 55.500 | 24.000 | 76.000 | 12.804*** |
| TURN | 22 | 0.846 | 0.309 | 1.946 | 21 | 0.568 | 0.126 | 1.552 | 0.278** |
| CAP | 22 | 0.750 | 0.096 | 2.403 | 21 | 0.218 | 0.014 | 0.706 | 0.531*** |
| AD | 23 | 3.565 | 2.000 | 5.000 | 19 | 3.553 | 1.000 | 5.000 | 0.013 |
| LAW | 23 | 0.348 | 0.000 | 1.000 | 22 | 0.318 | 0.000 | 1.000 | 0.030 |
| REGU | 23 | 5.275 | 4.145 | 5.927 | 22 | 4.630 | 3.578 | 6.230 | 0.646*** |
| ITEXT | 23 | 0.913 | 0.000 | 1.000 | 22 | 0.455 | 0.000 | 1.000 | 0.459*** |

**Panel B. Correlation matrix**

| Variable | EDU | SOPHI | ACCT | TURN | CAP | AD | LAW | REGU | ITEXE |
|---|---|---|---|---|---|---|---|---|---|
| EDU | 1.00 | | | | | | | | |
| SOPHI | 0.79 | 1.00 | | | | | | | |
| ACCT | 0.67 | 0.75 | 1.00 | | | | | | |
| TURN | 0.17 | 0.28 | 0.27 | 1.00 | | | | | |
| CAP | 0.47 | 0.61 | 0.46 | 0.49 | 1.00 | | | | |
| AD | -0.02 | 0.11 | 0.42 | -0.17 | 0.20 | 1.00 | | | |
| LAW | -0.01 | 0.17 | 0.42 | 0.01 | 0.25 | 0.54 | 1.00 | | |
| REGU | 0.62 | 0.67 | 0.66 | 0.02 | 0.43 | 0.31 | 0.34 | 1.00 | |
| ITEXE | 0.54 | 0.48 | 0.27 | 0.31 | 0.39 | 0.09 | -0.03 | 0.44 | 1.00 |

**Table 5-9 Univariate sort by news watcher efficiency proxies**

The table reports the average number of significant anomalies for news watcher quintiles. All markets are divided into quintiles based on higher education, investor sophistication and the accounting standard index respectively. Then the average number of significant anomalies is computed in terms of equal (value)-weighted hedged return, alpha from the q factor model and alpha from the Fama-French 5-factor model. The number of developed and emerging markets is also reported (N) for each quintile. See Table 5-3 for the hedged return calculation; and see Table 5-4 for the construction of the q factor model and the Fama-French 5-factor model.

**Panel A. Rank for variable EDU**

| | Hedged return | | Alpha q-factor model | | Alpha 5-factor model | | N | | |
|---|---|---|---|---|---|---|---|---|---|
| Group | EW | VW | EW | VW | EW | VW | Dev | Eme | All |
| 1 (Low) | 3.22 | 2.89 | 3.78 | 1.56 | 3.44 | 1.67 | 0 | 9 | 9 |
| 2 | 3.33 | 1.44 | 3.78 | 1.33 | 3.22 | 1.33 | 1 | 8 | 9 |
| 3 | 4.44 | 3.00 | 4.33 | 2.33 | 4.33 | 1.67 | 4 | 5 | 9 |
| 4 | 8.33 | 4.56 | 6.33 | 3.33 | 5.44 | 2.89 | 9 | 0 | 9 |
| 5 (High) | 6.44 | 3.22 | 5.44 | 2.22 | 5.56 | 2.44 | 9 | 0 | 9 |

**Panel B. Rank for variable SOPHI**

| | Hedged return | | Alpha q-factor model | | Alpha 5-factor model | | N | | |
|---|---|---|---|---|---|---|---|---|---|
| Group | EW | VW | EW | VW | EW | VW | Dev | Eme | All |
| 1 (Low) | 2.89 | 1.78 | 2.78 | 1.00 | 2.44 | 0.89 | 0 | 9 | 9 |
| 2 | 3.44 | 2.33 | 4.33 | 1.67 | 3.67 | 1.56 | 3 | 6 | 9 |
| 3 | 5.89 | 3.44 | 4.78 | 1.89 | 4.78 | 2.00 | 3 | 6 | 9 |
| 4 | 6.67 | 3.11 | 5.67 | 2.44 | 5.11 | 2.67 | 8 | 1 | 9 |
| 5 (High) | 6.89 | 4.44 | 6.11 | 3.78 | 6.00 | 2.89 | 9 | 0 | 9 |

**Panel C. Rank for variable ACCT**

| | Hedged return | | Alpha q-factor model | | Alpha 5-factor model | | N | | |
|---|---|---|---|---|---|---|---|---|---|
| Group | EW | VW | EW | VW | EW | VW | Dev | Eme | All |
| 1 (Low) | 2.86 | 2.43 | 3.43 | 1.57 | 2.43 | 1.57 | 1 | 6 | 7 |
| 2 | 6.14 | 3.29 | 6.14 | 2.57 | 4.86 | 2.86 | 5 | 2 | 7 |
| 3 | 4.71 | 2.43 | 4.43 | 1.57 | 3.86 | 1.57 | 5 | 2 | 7 |
| 4 | 7.75 | 4.63 | 6.88 | 3.13 | 6.50 | 3.25 | 7 | 1 | 8 |
| 5 (High) | 7.33 | 4.00 | 5.50 | 3.50 | 6.17 | 2.00 | 5 | 1 | 6 |

These findings provide support to the explanation of the difference in anomalies between developed and emerging markets. The results of the EDU sorting exemplify this explanation clearly, while emerging markets are spread from groups 1 to 3, they are concentrated in the first two groups where the number of anomalies are at their lowest. In other words, from group 1 to 3, most of emerging markets have lower education level than developed markets and the number of anomalies is greater in developed markets (there is an increasing trend of the number of anomalies from group 1 to group 3). This supports the conjecture that emerging markets are more likely to be in the early stage of the Phase I of the model where anomalies are less likely to be observed and news watchers have clear effect on the variations. By contrast, developed markets are meaningfully featured from group 3 and concentrated in groups 4 and 5, there are large increases from groups 3 to 4 which fits into the definition of Phase I and slight decreases from 4 to 5 which suggests there are a small number of developed countries which may be entering into Phase II. The results for SOPHI and ACCT provide similar results except that for SOPHI variables, after the peak at group 4 there is no sign of decreasing of number of anomalies in group 5. This suggests that if I use buyers' sophistication as a measure of news watcher efficiency, there is no sign of developed markets entering in the phase II of the news watcher efficiency and anomaly relationship. Overall, these findings suggest that developing markets are more likely to be concentrated in the early stage of Phase I while developed markets in the later stage of Phase I and early stage of Phase II.

