The Impact of Information Uncertainty on Stock Price Performance and Managers' Equity Financing Decision

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The Impact of Information Uncertainty on Stock Price Performance and Managers' Equity Financing Decision

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In Memory of My Best Friend, Dr. Bilei Zhou

Abstract

This thesis investigates the role of information uncertainty in determining the s-tock price performance and managers' equity financing decisions. The previous literature documents the experimental evidence of significant impact of information uncertainty on investors' preference and decision making. The first empirical (chapter 3) examines the interaction effect between information uncertainty and underreaction anomaly in UK stock market. The empirical evidence is consistent with behavioral finance theory that stocks with higher information uncertainty have greater abnormal adjusted returns, especially following bad news. Chapter 4 further tests the role of information uncertainty in cross-sectional stock returns within 30 global stock markets. The evidence confirms my conjecture that both growth options and information asymmetry are attributes to the information uncertainty. The empirical findings show that stocks with higher information uncertainty have lower future stock returns after controlling for information asymmetry and other characteristics of market and firm. Chapter 5 reports a positive correlation between information uncertainty and probability of equity issuance among industry firms in US market. The evidence shows that information uncertainty does not only affect the stock price performance, but also have influence in managers' equity financing decisions. Overall, our empirical work contributes to the literature with conclusive evidence that information uncertainty amplifies the extent of stock mispricing, which is consistent with behavioral finance and is in contrast to predictions of neoclassic finance theory.

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Statement of Copyright

Abbreviation

Table 1: List of Abbreviations

Abbreivation	Full term
ACCR	Accounting Rating
ADR	Anti-Director Right
AGE	Firm Age
CFR	Cash Flow Rights
COA	Capital Expenditure Over Total Asset
COV	Analyst Coverage
CR	Control Rights
DISP	Dispersion in Analyst Forecasts
DIV	Dividend Dummy
HML	Value Risk Factor in Fama french (1993)
IPOs	Initial Public Offerings
IU	Information Uncertainty
IVOL	Idiosyncratic Volatility
MB	Market-to-Book Ratio
MV	Market Valuation
SEOs	Seasoned Equity Offerings
SIZE	Total Asset Value
SMB	Size Risk factor in Fama French (1993)
TobinQ	Tobin's Q ratio
UMD	Momentum Factor in Carhart (1997)
VO	Trading Volume

Chapter 1

Introduction

Information uncertainty has been an old topic in finance even before the founding of modern financial theory. In the famous book of Knight (1921), the author, for the first time, establishes the academic definition of 'uncertainty' that an event is said to be uncertain if its probability of occurrence is unknown. The term 'uncertainty' is distinguished from 'risk', as the latter depends on the randomness with known probability. The author further argues that it is uncertainty, rather than risk, that rewards the investors with abnormal profits. However, since the introduction of Markowitz's (1952) portfolio theory, the focus of financial research in asset pricing rests mostly on risk bearing and compensation. The neoclassical asset pricing models such as Sharpe's (1964)capital asset pricing model, Merton's (1973) intertemporal capital asset pricing model, and Breeden's (1979) consumption capital asset pricing model assume that the distributions of risky asset payoffs are known to all investors before they make portfolio investment decisions. The assumption of complete information presents the asset pricing models in a simplified form, but ignores the issue of information uncertainty.

The academic interest in information uncertainty was reignited by the seminal experimental work of Ellsberg (1961), who finds that, in addition to riskiness, people are commonly and significantly averse to uncertainty. Although the axioms of preference under uncertainty were established in Savage's (1954) subjective expected utility (SEU), how uncertainty would impact the representative's utility and decision-making was not observed and convincing until the publication of Ellsberg's paper. This experiment has been repeated and refined in many research studies, the results of which are surprisingly consistent with the original work.

Although the experimental work concerning the uncertainty effect seems to be conclusive, the role of information uncertainty in the real market remains controversial. It is partially due to the fact that information uncertainty is entangled with market microstructure, investors' psychological biases, and other exogenous factors. The SEU theory predicts that investors with ambiguity aversion require compensation to hold assets with high information uncertainty, whereas other theories from behavioral finance and new neoclassic finance suggest an opposite effect.

In Miller's (1977) seminal paper, uncertainty is associated with investors' disagreement. In a complete market without uncertainty, the demand curve should be perfectly flat, as all investors would agree on the unique intrinsic value. However, the author suggests that uncertainty about a firm's fundamental value increases the divergence of opinions in the market, and shifts the demand curve into a slope. With short-sale constraints, pessimistic investors cannot trade in negative volume. Hence, the equilibrium price is inflated by investors with a more optimistic view, which generates the future stock returns. The prediction of Miller's theory contradicts the SEU theory, as information uncertainty generates a discount of stock returns rather than a premium for compensation.

Another aspect of information uncertainty literature focuses on the interaction effect of uncertainty and psychological biases. In the excellent survey of behavioral finance literature, Hirshleifer (2001) argues that information uncertainty may amplify the psychological biases amongst investors, which triggers larger misvaluation and drives the stock price away from its fundamental. The direction of the stock misvaluation depends on the type of investor bias. For instance, overconfidence is one type of well-documented bias, which leads to cross-sectional overpricing and low ex ante returns (Odean (1998)). When the news on a firm is more ambiguous to interpret, overconfident investors may give more weight to their own experience and neglect the recent public news. Hence, information uncertainty enhances the overconfidence effect and lowers the returns to investors by excessive trading. Moreover, uncertainty is also considered the shield of noisy traders. When information uncertainty increases at the firm or market level, the arbitrage risk also increases. Consequently, sophisticated traders, even if they have perfect knowledge of the true valuation, may temporally avoid the market (Shleifer and Vishny (1997)).

The school of Bayesian learning in financial research asserts that uncertainty will be resolved in the process of rational learning and updating. Pastor and Veronesi (2003, 2009) argue that information uncertainty may increase the firm's valuation because of Jensen's inequality in the dividend discount model. The augmented evaluation, however, is fully rational according to Bayesian law. The authors predict that information uncertainty positively contributes to stock price, but does not affect the cross-sectional stock returns. The aim of this thesis is to empirically investigate the role of information uncertainty in determining stock performance and affecting financing behavioral. The study is motivated by the fact that empirical evidence concerning the role of information uncertainty in the real market is essential for one's understanding, but currently inadequate to draw any conclusions. One of the main difficulties affecting the empirical research of information uncertainty is mainly the measure of information uncertainty. Unlike the riskiness that researchers can practically measure with many well-developed statistical techniques, uncertainty, like its definition, is difficult to capture by a neat and concise proxy.

To solve the problem of information uncertainty proxies, several proxies are used together to gauge the uncertainty level of common stocks. These proxies include firm market capitalization, firm age, shares turnover by volume, idiosyncratic volatility, the dispersion of analysts' forecasts, etc. Although each of these proxies is also used as a proxy in other academic research, together they jointly capture the effect of information uncertainty. For example, a firm's market capitalization is frequently used in the empirical test of size effect, and shares turnover by volume measures the liquidity in the literature of market microstructure and asset pricing models. Both of them are included for information uncertainty proxies. Large firms usually disclose more information to the market than small firms because of their increased media exposure, branding, public attention, etc. Hence, it is assumed that investors generally have more knowledge of these large firms. For shares turnover by volume, a higher trading volume means more disagreement amongst investors, and is logically considered to bear more uncertainty in the market level.

The second chapter reviews the literature in information uncertainty research from various viewpoints. The concept of information uncertainty and the building blocks of subjective utility theory are also introduced. In addition, the analogy and discrepancy between information uncertainty and information asymmetry are outlined. The research of information uncertainty is further discussed in the context of incomplete information, short-sale constraints, and investors' psychological biases. Chapters 3, 4 and 5 of the empirical analysis also provide a literature review, which is essential for hypothesis building.

As information uncertainty has been found to be a breeding ground for investors' psychological biases, the third empirical chapter (chapter 3) address the research question that whether firms with greater information uncertainty are subject to more abnormal returns from underreaction phenomenon. This study is motivated by the conjecture of Hirshleifer (2001) that information uncertainty increases the likelihood of investor irrationality and the magnitude of stock mispricing. The under-reaction to recent news has been documented in worldwide markets, and is conventionally regarded as the manifestation of investors' behavioral biases (Daniel, Hirshleifer, and Subrahmanyam (1998), Lakonishok, Shleifer, and Vishny (1994)). We test the magnitude of underreaction anomaly among various level of information uncertainty in the UK stock market. The empirical results reveal that high information uncertainty leads to large investors' under-reaction to recent news and therefore to greater earning and price momentum effects. Using five different proxies of information uncertainty, it is found that the earning (price) momentum amongst stocks with high information uncertainty is on average 1 percent (1.7%) higher per month than amongst stocks with low information uncertainty. The results further support the previous literature that attributes under-reaction to recent news to investor psychological biases.

Further to chapter 3's finding in time series analysis, chapter 4 investigates the role of information uncertainty in cross-sectional stock returns with an extended data sample. The empirical test of the fourth chapter is conducted in the international markets from 1988 to 2007. We try to answer what determines the magnitude of information uncertainty across the stocks, and whether information uncertainty universally influence the stock performance. One can conjecture that information uncertainty is jointly attributed to a firm's endogenous growth options and exogenous disclosure policy. A firm that is at the early life cycle, in a growing industry sector or emerging market, should naturally bear more uncertainty of its future profitability, as less experience is available. Secondly, disclosure policy determines the amount of information that outsider investors can acquire from the firm. Firms in the emerging markets are generally obligated to less disclosure requirement, and are therefore subject to greater information uncertainty.

One aim of this chapter is to examine the relationship between information uncertainty and a firm's growth options across the global markets. The market-to-book ratio is used as the main proxy for a firm's growth options, and analyst forecast dispersion and idiosyncratic volatility are used as the proxies of information uncertainty. The results reveal a positive relationship between a firm's growth options and information uncertainty across all markets. Given Cao, Simin, and Zhao's (2008) finding of a positive correlation between growth options and market level uncertainty, this study provides supportive empirical evidence for the nexus of uncertainty and growth opportunity in the individual firm's level in an out-of-sample test.

The role of information uncertainty is further tested in the cross-sectional returns, and stocks with previous high monthly uncertainty are found to outperform those with low uncertainty, especially in poorly protected, less mature markets. The negative relationship between uncertainty and future returns is largely attributed to extreme high uncertainty portfolios. Furthermore, when mutually controlling for potential growth and asymmetric information, a significant relationship no longer exists between information uncertainty and future returns. One can interpret this evidence that information uncertainty is composed of endogenous earnings volatility and exogenous asymmetric information. The former uncertainty increases the value of a firm's growth options, whereas the latter increases the investors' risk exposure and requires a higher premium. Previous research assumes that the magnitude of information uncertainty is given in the market and focuses on the normative rules of investors' decision-making. This study decomposes information uncertainty, and differentiates the impact of information uncertainty from different sources on investors' valuation.

The fifth chapter tests the influence of information uncertainty in equity financing decisions. The logic is that if information uncertainty would affect stock valuation from investors' perspective, managers who actively observe and respond to market conditions would also be affected by degree of information uncertainty. A large body of literature has documented that equity issuance decisions are positively affected by stock valuation. Managers tend to issue equity when the prior stock price is high or increases. Behavioral corporate finance interprets the market timing phenomenon as the consequence of stock mispricing, which managers try to exploit by selling their stocks. Hence, one can conjecture that, as information uncertainty leads to a higher level of mispricing, it will also lead to a higher probability of equity issuance if firms are subject to greater uncertainty. The results in Chapter 5 are consistent with the conjecture that firms with higher uncertainty tend to conduct more seasoned equity offerings[1]. After controlling for

[1]Pastor, Taylor, and Veronesi (2009)build a model of one representative controlling share-

stock valuation, the impact of information uncertainty in equity issuance is still significant.

holder who learn from firm performance and make initial public offering decision. Their model shows that firms with greater uncertainty are more likely to make equity offering decisions to exchange controlling rights for diversification benefits.

Chapter 2

Literature Review

2.1 Introduction

Information plays a central role in financial literature. The neoclassic finance theory relies heavily on rational expectation equilibrium models in which representative agents maximize their expected utility based on perfect information assumption. The classic asset pricing models such as Sharpe's (1964) capital asset pricing model, Ross's (1976) arbitrage pricing theory, and Merton's (1973) Intertemporal CAPM are built on a perfect market in which all information is precise and available to participants in the market. The critical assumption of a perfect market assures that investors know the true distributions of each risky asset and risk factors, and can strictly maximize their expected utility by investing in optimized portfolios.

Although these normative models are built on one representative agent, their implications are not compromised as long as all investors have the same information set. The reason is attributed to the two natures of these models. First, equilibrium means that there is no trading between investors once the market achieves a steady state. Every investor is better off holding the optimum portfolios in the equilibrium, regardless of his or her preference. Second, in the rational expectation setting, not only do all rational investors form and update their beliefs uniformly, but their subjective distribution is also correct and agrees with the ex ante distributions of asset payoffs.

This rational expectation framework dominates in normative financial research for its simplicity and generality. However, it neglects the fact that information is sometimes too sparse and inaccurate for investors to evaluate securities and decide on a firm's fundamental. In reality, investors deal with a large amount of news every day, much of which is not easy to interpret. Whether investors have a preference on receiving more precise information and how they update their beliefs from this noisy news matters in the real investment world. For instance, in Welch's (2000) survey, financial economists widely dispersed their view of expected equity premium.

2.2 Uncertainty And Psychological Biases

Recently, researchers start to examine information uncertainty in the context of behavioral finance. From the investors' perspective, a lot of evidence suggests that investors are likely to suffer more psychological biases with high uncertainty (Hirshleifer (2001)). According to cognitive psychology, irrational investors are also likely to place less emphasis on the news if its implication on stock price is difficult to assess (high uncertainty). Hence, they tend to be overconfident about their private information or focus too much on the previous value. In addition, the gradual-information-diffusion hypothesis argues that it takes more time for private signals to travel across the market with more ambiguity if public traders irrationally infer the insider traders' information and follow their strategy. Behavioral models, including Daniel, Hirshleifer, and Subrahmanyam (1998) Daniel, Hirshleifer, and Subrahmanyam (2001) and Hong and Stein (1999), provide the theoretical implications of information uncertainty based on earning and price momentum.

On the other hand, more information uncertainty implicitly increases the arbitrage risk. Delong, Shleifer, Summers, and Waldmann (1990) argue that irrational traders are likely to be encouraged by positive feedback from the market price, and therefore arbitrageurs may simply follow the irrational trading rather than correct it. The rationale of this mechanism is that it should be strong if the new feedback is not clear and biases the irrational expectation with a larger magnitude. Moreover, the cost of information acquisition increases with the information uncertainty, which further delays the time required for the price to converge to fundamental value. Thus, arbitrageurs may stay neutral to avoid undertaking period costs and liquidity risk (Shleifer and Vishny (1997)). Jegadeesh and Titman (1993) find that monthly stock returns persist within an intermediate term. For example, stocks with past higher returns continue to outperform those with past lower returns over six months to one year. This phenomenon does not change after controlling for other anomalies such as January or size effects. Furthermore, additional studies reveal that this phenomenon survives within and beyond the sample period and in global markets, which strongly disputes the view of data mining (Jegadeesh and Titman (2001),Rouwenhorst (1998)).

On the other hand, Bernard and Thomas (1989),Chan, Jegadeesh, and Lakonishok (1996) and Cohen, Gompers, and Vuolteenaho (2002) use different methodologies [1] but find identical implications that investors initially under-react to earnings announcements that are later absorbed into the market price with a short-term trend. These anomalies show that expected future stock returns are predictable, which challenges the rational asset pricing models and efficient market hypothesis. In particular, no prevailing rational asset pricing model can fully explain all cross-sectional and time-series anomalies (see Barberis and Thaler (2003) survey for details). An alternative explanation given by behavioral finance suggests that investors or even arbitrageurs 'leave the money on the table' because they and/or others are 'blinded' by systematic psychological biases.

Despite extensive research on the under-reaction anomaly, the rationale behind its existence remains controversial.Behavioral finance literature provides several potential explanations based on psychological biases such as overconfidence about private information, the disposition effect or neglected attention. However, Chan, Jegadeesh, and Lakonishok (1996) and Jackson and Johnson (2006) argue that price and earning momentum are closely related and attribute them to under-reaction to recent public information. Daniel, Hirshleifer, and Subrahmanyam (1998) also developed a model of a representative investor who is overconfident about his or her private information and biased by self-attribution. They argue that investors tend to be more overconfident when the feedback from a new price or information is inconclusive. In addition, the disposition hypothesis based

[1] Bernard and Thomas (1989) use standardized unexpected earnings to test post-earning-announcement-drift, while Chan, Jegadeesh, and Lakonishok (1996) further adopt analyst forecast revision as one additional measure of earning surprises. Apart from earning announcement and abnormal stock returns, Cohen, Gompers, and Vuolteenaho (2002) extract unexpected cash flow news by decomposing stock returns into expected return component and cash flow component.

on prospect theory and mental accounting suggests investors' tendency to realise gains and hold losses. Frazzini (2006) further provides empirical evidence that price-earnings-announcement drifts are much higher when capital gains and recent news have the same sign, which is consistent with the disposition hypothesis. Furthermore, Hirshleifer, Lim, and Teoh (2009) find that stocks with less attention generate a larger under-reaction effect, which could be explained by the distraction hypothesis.

2.3 Uncertainty And Asymmetric Information

Information uncertainty is also closely related to asymmetric information in the manner in which investors interpret noisy signals. Here, past research on the theoretic building of asymmetric information and its implications are reviewed. A discussion related to information uncertainty will then follow. Asymmetric information means that some investors possess more insider information about underlying firms. This leads to three major problems in corporate finance: adverse selection, which means the inability to distinguish between positive and negative investment opportunities, as investors prefer the one with the lower risk or higher safety; moral hazard, which means that managers will not stick to the investment plan if such a plan does not serve their interests; the third is monitoring cost, which is used to restrict the manager's ability to fool previous shareholders and new stock owners. Hence, asymmetric information is considered a risk factor for uninformed investors. Moreover, the environment of the market or market development is also crucial for investors' reactions to such asymmetric information. For example, in a market in which insider information trading is not restricted by regulators, insiders will most likely always trade based on the difference set he or she possesses and common market information. Therefore, the probability of insider trading is much higher for markets with poor credibility.

Easley and O'Hara (2004) focus on the role of asymmetric information in affecting a firm's cost of capital. They suggest that the composition of information between public and private information can affect risk exposure. It differs from the previous view of information structure that not only the public, but also the quality and quantity of private information are a determinant factor in cross-sectional stock returns. In their model, both informed and uninformed investors are risk averse and make rational investment decisions. Information is defined by a set of signals, a part of which uninformed investors cannot acquire. Informed investors hold optimum portfolios based on all information. Hence, their investment should be no different with the traditional mean-variance criteria. However, uninformed investors infer the excess asset demand of informed traders from observed price. In this setting, uninformed investors may conjecture the composition of private and public information (i.e. how much they do not know, but not the actual information).

In equilibrium, informed and uninformed traders hold different portfolios that rely on their subjective security market line. Expected returns with the same level of risk differ for these two types of investors due to different portfolios. Similar to Lintner (1969), heterogeneous beliefs among investors would not affect the efficiency of market portfolio as long as the average expectations of investors are correct. However, in Easley and O'Hara (2004) model, simply holding market portfolios is less effective than the optimal strategy of uninformed investors. The main reasons are 1) private information is not systematic; otherwise, it is of no value; 2) the optimal technique can help the uninformed learn some news. If informed traders hold more and the fraction of private information is large, there is a high possibility that positive news is forthcoming.

One important feature of this model is that rational uninformed investors cannot diversify the risks of asymmetric information. The previous literature stemming from Merton (1987) suggests that uninformed investors may reduce or exclude stocks with private information from their portfolios. However, in Easley and O'Hara's (2004) model, the expected utility of the uninformed is higher if they trade based on conjecture about the information structure. Another feature is that this different risk cannot be arbitraged away (i.e. longing the stocks with less private information and shorting the counterpart), since the unrevealed information contains both good and bad news. This trading strategy certainty increases the portfolio risks. On the other hand, informed traders will hold more stocks with good news than uninformed traders and fewer stocks with bad news. However, uninformed traders cannot mimic the portfolios, since they do not know the information.

The traditional asymmetric information theory suggests that large dispersion is caused by more private information, rather than uninformed investors reducing their holdings of the underlying assets and requiring higher returns. However, this paper suggests that dispersion may help to reveal information from the informed to the uninformed, thus reducing the required returns if uninformed investors can infer the fraction of informed investors and private information from the market price. This result is similar to the dispersion effect hypothesis that heterogeneous belief lowers future stock returns. To distinguish these two hypotheses, analysts should control for the information diffusion effect. The excess returns are negatively related to the fraction of informed traders and the precision of signals. When dispersion in analysts' forecasts increases, it may convert some informed traders to uninformed due to the absence of a private information signal. In addition, the dispersion in analysts' forecasts is related to the precision of the signals.

Following this line, Li (2005) shows that information quality has a negative impact on a firm's cost of capital. Noisier information could increase both the risk premium required by market participants and stock return volatility, as investors are disadvantaged by the uncertain dividend growth rate and estimation error.

2.4 Uncertainty, Undiversified Risk And Incomplete Information

Similar to asymmetric information, the research on incomplete information assumes that market participants have a different information domain and analyze its effect on the risk and return of securities. The remarkable paper by Merton (1987) presents a two-period model with different information endowment amongst investors. Uninformed investors face the parameter of uncertainty or estimate risk from certain assets. Since each investor may only hold a small proportion of all securities, they probably construct the portfolios by the known securities. He argues that the cost of information acquisition and diffusion results in a higher future return of the underlying asset than equilibrium with a complete market.

In contrast to Merton's setting, Williams (1977) assumes that investors disagree with the mean and covariance of securities returns. Hence, incomplete information may increase investors' estimate error from observed returns. In equilibrium, the security market line may still hold, as investors agree on the disagreement of stock prices. However, if the disagreement of stocks' covariance matrix is constant, the beta representation holds but is no longer efficient. Moreover, if the dispersion of opinion is observable, investors may require higher returns for more uncertain stocks. Varian (1985) further models a complete market by stating that in every condition there exists an Arrow-Debreu payoff. In his model, with constant or stable absolute risk aversion, dispersion lowers the asset price via aggregate consumption.

2.5 Uncertainty And Miller's Theory

Miller (1977) argues that stocks with investor disagreement and short-sale constraints should be priced at a premium. With a homogeneous expectation, the demand curve of a security is completely flat. In other words, no one will buy overpriced securities or sell underpriced securities, as the expectation is identical across all investors. Real financial markets, however, are consists of participants with different opinions on almost every aspect of market conditions and valuation. The heterogeneous beliefs on security prices will shift the demand curve from pure flat to stiff one. At this stage, pessimistic investors will sell the security to optimistic investors, and the equilibrium still holds at the fundamental value. Once the short sale is limited, so that pessimistic investors cannot sell as much as they want, the total supply is diminished. In Miller's model, these two conditions mutually inflate the current security prices and lower the future returns. In addition, Harrison and Kreps (1978) suggest that these optimistic investors may hold the securities and sell them to more optimistic investors, which is also known as the winner's curse.

Neoclassical finance responds to Miller's hypothesis with several challenges. Jarrow (1980) argues that stocks are somewhat correlated across the market. If the aggregate demand does not change, the rise of one stock price with dispersion effect and short-sale constraints will decrease other correlated securities' demands. Hence, in equilibrium, the final effect of dispersion in opinions is ambiguous, since it affects all stocks. William's (1977) model suggests that the initial disagreement of mean and covariance may move to agreement of covariance under heterogeneous beliefs and constant absolute risk aversion. This means that the future returns should be identical with different opinions.

However, Diamond and Verrecchia (1987) model a rational market maker in an incomplete market with short-sale constraints. They analyze the effects of strict and loose short-sale constraints and argue that loose short-sale constraints may theoretically improve the information revealed and absorbed into the market price, since the cost of the short-sale is relatively high to uninformed traders, but still profitable to informed traders. If the market maker sets the asset price with respect to this consideration, he or she may obtain more information about the selling orders and adjust the price accordingly. In other words, if the market maker is rational, disagreement and short-sale constraints will not affect the asset prices or leave any arbitrage.

Much empirical research examines this hypothesis. Amongst them, Diether, Malloy, and Scherbina (2002) found that stocks with high dispersion in analysts' forecasts will generate lower future returns, with the effect much stronger within small firms and past losers. Moreover, the dispersion may not be a risk factor, since it is negatively correlated with other risk factors such as market beta and volatility. Boehme, Danielsen, and Sorescu (2006) also synchronously control for the dispersion in opinion and short-sale constraints and find that overvaluation exists with both, but is not significant with only one proxy controlled. In addition, Doukas, Kim, and Pantzalis (2006) use the methodology in Barron, Kim, Lim, and Stevens (1998) to separate the dispersion in analysts' forecasts into a heterogeneous term and an uncertainty term. Their findings indicate that the uncertainty term increases the current price and lowers the future returns.

Other empirical literature tests the effect of short-selling stress on the underlying stock prices. Figlewski (1981) tested heavily short-sold stocks compared to others and found that the former insignificantly underperform. Figlewski and Webb (1993) further find no relationship between the percentage of stocks shorted and future returns. In contrast, Desai, Ramesh, Thiagarajan, and Balachandran (2002) use Nasdaq stocks and find supportive evidence for the premium hypothesis. Jones and Lamont (2002) use a short interest rate and show that stocks with a high short-sale cost generally earn less than others. D'Avolio (2002) argues that limited arbitrage is related to short-sale cost, which lowers the future returns of costly-shorted stocks. Furthermore, Nagel (2005) and Chen, Hong, and Stein (2002) suggest that corporate ownership is another indicator of short-sale cost, as a sparse ownership structure will increase the seeking cost. Bris, Goetzmann, and Zhu (2007) examines the stock return pattern with short-sale constraints in the worldwide stock market. They find that stocks in a more constrained market exhibit higher skewness, which indirectly supports the premium hypothesis.

2.6 Ambiguity Aversion

Risk and risk aversion are the foundation of expected utility theory in economics and finance. Generally speaking, riskiness to a representative agent is the volatility of his or her consumption plan. The classic utility theory posits that people prefer less volatility of consumption given any fixed consumption level.

It is assumed that people dislike riskier consumption plans and require compensation for them to choose riskier plans. This preference forms the cornerstone of modern finance theory: that riskier asset should have higher expected returns in the equilibrium. However, the measure of riskiness relies on the odds or distribution of the underlying assets' payoffs. Investors have to know the ex ante distribution of payoffs to determine the risk level of the underlying asset. However, such information endowment is not always granted to every participant. Therefore, another type of risk, Knight's (1921) uncertainty, may also affect investors' preferences and decision-making. Knight's uncertainty [2]

The distinction between risk and uncertainty is that the former can be explicitly described by the probability of outcomes, whilst the latter means insufficient or not precise enough information for decision makers to gauge the probability. Researchers sometimes use the terms 'ambiguity' or 'vagueness' to refer to Knight's uncertainty. Uncertainty is a broader concept that is difficult to quantify compared to conventional riskiness.

[2]'Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated . . . It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all.'– Knight (1921) 'Risk, Uncertainty and Profit' refers to the unknown distribution of assets' payoff that makes it difficult for investors to evaluate.

2.6.1 Ellsberg's Experiment

Although Knight (1921) introduced the definition of uncertainty to economics research, it was not until Ellsberg (1961) famous experiment that uncertainty was found to empirically affect the decision-making process. The classic design of Ellsberg's experiment is as follows. There are 90 balls in an urn, of which 30 balls are red, and the remaining 60 balls are either yellow or blue. Participants are asked to bet on the color of the ball drawn from the urn, as Table 1 shows. In the first round, participants can choose one of two gambles. If one chooses gamble A (B), he will receive £100 if the ball drawn from the urn is red (yellow). In the second round, participants have to make another choice of gamble. For gamble C (D), the participant will receive £100 if the ball is red or blue (yellow or blue). The probability of winning the gamble is uncertain for B and C, since the exact number of yellow and blue balls is not known. Assume the number of yellow balls is X. The probability of winning in each game shows that if one believes that X is less than 30, he should choose gamble A and C. Alternatively, if one assumes that X is higher than 30, he should choose gamble B and D.

This experiment has been performed repeatedly, and the majority of participants choose to bet on gamble A and D. This combination of choices seems to violate the expected utility theory, regardless of the participants' utility function and risk aversion. The preference of A over B, and D over C means that $U(100) * 1/3 > U(100) * X/90$ and $U(100) * 2/3 > U(100) * (1 - X/90)$. Rearranging these two inequalities results in $U(100) > U(100)$, which is obviously false. The evidence confirms the existence of ambiguity aversion; people do not like to make decisions when the probability of the outcome is unknown. In this experiment, one possible interpretation is that the participants lose some utility when betting on gambles B and C with an uncertain probability of winning. Taking ambiguity aversion into account, the inequality should be changed, as $U(100) * 1/3 > U(100) * X/90 - U(AA)$, and $U(100) * 2/3 > U(100) * (1 - X/90) - U(AA)$, where $U(AA)$ represents the utility loss caused by ambiguity aversion. Then the final inequality may stand as $U(100) > U(100) - 2U(AA)$.

2.6.2 Theoretical Buildings Of Ambiguity Aversion

Before modern financial theory became popular, investors considered uncertainty as a simple chance of gains and losses. However, since the 1950s, expected utility theory and portfolio selection postulate that rational investors are as concerned about risk as volatility or the covariance of stock payoffs with a certain mean, whilst uncertainty or unobservable probability is left to subjective utility theory and behavioral finance. In contrast to the assumption of prior known payoff distribution, subjective utility theory suggests that agents are also averse to uncertain odds of outcomes. In a clinical experiment involving scanning the human brain's reaction to such gambles, Hsu, Bhatt, Adolphs, Tranel, and Camerer (2005) provide solid and consistent evidence that aversion to ambiguity has the same mechanism as risk aversion.

Applying ambiguity aversion utility in asset pricing, Cvitanic, Lazrak, Martellini, and Zapatero (2006) generated a closed-form solution for the optimal portfolio of a utility maximizer who faces ambiguity the alphas and show that learning about the expected return can trigger a substantial amount of the demand. Buraschi and Jiltsov (2006)also studied the option pricing and volume implications for heterogeneous agents facing model uncertainty. Market incompleteness makes options non-redundant, whilst heterogeneity creates a link between differences in beliefs and option volumes. Hence, a dynamic relationship exists between option volume and implied volatility with uncertainty.Chateauneuf, Eichberger, and Grant (2007) also developed the simplest generalization of subjective expected utility that can accommodate both optimistic and pessimistic attitudes towards uncertainty-Choquet expected utility with non-extreme-outcome-additive (neo-additive) capacities. They showed that neo-additive capacities can be readily applied in economic problems. Lo (1996) proved that equilibrium exists for games with the subjective expected utility model. He generated a measure of probability with both a closed and convex principle to form a representative agent's expectation. In addition, Rigotti and Shannon (2005) generated an equilibrium model for decision-makers under uncertainty and risk, revealing that equilibrium prices and portfolio allocation vary with the underlying fundamental of a firm's value.

Although these models consider preference over ambiguity with the support of experimental evidence, they are not widely examined due to the following shortcomings. First, ambiguity is difficult, if not impossible, to measure and calculate. If the ambiguity level of an event could be quantified, ambiguity would no longer exist in the common sense. Secondly, theoretical work shows that the equilibrium of the financial market embedded with ambiguity only exists with many strict assumptions. Even Knight (1921) suggests that "nothing was to be learned by modeling agents unable to act in uncertain setting". A full review of ambiguity aversion literature is not the purpose of this chapter. Camerer and Weber (1992), Leippold, Trojani, and Vanini (2008), Maccheroni, Marinacci, and Rustichini (2006) and Rigotti and Shannon (2005) provide a more detailed analysis.

A close link between ambiguity aversion and information uncertainty is suggested by Epstein and Schneider (2008). Their model concerns ambiguity-aversion and investors' attitudes and decisions to ex post and ex ante information quality. Investors with ambiguity aversion derive their estimates of asset payoff distribution from information and generate multiple prior beliefs. When information does not have a conclusive implication about a firm's performance, or the signal is noisy, the imprecision leads to a likelihood of payoff distribution from the investor's view. Moreover, ambiguity aversion implicates that the investor always assumes the worst-case scenario, which means that their expectation is the outcome of a worst-case scenario. For example, if the weather forecast states that the probability of rain for tomorrow is 40 to 60 percent, ambiguity aversion agents would assume the probability is close to 60 percent. In this setting, their model suggests that 1) negative information has more influence on investor preference, as it seems more reliable than positive news, and 2) the anticipation of future low-quality information has a negative impact on investor preference.

The logic is that, when good (bad) news arrives, investors will take the lowest (highest) probability of the exact outcome happening. Hence, they place more emphasis on the credibility of bad news and react more asymmetrically to bad news. Second, investors may infer the quality of future information from the precision of past news and signals. Ambiguity aversion investors dislike securities with past inaccurate information, and require compensation for holding such assets. Moreover, Daniel and Titman (2006) distinguish between tangible and intangible information. The formal represents past solid accounting reports, whereas the latter refers to unexplained market returns that reflect market views about future earnings growth. Since intangible information is generally subject to the ambiguity of implication, investors often overreact to bad news and under-react to good news. This gives an alternative explanation to the behavioral finance literature.

In short, their model suggests that ambiguity has three implications on investment decision and asset pricing. First, given ambiguity aversion, securities with uncertain information require a premier for investors to hold them, due to a lack of confidence. Secondly, after uncertain information, agents respond asymmetrically; bad news affects them more than good news. Moreover, a security with poor future information quality will discourage investors. Consequently, the quality of past information lowers the investor's utility and hence requires a higher return. This argument is contradictory to learning with the Bayesian approach, which suggests that the quality of past information does not affect the expectations of future signal precision.

Chapter 3

Information Uncertainty And Underreaction To Recent News

3.1 Introduction

As discussed in introduction and literature review, the main objective of this thesis is to examine the role of information uncertainty in financial markets. This chapter addresses the question of whether information uncertainty has impact on future stock returns and/or underreaction anomaly. Several recent studies provide evidence that information uncertainty (or value ambiguity), which refers to the ambiguity of news implications on firm's fundamental value, plays a role in stock returns and short-term price continuation (momentum). Jiang, Lee, and Zhang (2005) and Zhang (2006) among others document that stocks with high information uncertainty are associated with larger price momentum and post-analyst forecast revision price drift (thereafter earning momentum)[1]. As they argue, information uncertainty encourages investors' underreaction to recent news and leads to momentum.