### 5.4.2. Regression Analysis

In order to control for potential alternative explanations I run a multivariate regression analysis. Stock market turnover (TURN) and market capitalization (CAP) are considered as measures of market efficiency in Watanabe, Xu, Yao and Yu (2013). Higher turnover and capitalization imply more efficient prices and hence a positive relation between the asset growth effect and market efficiency is in line with Q-theory. Higher turnover and capitalization should lead to a stronger link between investment decisions and shareholder value (Titman, Wei and Xie, 2013). In addition, Titman, Wei and Xie (2013) argue that corporate governance may lead to cross country differences in the asset growth anomaly. Griffin, Hirschey and Kelly (2011) suggest that the regulatory environment is one of the sources of cross country differences in news reaction. To control for corporate governance or regulation, I consider anti-director (AD), law system (LAW) and regulation (REGU). Further, Griffin, Hirschey and Kelly (2011) advocate insider trading as an explanation of the different level of information reaction across countries. Therefore, insider trading law enforcement (ITEXE) is included as another control variable. Variable definitions are given in Table 5-7.

Table 5-10 shows the regression results with a nonlinear specification of the news watchers proxies. The dependent variable is the number of significant anomalies measured by the 5% significant alpha in the multi-factor model regression. It reports multi-factor model analyses of both the q- and 5- factor models. Panels A and B report the results for alphas from the equal-weighted return analyses, while Panels C and D report those from the equal-weighted return analyses. The nonlinear cross sectional regression model is as follow:

$$\boldsymbol{NumAnomaly_i = \alpha + \beta_1 NW + \beta_2 NW^2 + \sum_{i=1}^{7} \theta_i \, Control_i + \varepsilon_i} \qquad \text{(Eq. 5-8)}$$

where NumAnomaly is the number of significant anomalies for each market, NW is new watcher efficiency (higher education, investor sophistication and accounting standard index), $NW^2$ is the square of new watcher efficiency. To capture the nonlinear relationship indicated by the simulation, I include the square of news watcher proxy. The negative sign of the squared term means that there is an inverted U shape. Control is control variable including dummy variable of developed markets, turnover, market capitalization, anti-director right, law system, stock exchange regulation, insider trading enforcement.

Table 5-10 has the following notable results. First, news watcher efficiency has a nonlinear relationship with the number of anomalies. This is especially the case for the equal weighted analyses. The coefficients for the quadratic term of the news watcher efficiency measures are negative and significant in most of the equations in Panels A and B. It suggests that as news watcher efficiency increases the number of anomalies increases and then decreases and this forms an inverted U-shape as predicted. Examining the turning point of the nonlinear curve, it suggests that the number of anomalies are at the highest when SOPHI, EDU and ACCT are at 4.55, 4.59 and 66.17 respectively according to the coefficients of NW and NW2 in panel A[29]. Comparing these values with the distribution of the news watcher variables in Panel A of Table 5-9, it clearly shows that these turning points are in between the means of the emerging and developed markets, with the means of the emerging market measures being lower than the turning points. I illustrate the effect of news watcher efficiency on the predicted number of anomalies using the parameters in Panel A of Table 5-10. I calculate the predicted value of the dependent variable (number of significant anomalies) by varying the news watcher efficiency variable (NW) from its sample minimum to maximum while holding other variables in the equation

[29] The turning point of a quadrative function ($y = ax^2 + bx + c$) can be found at $x = -\frac{b}{2a}$.

at their sample mean level. These graphs are reported in Figure 5-3. In Panel A, Panel B and Panel C, the figure plots the nonlinear relationship between predicted number of anomalies and investor sophistication, higher education and accounting standard respectively. It clearly shows that developed markets are likely to be located around the peak or after the peak while emerging markets tend to be located before the peak. This confirms the two-stage simulation results.

They demonstrate the nonlinear pattern of news watcher efficiency on the number of anomalies. Furthermore, emerging markets are more likely to be situated in the left side of the curve while developed markets are more likely to be on the right side of the curve.

A second notable result in Table 5-10 is that the Developed dummy is positive and highly significant when it enters into the regression alone. Importantly, however, its ability to explain the cross-sectional difference in anomalies disappears when the news watcher efficiency and other control variables are included. This suggests that the status of being either an emerging or developed market carries no information regarding a country's market anomalies once country specific characteristics have been controlled for. Finally, regarding the alternative explanations in Table 5-8, there are consistent results for the TURN and CAP variables that are often positive and significantly associated with number of anomalies – such results are consistent with the Q-theory explanations put forwarded in Titman, Wei and Xie (2013) and Watanabe, Xu, Yao and Yu (2013). Importantly these results suggest that the news watcher efficiency explanation is robust to the inclusion of these alternative explanations.

**Table 5-9 Cross-market regression: news watcher efficiency against alternatives**

This table reports the results of cross sectional regressions of the number of significant anomalies on new watcher efficiency proxies and control variables: $NumAnomaly_i = \alpha + \beta_1 NW + \beta_2 NW^2 + \sum_{i=1}^{7} \theta_i \, Control_i + \varepsilon_i$. The dependent variable is the number of significant anomalies measured by the 5% significant alpha in the multi-factor model regression. It reports multi-factor model analyses of both q- and 5- factor models. Panels A and B report the results for alphas from the equal-weighted return analyses, while Panels C and D report those from the equal-weighted return analyses. Developed is a dummy variable having the value of 1 for developed markets and 0 otherwise. The investor sophistication proxies include buyer sophistication (SOPHI), higher education and training (EDU) and accounting standard (ACCT). The control variables include a development dummy (DEV), capitalization (CAP), turnover ratio (TURN), anti-director right index (AD), a civil or common law dummy (LAW), stock exchange regulation (REGU) and an enforcement of insider trading law dummy (ITEXE). See the detail in Table 5-7 for the definition of information environment proxies and control variables. Adjusted R square and the number of observations are reported and the t values in parentheses are based on robust standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

**Table 5-10 (continued)**

**Panel A. q-factor model with equal-weighted return**

| | | | SOPHI | | EDU | | ACCT | |
|---|---|---|---|---|---|---|---|---|
| | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** |
| Intercept | 3.500*** | 7.50 | -19.832** | -2.08 | -26.562*** | -2.60 | -7.934* | -1.99 |
| NW | | | 11.083** | 2.28 | 11.583*** | 2.94 | 0.397*** | 4.88 |
| NW2 | | | -1.219* | -1.95 | -1.263*** | -2.72 | -0.003*** | -3.78 |
| Developed | 2.413*** | 3.38 | 0.707 | 0.64 | 1.702 | 1.00 | 0.087 | 0.10 |
| TURN | | | 0.253 | 0.31 | 1.338 | 1.43 | 1.649* | 1.79 |
| CAP | | | 1.560* | 1.70 | 0.953 | 1.07 | 1.393** | 2.37 |
| AD | | | -0.240 | -0.61 | -0.199 | -0.50 | -0.790* | -1.74 |
| LAW | | | 0.734 | 0.89 | 0.925 | 1.00 | 1.231* | 1.73 |
| REGU | | | -0.218 | -0.28 | 0.726 | 0.85 | 0.251 | 0.28 |
| ITEXE | | | 0.653 | 0.74 | 0.292 | 0.33 | 0.286 | 0.32 |
| | | | | | | | | |
| Adj R-Sq | 0.183 | | 0.284 | | 0.293 | | 0.314 | |
| Obs | 45 | | 40 | | 40 | | 33 | |

**Panel B. Fama-French 5 factor model with equal-weighted return**

| | | | SOPHI | | EDU | | ACCT | |
|---|---|---|---|---|---|---|---|---|
| | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** |
| Intercept | 3.364*** | 6.56 | -31.753*** | -3.78 | -27.488*** | -2.61 | -5.790 | -1.13 |
| NW | | | 15.671*** | 4.25 | 10.274*** | 2.74 | 0.183 | 1.69 |
| NW2 | | | -1.858*** | -4.00 | -0.996** | -2.12 | -0.001 | -0.98 |
| Developed | 2.028*** | 2.89 | 0.582 | 0.70 | -0.261 | -0.22 | 0.212 | 0.191 |
| TURN | | | 0.170 | 0.22 | 1.539** | 2.28 | 1.344 | 1.37 |
| CAP | | | 2.476** | 2.52 | 1.330* | 1.83 | 1.464** | 2.15 |
| AD | | | -0.267 | -0.88 | -0.069 | -0.24 | -0.264 | -0.64 |
| LAW | | | -0.221 | -0.29 | 0.393 | 0.47 | 0.468 | 0.62 |
| REGU | | | 0.743 | 0.90 | 1.079 | 1.08 | 0.580 | 0.60 |
| ITEXE | | | -0.678 | -0.82 | -1.014 | -1.16 | -0.947 | -0.82 |
| | | | | | | | | |
| Adj R-Sq | 0.137 | | 0.295 | | 0.261 | | 0.181 | |
| Obs | 45 | | 40 | | 40 | | 33 | |

**Table 5-10 (continued)**

**Panel C. q factor model with value-weighted return**

| | | | SOPHI | | EDU | | ACCT | |
|---|---|---|---|---|---|---|---|---|
| | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** |
| Intercept | 1.455*** | 5.71 | 1.241 | 0.22 | -12.470*** | -2.91 | -3.035 | -0.90 |
| NW | | | -1.452 | -0.45 | 4.580** | 2.23 | 0.096 | 0.83 |
| NW2 | | | 0.303 | 0.70 | -0.482* | -1.97 | -0.001 | -0.67 |
| Developed | 1.372*** | 2.91 | -0.411 | -0.72 | 0.192 | 0.21 | 0.197 | 0.28 |
| TURN | | | 0.549 | 1.10 | 0.810** | 2.01 | 0.897 | 1.62 |
| CAP | | | 0.821 | 1.54 | 1.171*** | 3.09 | 1.327*** | 3.30 |
| AD | | | 0.243 | 1.21 | 0.189 | 0.98 | 0.209 | 0.65 |
| LAW | | | 0.601 | 1.00 | 0.501 | 0.77 | 0.530 | 0.74 |
| REGU | | | -0.120 | -0.30 | 0.349 | 0.91 | 0.071 | 0.11 |
| ITEXE | | | 0.759 | 1.54 | 0.421 | 0.91 | 0.111 | 0.22 |
| | | | | | | | | |
| Adj R-Sq | 0.136 | | 0.351 | | 0.337 | | 0.229 | |
| Obs | 45 | | 40 | | 40 | | 33 | |

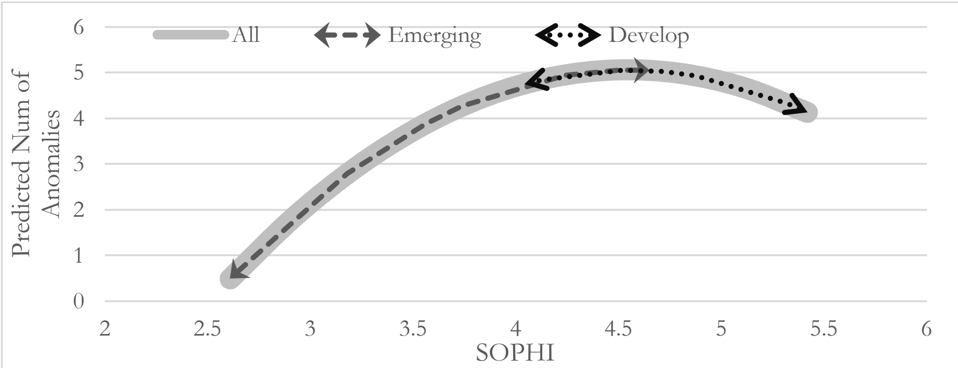
**Panel D. Fama-French 5 factor model with value-weighted return**

| | | | SOPHI | | EDU | | ACCT | |
|---|---|---|---|---|---|---|---|---|
| | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** | **Slope** | **t** |
| Intercept | 1.409*** | 4.94 | -11.704 | -1.57 | -17.730*** | -2.89 | -6.317** | -2.30 |
| NW | | | 5.234 | 1.42 | 6.602** | 2.47 | 0.150** | 2.39 |
| NW2 | | | -0.645 | -1.46 | -0.728** | -2.30 | -0.002*** | -2.74 |
| Developed | 1.156*** | 2.55 | -0.159 | -0.22 | 0.124 | 0.13 | 0.122 | 0.17 |
| TURN | | | 0.269 | 0.46 | 0.826 | 1.49 | 1.448* | 2.02 |
| CAP | | | 1.547*** | 2.58 | 1.048* | 1.76 | 1.202* | 1.94 |
| AD | | | -0.102 | -0.44 | -0.072 | -0.31 | -0.188 | -0.58 |
| LAW | | | 0.143 | 0.24 | 0.273 | 0.43 | 0.976 | 1.65 |
| REGU | | | 0.516 | 1.11 | 0.837* | 1.87 | 1.058* | 1.88 |
| ITEXE | | | 0.366 | 0.67 | 0.162 | 0.30 | -0.508 | -0.98 |
| | | | | | | | | |
| Adj R-Sq | 0.105 | | 0.176 | | 0.218 | | 0.239 | |
| Obs | 45 | | 40 | | 40 | | 33 | |