This chapter testes whether investors with greater information uncertainty underreact more to recent news, i.e. more information uncertainty should be associated with higher expected returns following good news, while, stocks with more information uncertainty should generate lower returns following bad news. This study, firstly, offers support to the literature that assesses the profitability of momentum strategies in the UK stock market (for example, Dissanaike (2002) and Hon and Tonks (2003)). This is of great interest to investors in order to devise appropriate tactics since a trading strategy based on this information can be proved quite profitable. Secondly, this is the first study of UK stock market exhaustively using 5 different proxies to measure information uncertainty: firm capitalization, firm age, analyst coverage, idiosyncratic volatility and dispersion in analyst forecast. Although each of them might also capture other issues, the common element of the five proxies is that they are exclusively measures of information uncertainty. Thirdly, this study serves as an out of sample test on whether conclusions drawn from the US experience can characterize other major markets and alternative trading environments such as the UK stock market.

In spite of extensive research on the underreaction anomaly, the rationale behind its existence remains controversial[2]. Behavioral finance literature provides several potential explanations based on psychological biases such as overconfi-

[1]McKnight and Todd (2006) show that European stocks with net upward revised forecasts earn higher future returns than otherwise similar stocks.

[2]See for example, Daniel, Hirshleifer, and Subrahmanyam (1998) and Hirshleifer (2001).

dence about private information, disposition effect or neglected attention[3]. Chan, Jegadeesh, and Lakonishok (1996) and Jackson and Johnson (2006) argued that price and earning momentum are closely related and attribute them to under-reaction to recent public information. Daniel, Hirshleifer and Subrahmanyam (1998, 2001) developed a model of a representative investor who is overconfident about his private information and biased by self-attribution. They argue that investors tend to be more overconfident when the feedback from new price or information is inconclusive. Furthermore, Frazzini (2006) provides empirical evidence that price/earning-announcement drifts are much larger when capital gains and recent news have the same implications, which is consistent with disposition effect.

Moreover, limits of arbitrage, the second cornerstone of behavioral theory, is plausibly greater as information uncertainty increases. First, it is likely for investors to lose time to assess new information when its implications are not clear. (Mendenhall (2004)). Even an experienced arbitrageur may face the risk of the news coming in between his trade actions and suffer a loss. The longer it takes for the price to converge to its intrinsic value, the riskier the arbitrager's position. Second, information uncertainty may encourage noise trading since less solid feedback can be obtained (Delong, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997)).

Alternative interpretation regarding incomplete information theory, considers the information uncertainty as a source of parameter risks or risk of asymmetric information. Stocks with high information uncertainty should be priced at a discount compared to absolute information equilibrium as a compensation for un-

[3]See for instance, Daniel, Hirshleifer, and Subrahmanyam (1998), Fama (1998) and Hirshleifer (2001) for a comprehensive review.

informed investors to hold such assets (Merton (1987), Easley and O'Hara (2004)). Moreover, the rational Bayesian learning suggests that investors adjust the estimates putting less weight on new information if this does not provide a clear picture about stock's fundamental value. Hence, when there is good news with high uncertainty, investors initially under-estimate the underlying stock returns. Along with disappearance of information uncertainty on fundamental value, investors update their beliefs rationally. Francis, Lafond, Olsson, and Schipper (2007) argue that investors initially response less to information with high uncertainty and large abnormal returns are mainly concentrated in portfolios with high uncertainty stocks. This hypothesis seems to predict a similar relation between information uncertainty and underreaction effect compared to behavioral theory. However, this could not explain why the profitability from momentum strategy is persistent over time and exists in the international market[4].

Consistent with the predictions our results provide evidence that greater information uncertainty leads to larger underreaction to recent news, as we find that earning momentum among stocks with high information uncertainty is on average 1% per month higher than among stocks with low information uncertainty. Similarly, the difference of price momentum between high and low information uncertainty stocks is 1.7% per month. We also find that returns between high and low idiosyncratic volatility (and dispersion in analyst forecast) portfolios are significantly larger following bad news compared to those following good news. This pattern suggests that these two proxies predict systematically lower future returns. One possible explanation is that they both capture the effect of diver-

[4]If investors were aware of the systematic under-reaction and information uncertainty, they would increase the profitability from price and earning momentum strategies, rather than waiting until the information uncertainty disappears.

gence of opinions among investors in the market[5]. According to Miller's (1977) theory, with large differences of investors' beliefs and short-sale constraints, pessimistic traders are kept out of the market and securities prices are biased upwards driven by the optimists who lead prices to unreasonable highs. Doukas, Kim, and Pantzalis (2006) argue that previous tests on divergence of opinion theory by dispersion in forecasts are still mixed up as they do not exclude the uncertainty effect. Finally, we do not find supportive evidence of incomplete information or rational learning. The stock returns in our sample could not be explained by a four-factor asset pricing model. Risk adjusted returns still illustrate the trends that high abnormal returns from price or earning momentum strategy are associated with high information uncertainty. In addition, robustness tests show the impact of information uncertainty on the price and earning momentum are persistent across the sub-periods and the difference between high and low information uncertainty stocks are economically significant with high Sharpe ratios.

The rest of the chapter is organized as follows. Section 3.2 reviews the literature and sets the testable hypothesis; Section 3.3 describes the data and methodology; Section 3.4 presents the results of the impact of information uncertainty on cross-sectional stock returns, earning momentum and price momentum; Section 3.5 provides robustness tests; Section 3.6 concludes the chapter.

[5]Diether, Malloy, and Scherbina (2002) use dispersion in analyst forecast to test Miller's (1977) theory while Boehme, Danielsen, and Sorescu (2006) measure divergence of opinion with idiosyncratic volatility (IVOL).

3.2 Relevant Literature And Testable Hypothesis

Jegadeesh and Titman (1993) firstly find monthly stock returns persist within an intermediate term, i.e. stocks with past higher returns continue to outperform those with past lower returns over six months to one year. This phenomenon stands after controlling for other anomalies such as January or size effects. Furthermore, additional studies show this phenomenon survives in an out of sample period and in global markets, which strongly disputes the view of data-mining (Jegadeesh and Titman (2001)). On the other hand, Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996) and Vuolteenaho (2002) use different methodologies but find identical implications that investors initially underreact to earnings announcement which are later absorbed into market price with a short-term trend. These anomalies show that expected future stock returns are predictable in time-series, which challenges the rational asset pricing models and efficient market hypothesis (Barberis and Thaler (2003)).

Behavioral finance is built on two cornerstones: 1) investor sentiment (i.e. psychological biases) and 2) limits of arbitrage. From the investors' perspective, recent evidence suggests that investors are likely to suffer more psychological biases with large uncertainty (Hirshleifer (2001)). According to cognitive psychology irrational investors are likely to put less weight on the news if its implication on stock price is hard to assess (high uncertainty) and hence tend to be overconfident about their private information or anchor too much on the previous value. In addition, the gradual-information diffusion hypothesis argues that it takes more time for private signals to travel across the market with more ambiguity if public traders irrationally infer the insider trader's information and follow their strategy. Behavioral models including Daniel, Hirshleifer and Subrahmanyam (1998, 2001) and Hong and Stein (1999) provide the theoretical implications of information uncertainty on earning and price momentum.

On the other hand, more information uncertainty implicitly increases the arbitrage risk. Delong, Shleifer, Summers, and Waldmann (1990) argue that irrational traders are likely to be encouraged by positive feedback from the market price, and therefore arbitrageurs may simply follow the irrational trading rather than correct it. The rationale of this mechanism is that it should be strong if the new feedback is not clear and biases the irrational expectation with a larger magnitude. Moreover, cost of information acquisition increases with the information uncertainty, which further delays the time for price to converge to fundamental value. Thus arbitrageurs may just stay neutral to avoid undertaking period cost and liquidity risk (Shleifer and Vishny (1997)).

Following the above discussion we can naturally set our hypothesis based on the fact that greater information uncertainty produces relatively higher (lower) stock returns following good (bad) news as: stocks with high information uncertainty should experience i) larger price momentum and ii) larger earning momentum, due to investors' underreaction.

3.3 Data And Methodology

3.3.1 Data Description

Our sample includes all stocks traded in UK market from February 1991 to December 2003. There are a total of 542 securities in the sample starting in February 1991, and as securities enter and leave the London Stock Exchange over the next 12 years, there are over 2861 securities in total over the entire sample period and an average number of 785 stocks for each month through the whole period respectively.

To avoid survivorship bias dead companies are held in the sample until they have no longer trading records. Monthly returns, market capitalization, firm age (years from the first date that underlying stock is covered), are obtained from Thomson Reuters DataStream. Analyst earning forecast, analyst coverage and standard deviation of analyst forecast are quoted from I/B/E/S database. Consistent with Jegadeesh and Titman (2001), we exclude stocks with past performance data less than twelve months to avoid IPOs effect.

The summary statistics in table 3.1 show that the average monthly return is 0.36% while firm' market value varies from 0.2 to 213734.8 million pounds. Firm age covers 1 to 228 months with a mean of 85 months (7.6 years) which indicates a relatively large portion of young firms and delisted stocks. The stock market in the sample period appears to an extent volatile with average DISP 4% and IVOL 10%.

Pair-wise correlation coefficients between each two variables are reported in the second panel of table 3.1. We find the monthly returns do not appear to have large correlation with other variables (from -0.05 to 0.076). We also observe positive coefficients among market value, firm age and analyst forecast, which is reasonable given that large firms have longer history and more analyst coverage compared to small ones. In addition, we observe that large firms are relatively less volatile than small ones

3.3.2 Measures Of Earning Momentum And Price Momentum

We track the post earnings announcements by analyst forecast revisions provided by I/B/E/S database. A positive (negative) revision means good (bad) news and zero revision means no news respectively. Stock returns are sorted by previous month's revision. If earning momentum effect exists in the UK market, positive (negative) return following positive (negative) revision is expected. Secondly, the indicator of price momentum is measured by past eleven-month average return with one-month lag. Stocks with past high returns would persistently outperform stocks with past low returns, if investors underreact to historical return pattern.

3.3.3 Measures Of Information Uncertainty

For information uncertainty, we use firm's market capitalization (MV), firm age(AGE), analyst coverage (COV), idiosyncratic volatility (IVOL) and dispersion in analyst forecast (DISP). Firm size measured as firm's market capitalization is a common factor for limited information, as suggested by Barry and Brown (1984) limited information hypothesis. They argue that small firms systematically have larger uncertainty. Hong, Lim, and Stein (2000) also suggest that with fixed cost of information acquisition, small firms would be less attractive to investors, which decrease the speed of information moving across the market. Pastor and Veronesi (2003) build a model and show that holding other factors constant, individual firm's endogenous uncertainty decreases with its life time. We use the log of (1+AGE) for proxy of information uncertainty as the marginal effect of years on uncertainty should reasonably decrease. In the same context, we use as third proxy the analyst coverage which is defined as the log (1+COV). More analysts covering the news of a firm should provide more information and decrease the uncertainty. Firm's idiosyncratic volatility (IVOL) is measured as standard deviation of twelve months' excess returns over stock index, and dispersion in analyst forecast (DISP), is measured as standard deviation of analyst forecast of following year earning per share estimates scaled by prior year end stock price. Diether, Malloy, and Scherbina (2002) report that I/B/E/S database contains stale analyst estimates and has round split flaws. Hence, analyst forecast and coverage are drawn from I/B/E/S detail history files.

3.3.4 Portfolio Construction

We adopt conventional portfolio strategy based on information uncertainty proxy and underreaction signals Portfolio strategy is commonly used in financial literature to test the effect of certain risk or characteristics factors on average stock returns. The advantage of portfolio strategy is obvious that it reduces the noise by averaging out the individual stock return variability. To test direct impact of information uncertainty on stock returns, we firstly construct one-way sorted portfolios by single information uncertainty proxy. In each month, we assign stock returns into five quintiles according to previous month information uncertainty proxy and hold portfolios for one month. At the beginning of next month, we repeat the assigning process so that there is no portfolio overlapping in any month. Portfolio performance is calculated as equally weighted stock returns in each portfolio over sample periods. To test interaction effect of information uncertainty and underreaction anomaly, we further construct two-way sorted portfolio. We first pool stocks into three groups according to analyst forecast revisions or past one month returns. In each group, we further rank stocks into five quintiles based on each information uncertainty proxy. For example, The portfolio of Winner and Low IU will contain stocks having highest previous month returns and bearing lowest information uncertainty.

3.3.5 Regression Analysis

Risk-factor model regression is a general approach to test whether an anomaly can be explained by a rational expectation theory. If the results of regressions do not provide significant abnormal return, the anomaly is plausibly driven by its sensitive to some potential risk factors. Otherwise, we may suggest the failure of the rational asset pricing model or efficient market hypothesis. Fama and French (1996) argue that the three-factor model works well to explain a majority of anomalies that can not be explained by CAPM. Their model includes two additional risk factors, size premium and value premium. The results of regression on three-factor model show that different anomalies are driven by different loading or sensitive to these risk factors (Fama and French (1996)). Moreover, since three-factor model does not capture the momentum effect, Carhart (1997) uses a similar methodology and generates a momentum factor. Hence, we use the Fama French three-factor plus Carhart (1997) momentum factor to test whether the price momentum and earning momentum effects can be explained by a rational approach. In other words, if the enlarged anomalous returns are compliments to risk factors, there should be no significant intercepts after regression. The regression is presented as:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{i,M}(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i UMD_t + \epsilon_t \quad (3.1)$$

Where $R_{i,t} - R_{f,t}$ the excess return of portfolio i over risk-free rate in time t, $R_{M,t} - R_{f,t}$ is the excess return of market index over risk-free rate and SMB_t, HML_t and UMD_t represent the size, value and momentum premiums, respectively.

3.4 Empirical Results

3.4.1 Information Uncertainty And Cross-Sectional Stock Returns

In this section (table 3.2), we examine how information uncertainty is related with the cross section of stock returns. High (low) information uncertainty stocks are those with small (large) size, small (large) age, small (large) analyst coverage, high (low) idiosyncratic volatility, and large (small) dispersion in analyst forecast, respectively. The top (bottom) portfolio includes stocks with the lowest level of information uncertainty. The results show that higher information uncertainty (IU) leads to significantly lower average return. The average zero investment portfolio (low minus high IU) is equal to 1.11% monthly returns (t-value 3.42). One potential explanation is that investors systematically over-estimate stock prices when the information is inconclusive (Odean (1998)). Investor overconfidence and excess trading are likely to be more pronounced within stocks with less feedback or unclear information. Moreover, the proxies for information uncertainty are commonly used as measures of arbitrage risk, which could further lead to persistent mispricing[6].

3.4.2 Information Uncertainty And Earnings Momentum

In table 3.3, we double sort stocks by previous news and information uncertainty proxies. Stocks are firstly assigned into good news, no news and bad news groups respectively and in each group we rank them in the same way as discussed above. The results strongly support the earnings momentum effect for every information uncertainty proxy. The portfolio strategy, which takes long position with recent good news and short position with bad news, generates return of 0.41% (t-value=2.08) for large firms and 1.42% (t-value=5.69) for small firms. The average differential of the zero-investment portfolio returns between extreme high and low uncertainty stocks is 1%. Moreover, the results suggest that the strategy that goes long the low uncertainty stocks and shorts the high uncertainty stocks is profitable with past bad news. For example, the low minus high portfolio sorted by firm's age earn 0.98% (t-value=2.91) with recent bad news, while that following good news does not earn significant returns. This evidence shows the earning momentum is more persistent with bad news or simply bad news passes

[6]Alternatively, information uncertainty may also lead to large disagreement among investors. Diether, Malloy, and Scherbina (2002) and Boehme, Danielsen, and Sorescu (2006) documented that IVOL and dispersion in analyst forecast are measurements of dispersion of opinion and that high dispersion leads to lower future returns according to Miller's (1977) theory.

more gradually across the market according to Hong and Stein (1999) model. Last but not least, we find that only the highest uncertainty portfolio sorted by IVOL generates negative return following good news, which may be due to over-reaction and optimistic trading upward bias to the price. All other portfolios support the under-reaction hypothesis. To sum up we find that: 1) Portfolios with high information uncertainty have larger and significant earning momentum. 2) Return differences between stocks with high and low uncertainty are relatively small with recent good news compared to recent bad news.

3.4.3 Information Uncertainty And Price Momentum

To analyze the role of information uncertainty on price momentum, the returns are double-sorted, firstly by past 11 months performance with one month lag and then ranked into 5 quintiles from the lowest to highest uncertainty respectively. A winner minus loser portfolio captures the momentum profits within each level of information uncertainty. In addition, low minus high portfolio with past high or low returns shows the effect of information uncertainty on past good or bad news respectively.

The evidence from table 3.4 is quite similar to our previous findings: The interaction effect between information uncertainty and momentum effect exists as high uncertainty stocks are associated with large momentum profits within all uncertainty proxies. Compared to the analyst forecast revision, we find that the momentum strategy generates higher returns, which suggests investors are likely to under-react more to market price signals than analysts' recommendations. For example, sorted by firm size, the winner minus loser strategy earns as twice as good-bad news. Overall, the average price momentum portfolios in the highest uncertainty quintile earn 1.7% more than those in the lowest uncertainty quintile. In addition, we also observe that low minus high uncertainty strategy is extremely profitable with past bad performance with average 1.6% return, which suggests that market reacts very slowly to past bad news with higher information uncertainty. This could be due to disposition effect that investors tend to hold losses and sell winners and information uncertainty just enhances this effect as investors do not obtain solid feedback. The price continuation holds for all portfolios except for the extreme low uncertainty stocks with poor past performance. This comes in support to our hypothesis that investors react more rationally to recent signals or arbitrageurs are willing to trade against the market when the uncertainty is relatively low.

3.4.4 Results from Four Factor Time-Series Regression

Table 3.5 shows that stocks with high information uncertainty have much larger loading on size premium. This finding suggests that stocks with high information uncertainty are robust to the size effect as small firms tend to underperform large ones in our sample. Fama (1998) suggests that some anomalies would reverse over time. Hence, we cannot reject the rational expectation explanation as the large lower returns for stocks with high uncertainty are probably due to large loading to negative size premium.

Table 3.6 presents the intercepts of regressions on portfolio returns sorted by analyst forecast revision and information uncertainty respectively. The risk-adjusted return patterns are analogous to the raw portfolio return, which indicates that the rational expectation model does not capture the interaction effect between information uncertainty and underreaction anomaly in our sample [7]. Hirshleifer (2001) and Daniel, Hirshleifer, and Subrahmanyam (2001) argue that stock returns may be jointly determined by fundamental risk and investor behavior. This, in turn, might be a potential explanation for the larger abnormal returns of stocks with higher information uncertainty and inadequate risk loadings [8].

3.5 Robustness Check

3.5.1 Profitability Of Momentum Strategies With Different Levels Of Information Uncertainty

In this section, we further test the profitability of different trading portfolios implied by the above findings. Results in Section IV indicate that the drifts to analyst earning forecast and past 11-month return are seriously interacted with information uncertainty, thus leading to larger spreads of price or earnings momentum. Following this evidence, we test whether this amplified effect is profitable. We use the Sharpe ratio to analyze the profitability of portfolios. We examine the profitability of price momentum by shorting past losers and buying past winners (Strategy I) and the profitability of earning momentum by buying stocks with positive analyst forecast revision and selling stocks with negative revision (Strategy II). Both strategies are compared between high and low information uncertainty

[7] We find that high uncertainty stocks are subject to large size premium and moderate value premium while the stocks with recent good (bad) news have large (small) loading on momentum factor. For space purposes we don't report these results that are available upon request.

[8] For reasons of brevity, we don't present the regression results of portfolio returns with uncertainty and momentum which are similar to table 3.6

portfolios.

Table tab:under7 shows the return, standard deviation and Sharpe ratios of portfolios in the lowest or highest level of information uncertainty. Momentum strategies within the highest information uncertainty portfolios generate significantly higher Sharpe ratios than the market portfolio, SMB portfolio, HML portfolio and UMD portfolio. Moreover, the Sharpe ratios of portfolios within highest information uncertainty portfolios are higher than those within the lowest information uncertainty. Sharpe ratios of strategy we range from 0.30 to 0.42 in the highest uncertainty quintile and from 0.14 to 0.21 in the lowest uncertainty quintile. Comparing with the compensation to certain risk factors such as market factor (Rm-Rf), size (SMB) and book-to-market (HML), the strategy in the highest uncertainty quintile is overwhelming. Consistent with Zhang (2006), we argue that the profitability of such strategies indicate an obvious arbitrage opportunity, which strictly violates the efficient market hypothesis.

3.5.2 Lag Of Portfolio Returns

Figure 3.1 depicts the lag of portfolio returns in order to test the persistence of momentum effect and the speed of adjustment to past news. Firm's market value is used as proxy of information uncertainty. The first diagram shows that the difference of returns between high and low uncertainty stocks is positive for past winners and negative for past losers, which is consistent with the results in table 3.4. The difference is relatively large for the first three months due to speedily diminishing excess returns from winner's portfolio. This result provides evidence that bad news is disclosed slowly across the market compared to good news. The second diagram shows that momentum strategy works continuously better when there is high information uncertainty. Since we use market value as proxy of information uncertainty, which does not vary significantly over several months, this return pattern addresses the interaction between size effect and momentum effect. Moreover, the speed of return adjustment is higher with high uncertainty. In short, the results indicate a strong link between momentum effect and information uncertainty.

3.5.3 Sub-Period Analysis

To examine whether previous analysis exists only within certain period, we further provide sub-period evidence. We separate the analysis into two periods, from February 1991 to June 1997 and from July 1997 to December 2003[9]. Table 3.8 presents two strategies including 1) Low minus high uncertainty strategy with past good or bad news and 2) past winner minus past lower strategy within low and high information uncertainty. We find large and significant momentum profits for high uncertainty portfolios while the same strategy following low uncertainty portfolios does not generate significant abnormal returns. In addition, the return difference between high and low uncertainty stocks is generally large with past losers and stocks with bad news respectively. The results are therefore robust to the sample-period bias.

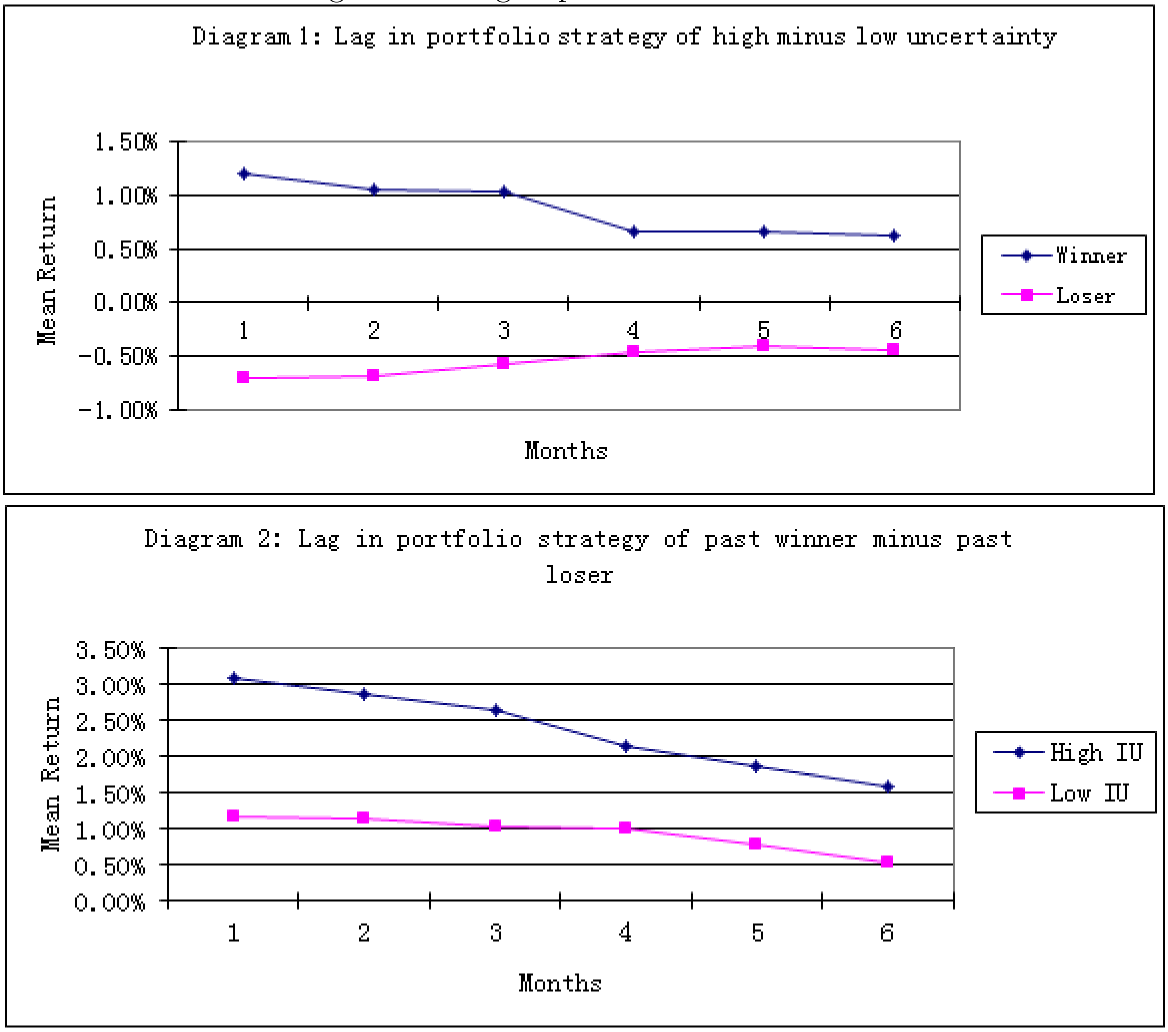
[9]The reason to separating sample by the year 1997 is twofold. First, this is the middle point of our sample period that separate subsamples evenly. Second, the Asian financial crisis burst out and has global impact that may change the firms' financial condition in our sample.

3.6 Conclusion

In this chapter, we provide further evidence from the UK stock market that information uncertainty leads to relatively lower future stock returns following bad news and relatively higher future returns following good news, suggesting that information uncertainty delays the flow of information into stock prices. Our results show that greater information uncertainty leads to larger underreaction to recent news, as we find that earning momentum among stocks with high information uncertainty is on average 1% per month higher than among stocks with low information uncertainty. Similarly, the difference of price momentum between high and low information uncertainty stocks is 1.7% per month. Such results offer useful implications to investors who can exploit momentum strategies and enjoy profits.

Our findings can be plausibly explained by the behavioral finance literature which suggests that if the slow market response to information is due to psychological biases, these biases will be larger and therefore will be slower when there is greater information uncertainty (ambiguity) about the implications of the information for a firm's value. The prediction power of information uncertainty is not unimportant. Although there may be other alternative explanations, all five proxies used, for first time in a UK study, to measure information uncertainty support our hypothesis and enhance the predictions of value ambiguity to the creation of marker anomalies and cross-sectional variations in stock returns.

Figure 3.1: Lag in portfolio formation



Stocks are firstly sorted into past winners and past losers by past 11-month returns with a certain lag. We further sort each group of stocks into five quintiles based on information uncertainty proxy by firm's market value. Each portfolio is equally weighted and reconstructed monthly. The first diagram shows the strategy of shorting low uncertainty stocks and buying high uncertainty stocks within past winners and past losers, respectively. The second diagram presents the strategy of shorting past losers and buying past winners within extreme high and low uncertainty quintiles, respectively. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year.

Table 3.1: Descriptive Statistics

Panel A displays descriptive statistics of the sample and Panel B the correlation matrix of all variables. The statistics include the number of stocks, average value, standard deviation, minimum value, median value and maximum value, respectively. The variables presented are stock's monthly return, firm size which is the market capitalization (in millions of pounds) at the end of month t, firm age which is the number of months since a stock was firstly recorded by Thomson Financial DataStream, analyst coverage which is number of forecasts reported to I/B/E/S database, dispersion in analyst forecasts which is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price, idiosyncratic stock volatility (IVOL) which is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t and momentum which is the average monthly return over past 11 months with one lag to month t). The sample includes all stocks traded in UK stock market from February 1991 to December 2003.

Panel A. Descriptive Statistics

	No. of Stocks	Mean	Std Dev.	Min	Median	Max
Monthly Return	262820	0.36%	15.29%	-826.14%	0.00%	815.48%
MV	262783	7012.4	108670.9	0.2	70.8	213734.8
AGE	262820	91.35	55.44	1	85	228
COV	167248	7.1061	6.79	1	5	51
DISP	132701	0.4002	22.87	0	0.0006	3035.75
IVOL	191049	0.1023	0.07	0.0034	0.0833	2.40
Momentum	196210	5.70%	51.39%	-806.58%	4.65%	388.72%

Panel B: Correlation Matrix (Spearman correlations are above the Pearson Correlations)

	Monthly Return	MV	AGE	COV	DISP	IVOL	Momentum
Monthly Return	1	0	0.03	0.02	0	-0.06	0.08
MV	0.06	1	-0.04	0.06	0.19	0	0
AGE	0.04	0.23	1	0.1	-0.02	-0.09	0.05
COV	0.04	0.8	0.14	1	0	-0.2	0.08
DISP	-0.03	-0.2	-0.41	-0.16	1	0.02	-0.03
IVOL	-0.06	-0.29	-0.08	-0.29	0.28	1	-0.37
Momentum	0.06	0.21	0.04	0.07	-0.2	-0.23	1

Table 3.2: Portfolio Returns by Information Uncertainty Proxy, Past returns and Analyst Forecast Revision

This table presents average monthly portfolio returns sorted by each information uncertainty and post-earnings-announcement drifts in our sample. In panel A, we sort stocks into quintiles based on past month proxy, including MV, AGE, COV, IVOL and DISP. In panel B, we sort stocks based on analyst forecast revision at the end of last month. All portfolios are equally weighted and stocks are held for one month. Return is stock's monthly return. Firm capitalization is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (IVOL) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses.

Panel A. Returns one-way sorted by information uncertainty proxy

IU	MV	AGE	COV	IVOL	DISP
u1(Low)	1.10%	0.73%	0.61%	0.91%	0.79%
u2	1.09%	0.35%	0.42%	0.85%	0.71%
u3	1.09%	0.46%	0.44%	0.57%	0.63%
u4	0.85%	-0.01%	0.20%	0.16%	0.21%
u5(High)	0.16%	-0.24%	0.15%	-1.19%	-0.26%
u1-u5	0.95%	0.97%	0.46%	2.10%	1.05%
	(3.22)	(3.46)	(1.47)	(4.96)	(3.98)

Panel B. Returns sorted by analyst earning forecast

	Good News (Positive Revision)	No News (Flat Revision)	Bad News (Negative Revision)
Return	0.69%	0.29%	-0.19%
	(3.87)	(1.81)	(-0.44)

Table 3.3: Portfolio Returns by Information Uncertainty Proxy and Analyst Forecasts Revision small This table presents average monthly portfolio returns two-way sorted by analyst forecast revision and information uncertainty proxy. We firstly categorize the stocks into 3 groups with upward (good news), flat (no news) and downward revision (bad news) respectively. For each group, we further sort the returns into five quintiles based on firm size, firm age, analyst coverage, idiosyncratic stock volatility and dispersion in analyst forecasts. All portfolios are equally weighted and stocks are held for one month. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (IVOL) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses. ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

	Low	IU2	IU3	IU4	High	Low-High
Panel A. MV						
Good News	0.78%	0.59%	0.92%	0.76%	0.88%	-0.10%
						(-0.26)
No News	0.54%	0.68%	0.54%	0.42%	0.04%	0.50%
						(1.51)
Bad News	0.37%	0.01%	-0.04%	-0.30%	-0.54%	0.91%
						(2.23***)
Good-Bad	0.41%	0.58%	0.96%	1.06%	1.42%	
	(2.08**)	(2.59***)	(4.58***)	(5.66***)	(5.69***)	
Panel B. AGE						

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Table 3.3continue from last page						
	Low	IU2	IU3	IU4	High	Low-High
Good News	0.88%	0.77%	0.91%	0.80%	0.61%	0.27%
						(0.77)
No News	0.78%	0.47%	0.65%	0.22%	0.11%	0.67%
						(2.11**)
Bad News	0.46%	0.08%	-0.01%	-0.51%	-0.52%	0.98%
						(2.91***)
Good-Bad	0.42%	0.69%	0.92%	1.31%	1.13%	
	(2.35***)	(3.54***)	(4.19***)	(5.82***)	(4.5***)	
Panel C. COV						
Good News	0.94%	0.72%	0.72%	0.82%	0.74%	0.20%
						(0.53)
No News	0.62%	0.88%	0.28%	0.43%	0.01%	0.61%
						(1.87*)
Bad News	0.33%	0.22%	0.07%	-0.37%	-0.76%	1.08%
						(2.84***)
Good-Bad	0.61%	0.50%	0.65%	1.19%	1.50%	
	(3.01***)	(2.34***)	(3.26***)	(5.63***)	(6.3***)	
Panel D. IVOL						
Good News	1.10%	1.17%	1.05%	0.73%	-0.12%	1.22%
						(2.66***)
No News	0.95%	0.83%	0.94%	0.21%	-0.68%	1.63%
						(3.34***)
Bad News	0.56%	0.39%	0.10%	-0.26%	-1.31%	1.87%
						(3.55***)
Good-Bad	0.54%	0.78%	0.95%	0.99%	1.19%	
	(4.15***)	(4.82***)	(5.6***)	(4.16***)	(3.85***)	

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Table 3.3continue from last page						
	Low	IU2	IU3	IU4	High	Low-High
Panel E. DISP						
Good News	1.00%	0.97%	0.84%	0.72%	0.42%	0.59%
						(2.12**)
No News	0.84%	1.22%	0.68%	0.35%	-0.21%	1.04%
						(2.66***)
Bad News	0.44%	0.17%	0.25%	-0.32%	-0.90%	1.34%
						(4.12***)
Good-Bad	0.56%	0.80%	0.59%	1.04%	1.32%	
	(3.68***)	(3.94***)	(2.96***)	(4.09***)	(4.4***)	

Table 3.4: Portfolios Returns by Information Uncertainty Proxy and Price Momentum

This table reports average monthly portfolio returns two-way sorted by price momentum and information uncertainty proxy. We first sort stock returns into three groups (winners, medians, losers) based on past 11-month returns with one month lag. For each group, we further sort the returns into five quintiles based on firm size, firm age, analyst coverage, idiosyncratic stock volatility and dispersion in analyst forecasts. All portfolios are equally weighted and stocks are held for one month. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (IVOL) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses. ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

	Low	IU2	IU3	IU4	High	Low-High
Panel A. MV						
Winner	0.77%	1.02%	1.23%	1.57%	1.42%	-0.65%
						(-2.07**)
Median	0.63%	0.56%	0.43%	0.41%	0.47%	0.16%
						(0.56)
Loser	-0.29%	-0.47%	-1.06%	-1.37%	-1.47%	1.18%
						(2.68***)
Winner-Loser	1.06%	1.49%	2.29%	2.94%	2.89%	
	(2.05**)	(3.35***)	(5.99***)	(8.58***)	(8.1***)	
Panel B. AGE						
Winer	0.99%	1.25%	0.96%	1.31%	1.51%	-0.53%

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Table 3.4–continued from previous page

						(-1.82*)
Median	0.61%	0.61%	0.51%	0.55%	0.22%	0.39%
						(1.76*)
Loser	-0.12%	-0.35%	-0.80%	-1.62%	-1.76%	1.64%
						(5.07***)
Winner-Loser	1.11%	1.60%	1.76%	2.93%	3.27%	
	(3.14***)	(4.99***)	(4.14***)	(6.96***)	(7.69***)	
Panel C. COV						
Winner	0.64%	0.93%	1.30%	1.46%	1.59%	-0.95%
						(-2.63***)
Median	0.75%	0.46%	0.54%	0.27%	0.49%	0.26%
						(0.85)
Loser	0.13%	-0.39%	-0.77%	-1.13%	-0.80%	0.93%
						(2.21**)
Winner-Loser	0.51%	1.32%	2.07%	2.59%	2.39%	
	(0.98)	(2.81***)	(4.99***)	(6.49***)	(7.01***)	
Panel D. IVOL						
Winner	1.21%	1.39%	1.28%	1.37%	0.79%	0.42%
						(1.14)
Median	0.77%	0.85%	0.70%	0.43%	-0.21%	0.98%
						(3.63***)
Loser	0.29%	-0.57%	-0.67%	-1.24%	-2.50%	2.79%
						(5.73***)
Winner-Loser	0.92%	1.96%	1.95%	2.61%	3.29%	
	(3.16***)	(5.92***)	(5.45***)	(6.26***)	(5.90***)	
Panel E. DISP						
Winner	1.23%	1.12%	1.20%	0.94%	1.13%	0.10%

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Table 3.4–continued from previous page

						(0.43)
Median	0.56%	0.78%	0.65%	0.40%	0.43%	0.13%
						(0.56)
Loser	0.21%	0.15%	-0.14%	-0.74%	-1.71%	1.93%
						(4.47***)
Winner-Loser	1.02%	0.97%	1.34%	1.68%	2.84%	
	(2.87***)	(2.50***)	(3.39***)	(3.59***)	(5.09***)	

Table 3.5: Four-Factor Regressions on Portfolios Returns by Information Uncertainty Proxy

This table shows the intercepts and loadings of the four-factor regression model for monthly portfolio returns by information uncertainty proxy. The regression is $R_{i,t} - R_{f,t} = \alpha + \beta_{i,M}(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i UMD_t + \epsilon_t$ Where $R_{i,t} - R_{f,t}$ the excess return of portfolio i over risk-free rate in time t, $R_{M,t} - R_{f,t}$ is the excess return of market index over risk-free rate and SMB_t, HML_t and UMD_t represent the size, value and momentum premiums, respectively. The portfolios are equally weighted and constructed based on information uncertainty proxies, including firm size, firm age, analyst coverage, idiosyncratic stock volatility and dispersion in analyst forecasts. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (Sigma) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses. ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

IU	mean	α	$\beta Rm - Rf$	βSMB	βHML	βMOM	adjusted R^2
Panel A. MV							

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Table 3.5 continued from previous page

IU	mean	α	$\beta Rm - Rf$	βSMB	βHML	βMOM	adjusted R^2
Low	1.10%**	-0.36%***	89.30%	0.90%**	-13.60%***	-21.20%	0.89
	(2.28)	(-29.24)	(0.19)	(2.19)	(-4.87)	(-0.89)	
High	0.16%	-0.15%***	77.60%***	115.80%***	-26.70%***	-32.30%	0.88
	(0.75)	(-20.55)	(19.66)	(3.47)	(-6.00)	(-0.88)	
Low-High	0.95%	-0.22%***	11.70%***	-114.90%**	13.10%***	11.10%	0.81
	(1.28)	(-3.62)	(22.75)	(-1.98)	(2.4)	(0.82)	
Panel B. AGE							
Low	0.73%	-0.06%***	90.60%***	26.90%*	13.20%***	-24.30%	0.85
	(0.29)	(-23.33)	(4.44)	(1.67)	(4.39)	(-0.85)	
High	-0.24%	0.09%***	98%***	106.9%***	-84.10%***	-29.30%	0.84
	(-0.37)	(20.61)	(14.41)	(8.68)	(-4.31)	(-0.85)	
Low-High	0.97%	-0.15%	-7.50%***	-80.00%***	97.30%	5.00%	0.56
	(0.61)	(-1.59)	(-10.89)	(-10.14)	(0.74)	(0.57)	
Panel C. COV							
Low	0.61%	-0.20%***	86.60%*	-9.80%	3.00%***	-33.00%	0.85
	(-1.05)	(-23.29)	(-1.68)	(-0.40)	(-6.22)	(-0.86)	
High	0.15%*	0.41%***	82.40%***	117.00%***	-52.30%***	-23.80%	0.82
	(-1.74)	(-17.95)	(-16.36)	(-5.6)	(-3.64)	(-0.83)	

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Table 3.5 continued from previous page

IU	mean	α	$\beta Rm - Rf$	βSMB	βHML	βMOM	adjusted R^2
Low-High	0.46%***	-0.62%	4.20%***	-126.80%***	55.30%	-9.20%	0.74
	(-2.93)	(-1.04)	(-20.09)	(-6.71)	(-1.59)	(-0.75)	
Panel D. IVOL							
Low	0.91%	0.01%***	75.80%***	30.80%*	10.40%**	-7.90%	0.87
	(0.07)	(27.13)	(7.06)	(1.83)	(-1.98)	(-0.87)	
High	-1.19%	-0.21%***	119.90%***	156.50%***	-103.90%***	-50.90%	0.86
	(-0.69)	(-20.4)	(17.07)	(8.67)	(-6.07)	(-0.87)	
Low-High	2.10%	0.22%***	-44.10%***	-125.70%***	114.30%***	43.00%	0.71
	(0.73)	(-7.62)	(-13.92)	(-9.69)	(5.2)	(0.72)	
Panel E. DISP							
Low	0.79%	-0.06%***	80.10%***	31.00%	5.80%**	-11.10%	0.81
	(0.33)	(-21.34)	(5.29)	(0.76)	(2.06)	(-0.81)	
High	-0.26%	-0.16%***	101.90%***	91.60%*	-17.70%***	-45.50%	0.84
	(-0.59)	(-19.79)	(11.41)	(1.69)	(6.19)	(-0.84)	
Low-High	1.05%	0.09%***	-21.80%***	-60.60%***	23.60%***	34.50%	0.54
	(0.39)	(4.78)	(-8.53)	(-2.54)	(5.3)	(0.55)	

Table 3.6: Four Factor Regressions on Portfolios Returns by Information Uncertainty Proxy and Analyst Forecast Revisions

This table shows the intercepts and loadings of the four-factor regression model for monthly portfolio returns by analyst forecast revisions and information uncertainty proxy. The regression is: $R_{i,t} - R_{f,t} = \alpha + \beta_{i,M}(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i UMD_t + \epsilon_t$ Where $R_{i,t} - R_{f,t}$ the excess return of portfolio i over risk-free rate in time t, $R_{M,t} - R_{f,t}$ is the excess return of market index over risk-free rate and SMB_t, HML_t and UMD_t represent the size, value and momentum premiums, respectively.. We firstly categorize the stocks into 3 groups with upward (good news), flat (no news) and downward revision (bad news) respectively. For each group, we further sort the returns into five quintiles based on firm size, firm age, analyst coverage, idiosyncratic stock volatility and dispersion in analyst forecasts. All portfolios are equally weighted and stocks are held for one month. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (Sigma) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses and ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

IU	MV	AGE	COV	IVOL	DISP
Panel A. Good News (Positive Revision)					
Low	-0.37%**	-0.25%	-0.03%	0.09%	-0.02%
	(-2.2)	(-1.06)	(-0.12)	(0.48)	(-0.1)
IU2	-0.28%	0.01%	-0.24%	0.08%	0.25%
	(-0.95)	(0.05)	(-0.91)	(0.35)	(0.97)
IU3	0.45%*	0.33%	0.31%	0.26%	0.42%*

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Table 3.6 continued from previous page					
IU	MV	AGE	COV	IVOL	DISP
	(1.65)	(1.19)	(1.14)	(1.02)	(1.76)
IU4	0.70%***	0.81%***	0.64%***	0.61%**	0.51%
	(2.55)	(3.21)	(2.41)	(2.06)	(1.8)
High	1.10%***	0.71%**	0.90%***	0.55%	0.07%
	(3.49)	(2.15)	(2.77)	(1.35)	(0.21)
Panel B. No News (Flat Revision)					
Low	-0.25%	0.20%	-0.12%	0.28%	0.04%
	(-1.03)	(0.8)	(-0.48)	(1.33)	(0.15)
IU2	0.58%**	0.08%	0.72%***	0.38%	0.75%
	(2.24)	(0.31)	(2.68)	(1.63)	(3.37)
IU3	0.70%***	0.65%***	0.40%	0.74%	0.26%
	(2.61)	(2.49)	(1.4)	(2.80)	(0.93)
IU4	0.71%**	0.40%	0.66%***	0.30%	0.48%
	(2.29)	(1.63)	(2.37)	(1.03)	(1.58)
High	0.22%	0.65%**	0.31%	0.30%	0.12%
	(0.71)	(1.91)	(1.01)	(0.78)	(0.34)
Panel C. Bad News (Negative Revision)					
Low	-0.79%***	-0.14%	-0.47%*	-0.49%***	-0.34%
	(-3.78)	(-0.53)	(-1.93)	(-2.42)	(-1.4)
IU2	-0.35%	-0.25%	-0.13%	-0.31%	-0.14%
	(-1.13)	(-0.79)	(-0.46)	(-1.26)	(-0.51)
IU3	-0.14%	-0.31%	0.00%	-0.24%	0.30%
	(-0.41)	(-1.01)	(0.01)	(-0.81)	(1.1)
IU4	-0.13%	-0.63%**	-0.45%	-0.27%	-0.46%
	(-0.4)	(-2.14)	(-1.52)	(-0.84)	(-1.37)
High	-0.07%	-0.13%	-0.43%	-0.19%	-0.76%**

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Table 3.6 continued from previous page					
IU	MV	AGE	COV	IVOL	DISP
	(-0.21)	(-0.41)	(-1.33)	(-0.44)	(-2.24)

Table 3.8: Sub-period Analysis

This table reports the effect of information uncertainty on earnings and price momentum in two sub-periods. The first period is from February 1991 to June 1997 and the second period is from July 1997 to December 2003. Panel A shows the portfolio return differential between extreme low and high uncertainty stocks (Low-High) following upward and downward analyst forecast revision (Good and Bad), respectively. It also shows the earning momentum strategy (Good-Bad) within extreme low or high uncertainty quintiles. Panel B presents the portfolio return differential between extreme low and high uncertainty quintile (Low-High) with past 11-month winners and losers, respectively. Price momentum strategy (winner-loser) within extreme high or low uncertainty quintile follows. Uncertainty proxies include firm size, firm age, analyst coverage, idiosyncratic stock volatility and dispersion in analyst forecasts. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (Sigma) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year. T-statistics are reported in parentheses. ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

		MV	AGE	COV	IVOL	DISP
Panel A: Sub-period test of analyst forecast revision and information uncertainty						
Sub-period from Feb 91 to Jun 97						
Good	Low-High	-0.0004	-0.002	0.0036	-0.78%**	-0.48%*

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		MV	AGE	COV	IVOL	DISP
Table3.8–continued from previous page						
		(-0.08)	(-0.59)	(0.71)	(-2.18)	(-1.73)
Bad	Low-High	0.78%*	0.005	0.87%***	0.003	-0.0009
		(1.93)	(1.57)	(3.2)	(0.71)	(-0.23)
Good-Bad	Low	0.62%***	0.0021	0.70%***	0.34%***	0.54%***
		(2.52)	(1.2)	(2.58)	(2.35)	(2.83)
Good-Bad	High	1.38%***	1.12%***	1.20%***	1.14%***	1.08%***
		(4.19)	(3.41)	(4.16)	(2.55)	(2.67)
Sub-period from Jul 97 to Dec 03						
Good	Low-High	-0.0016	0.0073	0.0004	2.14%***	0.78%*
		(-0.29)	(1.21)	(0.07)	(2.82)	(1.75)
Bad	Low-High	0.0088	1.15%***	1.03%*	2.20%***	1.46%***
		(1.6)	(3.1)	(1.89)	(3.37)	(2.62)
Good-Bad	Low	0.002	0.62%**	0.54%*	0.73%***	0.58%***
		(0.66)	(2.02)	(1.74)	(3.44)	(2.44)
Good-Bad	High	1.47%***	1.14%***	1.80%***	1.23%***	1.55%***
		(3.88)	(2.99)	(4.76)	(2.88)	(3.5)
Panel B: Sub-period test of past 11-month performance and information uncertainty)						
Sub-period from Feb 91 to Jun 97						
Winner	Low-High	-1.03%***	-1.13%***	-1.33%***	-0.78%**	-0.48%*
		(-4.97)	(-4.60)	(-5.23)	(-2.18)	(-1.73)
Loser	Low-High	0.0038	0.0075	0.0066	0.94%***	1.47%***
		90.84)	(1.55)	(1.46)	(2.33)	(3.84)
Winner-Loser	Low	0.0038	1.00%***	-0.0001	0.75%***	1.12%***
		(0.94)	(2.79)	(-0.03)	(3.04)	(3.71)
Winner-Loser	High	1.99%***	2.87%***	1.89%***	2.67%***	2.26%***
		(4.38)	(6.94)	(5.78)	(4.29)	(3.47)

Continued on next page

		MV	AGE	COV	IVOL	DISP
Table3.8–continued from previous page						
Sub-period from Jul 97 to Dec 03						
Winner	Low-High	-0.88%***	-1.46%***	-0.87%*	-1.22%**	-0.92%***
		(-2.66)	(-3.31)	(-1.72)	(-2.08)	(-2.44)
Loser	Low-High	1.49%**	2.12%***	0.0083	3.37%***	2.39%***
		(2.14)	(4.04)	(1.29)	(4.68)	(3.64)
Winner-Loser	Low	1.73%*	1.22%**	0.0102	1.09%**	0.0092
		(1.83)	(2.00)	(1.11)	(2.07)	(1.43)
Winner-Loser	High	3.79%***	3.67%***	2.88%***	3.91%***	3.43%***
		(7.08)	(4.95)	(4.82)	(4.23)	(3.78)

Table 3.7: Sharpe Ratios of Portfolio Strategies within Extreme Information Uncertainty Portfolios

This table gives the Sharpe ratios of several strategies. The Strategy I shorts the past losers and buys the past winners within extreme high and low information uncertainty quintiles, respectively. The Strategy II shorts the stocks with downward analyst forecast and buys those with the upward analyst forecast within extreme high and low information uncertainty quintile, respectively. Return is the average monthly return, Std.Dev is the standard deviation of all monthly returns, and Sharpe ratio is calculated by monthly portfolio excess return over FTSE all-share Index return divided by standard deviation of portfolio returns. Market beta ($Rm - Rf$), SMB and HML are the excess return of market index over risk-free rate, the size and value premium, respectively. Firm size is the market capitalization (in millions of pounds) at the end of month t. Firm age is the log of one plus the months since a stock was firstly recorded by Thomson Financial DataStream. Analyst coverage is the log of one plus numbers of forecasts reported to I/B/E/S database. Idiosyncratic stock volatility (Sigma) is calculated by standard deviation of monthly excess returns over FTSE all share index over the year ending at the end of month t. Dispersion in analyst forecasts is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. The sample includes all stocks traded in UK stock market from February 1991 to December 2003, except those listed within prior one year.

	All Stocks	Rm-Rf	SML	HML	
Return	0.39%	0.20%	-0.36%	0.49%	
Std. Dev	0.11	0.04	0.03	0.02	
Sharpe Ratio	0.03	0.05	-0.11	0.27	
	MV	AGE	COV	IVOL	DISP
Strategy I: Price momentum strategy with extreme low information uncertainty					
Return	1.25%	1.06%	1.11%	0.88%	1.35%
Std. Dev	0.076	0.06	0.08	0.05	0.07
Sharpe Ratio	0.16	0.18	0.14	0.17	0.21
Strategy I: Price momentum strategy with extreme high information uncertainty					
Return	2.79%	2.94%	2.73%	2.98%	2.81%
Std. Dev	0.07	0.08	0.06	0.09	0.1
Sharpe Ratio	0.38	0.37	0.42	0.33	0.3
Strategy II. Earning momentum strategy with extreme low information uncertainty					
Return	0.18%	0.53%	0.69%	0.63%	0.53%
Std. Dev	0.03	0.03	0.03	0.02	0.03
Sharpe Ratio	0.06	0.19	0.25	0.3	0.21
Strategy II. Earning momentum strategy with extreme high information uncertainty					
Return	1.29%	1.05%	1.08%	1.46%	1.43%
Std. Dev	0.04	0.04	0.03	0.05	0.05
Sharpe Ratio	0.36	0.27	0.32	0.32	0.28

Chapter 4

Information Uncertainty, Growth Options And Liquidity: International Evidence

4.1 Introduction

In chapter 3, the evidence from UK stock market shows that information uncertainty is positively associated with underreaction anomaly and leads the market to underreact to recent news. The consequent research question is that whether the influence of information uncertainty is prevalent in the global markets. Whether investors in different countries would treat uncertainty differently? To answer these questions, this chapter further investigates the impact of information uncertainty within 30 major stock markets to draw a more general inference.

The first goal of this chapter is to examine the relationship between information uncertainty and firms characteristics. Information uncertainty means ambiguity about a firm's fundamental value, which may arise from two conventional sources. 1) characteristics of the business or industry, such as technical innovation and high R&D expenditure; 2) the company's disclosure policy, including accounting standards and management voluntary disclosure. Although both sources of uncertainty would affect investment decisions of market participants, from the investors' perspective the mechanisms and outcomes are quite different. We argue that information uncertainty, unlike asymmetric information, is an endogenous characteristic of companies with growth options.

The evidence from pooled sample regression shows that information uncertainty is positively related to firm's growth options. Specifically, young firms and firms with higher market-to-book ratio tend to bear greater information uncertainty. The results also show that information uncertainty is significantly positively related to firm size, trading volume, and price impact, indicating that information asymmetry is another non-negligible attribute to information uncertainty. Moreover, firms in the markets with better investor protection, such as cash flow rights, are found to have lower information uncertainty. It confirms our conjecture that information uncertainty comes from two opposite source with diverged asset pricing implications.

We further test whether information uncertainty has positive or negative prediction power on cross sectional stock returns with the control of asymmetric information effect and other firm characteristics. Regarding to asymmetric information[1], outside investors would be reluctant to hold those equities with private

[1]Easley and O'Hara (2004) modelled a multi-asset economy with public and private information, and suggest that informed investors could always take advantage of the uninformed by holding more stocks with good news and fewer stocks with bad news. Moreover, Diamond and Verrecchia (1991) argue that market makers would be unwilling to provide liquidity for assets with private information, hence asymmetric information would increase the bid-ask spread.

information (Wang (1993); Admati (1985)). If information uncertainty generated by growth options are mistaken for information asymmetry, firms with greater information uncertainty will experience relatively higher stock returns to attract investors.

On the other hand, if investors perceive information uncertainty stemming from firm's growth options, stocks with greater information uncertainty would labeled as 'glamor' and demand higher prices (Chan, Jegadeesh, and Lakonishok (1996)). Intuitively, high expected earnings are accompanied by high earning volatility, otherwise, competitors from outside would eat out excess profits. In addition, companies in young industries have higher R&D intensity and lower tangible assets in hand. Contrary to the traditional viewpoint, Zhang (2005) argues that these companies can more easily cut costs and dispose of unproductive assets, while in good times they could invest more and become more productive. Moreover, companies in young industries are relatively smaller and face fewer barriers to switch to a more profitable business model. The negative relation of growth options and required return is consistent with empirical evidence that value stocks earn higher returns, especially in an economic downturn.

The portfolio strategy shows a negative relation between information uncertainty and stock future returns shows , which is more significant in developed markets. Moreover, this relationship seems to only exist in value-weighted portfolio, and disappear in equally weighted portfolio. One plausible explanation is that value-weighted portfolio putting more weights on big and mature firms, which mitigate the adverse effect of information asymmetry. It also explains why we find more significant negative correlation among developed markets, as investors in these developed markets face less adverse selection problem of asymmetric information. The results from Fama-Macbeth (1973) are consistent with findings in portfolio strategy. The cross sectonal stock returns are significantly correlated to information uncertainty even controlling risk exposure and other firm's characteristics, suggesting the impact of information uncertainty can not be explained by existing rational risk factors.

This chapter contributes to the literature in several ways. First, we give the international empirical evidence supporting the linkage between information uncertainty and growth options in young and emerging industries consistent with the rational learning model of Pastor and Veronesi (2003). Previous research about uncertainty focuses on exogenous information process with different levels of imprecision or asymmetric information. We postulate that uncertainty could be a firm characteristic, along with potential high earning growth and volatility.

Second, our cross-country result is consistent with predictions of disclosure theory and investor protection. There is in the context of corporate finance a rich literature about disclosure policy, legal system and shareholder rights (La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998);Wurgler (2000); Black (2001); Defond and Hung (2004)). The result in this chapter shows that stricter law and regulation and more transparency of disclosure can lower the cost of capital for firms, especially those with high uncertainty of future profitability. In addition, our result is consistent with John, Litov, and Yeung (2008), who find evidence that risk-taking and firm's growth rate is positively related to investor protection. We further argue that markets with good protection are essential for high technology innovation. With valuation uncertainty, the adverse selection problem is an important one for firms in young industries and those with high R&D.

Third, this analysis is also related to several empirical puzzles in the literature.

For example, with regard to increasing idiosyncratic volatility and stock returns, Campbell et al. (2001) found increasing and counter-cycle firm-level idiosyncratic volatility from 1960. Xu and Malkiel (2003) attributes this phenomenon to increasing ownership of institutional investors, while Berrada and Hugonnier (2008) suggest the earning surprise under the incomplete information setting drives up idiosyncratic volatility with asymmetric response. Here we give an alternative explanation, that idiosyncratic volatility is an indicator of unexplained future earning potential, and rises along with technical innovation. Ang, Hodrick, Xing, and Zhang (2006) make a similar suggestion, but their analysis is based on aggregate level. We also provide evidence of value effect in favour of Zhang (2005) rational expectation model. The stocks with higher potential earning and volatility are less risky and generate lower returns compared to other stocks.

This chapter is organized as: section 4.2 provides a review of related literature and develop main hypothesis; Data and methodology is described in section 4.3; Empirical results are discussed in section 4.4 and conclusions are drawn in section 4.5.

4.2 Literature Review

4.2.1 Information Uncertainty, Future Profitability And Equity Valuation

Pastor and Veronesi (2003) derive a model of stock valuation with uncertainty of future profitability. The salient feature of their model is convex relation between market-to-book ratio and uncertainty about expected earning growth rate .

They assume that the true growth rate of earning is not observable, while investors learn from the idiosyncratic shock to individual firms. They further assume the modelled company has a finite life cycle and is eventually liquidated with market value, i.e. the book value equals to market value at a fixed time spot. This assumption is somewhat unrealistic. The economic explanation behind it is that the excess profitability would decrease over firm and industry life with market competition, as would the earning multiplier. The implication is consistent with past empirical findings that: 1) After controlling the expected returns and expected profitability, M/B should increase with uncertainty about profitability; 2) M/B should decline along the lifetime due to learning process and diminished excess profitability; 3) The uncertainty effect should be stronger with younger firms and firms that pay no dividends (c=0); 4) Uncertainty does not affect the expected returns but does affect future cash flow; and 5) Uncertainty also increases the idiosyncratic stock volatility. Their empirical test provides supportive evidence with US stocks from 1963 to 2000. Pastor and Veronesi (2006) uses this model to calibrate the returns and volatility in the US stock market, and suggests that the peak of the technology bubble in the 1990s was driven by uncertainty of high future profitability. At aggregate market level, Cao, Simin, and Zhao (2008) find idiosyncratic volatility turns to stability after controlling firm's growth opportunity. They use Galai and Masulis (1976) model in which managers prefer investment opportunities that produce larger idiosyncratic volatility to increase shareholders' wealth. A new project with high idiosyncratic risk would require relatively low return, as it increases the expected future cash flow while having little impact on systematic risk. Their finding holds for the whole market level as well as for mature industries. Mazzucato and Tancioni (2008) find a positive relation between idiosyncratic volatility with firm-level innovation and R&D expenditure, while at industry level, this relation is mixed. They argue that investors have varied expectations of innovation outcomes from industry sectors. For very new sectors, hopes of individual firms' innovation are high, while for mature industries innovation shocks are not anticipated. Thus the effects of innovation on idiosyncratic risks are more significant for these two kinds of industries. In contrast, innovation in a high-tech but mature industry is already predicted by the market and thus has low impact on idiosyncratic risk. On the other hand, innovation and R&D expenditure is highly correlated to firm's idiosyncratic volatility at individual level, which is consistent with Pastor and Veronesi's hypothesis. Cao, Simin, and Zhao (2008) test the relation between idiosyncratic volatility and growth options at aggregate market level using Galai and Masulis (1976) model. The logic behind this is that managers, on behalf of shareholders, would choose investment opportunities with high idiosyncratic volatility. As, intuitively, companies' innovation has very low correlation from one company to another, expenditure in R&D would increase the idiosyncratic volatility along with the investment opportunity set for each individual firm. Cao, Simin, and Zhao (2008) use five proxies including an estimate of Tobin's Q, the ratio of the market value to book value, the debt to equity ratio, the ratio of capital expenditures to fixed assets, and a direct measure of the present value of growth options. Using daily data in the US stock market along with five different measures of idiosyncratic volatility, the results confirm their hypothesis that aggregate idiosyncratic volatility is positively related to both level and volatility of firm's growth options. Other research concerns not idiosyncratic volatility but the total volatility and firm's investment opportunity. Schwert (2002) uses a sample of high-tech industries in NASDAQ and finds that volatility of earnings predicts total equity return volatility. Chan, Lakonishok, and Sougiannis (2001) find that stock future return volatility is positively related to R&D intensity.

Another strand of the literature focuses on the relation between growth option and stock valuation. Research in this area suggests that firms with high growth opportunity have rationally high market valuation and lower conditional risks. A firm's assets can be roughly distinguished as assets in place and growth options. Assets currently in place are generated past profits, while growth options are the assets associated with net present value of future returns. Along the company's lifetime, positive cash flow from assets in place would decrease and new investment opportunity would add to the firm's fundamental value. In other words, turning from assets in place to growth options would increase the firm's market valuation and decrease current cash flows. Berk, Green, and Naik (1999) argues that changes of composition of these two types of asset would alter the firm's exposure to systematic risks. Zhang (2005) suggests that asset in place is much riskier than growth option, especially when economies decline. His model is based on costly reversibility and countercyclical price of risk that differentiate the asset in place and growth options. Costly reversibility means that cutting cost is much harder than expanding cost. When the economy as a whole is going up, firms with more growth options would need more adjustment cost to realize these investment opportunities, while more mature companies with assets in place would find it relatively easier to turn on full production. More importantly, when economies decline, value firms which contain more unproductive assets would face more cost to adjust their business model. Compared to growth firms, their valuation is more related to economic conditions, and hence bears more systematic risk. In addition, the price of risk is higher in bad times, which means that value firms would disinvest. Zhang's (2005) paper focuses on the value effect but is not bounded for other phenomena. The implication could give a dynamic view of capital investment for companies with diverse growth options.

Our research is also motivated by Daniel and Titman (2006). In their paper, incoming news is divided into tangible information and intangible information. The tangible represents the solid accounting information such as accrued earnings and cash flows, while intangible information comprises the other parts, not explained by stocks' performance. They suggest that expected stock returns are not determined by past accounting performance information, but are negatively related to the intangible information. More particularly, intangible information is related with firm's growth options, while tangible information, such as earning growth per share, is a measure of past performance. They further argue that taste for stocks of a company with potential growth opportunity leads to overvaluation, and that the bandwagon effect will reverse after such projects are realized. Although their analytical framework is focused on value effect, it offers a potential explanation of information uncertainty effect on stock returns, as intangible information is naturally ambiguous, and more concentrated in growth companies and industries. This provides another explanation of why information uncertainty is negatively priced.

4.2.2 Information Uncertainty And Corporate Governance

The seminal paper by Jensen and Meckling (1976) argues that shareholders have the residual rights on the company as their contract is open-ended. In this sense, potential earning growth will give them more advantage compared to creditors. With regard to corporate governance, research finds that the market worldwide could be classified into "market oriented" and "bank oriented" systems. The former refers to the Anglo-American market-based system, while the latter is the Japanese-German financial system. The classification is based on the relative portion of company financing from shareholders and creditors. There is no conclusion as to which system is better. However, since the Anglo-American system relies more on the equity market for external financing, shareholder rights are better protected in these markets. Cross-countries comparison shows the relatively low cost of equity in the US and other markets, along with outstanding minority shareholder protection (La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998)). With regard to firms with high earning growth and earning volatility, investors in the Anglo-American system would put more trust in managers and their decisions on investment projects. The success of NASDAQ for high-tech companies is a good example. However, note that the Anglo-American market is critiqued by the myopic view of market participants. Equity investors rely on quarterly and annual accounting reports to estimate firm's performance and reward managers with corresponding bonuses, while bankers usually establish a long-run relationship with company managers. Therefore, in the market oriented system managers pay more attention to short-term interests which may bias companies' investment decisions. This situation may be mitigated by option incentives or long-run contracts, which bound managers' incentive with a longer term goal.

Wurgler (2000) finds a close link between corporate governance and investment in growing industries in 65 countries. Developed financial sectors increase investment in their growing industries, and decrease investment in their declining industries, to a greater extent than do undeveloped financial sectors. The efficiency of capital allocation is negatively correlated with the extent of state ownership in the economy, positively correlated with the amount of firm-specific information in domestic stock returns, and positively correlated with the legal protection of minority investors. In particular, strong minority investor rights appear to curb over investment in declining industries.

Generally, a mature market should benefit and protect the investors in several ways. First, the accounting standard is one of the most important means by which investors, especially outsiders, can learn about the company's performance. A better accounting standard prevents asymmetric information and agency problems. Second, restriction of ownership concentration, namely anti-director right, is an efficient way to increase the cost of manipulation, as no controlling director or manager can easily benefit from other shareholders by means of information or policy advantage. Third, restriction on and punishment for manipulating trades and delivering illusive information are substantial considerations for investors. Although these activities are illegal in almost all countries, different laws and exchange regulations may result in different levels of protection for investors. As presented by La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998), common law generally offers the strongest protection for investors, followed by German and Scandinavian civil law, with French civil law offering the weakest protection. Within the common law system, as jurisprudence is established case by case, longer history of the market may lead to better protection. The series paper of La Porta, et al., (1998, 1999, 2000, 2002) on global corporate governance further build up a bunch of indices to measure the degree of investor protections and show that legal origin is one of the dominant characteristics of corporate governance.

Recently, some commentators have gone as far as predicting a worldwide convergence of corporate governance practice to the US model (see e.g. Hansmann and Kraakman (2000)). In a variant of this view, worldwide competition to attract corporate headquarters and investment is envisaged, similar to the corporate law competition between US states portrayed by Romano (1993). Such competition is predicted to eventually bring about a single standard resembling the current law in Delaware or, at least, securities regulation standards as set by the US SEC (see Coffee (1999)).

4.2.3 Idiosyncratic Volatility

Idiosyncratic volatility, also known as unsystematic or diversifiable volatility, represents the uncertainty of a single firm, which is not associated with market or industry risk. Risk and return trade-off is the key issue of modern financial economics. Portfolio theory, stemming from Markowitz (1952), argues that the firm-specified volatility can be diversified away through constructing portfolios with securities that are not fully correlated. Based on the statistical law of large number, a conventional wisdom of investment is that holding over twenty stocks could largely eliminate the portfolio volatility from firm-level shocks. The rational asset pricing theories such as Sharpe (1964),Lintner (1965) capital asset pricing model, and Ross (1976) arbitrage pricing theory, point out that idiosyncratic volatility should not be related to security return. With the assumption of complete market, investing in securities is frictionless, which means the investor can hold as many stocks as needed without transaction costs. Thus, a rational agent can easily diversify idiosyncratic volatility away by well-constructed portfolio and has no preference on high or low residual volatility. In the dynamic setting of complete market, the situation is roughly the same. Idiosyncratic volatility is theoretically orthogonal to stochastic discounted factor, and irrelevant to expected returns (Campbell (2000)). So in a complete market, agents should ignore the idiosyncratic volatility as it has no impact on portfolio payoffs and investors' welfare. However, the real markets are far from the perfect and complete assumption. Next, we collect the empirical evidence to find whether or not idiosyncratic volatility has impact on expected return, both at market level and at individual stock level.

Previous empirical work does not provide conclusive evidence of the exact relationship between firm-level volatility and expected returns. The empirical work in this area extends to three different levels: aggregate market level, industry and portfolio level and individual firms. In an early aggregate level study, Campbell, Lettau, Malkiel, and Xu (2001) use the disaggregate methodology to measure idiosyncratic volatility. They find that after the 1990s, the total idiosyncratic volatility has an upward trend, while at the market and industry levels it is relatively smooth and flat. Their analysis shows some potential reasons for such volatility patterns, for example new listed firms, firms at early stage, and technical innovation. Their findings suggest that to diversify these individual risks, a portfolio requires more stocks to be efficient. It also indicates a relation between aggregate volatility and counter-cycle movement and macro-economic growth. Goyal and Santa-Clara (2003) find no predictability of market variance to market return. They support the time-varying view of risk premium that the individual heterogeneity and market background risk are important factors for market returns. However, Bali, Cakici, Yan, and Zhang (2005) argue against this result and suggest the pattern is caused by equally weighted volatility. Using a value weighted portfolio strategy, they show that such relation is statistically insignificant.

In the cross-sectional tests, Ang et al.,(2006, 2009) show that stocks with recent past high idiosyncratic volatility, based on the Fama-French three factor model, have low future average returns in the US and other developed markets after controlling for world market, size, and value factors. They explain the negative relation as due to undiversified risk. Bali and Cakici (2008) test cross-sectional relation between firm-level volatility and expected stock return. Interestingly, their results indicate that previous empirical analysis may be biased by data-frequency, weighting scheme and breakpoints. After controlling these factors, they find no significant returns with high idiosyncratic volatility. At industry level, Bali and Cakici (2008) uses the GARCH model to estimate industry and portfolio-based idiosyncratic volatility to analyze conditional risk-return relationship.