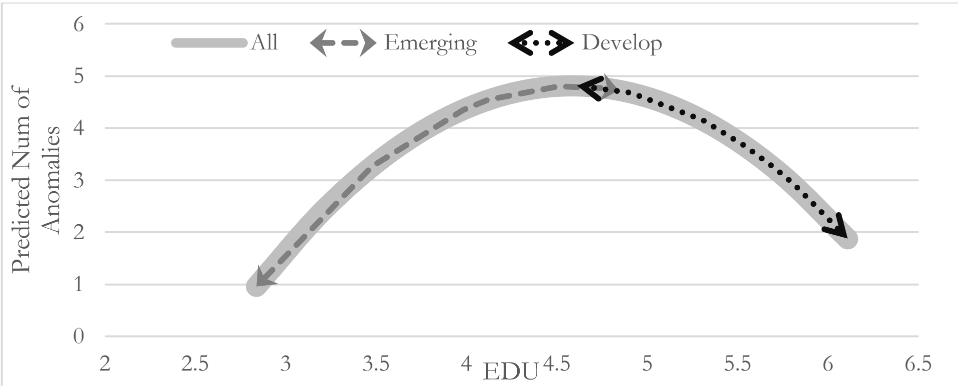
**Figure 5-3 Predicted effect of news watcher efficiency**

This figure reports the effect of news watcher efficiency on the predicted number of anomalies using the coefficients reported in Table 5-10 Panel A. The predicted values of the dependent variable (number of significant anomalies) are calculated by varying the news watcher efficiency variable (NW) from its sample minimum to maximum while holding other variables in the equation at their sample mean level. These predictions are plotted against the value of the NW variables. I also indicate the predicted ranges that covers the variations of NW for emerging and developed markets separately.

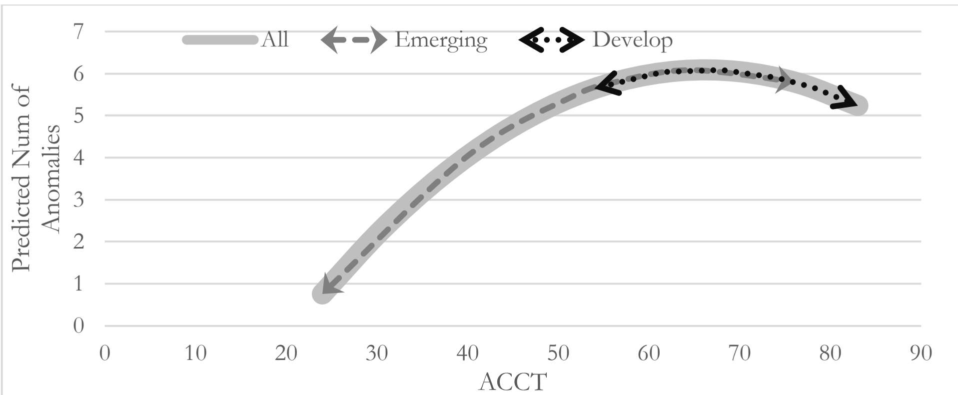
**Panel A. SOPHI**




**Panel B. EDU**




**Panel C. ACCT**



For the value weighted analyses in Panels C and D of Table 5-10, while most of the quadratic coefficients are negative, the coefficients are only significant in three out of the six equations. This suggests that the cross-sectional explanatory power of news watcher efficiency is weaker when the effect of small size firms is downplayed. Overall, Table 5-10 confirms that there is a nonlinear relationship between the news watcher efficiency proxies and anomalies, and this is especially the case for equal-weighted returns. Furthermore, the inclusion of news watcher efficiency helps explain the observed differences between emerging and developed market.

In addition, the slopes of squared ACCT are not always significantly negative. One reason is that the dependent variable is different in different regression specifications and the results of ACCT are sensitive to the number of anomalies measured in different models. Second, the number of observation for ACCT is quite small which may reduce the power of significance. Overall, the nonlinear relationship is weaker when ACCT is used as the news watcher proxy compared with higher education.

### 5.4.3. Effect of Size

The empirical analysis in the above section reveals a new puzzle. It shows that the difference between the developed and emerging markets is especially pronounced when the anomaly returns are equally weighted as compared to when they are value weighted. I also show that the alphas from the equal-weighted return portfolios demonstrate a stronger nonlinear relationship with news watcher efficiency in Table 5-10. This suggests that the well documented small size effect on anomalies is more pronounced in developed than in emerging markets and the role of news watchers might help to explain the reason behind this.

In order to understand the connection between firm size and anomalies, I start by examining the relationship between size and news watcher efficiency. Firm size can be a proxy for news watcher efficiency that affects the speed of information diffusion. Hong, Lim, and Stein (2000) argue that when investors face fixed costs of information acquisition, they devote more effort to learning about those stocks in which they can take large positions. This suggests that information about small firms is transmitted more slowly. If size is used as a proxy measure for news watcher efficiency, the theoretical extension in Section 5.3 predicts that there will be a nonlinear relationship between size and the number of observed anomalies. Specifically, there is an inverted U shape relationship between size and anomaly returns. Such a prediction is supported by Hong, Lim, and Stein (2000) who document that the smallest size firms (in the smallest two deciles; I refer to them as micro firms) have less anomalies than small size firms (in the third and fourth smallest deciles). In other words, there is an inverted U shape relationship between size and anomaly returns that is similar to the theoretical prediction of a two-phase effect[30].

Building on the above I propose that the difference between emerging and developed markets is stronger in equal- than in value- weighted returns because more of the small firms in emerging markets behave like micro firms where news watcher efficiency is at its weakest. To confirm this prediction, I replicate the analyses of size and anomalies by Hong, Lim, and Stein (2000) for emerging and developed markets separately. Figure 5-4 reports the plot of anomaly hedged returns by size decile for developed and emerging markets.

Figure 5-4 shows an inverted U shape relationship between size and anomaly returns in both markets. When comparing the two types of market, the anomalies in

[30] A clear inverted U shaped relationship between size and the hedged return of the momentum anomaly is presented in Figure 1 of Hong, Lim, and Stein (2000). Since the focus of Hong, Lim, and Stein (2000) was to test the prediction of Hong and Stein (1999) that there is linearity between size and anomalies, they quantify their conclusion in their abstract by acknowledging that they find support for the theory only "once one moves past the very smallest stocks" p1517.

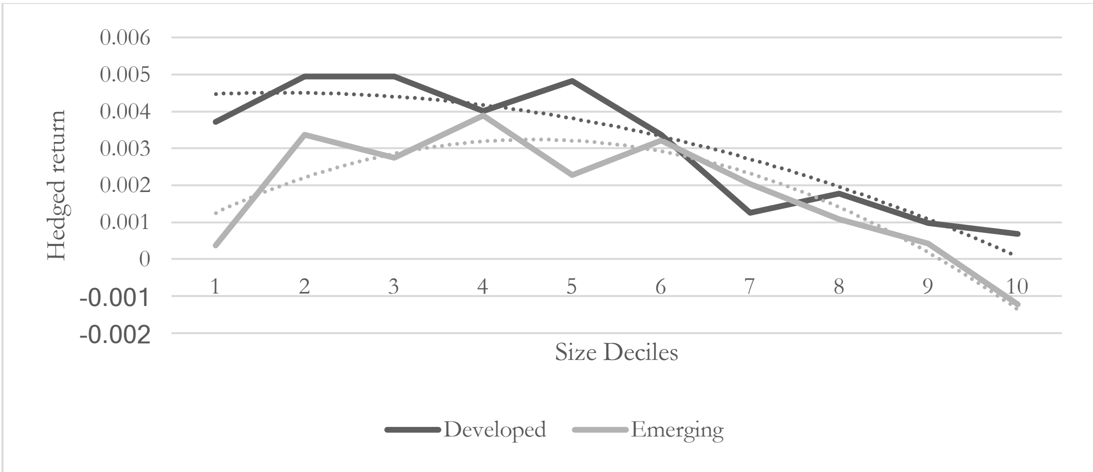
developed markets are stronger than is the case for emerging markets and this confirms the puzzle documented earlier. Importantly, this difference is much stronger at the small size deciles part of the plot and weaker at the larger size deciles part. The decreasing trend in the differences is observed in Panel B. Overall, this analysis explains why for equal weighted hedged returns the difference between emerging and developed markets is larger than is the case of value-weighted hedged returns. It suggests that more of the small stocks have behaved like US micro stocks that have close to zero anomalies. Therefore, I observe fewer anomalies in small firms in emerging markets. When the returns generated by firms across all sizes are equal weighted, the average number of anomalies is smaller for emerging markets. This evidence supports that the very low efficiency of news watchers for small size firms in emerging markets helps to explain why there are fewer anomalies in emerging market small size firms than in developed market small size firms.

Overall, to get results which can be compared with Hong, Lim and Stein (2000), I plot the anomaly return in each firm size by using more anomalies rather than a single anomaly. Although there are some swings from size 2 to size 5, the results showa similar pattern and the overall trend is inverted U shape.

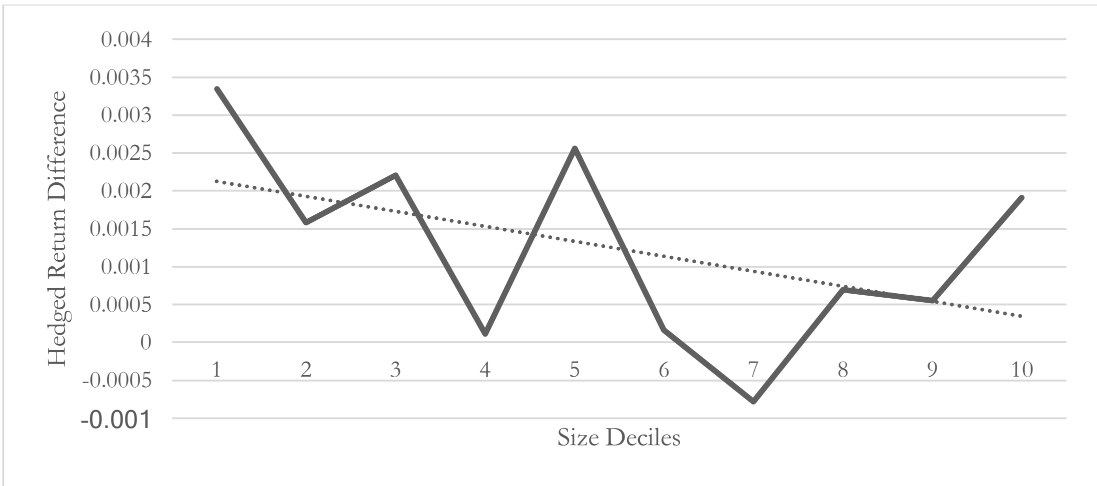
**Figure 5-4 Anomaly returns and firm size**

This figure reports anomaly returns by size decile for developed and emerging markets. Panel A plots the median return of each size decile. For each of the 16 anomalies, I rank firms into three groups based on 30 and 70 percentiles (break points are based on the NYSE in the US market and based on the entire sample in other markets). Anomaly return is the difference between the top and bottom groups. Independently, firms are divided into deciles based on market value. For both developed and emerging markets, I calculate the median of the hedged return in each size decile for each anomaly; I then compute the median across different anomalies in each size decile. Panel B plots the return difference between developed and emerging markets in Panel A.

**Panel A. Anomaly return**




**Panel B. Difference**



## 5.5. Conclusions

Asset pricing anomalies have played a vital role in the evolution of asset pricing theories. Newly documented anomalies post challenges to existing asset pricing models and stimulate the search for new theoretical and empirical pricing models that can take account of the apparent mispricing of risk. Therefore, asset pricing research in recent decades, since Fama and French's (1996) seminal paper, has been characterized by identifying a parsimonious multi-factor model that can account for the variations in the cross-sectional expected returns. Naturally, most of the 'developed' asset pricing theories have originated from research based on the developed markets. Therefore, the evolution of asset pricing research has been driven by observations in markets that are characterized as relatively more efficient and complete. However, the conclusions and relationships drawn from developed markets cannot always be literally extended to emerging markets. This chapter contributes to the evolution of asset pricing theory by studying asset pricing anomalies in a global context with the specific aim of exploring the differences between emerging and developed markets.