Moreover, researchers also argue that idiosyncratic volatility is a proxy for information uncertainty. Cao, Simin, and Zhao (2008) establish a theoretical link between growth options available to managers and the idiosyncratic risk of equity. Empirically both the level and variance of corporate growth options are significantly related to idiosyncratic volatility. Accounting for growth options eliminates or reverses the trend in aggregate firm-specific risk. Zhang (2006) and Jiang, Lee, and Zhang (2005) use idiosyncratic volatility as information uncertainty in the context of behaviour finance. They suggest that high sigma means the signs arriving at the market are comparatively noisy and carry limited arbitrage ability. With high noise news about the fundamental stock value, investors are subject to more behaviour biases, such as overconfidence and continuation. Kumar and Lee (2006) supports this view with retail investors' profiles, while Sadka (2006) argues that idiosyncratic volatility is related to market liquidity but not for behavioural reasons.

4.2.4 Investment Opportunity Set

Investment opportunity set or, more specifically, growth option, means companies' access to future potential profitable projects (i.e. those projects that can be exercised without the technology barrier). This characteristic attracted more attention during the technology industry boom of the 1980s and 1990s. In the economic sense, start-up companies have high future earning growth with high earning volatility. Along the life and industry cycle, firms eventually enter a mature stage with average profits across the industry sectors and the whole economy. The conventional wisdom tells us that potential earning is highest at the emerging stage of an industry and then starts to diminish. Hence, firms in young industries have larger investment opportunity set or growth potential. Meanwhile, in the era of technology added-value economics, even those full-fledged firms in mature industries need to adopt new technological innovations, such as IT systems, data mining and e-business. If they do not, they will be washed out by fierce competition with high operation costs. The literature about growth options diverges into two categories. The first regards corporate financing and focuses on the capital structure of growth companies, while the second analyzes the market reaction to those growth companies' information.

Logically, managers make decisions according to firms' available investment options and macro-economic and market conditions. The next question would be through which way and what instrument. Researchers have found that companies usually opt for a low debt ratio and prefer using equity rather than debt as an external funding source. The underlying reason is simply that managers may not know when any profit will be realized. To match the time and cost of future uncertain cash inflow, investors would rationally prefer to issue stocks, which is open-ended. A higher debt ratio would also prevent the company from investing in the future, so those companies usually have a low debt ratio with a low leverage value. Moreover, the capital needed for future investment may be costly. Hence, borrowing today would lead to decreased incentive for managers to invest tomorrow. If its leverage ratio and debt ratio is high today, the company may not have sufficient financial capacity to borrow more money tomorrow in such million pound business.

Empirical findings confirm the negative relationship between growth options and leverage ratio and debt ratio. Smith and Watts (1992) seminal paper documents that firm's leverage ratio, debt ratio and R&D expenditure are negatively related to the investment opportunity. Research also finds that firms with higher R&D expenditure would prefer to use equity issue rather than debt for external finance. Billett, King, and Mauer (2007) finds that covenant is important for debt issuing but prevents the information asymmetry. Jung, Kim, and Stulz (1996) and Zhang (2005) provide evidence that in primary markets, investors respond differently to equity issuing by growth firms and by mature firms. For the growth firms they do not observe a negative announcement effect, while in the sample of mature firms this effect exists and is significant. They explain this according to market investors' views of the needs of different types of firm. For mature industries, IPO or SEO carry a higher probability that the company does not operate well enough.

Another common factor related to growth option is market-to-book value. Since market value is the consensus of valuation of market participants, it changes over time. Growth companies with opportunity in hand would be much more likely to realize the earnings. So, investors react differently according to type of investment set. Other proxies frequently used are earning per share, dividend per share, R&D expenditure and its proportion to total assets.

4.2.5 Hypothesis Development

Past literature has documented that information uncertainty would influence the investment decision of market participants. However, the source of uncertainty is mixed. From the investors' point of view, high uncertainty may be caused by less publicly available information or by the lack of historical performance. Without sufficient or precise information released by companies, investors face large uncertainty of underlying firm's valuation. A large literature of asymmetric information would lower firm's value and require higher premium to compensate for higher unwanted risks (see Verrecchia (2001) for a comprehensive review).The first hypothesis in this chapter is that information uncertainty is positively correlated with information asymmetry.

However, research on information uncertainty is inevitably mixed with the asymmetric information effect or incomplete information effect. Companies with high growth opportunity also share some parallel characteristics, such as relatively small size and young age, low past dividend payout, and coverage by fewer analysts. Compared to mature companies, their mandated disclosure is of relatively low quality and outsiders face more asymmetric information controlling other variables (Core (2001);Verrecchia (2001)). Moreover, we also argue that in a less regulated capital market[2], this asymmetric information effect would further increase cost of

[2]Channelling funds to risky business is a key feature of the financial industry. However, the efficiency of allocation is distorted by uncertain information. Compensation for uncertainty motivates investors to engage in rapid growth business. On the other hand, ambiguity of valuation would discourage investment on the grounds of unforeseeable risk and potential loss. Interesting-

capital for growth companies. The logic here is that although these companies have incentive to disclose more information to attract external funding, markets with high aggregate level of asymmetric information would discourage participants' investing in high uncertainty business. This classic 'lemon market' problem has a significant effect on start-up companies, even though their potential earnings are appreciable.

On the other hand, uncertainty may also arise from the nature of the business and future earnings potential. Intuitively, firms in young industries or in the early stages of the life cycle would have higher potential earnings and higher earnings volatility. Pastor and Veronesi (2003) use a learning model and argue that these firms would have higher market-to-book ratios, with other things the same. Meanwhile, the value effect is robust that stocks with low (high) market-to-book ratio tend to generate higher (lower) future returns. Meanwhile, the value effect is robust that stocks with low (high) market-to-book ratio tend to generate higher (lower) future returns. There are several possible explanations. First, firms with growth potential have real options to adopt new investments when economies are on an upward turn. Zhang (2005) suggests that growth companies are less risky because it is easier for them to cut costs in bad times, compared to firms with assets in place. Campbell and Vuolteenaho (2004) argue that growth companies are subject to future cash flow shocks, while firms with assets in place are more sensitive to discount rate shocks. Our second hypothesis is that information uncertainty is positively associated with firm's growth options.

ly, with the development of financial markets and industry over many years, excess volatility to stock fundamentals (Shiller (2000)) and firm-level idiosyncratic risk (Campbell, Lettau, Malkiel, and Xu (2001)) tend to increase rather than decrease. This phenomenon suggests that investors face more uncertainty, notwithstanding the application of stricter regulation and the reduction of information cost brought about by communication innovation during the last two decades.

We further hypothesize that information uncertainty has mixed effect on underlying stock performance, depending on relative composition of information asymmetry and growth options. When uncertainty derives from limited information or asymmetric information, investors would treat it as a risk and require higher returns to hold underlying assets. According to Merton's (1987) incomplete information model, investors may require compensation for different information endowment. In his model, some investors may be unaware of certain securities or have limited information. Therefore, these assets are not widely held and bear undiversified risks. In developed financial systems, there are more institutional investors who face less information cost and transaction cost. Hence the premium for undiversified risk should plausibly be lower in these markets.

In contrast, if the uncertainty is driven by firm-specific growth potential, it would increase the stock value. Past empirical evidence is mixed as it is hard to separate these two types of uncertainty. In this chapter, we try to control both types of uncertainty and test the relation between uncertainty and cross-sectional stock returns. The testable hypothesis is that, when controlling asymmetric information, uncertainty should predict lower future returns, while when controlling firm's growth potential, uncertainty would be dominated by limited information, and positively priced.Therefore, we predict that in well developed markets, information uncertainty leads to higher stock values and lower future returns. This relation should be reversed in less developed markets.

Our hypothesis is summarized as following: After controlling the effect of limited information, information uncertainty is cross-sectionally concentrated in companies with higher growth potential and leads to overvaluation of today's price. After controlling growth options, uncertainty captures the risk of incomplete information or asymmetric information and requires higher returns. In developed countries, information uncertainty is more negatively priced with lower hidden information and better investor protection.

4.3 Data and Methodology

Our data sample, obtained by DataStream, includes both active and dead stocks from January 1988 to December 2007, selected according to the same criteria. There are 30 total market data in our sample period [3]. We exclude the stocks with less than one year performance history, and financial industry stocks. For individual and market indices prices we use the DataStream return index (RI), which is adjusted for past dividends. Following Ang, Hodrick, Xing, and Zhang (2009), we calculate daily and monthly returns in both local currency and US dollar, and risk-free rate by three month US treasure bill. As DataStream choose stocks from local markets and build each market index, each index contains fewer stocks than the local market. For example, there are only 10 stocks in the China Total Market Index, even though at the end of 2008 there were 1572 stocks in that market. Although it loses some testing power, DataStream Total Market Index contains both dead and live stocks, so it is free from survivorship biases. Moreover, it chooses stocks with the same criteria and allows comparison across the countries.

Accounting information and firm's characteristics are also given by DataStream. We use market capitalization (MV) dominated in US dollar to make it comparable across the countries. DataStream contains some flawed data. For

[3] DataStream provides 52 total market indices across the world. However, 22 out of 52 markets have less than 20 stocks in their index constitution. We have to drop these markets without enough number of stocks to prevent small sample problem

example, the largest market capitalization from its database is a Brazilian stock with unrealistic 2.97*1012 dollars. So we exclude stocks with market value in the highest and lowest 1%. The average market capitalization in our sample is 20.4 million dollars and the median is 40.2 million dollars. We also winsorize the book-to-market value (B/M) with 1% level. The average B/M is 0.72 and the median is 0.53. Left skewness of MV indicates more small firms in the sample and right skewness of B/M implies more growth companies.

Table 4.1 reports descriptive statistics of sample data. The second column is number of stocks, including live and delisted stocks, appearing in each stock market index during the sample period. FIRST OBS reports the starting date of each index. If the market index is constructed before Jan 88, we take Jan-88. MONTH is average months of firms traded during this sample period. It implies the life length of individual stocks. RET is monthly lognormal return calculated by return index (RI) from DataStream. SKEWNESS is average daily skewness within each country. RAW VOL is average individual standard deviation of monthly individual stock returns. IVAR is monthly average standard deviation of residuals calculated from Fama-French three factor model. We exclude firms in financial industries and firms without previous month market capitalization or book-to-market value. In our sample, Japan contains the most stocks, with 943. The latest starting date is Sept 7th 1993, in the Czech Republic. The average observation period is around 150 months. Individual volatility and idiosyncratic volatility appear to be higher in developing markets. Since these markets contain fewer stocks in the local market, the firm-level volatility is likely to be caused by under-diversification risks.

Figure 4.1 shows average idiosyncratic volatility within developed and emerging markets. The solid line represents developed markets and the dotted line represents emerging markets. From the pattern, we find that before 1997, emerging markets had more average idiosyncratic volatility than developed markets. This may be due to the appearance of new stock markets in the early 1990s. Since new markets tend to have relatively fewer listed stocks and investors have less historical information to conduct estimation, these stock markets have higher volatility and are not well-diversified. After 1997, we find that the two lines start to converge and co-move correspondingly, which is partly a result of on-going globalization and contagions among international markets.

4.3.1 Measure of Information Uncertainty

In this chapter, we use idiosyncratic volatility (IVOL) and dispersion in analysts forecast (DISP) as two measures of information uncertainty. The reason we drop other three measures of information uncertainty used in last chapter is due to firm characteristics clustering in different countries. For example, firms in developed countries, such as USA and UK are commonly large firms with longer trading history and more analysts coverage. moreover, comparing firm size internationally faces variability of exchange rate. For developing markets, exchange rate change is non-trivial especially during 90's Asian financial crisis. Analysts coverage is also subject to development of financial markets. Firms usually have more analysts estimates in well-developed markets. In contrast, idiosyncratic volatility and dispersion in analysts forecasts are more suitable proxies for firms in different market as they depend less on individual market development. Meanwhile, they are scaled measures that can be used indifferently across the markets.

Following Zhang (2005), we use idiosyncratic volatility and analyst forecast dispersion as proxies of information uncertainty. Analyst forecast dispersion is measured as standard deviation of analyst forecast of following year earnings per share estimates scaled by prior year end stock price. We follow Bali and Cakici (2008) to construct monthly idiosyncratic volatility by 1) market model 4.1, 2) CAPM 4.2, and 3) local Fama-French three factor model 4.1[4].

$$R_{i,t} = \alpha + \beta_{Mi} RM_t + \epsilon_{i,t} \tag{4.1}$$

$$R_{i,t} - Rf_t = \alpha + Mi\beta_{Mi}(RM_t - Rf_t) + \epsilon_{i,t} \tag{4.2}$$

$$R_{i,t} - Rf_t = \alpha + \beta_{Mi}(RM_t - Rf_t) + \beta_{Si} SMB_t + \beta_{hi} HML_t + \epsilon_{i,t} \tag{4.3}$$

where Rf_t, RM_t, SMB_t and HML_t represent risk-free rate, market index return, small-minus-big factor premium and high-minus-low factor premium, respectively. The idiosyncratic volatility is the variance of residual $\epsilon_{i,t}$ from firm-specific time series regression within the previous month.

4.3.2 Control Variables

We use firm size, turnover, and price impact (measured by absolute returns divided by trading volume) as proxies for limited information. Small firms usually capture less attention and give out less information due to fixed cost of disclosure. Barry and Brown (1985) use limited information to explain the size effects. Brown and Ferreira (2004)provide evidence that idiosyncratic risk is more severe in small

[4]Idiosyncratic volatility has been calculated in three ways. The results, however, do not differ significantly from each other. We only report the analysis of idiosyncratic volatility calculated by local Fama-French three factor model

firms. Price impact is commonly used for liquidity risk. Higher price impact means less liquidity of underlying stocks. Diamond and Verrecchia (1991) argues that more asymmetric information would increase the transaction cost of securities as market makers would provide less liquidity due to potential hidden information.

Turnover (VO) is monthly trading volume over common stock outstanding. Previous literature argues that information uncertainty would trigger more trading by market participants. Investors tend to systematically over-estimate stock prices when the information is inconclusive (Odean (1998)). Investor overconfidence and excess trading are likely to be more pronounced within stocks with less feedback or unclear information.

Price impact (PIM) is calculated by absolute return over trading volume. Kyle (1985) constructed a pioneering market microstructure model and used market depth to measure illiquidity. Amihud (2002) follows his model and suggests that price impact measures change in the dollar prices per share traded. Intuitively, investors may face a large loss to sell a stock when it is hard to find a trader to buy. The higher PIM indicates more illiquidity of underlying stock.

To control firm's growth potential, we use firm age, market-to-book ratio, capital expenditure over total assets and Tobin's Q. These accounting ratios are commonly used in the literature. In addition, we test the relation between uncertainty and stock returns across the industries. Intuitively, new and emerging industries have a higher growth potential, while their future earnings are hard to predict. Therefore, the uncertainty in mature industries would not have a positive impact on stock price as firms have limited earning growth potential. In other words, the over-valuation of uncertainty would not be valid without growth options.

Age takes natural log of the time span from first observation of this stock to current month. Pastor and Veronesi's (2003) model suggests that intrinsic uncertainty of a firm would diminish along its lifetime. Since there is more historical performance available to investors, the parameter uncertainty (they focused on earning growth rate) decreases. Intuitively, market participants know more and are more confident about a firm with longer history than about new firms such as IPOs. As our interest is on short-term uncertainty, regress on AGE controls the uncertainty due to firm's characteristics.

Leverage ratio is a firm's debt over common equity. Jackson and Johnson (2006) argues that firm-specific uncertainty can be considered as an option and stock price is the strike price. Hence, firm specific volatility would increase the delta of put option and increase the stock price. Johnson examined the relation between uncertainty and firm's return, and attributes the negative relation to firm's leverage ratio.

4.3.3 Method of Regression Analysis

We use pooled sample regression to test whether information uncertainty is statistically correlated to information asymmetry and growth options. The form of regression is as following:

$$IVOL_{i,t} = \alpha + \beta_1 AGE_{i,t-1} + \beta_2 M/Bi, t-1 + \beta_3 SIZEi, t-1 + \beta_4 VOi, t-1 \quad (4.4)$$

where independent variables include log of Firm's age (AGE), the log of Market-to-Book value (M/B), the log of total assets (SIZE), the previous month trading volume over number of total stocks outstanding (VO). Pastor and Veronesi (2003) report a negative correlation between firm's idiosyncratic volatility and firm age, as well as a positive relationship between idiosyncratic volatility and market-to-book ratio. By pooling all stocks together, our regression tries to explore such prediction across the international markets. Moreover, if information uncertainty is positively related to information asymmetry, the coefficients on SIZE and VO are expected to be significantly positive.

Ferreira and Laux (2007) find that idiosyncratic risk is also related to investor protection that greater investor protection would generate higher idiosyncratic volatility [5]. To control the difference in countries investors protection, we further add several control variables in regression 4.4 and test expanded form:

$$\begin{aligned} IVOL_{i,t} = \quad & \alpha + \beta_1 AGE_{i,t-1} + \beta_2 MB_{i,t-1} + \beta_3 MV_{i,t-1} + \beta_4 VO_{i,t-1} \\ & + \beta_6 ADR_{i,t-1} + \beta_7 ACCR_{i,t-1} + \beta_8 CFR_{i,t-1} + \beta_9 CR_{i,t-1} \end{aligned} \tag{4.5}$$

Where ADR is anti-direct measure; ACCR is accounting rating; CFR is cash flow rights; CR is control right. In the context of corporate governance, The ADR and CR are proxied for the benefits from exercising private information. All measures are obtained from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998) seminal paper on corporate governance and valuation.

We further adopt Fama-Macbeth (1973) methodology to test the cross-sectional relation between idiosyncratic volatility and firm's earning potential.The procedure is as follows: 1) Estimate monthly risk exposures of each security to its local Fama-French three factors using daily stock returns. 2)Regress idiosyncratic volatility on constant, market beta loading, size and value factor loadings, firm's age, firm's

[5] with less anti-takeover and better protection of minority shareholder rights, outsider investors have more incentive to collect and analyze company information. They could benefit from taking control of badly performing firms and exercising their private information.

market capitalization, book-to-market ratio, dividend payment dummy, leverage ratio, capital expenditure over total asset and Tobin's Q in the following form:

$$\begin{aligned} IVOL_{i,t} = \quad & \alpha + \beta_1 bMKR_{i,t} + \beta_2 bSMB_{i,t} + \beta_3 bHML_{i,t} \\ & + \beta_4 AGE_{i,t-1} + \beta_5 SIZE_{i,t-1} + \beta_6 BM_{i,t-1} + \beta_7 DIV_{i,t-1} \\ & + \beta_8 LEVERAGE_{i,t-1} + \beta_9 COA_{i,t-1} + \beta_{10} TobinQ_{i,t-1} \end{aligned} \tag{4.6}$$

3) Repeat step 2) and 3) and generate time series of each coefficients. 4) Each time series of coefficients are tested by time-series corrected t-test to see whether they are significantly different from zero.

4.3.4 Portfolio Construction

The second objective of this chapter is to examine the cross sectional relationship between information uncertainty and stock returns. We construct portfolios based on previous month idiosyncratic volatility and firm characteristics. This is a common methodology to examine the relation between average stocks' returns and lagged information, as it lowers the impacts of other noisy factors. In each month, we sort stocks into 5 quintiles based on previous month idiosyncratic volatility, which is calculated by standard deviation of residuals by local CAPM model. Within each portfolio, stocks returns are weighted by last fiscal year end market capitalization, and rebalanced monthly.Bali and Cakici (2008) find that this negative relation is significant in value weighted portfolios but not in equally weighted ones, which means market capitalization plays a role. In respond to their critique, we adopt both value-weighted and equal-weighted portfolio strategy.

Ang, Hodrick, Xing, and Zhang (2009) provide international evidence focusing on developed markets. Their findings are subject to two shortcomings. First, their test contains only value weighted portfolios. This raises the possibility that their results are driven by large firms' impact. Second, as some countries have limited number of stocks, they pool the stocks across regions and the world. Nevertheless, countries with fewer stocks would be given less weight in regional portfolios and lose certain information of market characteristics. Therefore, we conduct the portfolio test within each country and region separately.Our regional portfolios are classified by geographic continents. For example, Europe portfolio contains all stocks traded in European stock exchanges. As markets in the same continent are not identically developed, we further classify the countries into G7 group and Non-G7 group. The former group includes France, Germany, Italy, Japan, United Kingdom, and United States, while other countries are left in Non-G7 group.

4.4 Empirical Results

4.4.1 Determinants of Firm-Specific Uncertainty

The first purpose of this study is to examine how uncertainty is distributed in the market, and its relation with other firm characteristics. Table 4.2 reports the regression on information uncertainty measures across the global stock markets. The regression 4.4 on model 4.4 shows that AGE is negatively correlated with idiosyncratic volatility, which is consistent with Pastor and Veronesi's (2003) findings. The positive coefficient on M/B suggests that growth companies have more firm-specific uncertainty. There is a large literature about growth options and asset in place. Campbell and Vuolteenaho (2004) suggest that growth companies are subject to future cash flow beta shocks while value firms are subject to discount rate factor shock. Idiosyncratic volatility is calculated by past individual stock performance relative to market performance. It can be regarded as the unexplained part of stock valuation. Therefore, growth companies have higher idiosyncratic volatility as there is less correlation to past performance. Both loadings on TRADE and PIM are significantly positive with 4.50 and 2.87. It shows that information uncertainty is sensitive to firm's liquidity. When firm's stock is frequently traded, more information would be inferred and absorbed into market.

In the regression 4.6, we further control the investor protection proxies at market level. The coefficients on cash flow right (CFR) are significantly negative (-5.72 with t-stat -4.95 and -2.40 with t-stat -2.54). It is plausible that better protection of cash flow right motivate outside investors to explore underlying firm's perspective, resulting greater information transparency. The loadings on control right, on the opposite, are significant positive, suggesting that greater protection of existing shareholders discourage the information digging and collection by potential new investors. These observations are consistent with Ferreira and Laux's (2007) findings that idiosyncratic volatility is positively related to firm's openness to the takeover market, and investor protection. The coefficients on anti-director right (ADR) is significantly positive in regression of idiosyncratic volatility, and significantly negative to dispersion in analysts forecasts. One explanation of this seemingly questionable result is that the anti-director right weaken the ability of accounting manipulation by corporate directors (La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998)). More 'clear accounting treatment' will lower market investors' information risks. On the other side, Jensen (2003) argue that corporate tend to artificially boost up earnings to meet analysts forecasts in order to maintain high market valuation. With stronger anti-director rights and lower ability of corporate directors, firms' earning could be less smooth in history and more hard to predict.

Table 4.3 shows that worldwide, uncertainty is positively insignificantly related to market beta and size factor loadings, while it is negatively related to value premium loading. Coefficients on age and size are significantly negative, confirming that younger and smaller firms have higher idiosyncratic volatility. Guo and Savickas (2010) finds that negative pricing of idiosyncratic volatility co-varies with value effects in G7 countries. In our sample, book-to-market ratio is significantly positively related to idiosyncratic volatility. Stocks with past year dividend payment have lower idiosyncratic volatility. Dividend is usually considered as signals to the market, so the exercise of dividend distribution lowers the uncertainty. From another aspect, firms with potential growth opportunities usually pay lower, or zero, dividend. Myers and Majluf (1984) and Myers (1984) pecking order theory argues that internal funds are least costly for firm's investment. Therefore firms tend to keep more retained earnings if they have potential projects in view. Leverage worldwide and in North America is negatively related to idiosyncratic volatility. This relation may be dominated by the US stock market. The US financial system is commonly believed to be stock market driven, while in other countries such as Japan and Germany, firms rely more on the long-term relationship with banks. It is reasonable to assume that higher leverage ratios in the US market require a more certain future cash flow to avoid bankruptcy costs. Hence, these companies face less volatility of profitability and have lower uncertainty, while in other markets it is hard for companies in the early stage to finance in the stock market. Instead, they may seek funds from banks to lower the financing cost. Capital expenditure is a measure of firm's investment. Higher capital expenditure level means that firms have adopted more investment projects during the last fiscal year. Also, capital expenditure is higher for growing companies seeking to expand their business. Tobin's Q is positively related to idiosyncratic volatility. High Tobin's Q means a high market valuation of firm's value over book value. This estimate captures the growth potential from the market participant's perspective.

The result first of all confirms the view that information uncertainty, proxied by idiosyncratic volatility, is positively related to firm's growth options. Cao, Simin, and Zhao (2008) finds that market aggregate idiosyncratic volatility increases along with growth options. Our findings provide supportive evidence in the cross-sectional analysis. Another interesting result is from the comparison across the countries. Although idiosyncratic volatility is generally correlated to firm's growth potential, it has different degrees in each region. For example, in G7 countries, the coefficient on Tobin's Q is 3.43 with t-value 3.91, while this loading in non G7 countries is only 0.92 with insignificant t-value 0.34. Overall, it appears that idiosyncratic volatility captures more growth potential in G7 countries and North America. For non G7 countries, this relation is insignificant, probably due to noise from limited information and lack of disclosure. On the other hand, innovation and R&D expenditure is highly correlated to firm's idiosyncratic volatility at individual level, which is consistent with Pastor and Veronesi's hypothesis.Cao, Simin, and Zhao (2008) test the relation between idiosyncratic volatility and growth options at an aggregate market level, using Galai and Masulis (1976) model. They use daily data in the US stock market along with five different measures of idiosyncratic volatility. The results confirms their hypothesis that aggregate idiosyncratic volatility is positively related to both firm's level and volatility of growth options. Other research concerns not idiosyncratic volatility, but total volatility and firm's investment opportunity. Schwert (2002) uses a sample of high-tech industries in NASDAQ and finds that volatility of earnings predicts total equity return volatility. Chan, Lakonishok, and Sougiannis (2001) find that stock future return volatility is positively related to R&D intensity.

4.4.2 Performance Of Portfolios Sorted By Previous Month Idiosyncratic Volatility

Table 4.4 reports dollar dominated portfolio returns in major markets around the world[6]. The first (fifth) column contains the portfolio returns with lowest (highest) idiosyncratic volatility and high-low portfolio takes the strategy of buying the highest and shorting the lowest.In contrast to Ang, Hodrick, Xing, and Zhang's (2009) finding, the portfolio returns suggest that idiosyncratic volatility does not consistently predict negative one month future returns across the markets. In particular, only the high-low portfolio has a -1.37% value weighted return with robust t-value (-2.33). Other markets, including the UK, Canada, France, Netherlands, Switzerland and Mexico have negative but insignificant future returns. For example, France has a negative high-low portfolio return (-0.24%) but the t-value is -0.39. Moreover, it seems that negative arbitrage portfolio returns are attributed to extreme low returns of the highest volatility quintile. For the US and Canada, the best performance is given by the middle portfolio, with 1.66% and

[6]As DataStream select a part of stocks in each market to construct its Market Index, there are fewer stocks than in the real market. In order to avoid small sample bias, we construct portfolios in individual markets with at least 50 observations in each month. For example, although there are 73 firms in the Brazil Market Index, the average and median numbers of observations are only 46 and 31. Hence we have 15 major markets which meet the minimum observation requirement.

1.34%. Portfolio performance in other markets suggests a positive relation between lagged idiosyncratic volatility and stock returns. For example, in all Asian markets, high-low arbitrage portfolio gives positive returns with 2.78% (Hong Kong), 2.53% (Korea), 2.41% (Malaysia), 0.78% (Japan) and 0.18% (Australia). With the exception of Australia, these zero investment returns are significantly different from zero. The return patterns show an economically significant positive relation as both high-low 4-2 quintiles generate a positive return. It seems that in these Asian markets, stock returns increase along with idiosyncratic volatility.

This interesting finding has several implications. First, it rejects Ang et al.'s (2006) hypothesis that idiosyncratic volatility is negatively priced. They argue that idiosyncratic volatility could be a hedge against market innovation of aggregate volatility in line with Merton's (1973) intertemporal CAPM. However, in our sample, this argument has only weak validity in North America and Britain. Ang, Hodrick, Xing, and Zhang (2009) provide further supportive evidence in developed markets of a negative relation between idiosyncratic volatility and future returns. Compared to their results for G7 countries, we find contradictory evidence in Germany, Italy, and Japan. Since they construct the portfolios across regions, their results may lose information of individual markets. Moreover, covering different sample periods and excluding financial industry stocks might generate this opposite result.

Second, it seems contrary to Merton's (1987) hypothesis of undiversified risk premium. His model argues that investors dislike securities with less information and hence require higher premium to hold these assets. Idiosyncratic volatility measures the firm-specific risk unabsorbed in the market. Higher idiosyncratic volatility indicates more asymmetric information and underlying assets are riskier for uninformed investors. Nevertheless, investors in different countries tend to have opposite tastes for this firm-specific risk. One plausible reason is that Asian investors are more conservative than investors in the US and UK. Since the time span of the study covers the 1990's, when crisis hit most Asian financial systems, it is reasonable to expect that conservatism would be prevailing in these stock markets. To control this effect, we conduct a sub-sample test in section V.

Third, idiosyncratic volatility is a common proxy for divergence of opinions among investors. Higher idiosyncratic volatility may indicate more disagreement among investors. In the context of Miller's (1977) theory, stock prices reflect the most optimistic investor view, and pessimistic opinions are not exercised if short sale is not allowed or is limited. More disagreement leads to higher optimism in expectation of stock price, and hence lowers the stock returns. Although we do not have short sale data across the market, this view is not supported in our results as the US and UK have better mechanisms of short selling compared to other countries. If Miller's premium hypothesis is true, we should observe much larger negative future returns in other countries relative to the US and UK markets. However, be aware that our results are based on idiosyncratic volatility, which is a noisy proxy for both divergence of opinions and asymmetric information.

Table 4.4 panel B shows that most equally weighted portfolios have negative returns, but these returns are statistically insignificant. The only two significant values appear in Japan, at -0.50% (t-value -1.74), and the Netherlands, at -0.91% (t-value -1.88). Taking account of value weighted returns, we argue that these negative results are driven by small firms which have little weight but have negative idiosyncratic volatility - return correlation. This finding is consistent with Bali and Cakici (2008) empirical results. They report that in the US market, idiosyncratic volatility only has negative prediction power when portfolios are value weighted. We confirm their argument with international evidence that idiosyncratic volatility is negatively priced among small stocks. The difference here is that, for large firms, idiosyncratic volatility may predict opposite one-month future returns in different markets. Ang, Hodrick, Xing, and Zhang (2009) use Fama and Macbeth (1973) cross-sectional regression on excess returns by idiosyncratic volatility, risk factors and firm characteristics. This methodology gives the same weight to each stock in the regression and is not free from small firm biases.

Portfolios return patterns alone show a decreasing trend of idiosyncratic volatility. In each market, higher volatility has lower returns among quintiles. For example, the high to low quintiles of the Netherlands are 0.46%, 0.56%, 0.91%, 1.05%, 1.37%, showing a clear negative correlation between one month future returns and idiosyncratic volatility. This finding is consistent with past literature. However, we need to exercise caution when interpreting this return pattern as idiosyncratic volatility is also strongly correlated to firm characteristics, such as firm size and firm age. Brown and Ferreira (2004) find that idiosyncratic volatility is significantly priced in small firms controlling illiquidity and other factors. Their finding supports Merton's (1973) theory that idiosyncratic volatility could be a hedge against market volatility. Pastor and Veronesi's (2003) rational learning model suggests that young firms have higher idiosyncratic volatility, and along company's life, this firm-specific volatility would diminish to average level. Meanwhile, size effect is well documented in the literature, and its premium seems to change over time. Hence it is also likely that small (young) firms have higher idiosyncratic volatility and lower returns in our sample.

To test whether positive return and idiosyncratic volatility in the Asian market are driven by financial crisis, we further conduct a sub-sample test by splitting the sample period into ante-1997 and post-1998. The portfolio methodology is the same: sorting stocks based on previous one month idiosyncratic volatility. The result is slightly different from the whole sample performance. Before 1997, the Asian stock markets, except Japan, still have a positive relation between idiosyncratic volatility and future returns, although this relation becomes insignificant (probably due to smaller sample size). After 1998, all high-low arbitrage returns turn to negative and insignificant at 5% confidence level. Other markets keep almost the same condition with lower robust t statistics.

Another proxy we use for information uncertainty is analyst forecast dispersion, which is measured by standard deviation of earning forecast deviation scaled by mean forecast estimate. We follow Diether, Malloy, and Scherbina (2002) adjustment to raw forecast estimates, which contain the stale data problem. Analogous to the previous portfolio methodology, we assign each stock into 5 quintiles based on previous month divergence of analyst forecast. The low (high) quintile contains stocks with lowest (highest) disagreement. Dispersion in analyst forecast is, intuitively, a good proxy to measure uncertainty. Since earning forecasts are given by expert analysts, their disagreement could represent a common ambiguity about firms' fundamental value. However, this proxy is not free from shortcomings. First, analysts themselves may suffer belief biases or career concerns. Hong, Lim, and Stein (2000) argue that analysts providing optimistic estimates could enhance their career and promotion prospects. Doukas, Kim, and Pantzalis (2006) construct a proxy of information uncertainty from divergence of opinions. Their empirical findings suggest that dispersion in analyst forecast alone is a noisy measure of market disagreement. As I/B/E/S has more analyst coverage over firms in the US and other developed markets, this may place more weight on mature markets and hence bias our results. Therefore, we use dispersion in analyst forecast as a complementary proxy for information uncertainty.

Table 4.5 panel A shows that the United States markets have the most significant negative returns in the high-low zero investment portfolio (average -1.12% with t-value -1.93). Other portfolios give different signs of returns. Again, in most Asian markets, arbitrage portfolio returns are positive but not significant. For example, in Hong Kong, the portfolio with the lowest uncertainty generates an average 1.14% return and that with the highest uncertainty has an average 0.81% return. The arbitrage portfolio has a return of 0.47% with insignificant t-value -0.43. Table IV panel B reports equally weighted portfolio returns. We observe that the UK, Canada and Switzerland have a positive relation between disagreement and one-month future returns. This relation is economically significant as returns consistently increase along with higher divergence of opinions. Other markets contain both positive and negative zero investment portfolio returns with insignificant t-value.

According to Miller's theory, uncertainty alone cannot predict future returns without short-sale constraints. However, according to Bris, Goetzmann, and Zhu (2007), the US exerts the least constraints on short-selling. Comparing across the markets, if Miller's theory is true, markets with less short-sale feasibility should generally have higher future returns with the same level of uncertainty (Statistics of Dispersion across the Market). Our test fails to support this story of stock overvaluation based on market friction and investors' disagreement.

The above portfolio effects within each individual country indicate that there is no identical relation between one month future return and lagged uncertainty proxied by idiosyncratic volatility and dispersion in analyst forecast. However, we do observe some common patterns across the countries within one continent. High uncertainty always predicts negative future returns in North America and Britain, while a positive relation is found in Asian stock markets. Following Ang, Hodrick, Xing, and Zhang (2009), we construct intra-country portfolios within each region. We split Europe into west Europe, east Europe and north Europe. There are three reasons for this partition. First, most east Europe markets were established after 1993 and are relatively small and illiquid. Second, north Europe comprises countries commonly regarded as welfare societies with highly strict legal systems and investor protection (La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998)). Last but not least, west Europe has close intra-country links among states sharing the same currency. It is safe to consider their markets are highly open to other European Union member states.