I establish a puzzle, via a wide array of anomalies in 45 countries, that pricing anomalies are more readily observable in developed than in emerging markets. Furthermore, this is still the case after considering the newly introduced factors of investment and profitability (Hou, Xue and Zhang, 2015) and Fama and French, 2015). The performance of the factor models in explaining anomaly returns are comparable between the emerging and developed markets suggesting that these multi-factor models capture systematic risk factors that are general and applicable to both types of markets. However, these risk factors alone cannot solve the puzzle. More specifically, following a linear extension of the rational risk factor explanation, one would need to be able to demonstrate that holding anomaly portfolios in a developed market would have experienced higher systematic risk than a similar portfolio in an emerging market; it is difficult to identify a risk factor that would fit such a description.

Given the unresolved nature of the puzzle, I turn to behavioural theories for potential explanations. I find that a linear extension of the behavioural explanation that originated from developed markets to emerging markets is not able to provide an explanation to the puzzle either. For example, prior literature suggests that investor behavioural bias in combination with limits to arbitrage induces mispricing in the market. However, if this were to be the case, then emerging markets should have more anomalies than developed markets, as both of these two characteristics should be more acute in the former.

When digging deeper into the behavioural theories, I find that Hong and Stein's (1999) theoretical framework provides a good starting point for examining international variations. Their model focuses on the investor heterogeneity that avoids making assumption specific behavioural bias by a single representative agent. Building on Hong and Stein (1999), I show that the efficiency of news watchers in a market has a nonlinear impact on the observations of pricing anomalies. News watchers reveal private fundamental information in price gradually to sow the seeds of momentum. Therefore, the presence of news watchers is a necessary condition for observing short-term momentum and long-term reversal in the market. The absence of some anomalies in emerging markets can be attributed to the absence of news watchers who pay attention to that particular type of news. This is consistent with Bhattacharya et al. (2000) who argue that for information driven (fundamental) anomalies, investors have to be able to monitor and process the relevant data. Furthermore, the prediction also sheds new light on the role of firm size and anomalies. I show that the smallest size firms (micro firms) often have less pricing anomalies than other small size firms as news watcher efficiency is at its lowest in these micro firms. Overall, the study introduces the concept of news watcher efficiency and demonstrates its importance to understanding asset pricing anomalies across markets.

There are five limitations in this chapter. First, there is noise for the cross sectional regression due to less observations. Second, there is a lack of time series evidence to support the nonlinear prediction. Third, it would be more helpful if there are more proxies for news watcher efficiency so that the results can be more robust. Fourth, an anomaly may disappear or become weaker after the publication. Therefore, it is useful to divide the sample into sub-period samples so that we can check whether the phenomenon can be explained by the different sub-period samples. Fifth, the news watcher proxies in cross sectional regression are constructed by using particular time periods due to data availability, so it cannot cover the entire sample period for constructing anomalies. Therefore, the results of cross sectional regression depend on the assumption that the certain period can represent the entire time period.

# Chapter 6

# Conclusions

## 6.1. Introduction

From the 1970s onwards, the efficient market hypothesis has been tested for more than 40 years. Asset pricing anomalies are usually considered as evidence to reject the market efficiency hypothesis. According to the efficient market hypothesis, all the information is fully and correctly incorporated into stock prices, and therefore investors cannot earn abnormal returns without taking extra risk. The investigation of abnormal return also depends on an asset pricing model that is the benchmark to measure the abnormal return. The size effect (see Banz, 1977) challenges the efficient market hypothesis because the abnormal return based on CAPM is significant. However, this cannot be direct evidence against the efficient market hypothesis due to the problem of the asset pricing model being potentially inadequate. From the 1990s, the Fama-French 3-factor model has been examined many times and it is seen as outperforming CAPM. Previous anomalies, like the size effect, are explained under the new asset pricing model. Later on, many studies discover new anomalies which cannot be captured by the Fama-French 3-factor model. In addition, behavioural finance is emerging in explaining the anomalies. Therefore, how to explain the new anomalies is the task to be examined.

Among these new anomalies, Cooper, Gullen and Schill (2008) find asset growth is negatively correlated with future stock returns. The asset growth anomaly is an aggregate anomaly because firm asset growth includes both the financing and investment sides. In addition, asset growth is directly related to investment-based asset pricing models and hence it raises attention to the investment-based model (the importance of asset growth is also seen by Hou, Xue and Zhang, 2015; Fama and French, 2015[31]). In terms of explaining the asset growth effect, the debate between rational and behavioural explanations has no clear conclusion (see Lam and Wei, 2011). To this end, my study first investigates the asset growth anomaly in order to understand the underlying source of the effect. Then motivated by anomaly literature in the global context (see Watanabe, Xu, Yao and Yu, 2013), I examine multiple anomalies in international markets. Most importantly, by examining global markets, I dig further into the explanation of anomalies based on news watcher efficiency and explain why developed markets have more anomalies than emerging markets.

Chapter 3 shows results for the asset growth anomaly in different industries. Chapter 4 tests the overreaction explanation of the asset growth anomaly directly and explicitly by using asset growth sequences and turnover to measure the degree of investors' overreaction. Further, it tests the expectation error based on the correction of the asset growth portfolio before and after the formation date. Chapter 5 shows comprehensive evidence of 16 different types of anomalies in global markets and notes there are more anomalies in developed markets. Furthermore, I use the most recent asset pricing models to check the existence of anomalies and extend the Hong and Stein (1990) model to explain the difference between developed and emerging markets.

[31] Both Hou, Xue and Zhang (2015) and Fama and French (2015) add an investment factor into their new asset pricing models. The investment factor is constructed using asset growth. The difference is: the former construct the investment factor based on Q-theory; while the latter construct the investment factor based on empirical evidence.

## 6.2. Main Findings

### 6.2.1. Asset Growth Effect across Industries

Chapter 3 examines the existence of the asset growth anomaly in different industries. I first divide all firms into 44 industries based on the Fama-French 48 industries classification (excluding financial industries). For each industry, I run the regression of stock return on firm asset growth. The regression analysis finds that 13 out of 44 industries have a significant slope of asset growth. The variation of the asset growth slope across different industries provides an opportunity to check the relation between the asset growth effect and industry characteristics. I include average sales growth within an industry, concentration, advertising expenditure, R&D expenditure and the number of firms as the measurement of industry competition or growth opportunity. The regression results show that R&D expenditure and concentration are positively correlated with the asset growth effect, while the number of firms in an industry and advertising expenditure are negatively correlated with the asset growth effect. The evidence suggests that the asset growth effect varies given different industry characteristics. However, the empirical results do not state whether the industry characteristics represent the source of mispricing or whether it is a risk factor.