The regional value weighted portfolio returns in Table 4.6 show that idiosyncratic volatility significantly predicts portfolio returns in North America and west Europe. The zero investment strategy of buying high uncertainty and shorting low uncertainty generates -0.78% and -1.07%, with t-value -1.76 and -1.96, respectively. In other regions, this relation is insignificantly positive, which is consistent with prior portfolio performance in individual markets. For example, performance of the highest to lowest uncertainty quintiles in North America ranges from 0.56% to 1.34%, while in Asia it decreases from 0.71% to 0.26%. In east Europe and north Europe, these are no clear trends as the highest portfolio performance appears in the middle quintile. To compare with Ang, Hodrick, Xing, and Zhang's (2009) result, we combine all stocks in Europe to construct portfolios. The result shows a similar portfolio return pattern to that of west Europe. This is plausible as west Europe has larger market capitalization relative to new eastern markets and the four north markets. So, Ang, Hodrick, Xing, and Zhang's (2009) finding is probably driven by west Europe stock markets[7]. Panel B in table 4.6 reports the regional portfolios sorted by dispersion in analyst forecast. Only North America shows significant negative return (-1.01%, with t-value -1.83) in high-low return.

In sum, the portfolio analysis yields several findings. First, investors in different countries have divergent tastes for uncertainty. In North America, and in west Europe including Britain, value weighted portfolios sorted by prior one month idiosyncratic volatility exhibit negative relation between uncertainty and future one month returns. In contrast, stocks with higher firm-specific uncertainty require higher future returns in Asia and east Europe. The finding is confirmed at both country-level and regional-level. We argue that differing tastes regarding uncertainty are due to different levels of market development, investor protection, and market structure.

[7]Another potential explanation is given by uncertainty tolerance across the countries. The working hypothesis of this paper is that countries characterized by high uncertainty aversion grow disproportionately more slowly in industrial sectors where information is less available. The hypothesis is motivated by Rigotti, Ryan, and Vaithianathan (2008) theoretical model, which shows that tolerance of uncertainty is essential to the growth of emerging sectors about which little is known. The authors argue that Information opaqueness create obstacles for entrepreneurs, workers and investors to enter into high growth industries. It would further lower the allocation efficiency of social resources if the market is unable to provide prompt and accurate signals to investors. Comparative statistics of the model suggest that scarcity of this personality trait in the population leads to slower diffusion rates of new technologies and slower growth rates of opaque sectors.

4.4.3 Portfolio Returns Controlling Illiquidity And Growth Options

Previous analysis shows that information uncertainty is cross-sectionally related to both illiquidity and firm's growth options. In this sector, we control these two factors using portfolios. In each sub-test, we first sort stocks into 5 quintiles by control variable, and within each quintile, we further sort stocks based on idiosyncratic volatility into 5 sub-groups. Then we take average returns of each level of uncertainty across the five control quintiles. For example, to control size effect, we first sort stocks into size (1) to size (5). In each size quintile, we double sort stocks by idiosyncratic volatility into 5 sub quintiles. Then we have 25 portfolios. For each portfolio, we take value weighted returns based on individual stocks' market capitalization. Then we construct lowest uncertainty portfolio by average returns of lowest idiosyncratic volatility quintiles across 5 size groups. Table 4.8 reports the portfolios' returns by idiosyncratic volatility controlled with size, turnover, price impact, book-to-market ratio, Tobin's Q and capital expenditure over total asset.

Firm size is a widely used, although noisy, factor for limited information. If idiosyncratic volatility is only driven by limited information, we should observe no prediction of idiosyncratic volatility on future returns. In the sample of the whole world market, size does eliminate part of the uncertainty effect on future returns. The 5-1 portfolio difference becomes insignificant except for the Europe market. However, the pattern of returns does not change as highest uncertainty predicts lowest returns. One potential reason is that firm size also captures the uncertainty level . This double sorted portfolio eliminates the uncertainty as well as the level of asymmetric information. So the negative relation becomes insignificant in the sub-test.

Turnover and price impact capture the market liquidity. Higher trading volume provides more liquidity in the market. Price impact indicates the cost to sell a stock. The higher the price impact, the lower the market liquidity. We find that with control of liquidity, idiosyncratic volatility still has stronger negative relation with future returns. This is consistent with our hypothesis that when controlling the effect of illiquidity or risk of incomplete diversification, idiosyncratic volatility is more negatively priced. Moreover,

In panel B of Table 4.8, we control the firm's growth options. Generally, we find that the prediction power of idiosyncratic volatility for one month future returns turns to insignificant. For example, with control of book-to-market ratio, the 5-1 portfolio becomes insignificant across all samples. There are two possible explanations. One is from our hypothesis that information uncertainty is linked with growth opportunity. With control of potential growth, the higher valuation of uncertainty is bounded. Another explanation is closely related to value effect. Guo and Savickas (2010) suggests that idiosyncratic volatility co-varies with market level value effects. Hence high minus low idiosyncratic volatility may capture difference between growth companies and value firms. In that case, the correlation is decreased.

4.4.4 Fama-Macbeth Regression On Excess Stock Returns

We further examine whether future risk-adjusted returns are correlated to information uncertainty with or without control of asymmetric information and growth options. In the first step, we regress the cross-sectional firm excess returns on analyst forecast dispersion and idiosyncratic volatility with local, regional and international market excess returns. We further extend the regression with growth options proxies including one-lag market-to-book ratios, ROA, volatility of earnings per share, leverage ratio, and size, bid/ask spreads and trading volumes as asymmetric measurement. The testable hypothesis is whether coefficient on uncertainty proxies is significantly different from zero with and without controlling growth options measures and asymmetric information measures.

Table 4.7 reports the result from Fama and Macbeth (1973) cross-sectional regression. The tests are conducted in two steps. In the first step, we use time series regression of daily excess stock returns over market premium, size premium and value premium. Based on this regression, we obtain the idiosyncratic volatility as standard deviation of residuals from this model. In the second step, we regress next month excess returns in cross section. The independent variables include previous month idiosyncratic volatility; current month factor loadings, following Ang, Hodrick, Xing, and Zhang (2009); firm's market capitalization at the end of last month; book-to-market ratio at last fiscal year end; lagged six months returns with one month lag; last month turnover, which is trading volume over total stock outstanding; price impact measured by absolute returns over trading volume during last month; and individual stock skewness during the last three months with one lag. The estimated coefficients are reported and corresponding t-values are adjusted for autocorrelation by Newey and West (1987) test with lag three. Adjusted R-square takes the average of value, and number is average number of dependant variables over test periods. Equation (1) shows the relation between future returns and idiosyncratic volatility with control of firm's characteristics. We find that only in Europe does idiosyncratic volatility predict significant negative future returns. In Asia, idiosyncratic volatility is positively priced and in North America, it is negative but not significant. This is consistent with our hypothesis as information uncertainty captures both asymmetric information effect and value effects. The investor protection level in Asia is lower than in any other region. Therefore, asymmetric information dominates in these markets, requiring higher returns. At a global level this effect is mixed, as idiosyncratic volatility is positive but not significant. Coefficients on factor loadings on regional market premium are not significant. As these betas are measured within the short run, it is hard to persist for the next time periods. The coefficient of value beta in Asia is significantly positive, which suggests a strong value effect during this sample period. This finding seems reasonable as our sample covers the period of financial crisis, while value effect is usually considered as premium for financial distress risk (Fama and French (1996)).

In equation (2) we further control for the lagged returns, turnover and price impact. We find momentum effect prevails over other risk factors across all markets. Several papers have found that momentum effect is much stronger with higher information uncertainty. Investors tend to under-react to past information with higher idiosyncratic volatility (Zhang (2006),Jiang, Lee, and Zhang (2005)). So uncertainty effect is driven by momentum effect, we would observe that there would be no negative relation between idiosyncratic volatility and future returns after controlling the past several months' returns. Turnover here is a rough measure of trading activities by market participants. High trading volume may be triggered by more disagreement among investors or more overconfidence from investors. So we use turnover to control for market disagreement. The price impact is the liquidity of underlying asset. Larger price impact means less liquidity. The last control variable is idiosyncratic skewness, following the test of Ang, Hodrick, Xing, and Zhang (2009). In Barberis and Huang (2008) behavioural pricing model, the skewness may be priced according to objective preference. Han and Kumar (2010)also use skewness to indicate speculative characteristics. Higher skewness implies long right tails in payoff distribution, thus motivating more speculative trading.

The first finding in regression (2) is that the negative relation of idiosyncratic volatility is more severe after controlling these variables. Some coefficients in equation (1) turn from positive to negative, as in the sample in Asian markets. In North America, the idiosyncratic volatility becomes significantly negatively priced. We interpret this changing as indicating that turnover and price impact both control the liquidity in the market, which is linked to asymmetric information level. So, for the same asymmetric information level, higher information uncertainty predicts lower returns. Moreover, we find that European countries generally have stronger relation between idiosyncratic volatility and future returns. This may be partly due to good investor protection and efficient law systems. The scandal of US companies such as World.com and Enron lowered the credibility of market information during the late 1990s.

4.4.5 Subsample Test

Table 4.9 reports the value-weighted portfolio performance in each country in subsample periods. The whole sample is divided evenly by the year of 1997. The high minus low uncertainty portfolio performance shows similar pattern in both sub-periods. Stock portfolios with high uncertainty are associated with lower future returns in mature economies, while in developing countries, stock portfolio with high uncertainty have higher future returns. For example, the high minus low uncertainty portfolio returns in UK and US are -0.71% and -0.69% between 1988 and 1997,respectively. The same portfolios generate -1.13% and -1.48% for UK and US from 1998 to 2007. It is consistent with the finding of table 4.3 in the whole sample periods. Note that most Asian markets experienced the financial crisis in 1997. This continental event, however, seems to have no impact on the relationship between information uncertainty and future stock returns in our sample. The positive correlation between uncertainty and future stock returns in Malaysia, Hong Kong and South Korea is significant before and after the crisis.

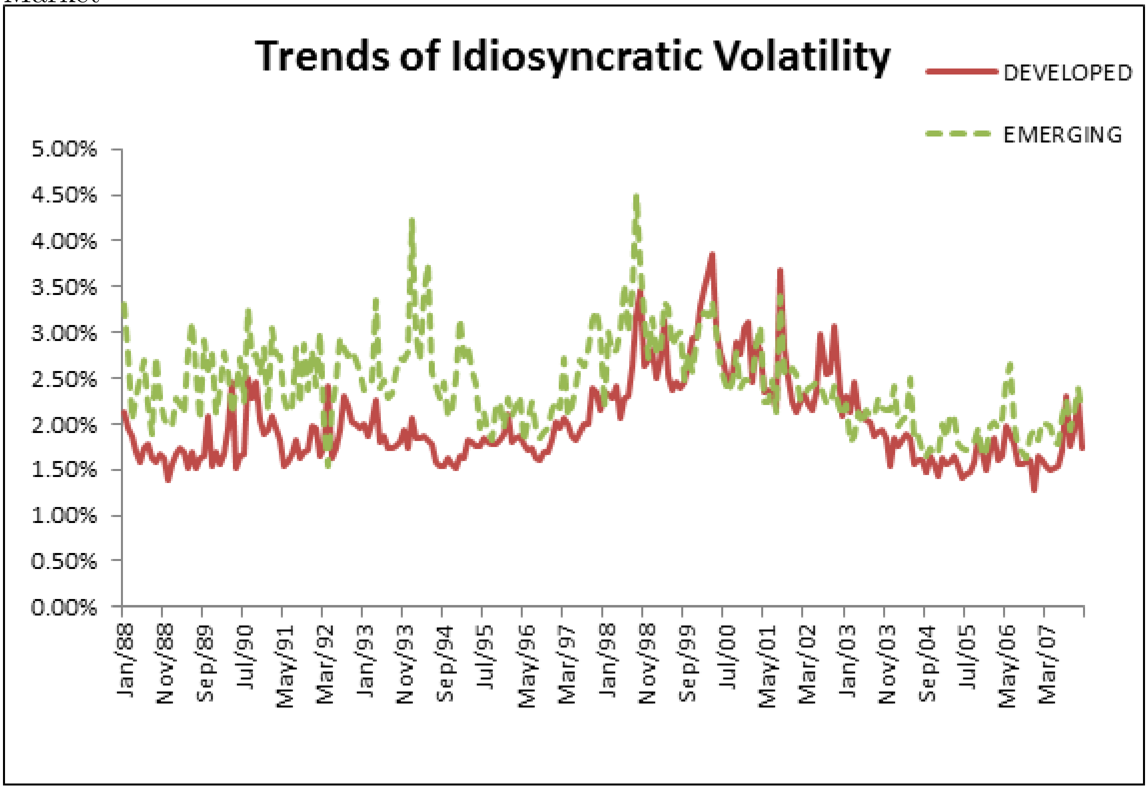
4.5 Conclusion

In this chapter, we find that information uncertainty, which is proxied by idiosyncratic volatility, captures both limited information effect and value effect. Our international evidence shows that in well developed markets with good investor protection, information uncertainty leads to lower future returns, while in less mature countries, future stock returns are higher following more uncertainty. The cross-sectional regression on idiosyncratic volatility shows that this measure of uncertainty is positively related to firm's growth options and level of market opaqueness across the world markets. Younger and smaller firms, companies paying no dividend and companies with higher capital expenditure and higher Tobin's Q all have higher level of uncertainty. On the other hand, we also find that stocks with higher illiquidity, lower trading volume and higher price impact have higher idiosyncratic volatility. This evidence is consistent with our hypothesis that uncertainty derives from both potential growth options and limited disclosure. We provide the international empirical evidence supporting the linkage between information uncertainty and growth options in young and emerging industries.

Our evidence is contrary to Ang, Hodrick, Xing, and Zhang (2009), who find that idiosyncratic volatility is significantly negatively priced across all markets. Our country level evidence shows that this negative relation is valid only in the United States, with -1.37% (t-value -2.33). In other countries it turns out to be insignificant and, especially in Asian markets, becomes positive and significant. In the regional based portfolio test, we find idiosyncratic volatility is negatively priced in Europe and North America. This might be due to market development. The results in our test support Wurgler's (2000) finding that better market development would motivate more efficient allocation of capital to growing companies.

The cross-sectional regression shows that idiosyncratic volatility is positively related to factor loading on value premium. Negative correlation between idiosyncratic volatility and future stock returns becomes more severe after controlling the illiquidity and limited information factor. On the other hand, with control of book-to-market loadings, this relation becomes insignificant. This evidence shows a clear link whereby idiosyncratic volatility captures both firm-specific uncertainty and undiversified risks. The fact that previous literature found mixed results may be due to the conjunction of both side effects. We also find no support for Miller's (1977) premium theory of uncertainty. The markets with short-sale feasibility are usually better developed. In these markets, idiosyncratic volatility is negatively related to future returns. However, we cannot reject this theory as we do not directly test the uncertainty with short selling.

Figure 4.1: Trends of Idiosyncratic Volatility between Developed and Emerging Market



This figure reports the trend of idiosyncratic volatility of developed and emerging market in our sample form jan 1988 to mar 2007. The classification of developed and emerging market is based on World Bank 2007's annual report.

Table 4.1: Descriptive Statistics

This table presents market statistics of all countries in the sample, which includes both active and dead stocks in DataStream world market constituents between Jan, 1988 to Dec, 2007. NUM is the total number of stocks and FIRST OBS is the date of first stock price in each country. MONTH is the average number of months of individual stocks. RET is the mean returns dominated in local currency. RAW VOL is aggregated monthly firm-level total volatility. SKEWNESS is adjusted based on size of sample. IVOL is monthly idiosyncratic volatility calculated by Fama French three factor models with daily stocks and market index returns during previous month.

Country	NUM	First OBS	Month	RET	RAW VOL	SKEW	IVOL
NORTH AMERICA							
CANADA	299	Jan-88	153.5	1.05%	12.84%	-0.02	2.49%
MEXICO	97	Jan-88	136.4	1.53%	12.92%	-0.13	2.32%
USA	758	Jan-88	183.5	1.25%	10.99%	-0.27	2.16%
EUROPE							
AUSTRIA	41	Jan-88	144.3	1.19%	9.45%	0.28	1.80%
BELGIUM	81	Jan-88	155.2	0.85%	8.82%	0.03	1.94%
FRANCE	248	Jan-88	161.3	0.93%	11.55%	-0.22	2.07%
GERMANY	234	Jan-88	164.4	1.03%	10.48%	0.1	2.14%
IRELAND	54	Jan-88	154.6	0.30%	13.17%	-0.01	2.74%
ITALY	139	Jan-88	146.9	0.65%	9.94%	0.06	1.97%
LUXEMBOURG	20	Mar-91	145.5	0.53%	11.63%	-0.05	3.21%
NETHERLANDS	139	Jan-88	173.5	0.58%	10.90%	-0.23	2.18%
PORTUGAL	38	Jan-88	151.3	0.65%	10.76%	0.74	2.15%
SPAIN	86	Jan-88	166	0.95%	15.41%	-0.01	3.01%
SWITZERLAND	98	Jan-88	172.7	1.22%	9.07%	-0.14	1.78%
UK	324	Jan-88	170.8	0.93%	10.46%	-0.33	1.87%
GREECE	43	Jan-88	140.4	1.66%	12.90%	0.68	2.38%
SLOVENIA	52	Jan-88	183.3	1.90%	10.77%	-0.25	2.10%
HUNGARY	27	Jan-91	117.1	0.73%	17.68%	0.44	3.22%
DENMARK	47	Jan-88	189	1.15%	9.43%	-0.04	1.85%
FINLAND	56	Jan-88	161.9	1.26%	9.89%	-0.15	2.05%
NORWAY	55	Jan-88	138.5	1.18%	8.92%	0	1.99%
SWEDEN	48	Jan-88	169.7	1.30%	10.09%	0.08	1.97%
ASIA							
AUSTRALIA	163	Jan-88	148	1.41%	10.35%	-0.07	2.02%
HONG KONG	110	Jan-88	132.2	2.05%	14.11%	0.18	2.85%
INDONESIA	77	Jan-90	150.6	3.00%	14.93%	0.36	2.72%
JAPAN	943	Jan-88	199	0.13%	10.71%	0.03	2.10%
MALAYSIA	86	Jan-88	186.9	1.09%	12.04%	0.22	2.79%
NEW ZEALAND	67	Jan-88	128.5	1.33%	12.53%	-0.27	2.53%
SINGAPORE	61	Jan-88	143.4	1.77%	11.86%	0.14	2.61%
SOUTH KOREA	115	Jan-88	156.7	0.98%	10.44%	0.28	1.90%

Table 4.2: Panel Regression of Information Uncertainty Proxy on Firm's and Market Characteristics

This table presents the estimates of coefficients of monthly time-series cross-sectional firm-level regression. $IVOL_{i,t} = \alpha + \beta_1 AGE_{i,t-1} + \beta_2 MBi,t-1 + \beta_3 SIZEi,t-1 + \beta_4 TRADEi,t-1 + \beta_6 ADR_i$
$+ \beta_7 ACCR_i + \beta_8 CFR_i + \beta_9 CR_i$ $DISP_{i,t} = \alpha + \beta_1 AGE_{i,t-1} + \beta_2 MBi,t-1 + \beta_3 SIZEi,t-1 + \beta_4 TRADEi,t-1 + \beta_6 ADR_i$
$+ \beta_7 ACCR_i + \beta_8 CFR_i + \beta_9 CR_i$
Information uncertainty is proxied by (IVOLt) idiosyncratic volatility of month t in panal A and (DISPt) analyst forecast deviation over last year end stock price. Idiosyncratic volatility is calculated as variance of residuals in time-series regression of individual returns on market returns over past one month. Dependent variables include: log of Firm's age (AGE), the log of Market-to-Book value (MB), the log of total assets (SIZE), the previous month trading volume over number of total stocks outstanding (VO). Control variable of countries' characteristics use La Porta et al (1998)'s data of anti-director right (ADR), accounting rating (ACCR), and La Porta et al(2002)'s measure of cash flow rights (CFR), and control rights (CR). M/B and Size are winsorized top and bottom 1% level. The sample period is from January 1988 to December 2007 for 43 countries and stocks in other 9 countries are included whenever they are covered by DataStream. Financial industry is omitted, and stocks with less than one year previous history are excluded. T-statstics are in parentheses and ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

	Panal A regression on IVOL		Panal B regression on DISP	
	(1)	(2)	(3)	(4)
Intercept	0.02**	0.02***	0.54*	2.14***
	(2.21)	(2.48)	(1.68)	(6.36)
AGE(t-1)	-2.23**	-2.59***	-1.59***	-1.42***
	(-8.45)	(-9.05)	(-12.20)	(-9.90)
MB(t-1)	0.86*	0.77	-4.10*	-4.30*
	(1.90)	(1.62)	(-1.87)	(-1.75)
SIZE(t-1)	0.7	0.84	6.27***	12.79***
	(1.43)	(1.25)	(3.64)	(4.41)
VO(t-1)		4.50***		2.40***
		(7.60)		(5.20)
PIM		2.87***		1.88**
		(4.19)		(3.04)
ADR		1.02***		-3.80***
		(29.31)		(-2.39)
ACCR		-0.09		-1.90***
		(-0.95)		(-4.83)
CFR		-5.72***		-2.40***
		(-4.95)		(-2.54)
CR		2.44***		1.11***
		(4.87)		(2.31)
Adj-R^2	7.49%	8.24%	3.02%	4.66%

Table 4.3: Regression on Idiosyncratic Volatility

This table reports Fama-MacBeth (1973) regression on idiosyncratic volatility t over 1) intercept, 2) risk factors loading on time t, 3) firm age, 4) firm size(SIZE) , 5) the log of Market-to-Book value (MB), 6) dividend dummy (DIV), which equals to 1 if firms pay dividend in the past one year, otherwise, it takes zero., 7) firm leverage (LEVERAGE) measured by firm's book liability over total assets, 8) capital expenditure over total asset (COA) 9) Tobin-Q which is calculated by sum of equity market value and book liability divided by book equity plus book liability. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007. T statistics are adjusted with Newey-West(1987) with lag 3 and reported in brackets. R2 is average adjusted R2 and NUM is average observations over tested periods.

	World	Asia	Europe	America	G7	NON-G7
intercept	4.69***	3.69***	5.24***	7.48***	5.78***	5.62***
	(9.80)	(3.72)	(4.29)	(5.24)	(5.67)	(2.69)
bMKR	7.48	4.32	7.69	1.99	1.37	26.13*
	(1.49)	(0.66)	(1.45)	(0.34)	(0.34)	(1.89)
bSMB	2.27	7.71	-1.21	0.57	3.09	-4.38***
	(0.57)	(1.14)	(-0.23)	(0.09)	(0.85)	(-0.32)
bHML	-7.52*	-2.39	-3.58	-17.86	-9.43	-2.09**
	(-1.77)	(-0.47)	(-0.39)	(-1.15)	(-1.37)	(-0.16)
AGE	-4.69***	-1.39	-1.18	2.19	-2.83	-5.62*
	(-3.47)	(-0.73)	(-0.77)	(0.41)	(-0.13)	(-1.85)
SIZE	-3.96***	-4.16*	-5.25***	-3.71***	-2.01***	-2.26
	(-4.13)	(-1.73)	(-2.88)	(-2.45)	(-2.77)	(-1.35)
MB	7.37***	10.58***	10.62***	13.28*	10.85***	21.83***
	(3.13)	(2.38)	(2.36)	(1.88)	(2.32)	(3.37)
DIV	-2.51***	-1.73***	-3.27***	-3.19***	-3.34***	-5.10***
	(-4.88)	(-4.17)	(-3.74)	(-5.12)	(-7.62)	(-3.11)
LEVERAGE	-2.76	2.98	10.73	-14.87***	1.5	4.57
	(-1.10)	(0.41)	(1.00)	(-2.37)	(0.30)	(0.23)
COA	0.07	0.04	0.2	0.16	0.2	0.04
	(1.22)	(0.23)	(1.61)	(0.66)	(0.99)	(0.17)
TOBINQ	1.88***	2.09	0.27	1.24	3.43***	0.92
	(6.47)	(1.36)	(0.13)	(0.91)	(3.91)	(0.34)
adj-R^2	13%	23%	17%	22%	18%	36%
Num	3317.3	1058.3	1234.65	812.3	2169.7	418.5

Table 4.4: Portfolios Sorted by Idiosyncratic volatility

This table reports the value weighted and equally weighted portfolio returns sorted by idiosyncratic volatility over previous month. Portfolios are rebalanced each month and held for one month. All returns are dominated in US dollar. Idiosyncratic volatility is measured with Fama French three-factor model by daily returns within previous month: $R_{i,t}-Rf_t = \alpha_i+\beta_{M,i}(RM_t-Rf_t)+\beta_{s,i}SMB_t+\beta_{h,i}HML_t + \beta_{u,i}UMD_t + \epsilon_{i,t}$ Where $R_(i,t)$ is individual daily stock returns, Rf_t is risk free rate, RM_t, SMB_t, $HML_t$are market returns, size premium and value premium respectively. Idiosyncratic volatility is calculated by standard deviation of $\epsilon_(i,t)$. The column 1 (5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. Column 5-1 is the monthly difference between highest and lowest portfolio returns. The T statistics are adjusted with Newey-West (1987) with lag 3 and reported in brackets. The average differences in column 5-1 are followed by ***,**,* if it is significant different from zero with 1%, 5%, 10% confidence level. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007.

COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
Panel A. Value Weighted Portfolio returns Sorted By IVOL						
UNITED STATES	1.03%***	1.53%***	1.66%***	1.24%***	-0.33%	-1.37%**
	(3.34)	(4.51)	(4.27)	(2.63)	(-0.51)	(-2.33)
CANADA	0.22%	1.13%***	1.34%***	0.75%	-0.71%	-0.93%
	(0.73)	(3.01)	(3.20)	(1.48)	(-0.90)	(-1.23)
NETHERLANDS	0.45%	1.19%***	0.65%*	0.85%*	-0.23%	-0.68%
	(1.61)	(3.72)	(1.77)	(1.79)	(-0.28)	(-0.86)
SWITZERLAND	1.02%***	0.79%**	0.84%**	0.91%**	0.51%	-0.52%
	(3.11)	(2.35)	(2.02)	(2.02)	(0.61)	(-0.63)
FRANCE	0.37%	0.90%**	1.04%***	1.00%***	0.14%	-0.24%
	(1.10)	(2.43)	(2.73)	(2.47)	(0.21)	(-0.39)
MEXICO	0.94%*	0.62%	0.17%	1.11%*	0.72%	-0.22%
	(1.88)	(1.09)	(0.27)	(1.67)	(0.85)	(-0.35)

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Table 4.4 continued from previous page

COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
UNITED KINGDOM	0.50%	0.64%*	0.64%*	-0.05%	0.32%	-0.18%
	(1.42)	(1.82)	(1.91)	(-0.15)	(0.55)	(-0.31)
AUSTRALIA	0.50%	0.79%**	0.25%	0.33%	0.68%	0.18%
	(1.34)	(1.97)	(0.61)	(0.69)	(0.93)	(0.28)
JAPAN	0.06%	0.08%	0.27%	0.49%	0.82%	0.76%**
	(0.15)	(0.19)	(0.65)	(1.15)	(1.49)	(1.96)
ITALY	0.27%	-0.12%	0.59%	1.12%**	1.36%*	1.09%*
	(0.62)	(-0.29)	(1.19)	(2.08)	(1.94)	(1.89)
GERMANY	0.70%*	0.98%**	1.21%*	0.69%	2.05%**	1.36%**
	(2.28)	(2.88)	(2.56)	(1.41)	(3.05)	(2.16)
SPAIN	-0.80%	-0.19%	0.98%	1.19%	0.68%	1.48%*
	(-1.36)	(-0.30)	(1.30)	(1.51)	(0.78)	(2.06)
MALAYSIA	-0.31%	-0.11%	0.03%	1.04%	2.10%**	2.41%***
	(-0.59)	(-0.18)	(0.05)	(1.31)	(2.08)	(2.91)
SOUTH KOREA	0.34%	0.70%	0.92%*	1.01%*	2.87%***	2.53%***
	(0.72)	(1.38)	(1.84)	(1.92)	(4.47)	(4.02)
HONG KONG	0.51%	0.80%*	0.65%	1.08%*	3.29%***	2.78%***
	(1.33)	(1.76)	(1.35)	(1.94)	(4.09)	(3.77)
Panel B. Equally Weighted Portfolio returns Sorted By IVOL						
UNITED STATES	1.05%***	1.11%***	1.02%***	1.18%***	1.03%**	-0.02%
	(4.60)	(4.37)	(3.80)	(3.60)	(2.19)	(-0.05)
CANADA	1.17%***	1.20%***	0.98%**	0.92%**	1.16%**	-0.01%
	(3.45)	(2.95)	(2.30)	(2.14)	(2.04)	(-0.02)
NETHERLANDS	1.37%***	1.05%***	0.91%**	0.56%	0.46%	-0.91%*
	(3.67)	(2.86)	(2.25)	(1.21)	(0.79)	(-1.88)
SWITZERLAND	1.53%***	1.64%***	1.26%**	0.65%	0.91%	-0.61%

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Table 4.4 continued from previous page						
COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
	(3.46)	(3.77)	(2.62)	(1.21)	(1.44)	(-1.07)
FRANCE	1.33%***	1.17%***	1.25%***	1.28%**	0.76%	-0.57%
	(3.60)	(3.30)	(3.01)	(2.64)	(1.29)	(-1.32)
MEXICO	1.53%**	1.12%	0.93%	1.51%*	1.01%	-0.52%
	(2.03)	(1.41)	(1.13)	(1.89)	(1.17)	(-0.89)
UNITED KINGDOM	1.11%***	1.19%***	0.58%	0.74%*	0.46%	-0.65%
	(3.00)	(3.21)	(1.53)	(1.74)	(0.84)	(-1.41)
AUSTRALIA	0.86%	1.22%**	1.35%***	0.48%	0.67%	-0.19%
	(1.06)	(2.39)	(2.74)	(0.82)	(0.97)	(-0.22)
JAPAN	0.34%	0.19%	-0.11%	0.01%	-0.17%	-0.50%*
	(0.70)	(0.37)	(-0.21)	(0.02)	(-0.28)	(-1.74)
ITALY	0.97%**	0.57%	0.54%	0.28%	0.74%	-0.22%
	(2.08)	(1.14)	(1.06)	(0.49)	(1.22)	(-0.58)
GERMANY	1.10%***	1.14%***	0.81%*	1.04%**	0.44%	-0.65%
	(3.18)	(3.05)	(1.81)	(2.16)	(0.76)	(-1.40)
SPAIN	-0.32%	0.38%	0.15%	1.47%	-0.05%	0.38%
	(-0.42)	(0.46)	(0.17)	(1.58)	(-0.05)	(0.60)
MALAYSIA	0.10%	0.54%	-0.28%	-0.30%	0.75%	0.65%
	(0.14)	(0.68)	(-0.35)	(-0.32)	(0.73)	(0.88)
SOUTH KOREA	0.09%	0.18%	0.57%	0.38%	0.78%	0.68%
	(1.50)	(0.35)	(1.17)	(0.72)	(0.17)	(-1.49)
HONG KONG	0.72%	0.42%	0.57%	1.05%	0.83%	0.11%
	(1.26)	(0.71)	(0.83)	(1.40)	(0.98)	(0.18)

Table 4.5: Portfolio Sorted By Dispersion in Analyst Forecast

This table reports the portfolio returns sorted by dispersion in analyst forecast measure by standard deviation of analyst forecast over mean forecast estimate over past one month. Portfolios are value weighted and equally weighted separately, and are rebalanced monthly. The column 1 (5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. Column 5-1 is the monthly difference between highest and lowest portfolio returns. The T statistics are adjusted with Newey-West (1987) with lag 3 and reported in brackets. The average differences in column 5-1 are followed by ***,**,* if it is significant different from zero with 1%, 5%, 10% confidence level. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007.

COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
Panel A. Value Weighted Portfolio Returns						
UNITED STATES	1.57%*	1.05%*	0.50%*	0.98%*	1.06%**	-1.12%*
	(1.80)	(1.87)	(1.71)	(1.92)	(2.40)	(-1.93)
FRANCE	0.86%	1.44%	0.93%*	0.88%*	0.16%	-0.73%
	(1.17)	(1.59)	(1.93)	(1.95)	(0.28)	(-1.06)
AUSTRALIA	1.01%**	0.88%*	1.30%	0.56%	0.29%	-0.68%
	(2.17)	(1.65)	(1.53)	(1.52)	(0.35)	(-1.35)
JAPAN	0.41%	0.21%	0.05%	-0.07%	0.54%	-0.66%
	(0.63)	(0.49)	(0.15)	(-0.16)	(0.81)	(-1.47)
GERMANY	0.41%	1.05%**	1.20%**	1.11%**	0.05%	-0.53%
	(0.92)	(1.98)	(2.51)	(2.29)	(0.07)	(-0.63)
HONG KONG	1.14%**	0.52%	1.74%**	1.20%*	0.81%	-0.47%
	(2.24)	(0.75)	(2.62)	(1.87)	(0.80)	(-0.43)
ITALY	0.61%	1.16%	1.35%*	-0.23%	0.22%	-0.46%
	(1.08)	(1.03)	(1.84)	(-0.30)	(0.34)	(-0.81)
SPAIN	0.28%	0.67%	0.07%	0.19%	0.07%	-0.21%

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Table 4.5 continued from previous page						
COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
	(0.40)	(0.90)	(0.11)	(0.29)	(0.09)	(-0.37)
MALAYSIA	0.60%	0.70%	0.87%	0.18%	0.66%	0.06%
	(1.09)	(1.24)	(1.13)	(0.25)	(0.83)	(0.13)
NETHERLANDS	0.23%	0.22%	0.76%	1.16%***	0.51%	0.48%
	(0.56)	(0.61)	(1.69)	(3.26)	(0.86)	(0.92)
SWITZERLAND	0.48%	-0.03%	1.10%*	0.86%	1.02%**	0.55%
	(1.37)	(-0.07)	(1.90)	(1.58)	(2.02)	(1.48)
MEXICO	0.56%	1.00%*	0.78%	1.64%**	1.02%	0.96%*
	(0.83)	(1.65)	(1.36)	(2.80)	(1.45)	(1.69)
UNITED KINGDOM	0.34%	0.57%	0.73%	0.79%*	1.30%**	0.96%***
	(0.61)	(1.18)	(1.36)	(1.70)	(2.01)	(3.15)
CANADA	0.45%	0.63%	0.97%***	0.35%	1.27%	1.23%
	(0.69)	(1.30)	(3.19)	(0.92)	(1.03)	(1.20)
SOUTH KOREA	0.16%	1.43%	0.73%	1.37%	1.49%*	1.55%**
	(0.37)	(1.23)	(1.32)	(1.38)	(1.67)	(1.91)
Panel B. Equally Weighted Portfolio Returns						
AUSTRALIA	1.27%**	0.71%*	1.19%**	0.98%*	-0.08%	-1.28%*
	(2.64)	(1.97)	(2.78)	(1.93)	(-0.16)	(-1.71)
FRANCE	1.06%*	1.24%***	0.74%*	0.93%**	0.70%	-0.45%
	(1.67)	(2.70)	(1.76)	(2.64)	(1.50)	(-0.70)
SPAIN	0.35%	0.52%	0.66%	0.50%	0.19%	-0.16%
	(0.52)	(0.76)	(1.00)	(0.73)	(0.26)	(-0.33)
ITALY	0.41%	0.61%	0.82%	0.73%*	0.23%	-0.13%
	(0.84)	(1.25)	(1.37)	(1.78)	(0.36)	(-0.31)
JAPAN	0.14%	0.12%	0.09%	0.08%	0.39%	-0.12%
	(0.30)	(0.31)	(0.22)	(0.19)	(0.64)	(-0.60)

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Table 4.5 continued from previous page

COUNTRY	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
GERMANY	0.48%	0.44%	0.87%***	0.91%***	0.41%	-0.07%
	(1.15)	(1.44)	(2.75)	(2.70)	(0.69)	(-0.12)
UNITED STATES	1.23%***	0.85%***	0.84%***	1.21%**	1.32%***	0.03%
	(3.56)	(2.66)	(2.78)	(2.62)	(3.33)	(0.08)
MALAYSIA	0.92%	0.87%	1.12%	0.53%	0.98%	0.14%
	(1.60)	(1.60)	(1.52)	(0.78)	(1.21)	(0.32)
NETHERLANDS	0.20%	0.73%**	0.66%*	0.88%**	0.45%	0.38%
	(0.56)	(2.07)	(1.89)	(2.55)	(0.97)	(1.32)
HONG KONG	0.72%	1.11%*	1.95%***	1.56%**	1.40%	0.59%
	(1.43)	(1.86)	(3.11)	(2.50)	(1.52)	(0.87)
SOUTH KOREA	0.41%	0.65%*	0.71%*	0.88%	0.96%	0.62%
	(0.91)	(1.73)	(1.81)	(1.57)	(1.52)	(1.02)
MEXICO	0.59%	0.95%*	0.76%	1.44%***	0.89%	0.78%
	(0.92)	(1.77)	(1.35)	(2.79)	(1.52)	(1.53)
SWITZERLAND	0.47%	0.40%	0.89%*	0.78%*	1.23%**	0.79%**
	(1.29)	(1.01)	(1.74)	(1.94)	(2.57)	(2.52)
UNITED KINGDOM	0.36%	0.44%	0.98%	0.76%**	1.19%**	0.83%**
	(1.22)	(1.28)	(1.77)	(2.05)	(2.53)	(2.64)
CANADA	0.24%	0.51%*	0.79%***	0.68%**	1.21%*	1.70%*
	(0.62)	(1.77)	(2.75)	(2.14)	(1.80)	(1.73)

Table 4.6: Regional Portfolio Performance

This table reports the regional portfolio returns sorted by idiosyncratic volatility(IVOL) and dispersion in analyst forecast(DISP). Idiosyncratic volatility is measured by standard deviation of residual from regional Fama French three factors model using daily returns over previous month. Dispersion in analyst forecast is the standard deviation of analyst forecast in previous month scaled by mean analyst forecast given by I/B/E/S. The column 1 (5) is the portfolio of stocks with the lowest (highest) information uncertainty. Column 5-1 is the monthly difference between highest and lowest uncertainty portfolio returns. The T statistics are adjusted with Newey-West (1987) with lag 3 and reported in brackets. The average differences in column 5-1 are followed by ***,**,* if it is significant different from zero with 1%, 5%, 10% confidence level. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007.

Panel A. Regional Portfolio Performance sorted by idiosyncratic volatility

Region	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
North America	1.34%***	1.18%***	0.77%*	0.90%**	0.56%	-0.78%*
	(4.07)	(2.98)	(1.78)	(2.03)	(0.91)	(-1.76)
West Eruope	1.25%***	0.40%	1.16%***	0.91%*	0.18%	-1.07%***
	(3.42)	(1.10)	(2.88)	(1.93)	(0.32)	(-1.96)
North Europe	1.09%**	1.24%**	1.68%**	0.54%	1.21%	0.12%
	(2.24)	(2.30)	(2.55)	(0.81)	(1.39)	(0.14)
East Europe	-0.14%	1.41%*	0.84%	0.93%	-0.10%	0.04%
	(-0.16)	(1.78)	(0.93)	(1.05)	(-0.09)	(0.04)
Asia	0.26%	0.43%	0.52%	0.41%	0.71%	0.45%
	(0.65)	(0.94)	(1.09)	(0.73)	(1.05)	(0.79)
Europe All	1.10%**	0.81%*	0.80%	1.18%**	0.28%	-0.82%
	(2.50)	(1.82)	(1.52)	(2.19)	(0.46)	(-1.31)

Panel B. Regional Portfolio Performance sorted By Dispersion Among Analysts Forecasts

Region	1 (lowest)	2	3	4	5 (highest)	H(5)-L(1)
North America	1.51%***	0.63%*	0.58%	0.93%*	1.24%**	-1.01%*
	(4.76)	(1.88)	(1.23)	(1.93)	(2.26)	(-1.83)
West Eruope	0.54%	0.78%**	0.89%**	1.17%***	1.06%**	0.76%
	(1.42)	(2.34)	(2.46)	(3.41)	(2.05)	(1.31)
North Europe	1.21%**	0.77%	1.05%*	1.65%***	1.61%***	0.39%
	(2.05)	(1.61)	(1.93)	(2.71)	(3.27)	(0.60)
East Europe	1.01%	1.05%*	0.49%	0.60%	0.67%	0.31%
	(1.15)	(1.91)	(0.70)	(0.77)	(0.73)	(0.44)
Asia	0.06%	0.42%	-0.13%	0.51%	2.02%***	1.92%***
	(0.16)	(1.01)	(-0.27)	(0.98)	(2.75)	(2.82)
Europe All	0.39%	0.92%***	0.71%**	1.10%**	0.26%	0.28%
	(0.87)	(2.82)	(1.97)	(2.55)	(0.24)	(0.32)

Table 4.7: Fama-MacBeth Regression on Monthly Returns

This table presents the cross-sectional regression on one month future returns using Fama and MacBeth (1973)'s methodology. The dependant variable is one month future returns Ri,t+1. Dependant variables include: 1) intercept, 2) idiosyncratic volatility measured by standard deviation of residual from regional Fama French three factors model using daily returns over previous month, IVOLi,t-1, 3) beta and factor loadings at t+1, 4) previous month end firm size (SIZE) and book to market ratio (B/M), 5) lagged returns over previous six months, 6) turnover measured with previous month trading volume divided by total common shares outstanding, 7) Price impact (PIM) following Amihud (2002) is measured by absolute returns over trading volumes. 8) (iSKEW) is skewness of individual stocks over previous 3 months. The (1) regression takes 1)-5) independent variables in regression and regression (2) includes all variables. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007. T statistics are adjusted with Newey-West(1987) with lag 3 and reported in brackets. R2 is average adjusted R2 and NUM is average observations over tested periods.

	(1)	(2)	(1)	(2)	(1)	(2)

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Table 4.7 continued from previous page

	(1)	(2)	(1)	(2)	(1)	(2)
Panel A	ASIA		North America		Europe	
Intercept	-1.54	-4.39*	7.97***	1.21	7.28***	2.3
	(-0.49)	(-1.72)	(3.53)	(0.55)	(3.20)	(1.02)
IVOLt-1	0.21*	-1.01	-0.6	-1.22*	-1.2	-2.54*
	(1.94)	(-0.95)	(-0.53)	(-1.73)	(-1.62)	(-1.91)
bMKRt+1	-0.125	-0.312*	-0.198	-0.288	-0.171	-0.108
	(-1.28)	(-1.71)	(-0.85)	(-1.43)	(-0.70)	(-0.48)
bSMBt+1	0.4	1.13	0.54	1.17	0.42	-0.97
	(0.02)	(0.08)	(0.35)	(0.87)	(0.23)	(-0.06)
bHMLt+1	0.246*	0.247**	-0.176	-0.114	-0.116	-0.113
	(1.95)	(2.24)	(-0.88)	(-0.66)	(-0.78)	(-0.84)
SIZEt-1	0.88	1.67**	8.04**	8.52**	4.74	5.16
	(1.07)	(2.20)	(2.23)	(2.55)	(1.07)	(1.15)
B/Mt-1	1.25***	1.17***	0.90***	1.04***	0.70***	7.14***
	(6.31)	(6.98)	(4.40)	(5.75)	(4.55)	(4.58)
lagged Ret t-7 t-1		1.09**		1.68***		1.94***
		(2.30)		(5.42)		(5.47)
VO t-1		1.46		2.08**		-3.82
		(0.85)		(2.28)		(-0.54)
PIM t-1		-0.01		-0.15		9.28
		(-0.05)		(-1.03)		(0.37)
iSKEWt-4 t-1		-2.56*		-3.24		-2.60*
		(-1.67)		(-1.58)		(-1.81)
Adjusted R2	0.09	0.22	0.08	0.21	0.07	0.21
NUM	1122.23	1122	760.64	760.6	1141.7	1141.7

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Table 4.7 continued from previous page						
	(1)	(2)	(1)	(2)	(1)	(2)
Panel B	WORLD		G-7		NON G-7	
Intercept	1.42	-5.11**	3.92*	-1.72	6.30***	1.22
	(0.61)	(-2.86)	(1.66)	(-0.81)	(2.70)	(0.57)
IVOLt-1	0.2	-2.19	-0.21	-1.14*	-0.51	-2.33**
	(0.34)	(-1.37)	(-0.36)	(-1.84)	(-0.55)	(-2.32)
bMKRt+1	-0.42	-0.102	-0.75	-1.47	0.76	0.22
	(-0.30)	(-0.81)	(-0.58)	(-1.26)	(0.45)	(0.14)
bSMBt+1	0.65	-0.73	-0.75	-2.51	-0.11	-0.69
	(0.06)	(-0.10)	(-1.00)	(-0.38)	(-0.94)	(-0.65)
bHMLt+1	-1.04	0.31	-0.31	0.108	-0.34	-1.18
	(-0.90)	(0.42)	(-0.43)	(0.02)	(-0.29)	(-1.05)
SIZEt-1	7.44*	1.02***	4.36	1.00***	6.52	8.94
	(1.96)	(3.52)	(1.29)	(3.32)	(1.27)	(1.48)
B/Mt-1	0.80***	8.75***	0.90***	0.953***	0.74***	0.854***
	(4.69)	(6.16)	(4.76)	(6.51)	(4.84)	(6.34)
lagged Ret t-7 t-1		1.47***		1.60***		1.83***
		(4.62)		(4.47)		(4.66)
VO t-1		1.88***		1.62**		6.18
		(2.63)		(1.98)		(0.72)
PIM t-1		-6.09		-2.26*		-1.34
		(-0.69)		(-1.83)		(-0.68)
iSKEWt-4 t-1		-3.63***		-2.89*		-2.64*
		(-5.09)		(-1.83)		(-1.86)
Adjusted R2	0.05	0.2	0.04	0.16	0.07	0.19
NUM	3336.03	3336	3024.57	3024.6	1003	951.5

Table 4.8: Portfolio Returns sorted by idiosyncratic volatility with control of Illiquidity and Growth Options

This table reports the portfolio returns sorted by idiosyncratic volatility with control of firm size (MV), turnover measured with trading volume over total stocks outstanding (VO), price impact (PIM) calculated by absolute returns over trading volumes, book to market value (B/M), Tobin-Q, capital expenditure over total asset (COA). For each month, we first sort stocks by control variable into 5 quintiles and within each quintile, we further sort stocks by idiosyncratic volatility. The 1 (5) portfolio returns are the average returns of stock with lowest (highest) idiosyncratic volatility across the 5 control groups. Row (5-1) is the difference in returns between highest and lowest quintile portfolio. The T statistics are adjusted with Newey-West (1987) with lag 3 and reported in brackets. The average differences in column 5-1 are followed by ***, **, *, if it is significant different from zero with 1%, 5%, 10% confidence level. Sample is constructed with stocks in DATASTREAM total market index and period covers from Jan 1988 to Dec 2007.

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Table 4.8 continued from previous page

	World	Asia	Europe	America	World	Asia	Europe	America	World	Asia	Europe	America
Panel A		MV				VO				PIM		
1 (Low)	0.77%**	0.35%	1.18%***	1.09%***	0.53%**	0.46%	1.37%***	0.76%***	0.57%**	0.39%	1.50%***	0.70%***
	(2.09)	(0.94)	(4.09)	(5.00)	(2.17)	(1.27)	(4.28)	(2.69)	(2.37)	(1.06)	(4.86)	(2.84)
2	1.03%***	0.08%	0.89%***	1.11%***	0.51%	0.34%	0.96%***	0.89%***	0.41%	0.29%	1.03%***	0.70%**
	(2.81)	(0.20)	(2.83)	(4.31)	(1.88)	(0.88)	(2.71)	(3.14)	(1.54)	(0.71)	(2.95)	(2.45)
3	1.01%**	-0.02%	0.87%**	1.08%***	0.37%	-0.23%	1.23%***	0.35%	0.43%	-0.21%	1.14%***	0.72%**
	(2.13)	(-0.05)	(2.50)	(3.87)	(1.25)	(-0.54)	(2.98)	(1.08)	(1.47)	(-0.50)	(2.85)	(2.26)
4	1.09%**	-0.04%	0.83%**	0.91%***	0.50%	-0.04%	0.88%*	0.41%	0.42%	0.05%	0.80%	0.62%
	(2.04)	(-0.08)	(2.14)	(2.81)	(1.36)	(-0.08)	(1.69)	(1.02)	(1.19)	(0.10)	(1.60)	(1.59)
5 (High)	0.39%	0.05%	0.52%	0.80%*	-0.24%	0.03%	0.12%	0.32%	0.01%	-0.20%	0.46%	0.06%
	(0.54)	(0.09)	(1.01)	(1.75)	(-0.51)	(0.06)	(0.16)	(0.61)	(0.01)	(-0.35)	(0.64)	(0.10)
5-Jan	-0.38%	-0.31%	-0.66%*	-0.29%	-0.77%**	-0.43%	-1.26%**	-0.44%	-0.56%	-0.58%	-1.04%*	-0.64%
	(-0.77)	(-0.97)	(-1.73)	(-0.75)	(-2.04)	(-1.06)	(-2.06)	(-1.05)	(-1.37)	(-1.37)	(-1.72)	(-1.23)

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Table 4.8 continued from previous page

	World	Asia	Europe	America	World	Asia	Europe	America	World	Asia	Europe	America
Panel B		B/M				Tobin Q				COA		
1 (Low)	0.83%***	0.27%	1.19%***	0.91%***	0.80%***	0.24%	1.20%***	0.89%***	0.70%***	0.43%	1.20%***	0.84%***
	(4.10)	(0.71)	(4.05)	(4.10)	(3.60)	(0.58)	(3.93)	(4.00)	(3.18)	(0.98)	(4.01)	(3.47)
2	0.68%***	-0.02%	0.96%***	1.00%***	0.66%**	0.15%	0.90%***	1.00%***	0.67%**	0.18%	0.95%***	0.91%***
	(3.96)	(-0.05)	(2.95)	(3.96)	(2.49)	(0.35)	(2.86)	(4.08)	(2.60)	(0.38)	(2.92)	(3.62)
3	0.54%***	-0.09%	0.75%**	0.88%***	0.57%*	-0.09%	0.91%**	0.92%***	0.68%**	0.03%	0.90%**	0.89%***
	(3.03)	(-0.22)	(2.03)	(3.03)	(1.88)	(-0.19)	(2.40)	(3.14)	(2.57)	(0.06)	(2.51)	(3.24)
4	0.55%**	0.02%	0.94%**	0.73%**	0.51%	-0.04%	0.99%**	0.56%	0.51%	-0.10%	0.61%	0.67%**
	(2.19)	(0.04)	(2.29)	(2.19)	(1.50)	(-0.08)	(2.43)	(1.62)	(1.64)	(-0.20)	(1.44)	(2.31)
5 (High)	0.27%	0.09%	0.54%	0.36%	0.24%	-0.29%	0.40%	0.46%	0.35%	-0.24%	0.64%	0.77%*
	(0.71)	(0.17)	(1.03)	(0.71)	(0.57)	(-0.54)	(0.77)	(0.98)	(0.85)	(-0.44)	(1.10)	(1.87)
5-Jan	-0.56%	-0.19%	-0.65%	-0.56%	-0.56%*	-0.53%	-0.80%*	-0.43%	-0.35%	-0.67%**	-0.56%	-0.07%
	(-1.28)	(-0.53)	(-1.53)	(-1.28)	(-1.74)	(-1.17)	(-1.93)	(-1.08)	(-1.06)	(-2.14)	(-1.17)	(-0.18)

Table 4.9: Sub-Sample Portfolio Performance

This table reports the sub-sample portfolio returns which is split the sample period into pre and post 1998. Portfolios are constructed by idiosyncratic volatility measured with Fama French three-factor model by daily returns within previous month. Portfolios are rebalanced each month and held for one month. All returns are dominated in US dollar. The column 1 (5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. Column 5-1 is the monthly difference between highest and lowest portfolio returns. The T statistics are adjusted with Newey-West (1987) with lag 3 and reported in brackets. The average differences in column 5-1 are followed by ***,**,* if it is significant different from zero with 1%, 5%, 10% confidence level.

COUNTRY	1 (lowest)	2	3	4	5 (highest)	1-5
Panel A. Value Weighted Portfolio sorted by IVOL during Feb 1988 to Dec 1997						
SWITZERLAND	2.16%***	2.83%***	1.44%*	-0.50%	0.20%	-1.96%*
	(2.68)	(3.85)	(1.73)	(-0.63)	(0.20)	(-1.90)
AUSTRALIA	0.96%	-0.14%	0.98%	-0.39%	-0.34%	-1.29%
	(1.37)	(-0.21)	(1.21)	(-0.39)	(-0.29)	(-1.21)
UNITED KINGDOM	1.62%**	1.54%**	0.49%	0.63%	0.91%	-0.71%
	(2.31)	(2.42)	(0.84)	(0.96)	(1.16)	(-0.92)
UNITED STATES	1.65%***	1.26%**	1.60%***	1.91%***	0.96%	-0.69%
	(3.74)	(2.27)	(3.18)	(3.42)	(1.66)	(-1.33)
JAPAN	0.27%	-0.01%	-0.49%	-0.32%	-0.36%	-0.63%
	(0.33)	(-0.01)	(-0.58)	(-0.36)	(-0.39)	(-1.52)
NETHERLANDS	1.98%***	1.95%***	1.20%**	1.68%**	1.85%***	-0.13%
	(3.47)	(3.66)	(2.29)	(2.44)	(2.99)	(-0.20)
FRANCE	0.97%	1.44%**	0.94%	1.27%*	0.91%	-0.07%
	(1.53)	(2.20)	(1.17)	(1.73)	(1.25)	(-0.13)
ITALY	0.72%	-0.12%	0.94%	-0.02%	0.66%	-0.07%
	(0.90)	(-0.14)	(1.01)	(-0.02)	(0.78)	(-0.11)

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Table 4.9 continued from previous page

COUNTRY	1 (lowest)	2	3	4	5 (highest)	1-5
HONG KONG	0.29%	0.22%	0.19%	0.99%	0.64%	0.35%
	(0.30)	(0.23)	(0.18)	(0.83)	(0.54)	(0.38)
CANADA	0.97%**	1.38%**	1.33%**	1.69%**	1.32%*	0.35%
	(2.05)	(1.98)	(2.23)	(2.33)	(1.75)	(0.46)
SPAIN	-1.56%	-1.56%	-2.04%	-0.45%	-1.11%	0.70%
	(-1.53)	(-1.27)	(-1.63)	(-0.39)	(-0.80)	(0.65)
MALAYSIA	-0.32%	-0.18%	-1.49%	-1.67%	0.39%	0.70%
	(-0.33)	(-0.18)	(-1.18)	(-1.23)	(0.31)	(0.69)
GERMANY	1.56%***	1.50%**	0.65%	1.04%	2.28%***	0.72%
	(2.69)	(2.37)	(0.98)	(1.50)	(2.94)	(1.13)
MEXICO	1.62%	1.70%	2.14%	2.27%	2.68%*	1.06%
	(1.22)	(1.08)	(1.41)	(1.60)	(1.78)	(0.99)
SOUTH KOREA	-0.89%	-0.54%	0.84%	0.80%	0.52%	1.41%*
	(-0.88)	(-0.57)	(0.99)	(1.03)	(0.64)	(1.67)
Panel B.Value Weighted Portfolio sorted by IVOL during Jan 1998 to Dec 2007						
CANADA	1.63%***	1.16%	1.30%	0.66%	-0.68%	-2.32%**
	(2.96)	(1.90)	(1.62)	(0.75)	(-0.60)	(-2.19)
FRANCE	1.59%***	1.83%***	1.33%**	0.20%	-0.09%	-1.68%*
	(2.80)	(3.51)	(2.35)	(0.25)	(-0.08)	(-1.69)
UNITED STATES	1.17%***	1.02%*	0.09%	0.00%	-0.31%	-1.48%*
	(2.46)	(1.68)	(0.15)	(0.00)	(-0.30)	(-1.67)
MEXICO	2.68%***	1.19%	1.60%	1.00%	1.42%	-1.27%
	(3.37)	(1.31)	(1.81)	(1.05)	(1.28)	(-1.48)
GERMANY	1.19%*	1.38%**	1.58%	1.92%*	0.06%	-1.13%
	(1.80)	(2.24)	(1.41)	(2.02)	(0.05)	(-1.06)
UNITED KINGDOM	1.18%**	1.06%**	0.84%	0.83%	0.05%	-1.13%

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Table 4.9 continued from previous page

COUNTRY	1 (lowest)	2	3	4	5 (highest)	1-5
	(2.06)	(2.64)	(1.50)	(1.28)	(0.05)	(-1.27)
NETHERLANDS	0.90%*	-0.05%	0.83%	-1.75%	-0.12%	-1.02%
	(1.91)	(-0.09)	(1.11)	(-1.25)	(-0.10)	(-0.83)
JAPAN	0.36%	0.31%	0.13%	-0.27%	-0.64%	-1.00%
	(0.75)	(0.54)	(0.22)	(-0.45)	(-0.76)	(-1.57)
ITALY	1.43%**	0.60%	1.60%	1.23%	0.55%	-0.88%
	(2.47)	(0.86)	(1.97)*	(1.43)	(0.52)	(-0.93)
AUSTRALIA	1.88%	1.33%	1.93%	1.76%	1.37%	-0.51%
	(3.20)	(1.86)	(3.07)	(2.39)	(1.22)	(-0.53)
SPAIN	0.95%	0.73%	0.75%	1.25%	0.48%	-0.47%
	(0.66)	(0.49)	(0.51)	(0.84)	(0.28)	(-0.28)
MALAYSIA	1.08%	0.67%	-0.09%	0.67%	1.76%	0.68%
	(0.92)	(0.59)	(-0.08)	(0.49)	(1.45)	(1.27)
HONG KONG	0.11%*	0.43%	1.74%*	0.59%	1.85%***	1.76%**
	(1.80)	(0.42)	(1.81)	(0.56)	(2.78)	(2.15)
SOUTH KOREA	0.49%**	0.89%	1.31%	0.65%	1.47%*	0.98%**
	(2.57)	(1.55)	(1.59)	(0.94)	(1.83)	(2.03)
SWITZERLAND	1.00%**	1.12%	-0.01%	1.04%	1.69%	0.69%
	(2.58)	(1.45)	(-0.01)	(1.17)	(0.99)	(0.40)

Chapter 5

Information Uncertainty and Equity Financing Decisions

5.1 Introduction

In chapter 3 and 4, we have documented the non-trivial role of information uncertainty in stock market valuation. As managers are found to exploit favorable market condition in financing and investment decision (Baker (2009)), we further conjecture that information uncertainty would also affect manager's decision making. More specifically, we ask whether information uncertainty would affect manager's equity financing decision. Plenty of empirical evidence shows that market valuation has a substantial impact on corporate financing decisions. Baker and Wurgler (2002) argue that corporate managers prefer to issue equity when the prior stock valuation is high and repurchase stocks when they believe the stocks are undervalued. If the short-term stock price fluctuation is unrelated to the fundamentals of the underlying firm, managers may time the market and issue stocks to gain from the temporal low cost of equity. Although much empirical work has shown the positive relationship between market valuation and the net supply of corporate equity, little effort focuses on the role of information uncertainty in equity issuance. Information uncertainty or ambiguity refers to when the information is too ambiguous to imply the firm's fundamental value. Many papers have shown that information uncertainty is significantly associated with stock mispricing, which may in turn substantially affect the firm's financing decisions.

This chapter addresses the question of how information uncertainty affects corporate financing decisions. The market timing theory argues that managers issue equity following high market valuation to exploit short-term stock mispricing. Information uncertainty may enlarge the short-term market fluctuations through amplifying investor biases. Hirshleifer (2001) suggests that information uncertainty leaves more room for psychological biases, and misvaluation effects are expected to be stronger in firms with higher uncertainty. Zhang (2006) and Jiang, Lee, and Zhang (2005) find supportive evidence that stocks with more information uncertainty tend to be overpriced on average. Moreover, Zhang (2006) also finds that short-term price continuation is positively related to the uncertainty level of underlying stocks. It implies that investors tend to under-react to the news of stocks with high information uncertainty. Therefore, managers should perceive more market misvaluation, if their firms are subject to more information uncertainty.

Previous literature has mainly focused on the impact of stock returns on the firm's financing decisions, whilst little is known about whether information uncertainty plays a role in corporate finance. Since market valuation and stock returns are not a clean proxy for investor sentiment, the studies based on market valuation and stock returns cannot distinguish between behavioral and rational expectation interpretation. Firstly, uncertainty about a firm's future prospects increases the estimated present value through Jensen's inequality (Pastor and Veronesi (2003)). Secondly, higher uncertainty of future payoffs benefits shareholders in a levered company (Johnson (2004)). Thirdly, managers and investors are more overconfident and optimistic when the outcomes are difficult to value.

The univariate test confirms the findings of market timing behavior in equity offerings that equity issuers tend to exploit the 'window of opportunity' by selling overpriced stocks to new shareholders. Firms also tend to conduct more equity offerings when market valuation is higher and post-stock performance is poor. The test of long-run post-issue stock performance confirms their prediction that firms with a poor long-run performance have a higher probability of equity issuances.

The relationship between information uncertainty and equity offerings decisions was also further tested. Within all industry firms, the evidence shows that firms with higher information uncertainty tend to issue more seasoned equity offerings (SEOs). The probability of an issuer in the highest information uncertainty quantile is 5.4 percent, which is approximately three times higher than an issuer in the lowest information uncertainty quantile (1.8%). Zhang (2006) discovered an interaction effect between information uncertainty and stock returns. To guarantee that this pattern is not contaminated by past stock valuation, all firms are double sorted by information uncertainty and prior stock returns. The evidence shows that controlling prior stock returns, firms with higher information uncertainty consistently have a higher likelihood of issuing equity. Both the maximum issuance and highest probability of equity issuance appear in the quantile of highest prior stock returns and highest information uncertainty. This finding suggests that managers tend to time the market not only by stock market valuation, but also by the information uncertainty to which outside investors are subject.

Using the cumulative abnormal returns (CARs) around the SEOs, it is found that firms with the highest information uncertainty have lower CARs. This indicates that equity issuance is a poorer signal when outsiders have more difficulty evaluating the underlying stock. The evidence also suggests that issuers with more information uncertainty have a higher valuation than other issuers. In addition, they suffer more wealth loss during the short window of announcement periods. This further confirms that information uncertainty captures the magnitude of stock mispricing, rather than growth options in the pecking order theory.

This chapter contributes to the literature in several ways. First, there is an ongoing debate between behavioral and traditional finance theories on the market timing phenomenon in equity financing. Behavioral finance argues that market timing behavioral is due to the failure of market efficiency, as a result of either irrational market participants or irrational managers. On the other hand, several neoclassic finance models suggest that market timing can be simply explained by rational expectations or a change in risk-adjusted returns. The test in this study shows that the market timing of equity issuance is more severe when the information uncertainty of the issuer is higher, which confirms the view of market inefficiency.

Second, financial economics theory offers two different interpretations of information uncertainty affecting investors' expectations and utility. From the view of the subjective utility theory, investors with ambiguity aversion interpret the new uncertain information as a worst-case scenario, and require compensation for bearing ambiguity. The market should respond more negatively to stock issuance with more information uncertainty. On the contrary, the literature of behavioral finance suggests a positive relationship between behavioral biases and information uncertainty. When the underlying information is too vague to interpret, investors' expectations incorporate more behavioral biases, they are overconfident about their private information, and they under-react to recent news. In the theory of rational managers responding to an irrational market, Stein's (1996) seminal work argues that two market conditions are necessary for managers to successfully exploit the opportunity of market mispricing.

The rest of the chapter is organized as follows. Section 4.2 briefly reviews the literature of SEO studies and builds up the hypotheses. Section 4.3 describes the sample of the test used in this study, and the main proxies of information uncertainty. The main empirical results are reported and analyzed in Section 4.4, and the conclusion follows in Section 4.5.

5.2 Literature Review And Hypothesis Development

5.2.1 Previous Literature About Seasoned Equity Offerings

Many financial studies have documented that there are notable stock price run-ups right before firms issue seasoned equities, and a poor long-term performance follows the SEOs. Several explanations have been proposed for the 'anomalous' price performance, which can be classified as either behavioral or neoclassic. Behavioral finance argues that stock price run-up reflects the investors' over-valuation for non-fundamental reasons, and managers are motivated to issue equity to take advantage of the temporal low cost of external equity. The neoclassic finance suggests that high stock valuation is the consequence of a firm's decreased risk. In the real-option pricing models, firms exercise their growth options in operating projects. Since growth options are riskier than the existing assets, the realization lowers the fundamental risks of the underlying firm, and therefore inflates the stock price.

In the famous survey study of Graham and Harvey (2001), the authors found that CFOs consider the prior stock price performance as the third influential factor to make equity financing decisions in the United States. Bancel and Mittoo (2004) also conducted a similar survey in seventeen European markets. Over 50 percent of the CFOs who responded to their questionnaire ranked the 'high stock price' as the second factor of the common stock policy, higher than the target debt ratio, ownership dilution, etc.

The empirical study of stock price run-ups prior to SEOs dates back to 30 years ago. Early studies, including Asquith and Mullins (1986) and Masulis and Korwar (1986), have shown that the stock market valuation of SEO firms is much higher than non-issue firms, and SEO firms undergo a significant downward price revision when releasing the news of equity issuance. Asquith and Mullins (1986) also analyzed a sample of 531 SEOs in the utility and industry sections and reported a -2.7 percent stock price drop on the announcement day. Masulis and Korwar (1986) constructed a sample of SEOs from the Wall Street Journal during the 1960s and 1970s. They found the announcement effect similar to the former study, although industry firms have a worse short-run performance than utility firms.

Loughran and Ritter (1995) also reported superior stock returns the year before SEOs. In their seminal paper, they find, more importantly, the long-run underperformance of SEO firms three to five years after the equity issuance. The authors provide two explanations. One is the 'market timing' hypothesis in which managers are aware of the current market overvaluation of the firm's stocks, and anticipate a subsequent price drop. To benefit from the 'window of opportunity, managers sell overpriced equity before the price downward correction. Alternatively, they suggest that the 'New Issue Puzzle' may be not at all anomalous if the benchmark to SEO firms is not correctly chosen.

The literature provides several interpretations to explain why issuers tend to outperform before the issuance and underperform afterwards. One possibility is that the empirical findings of abnormal returns are due to the incorrect benchmark or misspecified asset pricing models. As suggested by Loughran and Ritter (2000) and Fama (1998), the test of abnormal stock performance is a joint test of market equilibrium and the correct asset pricing model. The findings of abnormal stock returns may be attributed to either the failure of market efficiency, or misspecification of the asset pricing model. Eckbo, Masulis, and Norli (2000) argue that SEO issuers have a significant change of their systematic risk because of a lower leverage ratio. They use a six-factor asset pricing model to adjust raw returns, and find no abnormal stock performance. Brav, Geczy, and Gompers (2000) also constructed the benchmark portfolio with non-issuers only, and found that abnormal returns only remain within small capitalization and low market-to-book SEO firms.

The agency cost hypothesis offers another explanation for the patterns of stock performance concerning SEO issuance. Teoh, Welch, and Wong (1998) argue that managers may purposely or unknowingly manipulate accounting information before SEOs. They find that issuers with a higher use of accruals right before SEOs have poorer future returns. Jung, Kim, and Stulz (1996) compared the SEOs with different Tobin's Q, which is the conventional proxy for a firm's investment opportunity. They found that SEO issuers with a higher Tobin's Q generated an insignificant announcement return. Their findings suggest that issuers with no solid investment opportunities are subject to higher agency costs because managers try to control more financial resources whenever the market condition is good.

Loughran and Ritter (1997) offer an alternative interpretation based on overoptimistic managers and investors. When prior stock performance is good, both managers and investors tend to believe that the price run-up is the consequence of effective operations and superior profitability rather than irrational stock overpricing. Kim and Weisbach (2008) also found that most equity issuers worldwide tend to invest more after SEOs, which reflects the manager's optimistic view of a firm's outlook. Fu (2010) further investigated the capital expenditure after the SEOs, finding that equity issuers tend to overinvest more than non-issuers. He also found that firms investing more heavily after SEOs tend to have a lower future stock performance with the control of the firm's characteristics and pre-issue performance.

The first hypothesis of this chapter is to retest the market timing behavior of SEO issuance in this study's sample. The researcher tested whether prior stock valuation and price run-ups are positively related to the probability of equity issuance, and whether future stock performance predicts a lower probability of equity issuance. The previous empirical methodology of testing the stock price pattern around SEO issuer usually involves the sample of issuers or comparing the difference between equity and debt issuance. This study includes all industry firms, both issuers and non-issuers, to test whether, and to what extent, equity financing decisions are affected by market valuation and a firm's characteristics.

Schultz (2003) argues that the firms may have long-run underperformance when their previous stock price is high, regardless of issuing equity decisions. This methodology avoids this 'pseudo market timing problem' using logistic regression on all industry firms. If non-issuers have a similar stock price pattern as issuers, the pre- and post-stock performance has no significant prediction power over equity issuance decisions.