### 6.2.2. Asset Growth Effect, Growth Sequence, Asset Turnover and Net Profit Margin

Chapter 4 shows results as to whether overreaction is the source of the asset growth effect. The asset growth anomaly is tested in growth sequence groups, asset turnover groups and net profit margin groups. According to representativeness introduced by Barberis, Shleifer and Vishny (1998), I propose that consecutive growth trend can measure the degree of investors' overreaction to asset growth, that is, overreaction becomes stronger as the growth trend increases. Based on the residual income model, I decompose the return on assets into asset turnover and net profit margin which can affect the degree of overreaction to asset growth. Specifically, the higher the asset turnover the stronger the asset growth effect. In contrast, the higher the net profit margin the weaker the asset growth effect. The group analyses show three main results. First, the hedge return between low asset growth and high asset growth is increasing monotonically when the growth trend is from 1 year to 4 years. In addition, the slope of asset growth in a regression of stock return on asset growth with controls for the book-to-market ratio, firm size and the past 6-month return is steeper as the growth trend increases. Further, the significant difference between the bottom and top sequence group in terms of both spread and slope also confirm a stronger asset growth effect in the longer sequence group. This is the first evidence to support overreaction. The growth trend is a proxy of the overreaction level. Therefore, if overreaction is the source of the asset growth anomaly, the asset growth anomaly should be stronger with stronger overreaction. Both the return spread and the slope coefficient confirm this hypothesis. Second, for the asset turnover rank, the full sample regression shows that the slope of asset growth is getting steeper when the asset turnover is increasing and the slope difference between the lowest and highest groups is significant. Furthermore, I divide the sample into low asset growth and high asset growth groups.

Given the fact that investors will weigh more on asset turnover for fast growth firms, the overreaction should be stronger for high asset turnover firms in high asset growth groups. The regression slope exactly discovers the results and, therefore, I find a second round of evidence to support the role of overreaction in explaining the asset growth effect. Third, similar to the test of asset turnover rank, I undertake the analysis by using net profit margin rank. Net profit margin also has a different influence on high and low growth firms. On the one hand, investors put more weight on asset turnover for fast growth firms so net profit margin will reduce the level of overreaction for high growth firms. On the other hand, for low growth firms, investors should overreact more to low growth firms with low net profit margin. The regression slope indeed confirms this hypothesis: the slope becomes even less negative as the net profit margin increases and the significant difference between the low and high net profit margin groups in the full sample is driven by the low asset growth group.

Furthermore, I run multivariate analysis to check if these overreaction measurements can still have explanatory power after controlling for existing explanations. The existing explanations of the asset growth effect are Q-theory with investment frictions and limits-to-arbitrage. Following Lam and Wei (2011), I include 10 proxies for limits-to-arbitrage and 4 proxies for investment frictions as control variables. Lam and Wei (2011) suggest that the high correlation between investment friction and limits-to-arbitrage is the reason why it is difficult to distinguish between the two explanations. The correlation matrix shows some high correlation among these control variables, for example, the number of institutional shareholders has a correlation of 66%, 60% and 66% with analyst coverage, dollar trading volume and total assets respectively. To group control variables that capture similar information and avoid multicollinearity in the regressions, I conduct principal component analysis. Due to data availability and in order to make the test robust, I also run two versions of principal components analysis by combining different control variables. The factor analysis shows that three factors are generated. The first factor captures firm size (for example, total asset, firm age and analyst coverage), the second factor captures firm specific risk (for example, idiosyncratic volatility and cash flow volatility), and the third factor captures transaction cost (for example, bid-ask spread and illiquidity). The baseline regression without controlling for investment frictions and limits-to-arbitrage shows a significantly negative sign for the slope of the growth sequence and for the slope of asset turnover; and a significantly positive sign for the slope of net profit margin. After controlling for investment friction and limits-to-arbitrage, the slope of the interaction term of sequence and asset growth is still highly significant; the slope of the interaction term of the net profit margin and asset growth is significant in one specification; but the asset turnover loses explanatory power (this may result from losing observations if I include more control variables because this requires valid data for each of the variables). Overall, the results confirm that the asset growth effect becomes stronger with a longer growth sequence and lower net profit margin even controlling for investment frictions and limits-to-arbitrage.

To summarize, the contribution to the current literature is that the results directly link the asset growth effect with investors' overreaction and support overreaction as the source of the asset growth anomaly. Li and Zhang (2010) support Q-theory after comparing with limits-to-arbitrage. Lam and Wei (2011) indicate that both Q-theory and limits-to-arbitrage have similar amounts of explanatory power. Lipson, Mortal and Schill (2011) find no asset growth effect in low idiosyncratic volatility which supports mispricing explanation, but there is no control for Q-theory. My study uses growth trend, asset turnover and net profit margin to measure the level of overreaction and finds results consistent with the overreaction hypothesis. Although limits-to-arbitrage is also a mispricing-based explanation, it is a second place solution. The limits-to-arbitrage already assumes mispricing in the first place rather than testing how the initial overreaction relates to the asset growth anomaly.

### 6.2.3. Asset Growth Effect and Expectation Error

In addition to testing the overreaction explanation, I also check if there is expectation error for the asset growth portfolio conditional on one period ahead asset growth and compare the error between three days around the earning announcement date and the non-earnings announcement date. I show the results in Chapter 4. For portfolios with high asset growth in year t, if the firms have low asset growth in year t+1, the average monthly return in the following one year after formation is -0.1%; In contrast, if the firms continue to have high asset growth in year t+1, the average monthly return is 1%. The difference of -1.1% is significant, so the lower return for high asset growth firms occurs when the following asset growth reverses. Such difference of these conditional portfolios is larger around the earnings announcement date, but there is only a tiny difference (nearly zero) outside the earnings announcement date. This indicates that investors are likely to make expectation errors based on firms' performance. The expectation error is -0.31% and significant when high asset growth firms reverse to low asset growth group while the error is close to zero and insignificant if the high asset growth firms can continue to the high growth. And, therefore, this confirms that investors do make expectation errors when they value the stock price based on asset growth and there is a correction after realized performance cannot support their expectation. As a result, it is consistent with the overreaction explanation that investors overreact to firm asset growth and there is a reversal after the investors know the realized asset growth.