Hypothesis 1: The probability of equity issuance should be positively associated with prior stock valuation and price run-up, and negatively associated with future stock performance.

5.2.2 Information Uncertainty And Corporate Market Valuation

Recent studies have found that information uncertainty plays a significant role in stock valuation. Subjective utility theory stemming from Savage (1954) suggests that representative investors should be averse to Knight (1921) uncertainty, and they require compensation to hold an asset with greater uncertainty. In line with this literature, Epstein and Wang (1994), and Uppal and Wang (2003) derive the asset pricing models, taking the ambiguity aversion into account. Epstein and Schneider (2008) argues that when information does not provide a clear and conclusive implication about the underlying value of a firm, investors will assume the worst-case scenario and discount the firm's evaluation as a result of uncertainty.

On the other hand, behavioral financial theory suggests that investors tend to be more optimistic about the firm's fundamental when the market information is subject to more uncertainty. Hirshleifer (2001) suggests that information uncertainty amplifies the psychological biases amongst investors. One reason is that information uncertainty may cause obstacles for investors to adjust their expectations correctly. According to Black (1986) and Delong, Shleifer, Summers, and Waldmann (1990) model, investors with a na?ve feedback trading strategy or 'noise' investors will survive in the market if the signal of a true firm's fundamental is not strong enough. Moreover, information uncertainty also increases the cost of arbitrage, which makes stock mispricing more persistent. Shleifer and Vishny (1997) posit the possibility of bankruptcy of a professional arbitrager when the cost of arbitrage is high. In addition, Jiang, Lee, and Zhang (2005) show that it is more costly and riskier for an arbitrager to trade a security with higher information uncertainty.

Moreover, Pastor and Veronesi (2003, 2005) suggest that information uncertainty can inflate the stock price in a rational way because of Jensen's inequality. The uncertainty of a firm's profitability appears in the reciprocal of their standard discounted cash-flow model. When the volatility of a firm's future growth rate or profitability transfers from the reciprocal to the expectations of a firm's present value, the evaluation of the firm's fundamentals will be higher than that with no information uncertainty. Pastor and Veronesi's (2003) model also predicts an increasing and convex relationship between the firm's valuation and information uncertainty. In an alternative treatment of uncertainty within valuation models, Johnson (2004) posits that information uncertainty increases the shareholders' value depending on the firm's leverage ratio.

Miller (1977) models the stock pricing mechanism with a divergence of opinion and short sale constraints. He shows that when information uncertainty is higher, investors have greater disagreement about the firm's fair valuation. If the market is perfect (i.e. stocks are traded frictionless and investors are able to trade any amount, positive or negative and as much as they want), there will be no impact on the stock price. However, if the short sale is limited or banned, even though the market consensus remains unchanged, pessimistic investors cannot reveal their lower evaluation. Hence, the stock price with short-sale constraints will be inflated by optimistic investors. His theory predicts that information uncertainty is positively related to stock overpricing in an imperfect market.

5.2.3 Information Uncertainty and Equity Financing Decisions

Given the previous empirical evidence and the findings from Chapter 3 and 4, firms with greater information uncertainty tend to be more overpriced. One can hypothesize that if the market timing behavior of SEO firms is the result of stock market inefficiency, firms with higher information uncertainty have a higher probability of issuing equity (Hypothesis 2).

Stein (1996) also points out that managers are motivated to time the market if they observe the stock overpricing, and they believe that overpricing will not be corrected in the transaction of equity offerings. These two conditions should exist simultaneously; otherwise, selling the equity to new shareholders will not benefit the issuing firms. As reported in Jiang, Lee, and Zhang (2005) and Zhang (2006), information uncertainty causes a slow reaction to the new information and increases the cost of arbitrage. Hence, one can further hypothesize that information uncertainty predicts a higher probability of SEO issuance, even controlling for the prior stock valuation (Hypothesis 3).

To ensure that information uncertainty is an indicator of stock mispricing, this study further examines the announcement effect of SEOs. The pecking order theory suggests that growth firms have higher uncertainty and use more equity financing. The reason is that growth firms tend to obtain credible investment opportunities and investors feel more confident in their usage of proceeds from SEOs. The proxies of information uncertainty may capture the characteristics of growth firms instead of stock mispricing. This theory also predicts that growth firms are subject to less adverse selection cost and generate better announcement stock performance. In contrast, market timing behavior suggests that information uncertainty is associated with stock mispricing, and firms with a higher uncertainty level will generate poor announcement returns. The competing test was run on the announcement effect between the pecking order theory and the market timing hypothesis. Hypothesis 4: information uncertainty will be negatively associated with the announcement returns of SEO issuers if managers try to time the market; information uncertainty will be positively associated with the announcement returns of SEO issuers if uncertainty stems from the growth options of issuing firms.

5.3 Data And Methodology

This sample of seasoned equity offerings was obtained from Thomson One Banker (SDC) database. The sample period covers the period of 1970 to 2008, which allows for at least one year's post-issue performance in the analysis. All equity issuers remaining in the sample should meet the following criteria:

1. The SEO issuer must be a listed firm on the NYSE, AMEX or NASDAQ

stock exchange, and be incorporated in the United States (domestic firms).

2. Issues other than common stocks are excluded, such as rights, preferred stocks, and unit trusts. Pure secondary offerings in which current shareholders instead of the underlying company receive all of the proceeds are also excluded. For combined offerings, only the proceeds of the primary offerings are kept and the proceeds of the secondary offerings are subtracted from the total amount of cash raised in the issue.

3. The SEO issuer must not be in the financial industry (SIC code between 6000 and 6999), or in the regulated utility industry (SIC code between 4910 and 4949). Financial companies normally have a different corporate structure than industry firms, which will distort the leverage statistics and profitability measures (Fu (2010)). Public utility firms are also heavily regulated, thus making their investment and financial decision-making less discretionary. Hence, the managers of utility firms have more difficulty and less motivation to time the market.

4. The SEO issuer must have a non-missing book value and market value from merged COMPUSTAT and CRSP in the fiscal year prior to issuance.

5. If an issuer conducts multiple offerings within a one-year time interval, all of the proceeds are combined into one observation, and only the first announcement date is used as the equity issuance date of those multiple issuers.

After filtering the raw data of SEOs with the above five criteria, there are 5134 observations remaining in the sample. Table 5.1 reports the distribution of SEO issuers in each year from 1970 to 2008. The number of equity issuance varies widely in different fiscal years and co-varies with the macroeconomic condition. For example, during the technical bubble from 1991 to 2000, the average number of issuances was approximately 238 per year, whereas after the bubble collapsed in 2001, the average number dropped to 80 issuers per year. The highest number of issuances appears in 1983, which is largely due to the inclusion of NASDAQ issuers in the American SEOs market. This is consistent with the findings of Brav, Geczy, and Gompers (2000), that the equity offerings in NASDAQ significantly change the issuers' characteristics, lowering the average offering size and increasing the equity issue volume.

The proceeds of SEOs reported here have been adjusted by the CPI in 2001, which keeps them comparable across the entire sample period. The sum of the annual proceeds co-varies with the number of issuances. The mean of the proceeds also shows an inverse pattern of issue numbers in which the average proceeds of the SEOs appear to be greater in the year of a smaller number of SEOs and vice versa. The median of the proceeds over the market value of the issuer measuring the relative market impact of the SEOs was approximately 10 percent in the 1970s, and 15 percent afterwards. The median of the proceeds over the issuer's asset is positively correlated with the number of SEOs across the sample periods.

The level of information uncertainty can be measured using three main proxies: idiosyncratic volatility (IVOL), stock turnover by volume(VO), and firm age (AGE)[1]. Idiosyncratic volatility is the standard deviation of residue returns, calcu-

[1]Each proxy has been recalculated using different methods, and reanalysed in the following empirical tests. For example, IVOL was calculted by 52 weeks of residual returns, and 12 months of residual returns in addition to daily residual returns, adjusted by the market model, CAPM, four-factor models in addition to Fama-French three-factor model. The results are consistent with those tabulated in this chapter. Hence, the main results are only reported here for parsimony. Nevertheless, all unreported results are available upon request.

lated by regressing daily returns on Fama-French's three risk factors. The median monthly idiosyncratic volatility of issuers increased from approximately 2 percent in the 1970s to 4 percent in the 2000s, which is consistent with the upward trend of idiosyncratic volatility in the United States market (Campbell, Lettau, Malkiel, and Xu (2001)). The turnover by volume is calculated by the average monthly trading volume divided by the total number of shares outstanding. The median turnover ratio of issuers also increased from 33 percent in 1970 to 243 percent in 2008, which reflects the innovative information techniques and improved trading system that lower the cost of transactions (Campbell, Lettau, Malkiel, and Xu (2001),Chordia, Roll, and Subrahmanyam (2001)). Firm age is the number of years since the first date that the firm is reported in the CRSP database to the year in question. The median age of issuers is four years, showing that young firms conduct more SEOs in this sample.

All of the industry firm-year observations from CRSP and COMPUSTAT were then downloaded to calculate the probability of SEO issuance amongst the corresponding listed firms. Following DeAngelo, DeAngelo, and Stulz (2010), the firm-year observations of both the issuer and non-issuer should meet the following conditions

1. industry firm only (SIC code is outside of 6000-6999 and 4910-4949
2. ordinary common stock only (CRSP stock code 10 and 11)
3. company stock listed on NYSE, AMEX, and NASDAQ (CRSP exchange code 1,2, and 3)
4. incorporated in the United States

5. non-missing book value from COMPUSTAT and market value from CRSP

6. firm-year observation between 1970 to 2008.

These conditions ensure that the sample of industry firms is consistent with the selection criteria for the SEOs.The logistic regression of SEOs on information uncertainty, market valuation and other control variables as following equation.

$$\begin{aligned} SEO\ Dummy = \ & \alpha_1 IVOL + \alpha_2 TurnOver + \alpha_3 1/AGE + \beta_1 Prior12AR \\ & +\beta_2 Post12AR + \gamma_1 LogAsset + \gamma_2 Z - Score \\ & +\gamma_3 BookLeverage + \gamma_4 Tangibility + Constant \end{aligned} \tag{5.1}$$

where IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. Turnover is average monthly trading shares volume divided by number of shares outstanding. 1/Age is the reciprocal of number of years since the firm was firstly recorded in CRSP database up to the year in question. Prior12AR and Post12AR are prior and post 12 month adjusted stock returns by CRSP value-weighted stock index. Log Asset is the natural logarithm of firm's book asset value in the previous fiscal year end. Book leverage is long term debt minus the debt within one year due divided by book asset value. Tangibility is the tangible asset divided by total asset. Altman's Z-score is calculated by$Z = 0.012\frac{WC}{TA} + 0.014\frac{RE}{TA} + 0.033\frac{EBIT}{TA} + 0.006\frac{MV}{BookLiability} + 0.999\frac{Sales}{TA}$ where WC, TA, RE, MV are working capital, total asset, retained earnings and market value of equity, respectively.

5.4 Empirical Results

5.4.1 Univariate Test On Market Valuation And Probability Of Issuance

Table 5.2 reports the SEO issuers' characteristics and probability of issuance partitioned by the market-to-book ratio, and pre- and post-adjusted returns. Fama and French (1993) is followed to calculate the market-to-book ratio using the previous year-end market valuation divided by the last fiscal year end's book equity value. Panel A rank the firms into five quantiles according to their market-to-book ratio within each calendar year. Take year firms in 2001 and 2002 as an example. The market-to-book ratio of all industry firms is first calculated in these two years. Then all of the firms are ranked according to their market-to-book ratio in 2001 and 2002 separately, so that some firms may be in the first quantile (lowest M/B ratio) in 2001, and in the second or third quantile in 2002. Panel B to G further calculates the stock returns adjusted by their value weighted CRSP index to measure their pre- and post-stock performance. The adjusted stock returns are then partitioned into eight quantiles within each calendar year. The firm-year observation is excluded if there are less than 7, 14 and 21 monthly stock returns in the previous or post 12, 24 and 36 month periods, respectively.

Consistent with the market timing phenomenon of equity offerings (Baker and Wurgler (2002)), firms with a high stock market valuation tend to issue more SEOs in the sample. In Panel A, firms in higher market-to-book quantiles issue more seasoned equities than those in lower quantiles. In addition, firms in the lowest market-to-book subgroup have only 253 SEO issues, compared to 1623 offerings in the highest subgroup. The percentage of total proceeds shows a consistent pattern that firms in higher valuation quantiles raise more funds compared to those with lower market valuations. Approximately 57 percent of the total proceeds are raised by firms in the fourth and fifth market-to-book quantiles. However, all quantiles have similar median proceeds of approximately 26 million dollars, indicating that the offering size of the individual issuers is not affected by the valuation. The difference of the total proceeds amongst the quantiles is attributed to the frequency of SEOs, as firms with a higher market valuation are more likely to use equity financing.

The median of idiosyncratic volatility is 2.96 percent in all market-to-book quantiles. The highest market-to-book quantile has a slightly higher idiosyncratic volatility. Except for the lowest market valuation quantile, the median IVOL increases along with the market valuation. The median of a firm's age is eight years, and is lower for the highest valuation quantile. This pattern is reasonable in that they both measure the information uncertainty of the underlying firms. This evidence is consistent with the empirical findings of Pastor and Veronesi (2003). They argue that information uncertainty will increase the firm's valuation because of Jensen's inequality. In their empirical test, they also found a positive relation between idiosyncratic volatility and market-to-book ratio, and a negative relation between firm age and market-to-book ratio.

The median monthly turnover ratio by volume of all issuers is approximately 0.51. Issuers in higher market-to-book ratio quantiles have a higher turnover ratio. The highest quantile has a monthly turnover ratio of 0.93, whereas the lowest one only has a ratio of 0.25. Baker, Stein, and Wurgler (2003) suggest that trading volume is a suitable indicator of investor sentiment. A higher turnover ratio indicates that investors are more optimistic about the underlying stock performance, which may lead to the overpricing of a firm's stock. The results in Column 7, Panel A show that turnover ratios are positively correlated to market valuation.

Unsurprisingly, the probability of SEOs in a given year (Column 8) further indicates that firms tend to conduct more equity offerings when the previous market valuation is high. The average probability of equity issues amongst all industry firms is 3.61 percent, which is similar to the findings in DeAngelo, DeAngelo, and Stulz (2010). The probability of SEO issuance in the lowest market-to-book quantile is only 0.85 percent. This suggests that firms with low market valuations are unlikely to raise proceeds by equity financing. The highest quantile of market-to-book ratio has a 5.63 percent probability of issuing equity, thus indicating that 1 out of 17 firms in the highest quantile conduct SEOs every year.

In addition to the market-to-book ratio, prior adjusted stock returns are also used to test the relation between the probability of equity issuance and stock valuation. The market-to-book ratio not only captured the market valuation, but also measures the growth opportunity of the underlying firms. Myers and Majluf (1984) suggest that growth companies have more growth opportunities and face less adverse selection cost. Compared to other mature companies, firms in the growing phrase have more investment opportunities and are more likely to raise and invest the proceeds of SEOs in positive NPV projects. Therefore, investors expect that the SEOs of growth firms are more valuable than the equity issues of mature firms. In equilibrium, the market would react more positively to the SEO announcement by growth firms. Therefore, growth companies tend to conduct more SEOs in equilibrium because of the lower cost of equity financing. This rational neoclassical model does not rely on market misvaluation and investor sentiment. To prevent the results of this study from the different costs of equity between growth and value firms, price performance was used as an additional proxy of the market valuation.

Panels B to D use pre- and post-stock performance to investigate the market timing behavior and equity offerings. To measure stock performance within a certain time interval, average monthly stock returns are adjusted by the CRSP value-weighted index. Panel B, C and D all show that firms conduct more equity offerings when the prior price run-up is higher. For example, for the prior 12-month adjusted stock returns, the number of equity issuances increased from 51 with the lowest prior returns (less than -75%) to 839 in the highest adjusted return quantile (higher than 75%). The probability of equity issues is also higher (lower) amongst previous greater (poorer) stock performance. The same pattern is found when partitioning the sample based on prior 24 and 36 months of adjusted stock returns (Panel C and D). The evidence confirms the findings in Graham and Harvey's (2001) survey that firm managers consider previous stock price run-up as an important factor in equity offering decisions. When the previous price significantly increases, managers tend to believe that the current market condition is superior, and issuing equity will benefit the firm as a result of the low cost of equity.

Columns 5 to 7 in Panel B, C and D indicate that stocks with greater abnormal stock returns, both positively and negatively, have higher information uncertainty. For example, in Panel B, Column 5, the idiosyncratic volatility decreases from 4.43 percent (RET¡-75%) to 2.20 percent (-25%¡RET¡0), and then climbs up to 6.21 percent (RET¿75%), showing a rough U shape. The other two proxies, firm age and turnover, generate the same pattern. Zhang (2006) argues that higher uncertainty increases the magnitude of stock mispricing because uncertainty amplifies investor biases. Consistent with his suggestion, the evidence in this study shows that extreme stock performance, either positive or negative, is accompanied by higher information uncertainty.

The previous literature of seasoned equity offerings documents that the stock returns following the issuance are much poorer than the benchmark portfolios. Panels E, F and G report similar patterns of long-term abnormal returns after equity issuance. This downward post-performance trend is even more significant when the testing periods are extended. The number of issuers with extreme poor post-issuer returns (RET¡-75%) is 371 after one year, whilst this figure increases to 1535 after three years. However, the probability of SEO issuance has no significant change, suggesting a corresponding increasing number of industry firms with extremely poor performance. Loughran and Ritter (1995) argue that managers may knowingly sell overvalued stocks before the market valuation turns downwards, thus benefiting the current shareholders through the 'window of opportunity'. The results of long-run post-issue stock performance support their prediction that firms with a poor long-run performance have a higher probability of equity issuances. A possibility is that this evidence may be also due to the endogenous consequence of an over-valued equity issuer (Shleifer and Vishny (2003)). For example, if the firm equity is currently overpriced, the stock valuation will drop to the fundamental in the long run, regardless of whether the company issues equity. If the managers naively react to the previous market valuation and issue equity after a high market valuation, poor long-run returns of equity issuers will also be observed. In addition, Fama and French (2000) suggest that the profitability of firms and industries is mean reverting because of market competition. Even a high market valuation is rationally derived from the temporary superior profitability of the underlying company. Hence, the operating performance should return to the market or industry average level. This provides an alternative explanation that managers may foresee the future of decreasing profitability, and sell equity without making any market mispricing assumptions.

In short, the above univariate test provides supportive evidence of the market timing theory that firms issue equity to exploit the 'window of opportunity'. Firms tend to conduct more equity offerings when their market valuation is higher and their post-stock performance is lower. Moreover, issuers with a higher number of absolute abnormal returns tend to be the firms with higher information uncertainty. However, the univariate test cannot clearly prove alternative explanations, since the market timing hypothesis, pecking order theory and other neoclassical corporate finance theories have all offered interpretations about the pattern of stock performance involving equity offerings.

5.4.2 Double-Ranked Portfolio Test On Information Uncertainty, Market Valuation, And Equity Offerings

In the previous section, the evidence shows that information uncertainty is correlated to the magnitude of abnormal returns. Since the stock performance has a significant impact on equity offering decisions, the univariate test fails to distinguish the influence of information uncertainty in equity offerings. This section uses a double-sorted portfolio to isolate the effect of price inflation, and investigate how information uncertainty affects equity offering decisions. First, all of the industry stocks are sorted according to their prior 12 months of abnormal returns and adjusted by the CRSP value-weighted stock index. The abnormal returns are then partitioned into eight groups. The stocks of each group are then further sorted into five groups according to their information uncertainty level, using idiosyncratic volatility, turnover and age as proxies. For each proxy, a total of 40 groups are obtained with ranked information uncertainty and different ranges of prior abnormal stock returns.

Table 5.3 reports the number of equity issuances and the probability of the issue in each subgroup. Panel A uses idiosyncratic volatility as a proxy of information uncertainty. Column 9 reveals that information uncertainty increases the number and probability of equity issuance without controlling the prior stock returns. In each column (1 to 8) with the same range of prior abnormal stock returns, firms with higher information uncertainty have a greater tendency to issue equity. For example, when prior abnormal returns are between 0 and 25 percent (Column 5), the lowest uncertainty quantile has a 1.66 percent probability of equity issuance, whereas the highest quantile has a probability of 3.63 percent.

The evidence supports the hypothesis that firm managers prefer to issue equity when information uncertainty of the firm is higher. The reason is that when outside investors face more information uncertainty, they may be subject to more behavioral biases. Kumar and Lee (2006) found that investors are more optimistic about future returns when the stock is difficult to value. Zhang (2006) also provides evidence that investors are more overconfident when the stocks contain more information uncertainty. In recent corporate finance development, Baker (2009) points out that those company managers may make financing decisions by responding to capital market conditions. Baker, Stein, and Wurgler (2003) also found evidence that investor sentiment plays a role in the firm's financing decisions. The evidence of this study indicates that information uncertainty affects investor sentiment and further influences the managers' market timing behavior.

The evidence also indicates that managers time the market to offer seasoned equity not only by the price run-ups or market valuation, but also by investor sentiment. In each row with the same uncertainty level, the probability of equity issuance increases along with prior abnormal stock returns. For example, in the third row with a median uncertainty level, the probability of equity issuance is approximately 1 percent and 2 percent amongst all firms with negative prior adjusted returns, and this number rises gradually with the increasing prior returns. The group with the highest prior returns and information uncertainty (Column 8, Row 5) also has the largest number and probability of equity issuances (273 SEOs and 9.42%).

Moreover, since information uncertainty increases stock mispricing, it sends a signal to managers that their stock is currently mispriced. Managers may issue equity in response to this mispricing signal if the current stock valuation is high, expecting a future downward adjustment of the stock price. Third, Jiang, Lee, and Zhang (2005) also argue that information uncertainty increases the cost of arbitrage. Shleifer and Vishny (1997) suggest that the limit of arbitrage may cause long-lasting security mispricing. Hirshleifer (2001) posits that if the market is subject to systematically psychological biases, irrational investors may 'arbitrage away the arbitrageurs'.

In a nutshell, the pattern of the number of SEOs and the probability of equity issuance in a given year clearly shows that information uncertainty is an important determinant of a firm's equity financing decisions. Firm managers prefer to issue equity when information uncertainty of the firm is higher. Meanwhile, it is consistent with Table 5.2 that stock market valuation has prediction power of SEO issuance.

5.4.3 Logistic Analysis Of SEO Issuance Decisions Based On Information Uncertainty, Market Valuation And The Firm's Characteristics

Logistic regression was run on all of the industry firms to test whether the probability of SEO financing decisions is positively related to the firm's information uncertainty or prior stock performance, and negatively related to their post-stock performance after controlling for common factors in the SEO studies. Idiosyncratic volatility, turnover, and firm age were used as proxies of information uncertainty, and the SEO issuance on these proxies was regressed separately and jointly. The dependent variable equals one if the industry firm conducted a SEO in a given year, and zero otherwise. The prior stock performance is measured by the previous 12 months of abnormal stock returns adjusted by the CRSP value-weighted index, whilst the post-stock performance uses 12 months of abnormal stock returns.

In untabulated results, the logistic regression was also run using other stock performance measures, including raw stock returns, abnormal stock returns adjusted by the CRSP equally-weighted index and the Standard & Poor's stock index. The results are consistent with those reported here, indicating that the choice of stock return adjustment method does not change the pattern of the market timing phenomenon. In addition, several control variables that are frequently used in testing SEO determinants were included in the logistic regression. A log of the total assets in dollars of the firm's 2001 purchasing power was used to control firm size. Large firms tend to have more tangible assets and use more debt financing instead of equity offerings. To control the leverage effect, the book leverage ratio was used, which is the long-term debt minus the debt due within one year divided by the book asset value. The market leverage ratio was not used, as the market value is correlated with the prior stock valuation. Firms with a higher leverage ratio and lower debt capacity prefer to raise funds by equity offerings. Tangibility and Altman's (1968) Z-score are used to control for a firm's debt capacity. Tangibility is the tangible assets divided by the total assets. Altman's (1968) Z-score is calculated using the following formula:

$$Z = 0.012\frac{WC}{TA} + 0.014\frac{RE}{TA} + 0.033\frac{EBIT}{TA} + 0.006\frac{MV}{BookLiability} + 0.999\frac{Sales}{TA} \tag{5.2}$$

where WC, TA, RE, and MV are working capital, total assets, retained earnings and the market value of equity, respectively. Baker, Stein and Wurgler (2003) argue that firms with a lower debt capacity rely more on equity financing. The logistic regression was run as follows:

$$SEO\ \ Dummy = \alpha_1 IVOL + \alpha_2 VO + \alpha_3 1/AGE + \beta_1 Prior12AR + \beta_2 Post12AR + \gamma_1 LogAsset + \gamma_2 Z - S \tag{5.3}$$

Table 5.4 reports the logistic regression on all industry firms from 1970 to 2008. Columns 1 to 3 tabulate the results using separate information uncertainty, whilst Column 4 includes all of the proxies in a single regression. The logistic regression shows that all information uncertainty proxies have significant coefficients, indicating that the probability of SEO issuance is positively related to the firm's information uncertainty level. The coefficient on idiosyncratic volatility is 13.7, with a z-statistics of 14.8. Turnover and the reciprocal of age have positive coefficients of 0.15 (z-statistics 16.60) and 4.84 (z-statistics 27.55). This confirms the results in Table 5.3 that even after controlling for market timing factors and the firm's characteristics, information uncertainty still has a strong predictive power over SEO issuance. When these three proxies are combined into a single regression (Column 4), they still have a significant relation to SEO issuance.

The evidence is consistent with the market timing hypothesis documented in the SEO literature that SEO issuers tend to have a higher prior stock performance and poor post-issue performance. The coefficients on the prior 12 months of abnormal returns are all significantly positive, whereas the post 12 months of abnormal returns are negatively related to the probability of SEO issuance. For example, in Column 4, the coefficient on prior stock performance is 0.28 with a z-statistics of 18.22, and the post-stock performance has a coefficient of -0.32 with a z statistics of -8.91. Both loadings are statistically significantly below the 0.1 percent confidence level.

Consistent with the previous literature, Table 5.4 also shows that the loadings on the book leverage ratio are positively significant (z statistics from 4.90 to 7.60). If firms with a higher debt ratio need to raise external funds, they are more likely to issue equity rather than debt, as debt financing will further increase their leverage ratio and bankruptcy costs. The loadings on the log asset are also significantly negative, as predicted. Large firms usually have a higher debt capacity and fewer growth opportunities than small firm. The pecking order theory by Myers and Majluf (1984) argues that firms with fewer growth opportunities face higher adverse selection costs. Hence, these firms use equity financing only after running out of debt capacity. The tangibility measure also supports the pecking order model in that firms with a higher tangibility ratio tend to conduct fewer SEOs.

5.4.4 Logistic Regression On SEO Issuance In The Groups Partitioned By Information Uncertainty

The previous section reveals that information uncertainty is positively related to the probability of SEO issuance. Hence, one can further hypothesize that the market timing phenomenon of SEOs should be more significant within industry firms with a higher level of information uncertainty. Information uncertainty also amplifies investor behavioral biases, leading to higher stock mispricing. If managers perceive their stock to be mispriced, they are more likely to benefit from stock overpricing by issuing seasoned equity. On the contrary, firms with less information uncertainty are less subject to misvaluation. If managers observe a high market valuation but less information uncertainty, they may believe that the high stock valuation reflects the firm's superior fundamental, which should persist in the future. In that case, managers have fewer motives to sell correctly priced stocks.

Therefore, the testable hypothesis is that prior stock performance should predict SEO issuance more significantly when the uncertainty level of the underlying firms is higher. To test the hypothesis of interaction between information uncertainty and stock performance in predicting SEO issuance, all of the industry firms first have to be ranked into five groups from lowest to highest information uncertainty. Then the logistic regression is run in each subgroup of industry firms.

Table 5.5 reports the logistic regression in the subgroups sorted by the information uncertainty level. In Panel A, all of the industry firms are partitioned by idiosyncratic volatility into five groups. From the lowest to highest information uncertainty subgroups, the equity issuance probability becomes more sensitive to the prior 12 months of adjusted stock returns. The loading of prior stock returns is 0.71 (t-statistics 10.06) in the highest uncertainty subgroup, which is three times higher than the loading in the lowest uncertainty subgroup (0.2 with t-statistics 4.54). The evidence of increasing equity issuance probability along with information uncertainty suggests that equity financing decisions are more sensitive to previous stock performance when the price signals contain more noise. This finding is consistent with the view of Loughran and Ritter (1995) that managers tend to issue equity in order to exploit stock overpricing. Since information uncertainty increases the likelihood of mispricing, they presume a good window of opportunity when good stock performance is accompanied by noisy signals. The loadings on post-issue stock performance further confirm the mispricing interpretation that higher uncertainty issuers have more negative and significant coefficients of post-12 months of returns. The coefficient of post-issue returns is -0.33 (t-statistics -3.48) in the lowest uncertainty group, whereas the highest uncertainty group has a coefficient of -0.45 (t-statistics -4.91). Taking both the pre- and post-issue stock performance into account, the evidence suggests that the probability of equity issuance is more sensitive to the 'window of opportunity' when information uncertainty is high.

In addition, Rows 1 and 2 in Panels B and C report the sensitivity of equity issuance probability to the pre- and post-12 months of adjusted stock returns grouped by turnover ratio and the firm's age, respectively. The results show similar loading patterns and significance as the results in Panel A. From the lowest to highest turnover ratio groups, the coefficients on the previous 12 months of adjusted stock returns increase from 0.21 (t-statistics 3.66) to 0.51 (t-statistics 6.16), and the loadings on post-stock returns decrease from -0.32 (t-statistics -1.74) to -0.49 (t-statistics -4.10). In the youngest firm group (Row 5 in Panel C), the probability of equity issuance has a coefficient of 0.52 (t-statistics 12.69) on the previous 12 months of returns, whilst the oldest firms have a coefficient of 0.28 (t-statistics 8.73). The evidence using all three proxies of information uncertainty gives a consistent implication that, when firms have a higher level of information uncertainty, they are more likely to time the market to issue equity. The evidence here supports the hypothesis that stock misvaluation is associated with information uncertainty, and managers tend to issue equity when the underlying stock is overpriced.

In the logistic regression, several control variables such as the firm's assets, z-score, book leverage, and tangibility were included. The firm's assets are shown in a log of the firm's assets value adjusted by the 2001-based CPI index. The loadings on firm assets and book leverage are all negatively significant, which is consistent with Frank and Goyal (2003)Frank et al.'s (2003) empirical findings. Interestingly, no correlation was found between the Z-score and the probability of equity issuance. Since the Z-score captures the bankruptcy likelihood of the underlying firms, one may expect that firms with a higher Z-score would depend more on equity financing rather than issuing debt (Altman (1968)). Although the Z-score has insignificant coefficients on the probability of equity issuance in this study, it is reasonable, as firm size, book leverage, and tangibility, which all measure the likelihood of bankruptcy, were included.

In short, the logistic regression on equity issuance probability amongst industry firm groups partitioned by the information uncertainty level is consistent with the results in Section 5.4.3. Information uncertainty and market valuation has an interactive effect on SEO issuances. Firms with a higher valuation uncertainty level are more sensitive to stock market valuation to make equity financing decisions.

5.4.5 Announcement Effect Around Seos Issuance Partitioned By Information Uncertainty Proxies

Two days of cumulative abnormal returns (CARs)[2] around the SEOs announcement dates were used to test the hypothesis that information uncertainty is associated with stock mispricing in equity issuance. The abnormal returns are the individual stock returns adjusted by the CRSP value-weighted index:

$$AR_{i,t} = R_{i,t} - MR_t \tag{5.4}$$

where $R_{i,t}$ is individual firm i in date t, and MR_t is the CRSP value-weighted index return on day t. The abnormal returns from two days before the announcement date to two days after were then summed. The CARs of each SEO issuer is calculated as follows:

$$CAR_i = \sum_{t-2}^{t+2} AR_{i,t} \tag{5.5}$$

Table 5.6 reports the two-day CARs of SEOs issuers partitioned by the information uncertainty proxies. In Column 1, the average announcement returns gradually decrease from the lowest IVOL groups (Row 1) to the highest IVOL group. The highest IVOL group has significant -2.95 percent CARs (t-statistics -9.98), which is three times higher than the CARs in the lowest uncertainty group (-0.94% with t-statistics -4.35). The SEO issuers partitioned by turnover ratio and firm age

[2] CARs were also tested in different windows, including (-1,+1), (-5, +5), (-10, +10), producing similar results.

perform the same pattern of the announcement effect. Higher information uncertainty is associated with more significant negative CARs around the announcement of SEOs. This confirms the hypothesis that information uncertainty is an indicator of stock mispricing.

Following Campbell et al. (1997), the daily CARs from -5 to +5 day were constructed around the SEOs announcement date. Chart 1 shows an obvious downward trend of abnormal stock returns of SEOs with high idiosyncratic volatility before the announcement date. In contrast, SEO issuers with low idiosyncratic volatility have much flatter and more positive announcement returns. The discrepancy of CARs between the high and low uncertainty group appears consistently in Chart 2 and 3. In Chart 2, the SEOs with a higher mean turnover ratio underperform those with a lower turnover ratio from three days before the announcement to the announcement date. In Chart 3, younger firms generate lower CARs than mature firms before the announcement dates of the SEOs. It is important to note that the short-run market reaction to younger SEO firms is lower than mature firms, which is inconsistent with the prediction of the pecking order theory. This theory suggests that young firms with more investment opportunities are subject to lower adverse selection costs, which contradicts the findings of this study.

In short, the announcement effect is more negative for SEO firms with higher information uncertainty. The evidence suggests that investors have a lower evaluation of SEOs when firms are subject to higher uncertainty. Given that firms with higher uncertainty tend to have a greater probability of SEO issuance, the possible interpretation is that information uncertainty indicates greater stock mispricing.

5.5 Conclusion

This chapter investigated the role of information uncertainty in the firm's equity financing decisions. Idiosyncratic volatility, shares turnover ratio, and firm age were all used as proxies for information uncertainty. Most of the previous empirical tests of SEO issuance focus only on the issuers, whereas this study included all industry firms, both issuer and non-issuer, in the sample test. By comparing the characteristics of issuer and non-issuer, not only can one examine whether information uncertainty and stock valuation affect the SEO decisions, but one can also test to what extent these factors have a influence in terms of equity financing. Furthermore, one can hypothesise that information uncertainty is an indicator of the magnitude of stock mispricing; firms with higher information uncertainty are subject to greater misvaluation. To test this hypothesis, CARs were used for the short-run announcement effect of SEOs, and to examine the discrepancy of CARs amongst information uncertainty quantiles.