### 6.2.4. Facts of Multiple Anomalies in Multiple Markets

Chapter 5 covers 16 different types of popular anomalies and 45 markets globally. I show comprehensive results with multiple anomalies in multiple markets compared with the previous literature. There are some studies with different anomalies but only for one market (Fama and French, 2008; Li and Zhang, 2010; Stambaugh, Yu and Yuan, 2012, Hou, Xue and Zhang, 2015) and some global studies but only for a particular anomaly (Griffin, Hirschey and Kelly, 2011; Chui, Titman, Wei and Xie, 2012). Griffin, Kelly and Nardari (2010) includes 46 markets but only three anomalies. With many anomalies in the context of international markets, I can compare the number of anomalies between developed markets and emerging markets. Existing global studies with a single anomaly show that the anomaly is more prominent in more developed markets than less developed markets (Ang, Hodrick, Xing and Zhang, 2009; Kaniel, Ozoguz and Starks, 2012; Watanabe, Xu, Yao and Yu, 2013; Titman, Wei and Xie, 2013).

I divide all the 16 anomalies into two categories based on if the anomaly construction needs accounting information or price (volume) information. As a result, there are 8 accounting anomalies and 8 market anomalies. The study uses both equal-weighted and value-weighted hedge return as the measurement of the anomalies. For equal-weighted returns, developed markets exhibit more anomalies, with 10 of the 16 anomalies being significant (asset growth anomaly, asset-to-market anomaly, book-to-market anomaly, gross profit anomaly, financial distress anomaly, working capital accrual anomaly, beta anomaly, illiquidity anomaly, idiosyncratic volatility anomaly and momentum effect). On average across the anomalies, 9 (11) developed markets show significant accounting (market) anomalies versus 3 (6) for the emerging markets. For value-weighted returns, the difference between developed markets and emerging markets is reduced. However, on average, significant accounting (market) anomalies are shown in 5

(6) developed markets and in 2 (3) emerging markets. Overall, the results show that developed markets tend to have more significant anomalies than emerging markets. With more anomalies, I confirm the fact which is consistent with previous single anomaly studies. Therefore, the fact that developed markets tend to have more significant anomalies than emerging markets is not by chance.

The existence of an anomaly relies on an adequate asset pricing model. Hou, Xue and Zhang (2015) construct a q factor (four-factor) model and Fama and French (2015) construct a five-factor model. Both of these two recent models provide a tool to check the existence of an anomaly and the alpha from the model is the measurement of the anomaly. For the q factor model, the equal (value) weighted alpha shows that more developed markets have significant anomalies than emerging markets in 7 (4) out of 16 anomalies. Similarly, for the Fama-French five-factor model, developed markets show more significant anomalies than emerging markets in 8 (4) out of 16 anomalies in terms of equal (value) weighted alpha. In summary, the new asset pricing models show a reasonable amount of explanatory power to capture some of the anomalies and they reduce the anomaly difference between developed and emerging markets. However, the improvement of the asset pricing model cannot explain the difference completely and there is still something left unexplained. And this motivates me to find a unified theory to explain the phenomenon. The unified explanation is also tested in Chapter 5 and summarized in the next session.

### 6.2.5. Hong and Stein (1999) Model and News Watcher Explanation

To explain the fact that developed markets have more anomalies than emerging markets, I revisit the Hong and Stein (1999) model and extend the model. The simulation of the model predicts a nonlinear relationship between news watcher efficiency (information diffusion speed) and the number of anomalies. Specifically, in the first stage where the information diffusion is extremely slow, there is no clear price change and a low level of momentum activities, and hence there are fewer anomalies. In the second stage, both price change and momentum intensity are more obvious when information diffusion becomes faster and, therefore, more anomalies can be observed. As the information diffusion is even faster, price will immediately reflect all information and there is no anomaly. In Chapter 5, higher education, investor sophistication and accounting standard are used to measure news watcher efficiency or information diffusion. For each of the proxies, the results show better news watcher efficiency in developed markets than emerging markets. The nonlinear regression confirms the inversed U shape implied by the model. The slope of squared news watcher efficiency term is significantly negative especially for equal weighted alpha of the q factor model and the Fama-French five-factor model.

In addition, in Chapter 5, I find a smaller difference between developed and emerging markets for value-weighted results than equal-weighted results. To understand why this is observed, I show that the difference of average hedge return between developed and emerging markets is largest in small size firms. And, therefore, the large difference in small firms puts more weight on small firms when examining the equal-weighted results.

To summarize, my thesis confirms the asset growth anomaly is robust even after the anomaly is published and the asset growth effect exists in some industries rather than in each industry. Secondly, I explicitly examine whether overreaction is the source of the asset growth anomaly, and this provides evidence to support a behavioural explanation against Q-theory explanation. Finally, I show more anomalies in developed markets than emerging markets. Further, I give a unified explanation to explain the puzzle -- the inverted U shape relation between news watcher efficiency and anomalies. Overall, my thesis contributes to the understanding to asset pricing anomalies.

### 6.2.6. Limitations and Future Research

This study provides evidence about the asset growth anomaly in different industries and an overreaction explanation to the asset growth effect. However, the industry analysis of the asset growth anomaly is mainly based on empirical analysis which reflects how the asset growth anomaly varies with industry characteristics. It lacks a strong hypothesis development or underlying theory. Therefore, establishing the link between theory and industry results is important for future research.

To examine the overreaction explanation to the asset growth effect, I also show a stronger asset growth anomaly as the growth sequence is increasing. However, Cooper, Gullen and Schill (2008) show that past asset growth can predict negative return in the next five years. According to this evidence, one can also predict that a longer growth sequence should have stronger asset growth effect. Although my prediction is motivated by investors' representativeness bias, ideally we would want to determine if they are the same effect. In addition, the study also shows the evidence of how the asset growth anomaly varies positively (negatively) with asset turnover (net profit margin). However, to further test whether the asset growth anomaly is stronger when the degree of overreaction is high, a more direct test could be undertaken in future reserach. The elasticity of future asset turnover (net profit margin) with respect to current asset growth is one possible way forward. If investors overreact to asset growth, there should be a negative elasticity which forces investors to correct their overreaction and therefore we can observe the reversal.

Furthermore, this study shows evidence on multiple anomalies in the context of global markets and suggests a news watcher efficiency explanation. The simulation results based on Hong and Stein's (1999) information diffusion model provide a nonlinear relation between anomaly and market development. However, the design of the empirical test could be changed in future research. The proxies for news watcher efficiency may not be the best choice due to data availability. The problem is that the news watcher efficiency proxies only cover the latest period but no information for the beginning periods when the anomalies are constructed. Therefore, ideally the results need to be checked for robustness unless the current news watcher efficiency can represent the whole period. In addition, to make the results even stronger, the inverted U shape should be confirmed not only in the cross sectional level but also in the time series level.

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