The empirical findings of this study can be concluded as follows. First, the market timing phenomenon of SEO issuance documented in the literature has been confirmed. Firms with a previous high market valuation and price run-ups tend to issue more SEOs than their counterparts. Firms with a future lower stock performance also have a higher probability of SEO issuance. Second, the probability of SEO issuance is positively related to information uncertainty. Hence, firms with higher idiosyncratic volatility, shares turnover ratio, and younger firm age tend to carry out more equity financing.

The empirical results from the double-sorted portfolios also show that the impact of information uncertainty on SEOs is persistent with control of the stock valuations. Thirdly, the short-run announcement effect is more significantly negative for SEO firms with higher information uncertainty. This supports the conjecture that information uncertainty serves as an indicator of investor sentiment, as higher information uncertainty reflects a more optimistic view of investors. Given that information uncertainty is positively associated with stock overpricing, the evidence suggests that the market timing behavior of SEOs is the result of market inefficiency, in that managers sell stocks to benefit from temporal stock overpricing.

Table 5.1: Sample Description and Median Information uncertainty Proxies of SEO Issuers

This table reports the sample distribution of SEOs in each year from 1970 to 2008. The number of SEO issues includes both pure primary offerings and combined offerings, but exclude pure secondary offerings. SEO proceeds are adjusted by CPI index based on year 2001. If a SEO is combined offerings, we only report the proceeds of primary offering in this issuance. MV is firm's market value at the end of last fiscal year. Asset is asset value previous fiscal year. Both market value and asset value are adjusted by CPI index based on year 2001. Turnover is average monthly trading shares volume divided by number of shares outstanding. Age is the number of years since the firm was firstly recorded in CRSP database upto the year in question. IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively.

Year	Number	Sum of Proceeds	Mean Proceeds	Median Proceeds Over MV	Median Proceeds Over Asset	Median Turnover	Median Age	Median IVOL
1970	33	2323.42	70.41	7.30%	10.18%	33.40%	4	2.64%
1971	77	4595.9	59.69	9.23%	10.83%	47.71%	5	2.41%
1972	146	5589.74	38.29	11.66%	13.68%	49.17%	1	2.21%
1973	27	1465.8	54.29	15.30%	15.12%	54.24%	1	2.81%
1974	16	1093.43	68.34	10.45%	9.91%	11.49%	2	2.54%
1975	26	3471.64	133.52	9.72%	8.54%	26.73%	3	2.33%
1976	54	6391.83	118.37	10.71%	7.97%	31.36%	5	2.02%
1977	25	2665.28	106.61	13.04%	10.08%	27.78%	5	2.00%
1978	55	1354.73	24.63	13.16%	11.49%	57.87%	6	2.34%
1979	57	1668.91	29.28	12.88%	15.87%	60.73%	7	2.44%
1980	168	6928.16	41.24	12.68%	22.35%	70.71%	8	2.83%
1981	172	7844.78	45.61	18.16%	23.43%	46.15%	6	2.76%

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Table 5.1 continued from previous page

Year	Number	Sum of Proceeds	Mean Proceeds	Median Proceeds Over MV	Median Proceeds Over Asset	Median Turnover	Median Age	Median IVOL
1982	136	6732.89	49.51	11.92%	18.34%	87.83%	5	2.54%
1983	400	18808.87	47.02	15.31%	20.52%	77.14%	11	2.63%
1984	74	2124.18	28.71	16.13%	18.51%	58.81%	5	2.32%
1985	136	5250.61	38.61	14.22%	21.42%	92.68%	5	2.50%
1986	146	8270.59	56.65	15.64%	18.61%	94.44%	4	2.87%
1987	131	8731.33	66.65	24.14%	24.51%	102.05%	5	3.45%
1988	56	2139.68	38.21	17.00%	14.29%	70.12%	4	2.45%
1989	96	3350.88	34.91	16.70%	26.02%	117.77%	4	2.83%
1990	87	4074.88	46.84	17.96%	21.17%	100.48%	6	3.31%
1991	248	19055.7	76.84	14.36%	24.57%	138.05%	6	3.44%
1992	213	13713.92	64.38	15.33%	22.45%	117.19%	6	3.37%
1993	287	13209.14	46.02	16.43%	25.27%	129.42%	4	3.46%
1994	202	11637.4	57.61	15.37%	22.47%	126.11%	4	3.18%
1995	277	20129.22	72.67	15.59%	32.79%	170.16%	3	3.41%
1996	338	24349.44	72.04	16.70%	33.97%	158.52%	4	3.77%
1997	269	18434.74	68.53	15.35%	26.51%	163.08%	4	3.37%
1998	180	17766.56	98.7	15.47%	22.17%	147.55%	3	3.86%
1999	195	28001.7	143.6	10.76%	28.63%	242.21%	4	4.61%
2000	173	33660.59	194.57	17.69%	37.05%	287.44%	4	6.34%
2001	94	12852.17	136.73	11.94%	18.17%	207.01%	6	4.11%
2002	92	10434.96	113.42	16.49%	12.21%	160.55%	9	3.14%
2003	111	11811.97	106.41	10.29%	17.99%	173.17%	7	3.39%
2004	76	6713.55	88.34	13.34%	12.49%	168.09%	11	2.60%
2005	73	7480.92	102.48	11.28%	19.07%	178.11%	11	2.39%

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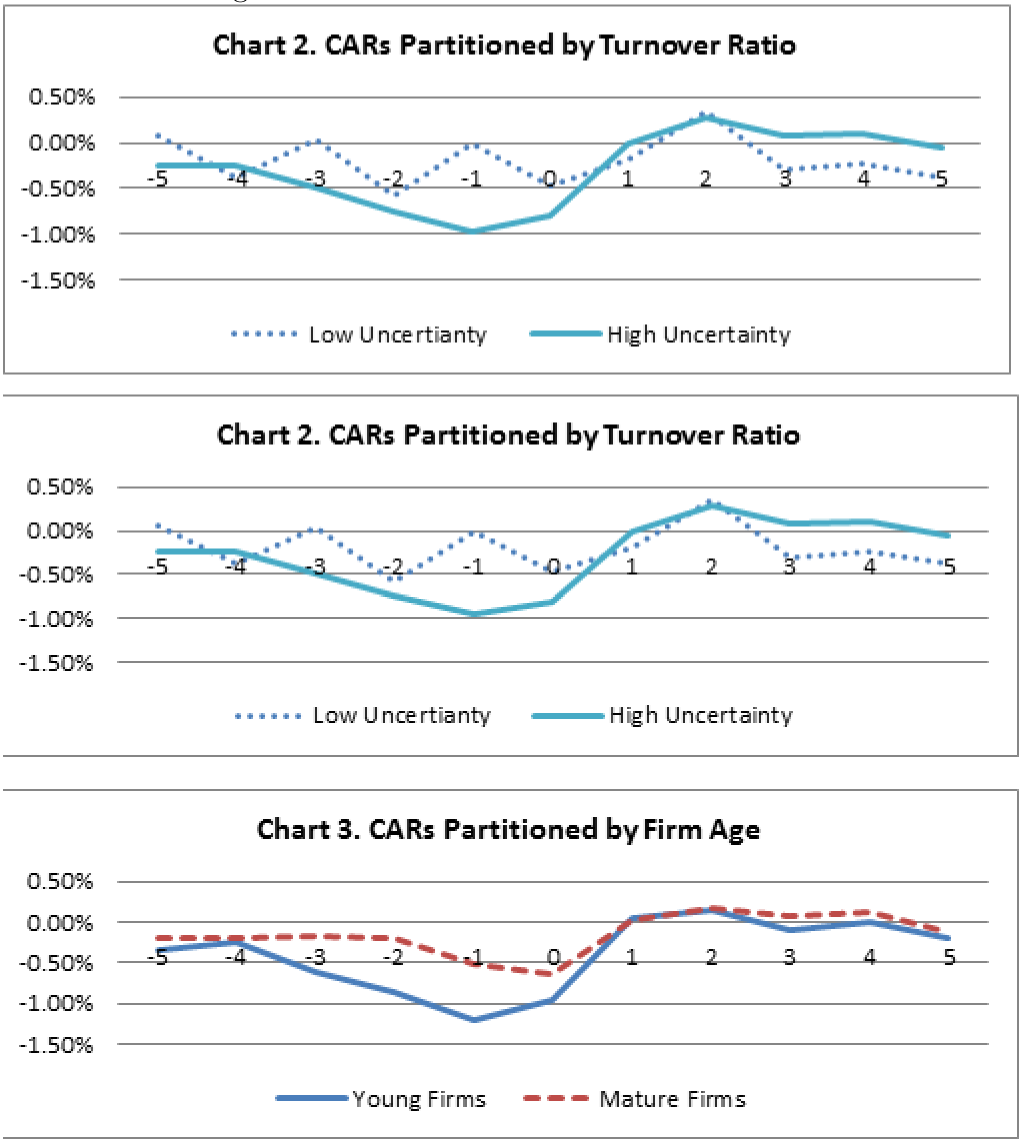
Table 5.1 continued from previous page								
Year	Number	Sum of Proceeds	Mean Proceeds	Median Proceeds Over MV	Median Proceeds Over Asset	Median Turnover	Median Age	Median IVOL
2006	62	5150.03	83.07	11.61%	16.13%	165.75%	9	2.69%
2007	90	9167.22	101.86	14.43%	18.89%	212.36%	5	3.06%
2008	36	3872.41	107.57	19.90%	17.41%	243.76%	7	5.25%

Figure 5.1: CARs around SEOs announcement date



This figure shows the abnormal returns of SEO issuers 5 days around announcement date. We partitioned our sample issuers into two subsamples according to information uncertainty level. Chart 1 shows CARs of firms with the highest and lowest idiosyncratic volatility. Chart 2 shows CARs with highest and lowest turnover ratio. Chart 3 shows the CARs of young and mature firms. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively.

Table 5.2: Number and Probability of SEOs, Proceeds, Firm Characteristics of Industry Firms Sorted by Market valuation, Prior and Post Abnormal returns

This table reports the sample distribution partitioned by market valuation, prior and post adjusted stock returns of SEO issuers. Market-to-book ratio (MTBV) is firm's market value divided by at the end of last fiscal year. Prior and post returns are raw stock returns adjusted by CRSP value-weighted index returns. SEO proceeds are adjusted by CPI index based on year 2001. . Turnover is average monthly trading shares volume divided by number of shares outstanding. Age is the number of years since the firm was firstly recorded in CRSP database upto the year in question. IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. Probability of an issue in a given year is the number of SEO issuers divided by the number of industry firms in the given year. In panel A, the sample of SEOs is partitioned by market-to-book ratio in each year into 5 quantiles. In panel B to G, the SEOs are partitioned by prior and post 12, 24 and 36 months' stock performance into 8 groups. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively.

Panel A. Market-to-Book Ratio								
all	5138	1.59	26.01	100.00%	2.96%	8	0.51	3.61%
Quintile1(LOW)	253	0.54	28.5	5.93%	3.13%	9	0.25	0.89%
Quintile2	603	1.01	28.51	13.80%	2.75%	10	0.39	2.12%

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Table 5.2 continue from previous page

	Number MTBV	Median Proceeds	Median Of Total Proceeds	Percent IVOL	Median AGE	Median Turnover	Median of An issue in A given year	Probability
Quintile3	1112	1.59	25.36	22.15%	2.71%	10	0.54	3.90%
Quintile4	1547	2.58	24.75	27.71%	2.82%	8	0.72	5.43%
Quintile5(HIGH)	1623	5.71	26.45	30.42%	3.51%	5	0.93	5.69%
Panel B. Previous 12-month Adjusted Stock Return								
$RET > -75\%$	51	1.34	31	0.88%	4.43%	8	0.73	1.40%
$-50\% > RET > -75\%$	173	1.26	24.95	4.01%	3.24%	10	0.54	1.66%
$-25\% > RET > -50\%$	397	1.22	31.48	10.51%	2.41%	13	0.45	1.88%
$0 > RET > -25\%$	617	1.37	28.75	17.71%	2.20%	13	0.41	2.13%
$25\% > RET > 0$	645	1.53	34.25	20.69%	2.38%	11	0.43	2.84%
$50\% > RET > 25\%$	526	1.7	28.81	13.62%	2.67%	10	0.53	4.21%
$75\% > RET > 50\%$	381	1.88	27.6	10.32%	3.33%	9	0.67	5.94%
$RET > 75\%$	839	2.34	28.5	22.27%	6.21%	6	0.98	7.87%
Panel C. Previous 24-month Adjusted Stock Return								
$RET > -75\%$	188	1.18	25.22	5.78%	3.49%	10	0.55	1.55%
$-50\% > RET > -75\%$	233	1.2	36.17	7.91%	2.74%	12	0.47	1.82%
$-25\% > RET > -50\%$	317	1.21	31.05	9.51%	2.27%	14	0.41	1.92%

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Table 5.2 continue from previous page

	Number MTBV	Median Proceeds	Median Of Total Proceeds	Percent IVOL	Median AGE	Median Turnover	Median of An issue in A given year	Probability
$0 > RET > -25\%$	397	1.35	33.64	13.92%	2.10%	14	0.4	2.30%
$25\% > RET > 0$	368	1.54	37.22	14.39%	2.16%	14	0.42	2.69%
$50\% > RET > 25\%$	286	1.64	38.01	10.28%	2.29%	13	0.47	3.00%
$75\% > RET > 50\%$	215	1.73	31.94	7.73%	2.80%	10	0.52	3.42%
$RET > 75\%$	1002	2.13	26.3	30.47%	4.91%	8	0.78	5.81%
Panel D. Previous 36-month Adjusted Stock Return								
$RET > -75\%$	285	1.14	31.25	10.17%	4.31%	10	0.5	1.56%
$-50\% > RET > -75\%$	201	1.17	39	7.71%	3.03%	12	0.42	1.78%
$-25\% > RET > -50\%$	247	1.24	41.74	9.80%	2.48%	14	0.39	2.00%
$0 > RET > -25\%$	236	1.36	35.27	10.17%	2.19%	15	0.4	2.08%
$25\% > RET > 0$	224	1.49	34.68	9.27%	2.09%	15	0.41	2.32%
$50\% > RET > 25\%$	211	1.62	38.06	9.80%	2.06%	15	0.46	2.90%
$75\% > RET > 50\%$	184	1.72	34.48	6.20%	2.14%	14	0.48	3.39%
$RET > 75\%$	966	2.06	27.43	36.90%	2.54%	12	0.71	4.84%
Panel E. Post 12-month Adjusted Stock Return								
$RET > -75\%$	371	2.59	28.5	6.64%	4.55%	4	0.88	6.30%

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Table 5.2 continue from previous page

	Number MTBV	Median Proceeds	Median Of Total Proceeds	Percent IVOL	Median AGE	Median Turnover	Median of An issue in A given year	Probability
$-50\% > RET > -75\%$	717	2.02	22.94	12.16%	3.82%	6	0.73	5.52%
$-25\% > RET > -50\%$	1086	1.65	24.27	20.82%	3.05%	8	0.57	4.45%
$0 > RET > -25\%$	1042	1.54	30.04	24.25%	2.47%	11	0.45	3.29%
$25\% > RET > 0$	722	1.48	32.84	18.46%	2.36%	11	0.43	2.92%
$50\% > RET > 25\%$	421	1.43	28.95	8.39%	2.64%	10	0.46	3.06%
$75\% > RET > 50\%$	221	1.43	28.46	4.22%	3.04%	8	0.5	3.10%
$RET > 75\%$	307	1.44	22.5	5.07%	3.85%	7	0.54	2.59%
Panel F. Post 24-month Adjusted Stock Return								
$RET > -75\%$	1120	2.25	23	17.37%	3.80%	5	0.73	6.97%
$-50\% > RET > -75\%$	776	1.85	27.45	19.54%	3.18%	8	0.61	5.17%
$-25\% > RET > -50\%$	726	1.63	24.99	16.18%	2.69%	10	0.51	3.85%
$0 > RET > -25\%$	572	1.55	32.55	14.62%	2.37%	11	0.44	3.00%
$25\% > RET > 0$	435	1.52	34.41	12.21%	2.29%	12	0.42	2.89%
$50\% > RET > 25\%$	280	1.44	27.45	8.20%	2.40%	11	0.43	2.73%
$75\% > RET > 50\%$	182	1.37	29.64	4.50%	2.61%	10	0.42	2.76%

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Table 5.2 continue from previous page

	Number MTBV	Median Proceeds	Median Of Total Proceeds	Percent IVOL	Median AGE	Median Turnover	Median of An issue in A given year	Probability
$RET > 75\%$	436	1.29	23.58	7.39%	3.29%	8	0.45	2.46%
Panel G. Post 36-month Adjusted Stock Return								
$RET > -75\%$	1535	2.09	22.43	27.18%	3.48%	6	0.65	6.78%
$-50\% > RET > -75\%$	614	1.8	31.26	17.73%	2.86%	8	0.55	4.65%
$-25\% > RET > -50\%$	485	1.64	27.31	12.66%	2.53%	10	0.46	3.49%
$0 > RET > -25\%$	359	1.55	34.41	10.97%	2.33%	11	0.43	2.88%
$25\% > RET > 0$	307	1.51	33.5	9.91%	2.29%	12	0.41	2.96%
$50\% > RET > 25\%$	180	1.45	31.32	4.63%	2.36%	12	0.41	2.34%
$75\% > RET > 50\%$	159	1.41	31.5	5.12%	2.50%	10	0.41	2.79%
$RET > 75\%$	482	1.23	27.59	11.81%	3.09%	8	0.42	2.40%

Table 5.3: Number and Probability of Industry Firms Sorted by Information uncertainty and Prior 12-month Abnormal Returns

This table reports the number and probability of equity issuance (in parentheses) among industry firms partitioned by information uncertainty proxies and prior 12-month stock performance. All industry firm-year observations are firstly sorted by the information uncertainty proxy into 5 groups within each calendar year. Then in each subgroup, firm-year observations are further partitioned by prior 12-month stock returns adjusted by CRSP value-weighted stock returns into 8 groups. We use idiosyncratic volatility (IVOL), turnover and firm age as proxies of information uncertainty. Turnover is average monthly trading shares volume divided by number of shares outstanding. Age is the number of years since the firm was firstly recorded in CRSP database upto the year in question. IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively.

	Prior 12-month Abnormal Returns								
IU	$> -75\%$	$-50\% - -75\%$	$-25\% - -50\%$	$0 - -25\%$	$25\% - 0$	$50\% - 25\%$	$75\% - 50\%$	$> 75\%$	ALL
IVOL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	1	0	26	102	138	79	46	28	420
	(4.76%)	(0.00%)	(0.93%)	(1.15%)	(1.66%)	(2.21%)	(3.86%)	(3.81%)	(1.63%)
2	25	74	70	57	43	31	23	114	437

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	Prior 12-month Abnormal Returns								
IU	> −75%	−50% − −75%	−25% − −50%	0 − −25%	25% − 0	50% − 25%	75% − 50%	> 75%	ALL
	(0.96%)	(1.63%)	(1.47%)	(1.68%)	(2.22%)	(2.65%)	(3.21%)	(5.34%)	(2.06%)
3	0	9	73	157	200	167	116	167	889
	(0.00%)	(1.03%)	(1.82%)	(2.28%)	(3.57%)	(4.87%)	(6.62%)	(8.38%)	(3.61%)
4	7	39	99	160	158	143	121	257	1000
	(2.69%)	(2.16%)	(2.11%)	(2.98%)	(4.01%)	(5.75%)	(7.75%)	(8.85%)	(4.34%)
High	18	51	129	141	106	106	75	273	883
	(2.56%)	(1.75%)	(2.66%)	(3.17%)	(3.63%)	(5.75%)	(6.27%)	(9.42%)	(4.06%)
Turnover	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	2	5	12	31	32	15	8	11	116
	(0.45%)	(0.30%)	(0.27%)	(0.45%)	(0.62%)	(0.70%)	(0.93%)	(1.33%)	(0.52%)
2	4	15	27	54	43	50	29	29	251
	(0.74%)	(0.75%)	(0.62%)	(0.87%)	(0.93%)	(2.12%)	(2.71%)	(2.29%)	(1.12%)
3	5	13	73	115	138	100	65	94	603
	(0.70%)	(0.59%)	(1.74%)	(2.07%)	(3.24%)	(4.43%)	(6.09%)	(5.77%)	(2.75%)
4	7	49	111	167	175	163	95	205	972
	(0.73%)	(2.22%)	(2.96%)	(3.58%)	(4.62%)	(7.15%)	(7.29%)	(9.41%)	(4.60%)
High	31	86	164	222	227	166	153	419	1468

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Table 5.3 continue from previous page

	Prior 12-month Abnormal Returns								
IU	$> -75\%$	$-50\% - -75\%$	$-25\% - -50\%$	$0 - -25\%$	$25\% - 0$	$50\% - 25\%$	$75\% - 50\%$	$> 75\%$	ALL
	(3.51%)	(4.47%)	(5.11%)	(5.48%)	(6.57%)	(6.62%)	(9.70%)	(11.02%)	(6.86%)
AGE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	6	19	75	111	140	84	63	84	582
	(2.19%)	(1.36%)	(1.56%)	(1.20%)	(1.86%)	(2.47%)	(4.60%)	(5.20%)	(1.96%)
2	0	14	30	35	63	50	32	58	282
	(0.00%)	(1.44%)	(1.27%)	(1.03%)	(2.34%)	(3.41%)	(4.42%)	(5.58%)	(2.19%)
3	7	26	49	107	103	98	71	159	620
	(1.39%)	(1.42%)	(1.23%)	(2.06%)	(2.47%)	(4.00%)	(5.46%)	(7.64%)	(2.88%)
4	18	55	119	182	175	161	119	300	1129
	(1.42%)	(1.53%)	(1.86%)	(2.43%)	(3.13%)	(4.59%)	(5.82%)	(7.54%)	(3.33%)
High	20	59	124	182	164	133	96	238	1016
	(1.47%)	(2.25%)	(3.50%)	(5.11%)	(6.05%)	(7.96%)	(9.83%)	(12.22%)	(5.52%)

Table 5.5: Logistic regression on SEO decision within portfolios partitioned by information uncertainty level

This table reports the logistic regression of SEOs partitioned by information uncertainty level. We use idiosyncratic volatility, turnover and firm age as proxies for information uncertainty. IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. Turnover is average monthly trading shares volume divided by number of shares outstanding. Age is the reciprocal of number of years since the firm was firstly recorded in CRSP database up to the year in question.$SEO\ Dummy = \alpha_1 IVOL + \alpha_2 TurnOver + \alpha_3 1/AGE + \beta_1 Prior12AR + \beta_2 Post12AR + \gamma_1 LogAsset + \gamma_2 Z - Score + \gamma_3 BookLeverage + \gamma_4 Tangibility + Constant$ Where prior12AR and Post12AR are prior and post 12 month adjusted stock returns by CRSP value-weighted stock index. Log Asset is the natural logarithm of firm's book asset value in the previous fiscal year end. Book leverage is long term debt minus the debt within one year due divided by book asset value. Tangibility is the tangible asset divided by total asset. Altman's Z-score is calculated by $Z = 0.012\frac{WC}{TA} + 0.014\frac{RE}{TA} + 0.033\frac{EBIT}{TA} + 0.006\frac{MV}{BookLiability} + 0.999\frac{Sales}{TA}$ where WC, TA, RE, MV are working capital, total asset, retained earnings and market value of equity, respectively. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively. t-statistics is reported in parenthesis and ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

	Low Uncertainty	(2)	(3)	(4)	High Uncertainty
Panel A IVOL					
pre12vwadj	0.20***	0.36***	0.26***	0.50***	0.71***
	(4.54)	(8.87)	(8.24)	(8.39)	(10.06)
post12vwadj	-0.33***	-0.39***	-0.41***	-0.53***	-0.45***
	(-3.48)	(-3.91)	(-3.56)	(-3.65)	(-4.91)
Log Asset	-0.30***	-0.13***	-0.20***	-0.08***	-0.14***
	(-5.68)	(-3.91)	(-5.03)	(-2.59)	(-4.43)

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Table 5.5continue from previous page					
	Low Uncertainty	(2)	(3)	(4)	High Uncertainty
Z-score	0	0	0	0	0
	(-0.24)	(-0.77)	(0.47)	(-0.33)	(-0.61)
Book Leverage	-1.82*	0.71**	-1.66***	0.16	-1.63***
	(-4.27)	(2.25)	(-4.71)	(0.57)	(-5.60)
Tangibility	-0.02	-1.08***	-0.08***	-0.33	-0.04
	(-0.05)	(-4.76)	(-2.8)	(-1.47)	(-0.16)
Constant	-4.57***	-4.79***	-3.96***	-3.79***	-3.43***
	(-21.12)	(-22.49)	(-21.69)	(-21.30)	(-21.38)
$Pseudo - R^2$	0.05	0.03	0.05	0.06	0.04
Panel B Turnover					
pre12vwadj	0.21***	0.33***	0.34***	0.35***	0.51***
	(3.66)	(4.43)	(5.56)	(6.02)	(6.16)
post12vwadj	-0.32*	-0.27**	-0.37***	-0.25***	-0.49***
	(-1.74)	(-2.21)	(-2.42)	(-4.04)	(-4.10)
Log Asset	-0.22***	-0.05	-0.02	-0.01	-0.02
	(-3.62)	(-1.54)	(-0.68)	(-0.59)	(-1.08)
Z-score	0	0	0	0	0
	(-0.25)	(-0.38)	(-1.02)	(0.87)	(-0.04)
Book Leverage	0.63	0.07	-0.34	-0.3	-1.27***
	(0.94)	(0.18)	(-1.00)	(-1.10)	(-5.89)
Tangibility	0.08	0.57*	0.91***	0.12	0.68***
	(0.14)	(1.77)	(3.49)	(0.54)	(3.74)
Constant	-6.26***	-4.33***	-3.73***	-3.07***	-2.19***
	(-16.66)	(-20.85)	(-22.14)	(-21.94)	(-19.48)
$Pseudo - R^2$	0.07	0.05	0.05	0.03	0.04
Panel C. 1/AGE					

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Table 5.5continue from previous page					
	Low Uncertainty	(2)	(3)	(4)	High Uncertainty
pre12vwadj	0.28	0.33	0.28	0.45	0.52
	(8.73)	(9.00)	(8.74)	(11.72)	(12.69)
post12vwadj	-0.44	-0.46	-0.61	-0.2	-0.45
	(-3.83)	(-3.28)	(-6.34)	(-3.93)	(-7.23)
Log Asset	-0.09	-0.16	-0.15	-0.21	-0.2
	(-3.88)	(-4.50)	(-6.54)	(-11.30)	(-11.23)
Z-score	0	0	0	0	0
	(-0.41)	(-1.50)	(-0.84)	(-0.32)	(0.13)
Book Leverage	1.22	0.2	-0.52	-1.48	-1.36
	(4.43)	(0.56)	(-2.13)	(-7.49)	(-7.34)
Tangibility	-0.83	-0.75	-0.61	-0.08	-0.24
	(-4.06)	(-2.65)	(-3.18)	(-0.50)	(-1.60)
Constant	-5.09	-4.96	-4.38	-3.42	-4.07
	-30.55	-23.46	-32.3	-35.89	-42.74
$Pseudo-R^2$	0.03	0.06	0.04	0.04	0.05

Table 5.4: Logistic Regression of SEO Decision on Information uncertainty, Market Valuation, and Firm's Characteristics

This table reports the logistic regression of SEOs on information uncertainty, market valuation and other control variables as following equation.$SEO\ Dummy = \alpha_1 IVOL + \alpha_2 TurnOver + \alpha_3 1/AGE + \beta_1 Prior12AR + \beta_2 Post12AR + \gamma_1 LogAsset + \gamma_2 Z - Score + \gamma_3 BookLeverage + \gamma_4 Tangibility + Constant$ where IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. Turnover is average monthly trading shares volume divided by number of shares outstanding. 1/Age is the reciprocal of number of years since the firm was firstly recorded in CRSP database up to the year in question. Prior12AR and Post12AR are prior and post 12 month adjusted stock returns by CRSP value-weighted stock index. Log Asset is the natural logarithm of firm's book asset value in the previous fiscal year end. Book leverage is long term debt minus the debt within one year due divided by book asset value. Tangibility is the tangible asset divided by total asset. Altman's Z-score is calculated by$Z = 0.012\frac{WC}{TA} + 0.014\frac{RE}{TA} + 0.033\frac{EBIT}{TA} + 0.006\frac{MV}{BookLiability} + 0.999\frac{Sales}{TA}$ where WC, TA, RE, MV are working capital, total asset, retained earnings and market value of equity, respectively. SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively. t-statistics is reported in parenthesis and ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.

	(1)	(2)	(3)	(4)
IVOL	13.7***			8.56***
	(14.8)			(6.96)
Turnover		0.15***		0.14***
		(16.60)		(15.11)
1/AGE			4.84***	4.95***
			(27.55)	(26.91)
Prior 12 Month AR	0.33***	0.27***	0.33***	0.28***
	(23.11)	(17.99)	(22.75)	(18.22)
Post 12 Month AR	-0.41***	-0.36***	-0.37***	-0.32***
	(-11.30)	(-9.91)	(-10.61)	(-8.91)
Log Asset	-0.08***	-0.05***	-0.16***	-0.09***
	(-8.42)	(-5.68)	(-17.13)	(-8.24)
Z-Score	0	0	0	0
	(0.17)	(-0.36)	(-0.23)	(-0.59)
Book Leverage	0.66***	0.53***	0.78***	0.58***
	(6.35)	(4.90)	(7.60)	(5.38)
Tangibility	-0.23***	-0.43***	-0.29***	-0.45***
	(-2.75)	(-5.00)	(-3.45)	(-5.25)
Constant	-3.85	-3.91***	-4.84***	-4.48***
	(-52.76)	(-71.64)	(-72.20)	(-49.70)
$Pseudo - R^2$	0.03	0.04	0.03	0.06

Table 5.6: CARs 2-day around SEO issue date

This table reports the cumulative abnormal returns (CARs) around SEO announcement date partitioned by information uncertainty. We use idiosyncratic volatility, turnover and firm age as proxies for information uncertainty. IVOL (idiosyncratic volatility) is the residual return volatility, calculated by regression daily returns on Fama-French three factor model. Turnover is average monthly trading shares volume divided by number of shares outstanding. Age is the reciprocal of number of years since the firm was firstly recorded in CRSP database up to the year in question. The abnormal returns are the individual stock returns adjusted by CRSP value weighted index.

$$AR_{i,t} = R_{i,t} - MR_t \tag{5.6}$$

Where Ri,t is individual firm i in date t, and MRt is CRSP value weighted index return on day t. we then sum up the abnormal returns from two days before the announcement date to two days after. The CARs of each SEO issuer is calculated as following:

$$CAR_i = \sum_{t-2}^{t+2} AR_{i,t} \tag{5.7}$$

SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively. t-statistics is reported in parenthesis followed by number of SEOs. ***, **, * indicate the significance at one, five and ten percent confidence level, respectively.SEO issues are obtained from Thomason one banker (SDC) database. Accounting and stock data is downloaded from COMPUSTAT and CRSP, respectively.

	IVOL	TURNOVER	1/AGE
low	-0.94%***	-3.08%***	-1.17%***
	(-4.35)	(-3.31)	(-4.37)
	524	225	634
2	-4.40%***	-2.34%***	-1.38%***
	(-6.54)	(-6.19)	(-2.81)
	764	562	300
3	-1.44%***	-2.35%***	-2.66%***
	(-7.90)	(-8.15)	(-8.06)
	1158	1006	659
4	-2.33%***	-2.29%***	-2.56%***
	(-11.21)	(-9.72)	(-9.41)
	1475	1417	1168
high	-2.95%***	-2.21%***	-2.83%***
	(-9.98)	(-7.51)	(-11.39)
	1373	1390	2545

Chapter 6

Conclusions

6.0.1 Summary and Conclusion

This thesis has examined the role of information uncertainty in determining the stock price performance and affecting the equity financing behavioral. The experimental studies on investor's decision making under poor/imprecise information have inclusively shown the significant influence of information uncertainty and universality of ambiguity aversion among investors. The opinions among researchers, however, have not reached an agreement about how information uncertainty would affect the stock pricing and, therefore, require more empirical evidence to shed light on this issue. We adopt a set of proxies for information uncertainty and apply the empirical tests on the influence of these proxies in time series and cross sectional stock performance, as well as the market timing behavioral of seasoned equity offerings. The evidence suggests that information uncertainty can amplify the investor's psychological biases and increase the extent of stock mispricing. The impact of information uncertainty appears to be universal across the international markets, and depends mutually on market environment and firm's growth options. The positive relationship between information uncertainty and misvaluation documented in our study helps to explain the market timing behavioral of seasoned equity offerings and contributes to the behavioral corporate finance.

Chapter 3 examines the role of information uncertainty in determining future stock returns in the context of underreaction anomaly. The results show that both earning momentum effect and price momentum effect are more significant among stocks with high information uncertainty. Furthermore, stock returns between high and low information uncertainty portfolios are significantly larger following bad news compared to those following good news, indicating a positive relationship between ambiguity aversion and stock overpricing.

This result is consistent with the predictions of behavioral finance that investors are subject to larger psychological biases when the information of underlying company is hard to interpret or evaluate (Hirshleifer, 2001; Daniel et al, 1998, 2001). The evidence is also consistent with the literature of limited arbitrage which suggests that the cost of arbitrage is parallel with the noise trading behaviour and ambiguous signals/feedbacks to the market (DeLong, et al, 1990; Shleifer and Vishny, 1997). Moreover, we find no evidence of discount effect on uncertainty, which is in contrast to the prediction of incomplete market hypothesis (Merton, 1987).

In Chapter 4, we empirically test the interaction effect between information uncertainty and firm's growth options on cross sectional stock returns across the global markets. We find that the growth options can explain the varying levels of information uncertainty among stocks, which confirms our conjecture that the uncertainty of future earnings forms the corresponding value ambiguity. We also find a positive correlation between value ambiguity and information asymmetry. These findings show a new insight that information uncertainty is jointly determined by endogenous volatility of profitability and exogenous level of information asymmetry. The confounding empirical evidence in the past literature may be the results of conflicting effect of endogenous and exogenous attributes of uncertainty. The Merton's (1987) incomplete market hypothesis and Epstein and Schneider's (2008) imprecise information model consider the uncertainty effect from the angle of exogenous uncertainty aversion and sharing among investors, and predict the stock price discount for information uncertainty. On the other hand, Pastor and Veronesi (2003, 2008) analyze the endogenous uncertainty stemming from the volatility of future earnings. Their model suggests a stock price premium for bearing uncertainty of future profitability according to Jensen's inequality.

Our empirical work builds a bridge between these two opposite interpretation, and shows the joint effect of endogenous and exogenous attributes on information uncertainty. The results further indicate that when controlling information asymmetry, the information uncertainty predicts negative future returns, which is consistent with Pastor and Veronesi's (2003) premium hypothesis. We also find that the portfolios buying stocks with high uncertainty and shorting stocks with low uncertainty generate more significantly negative returns in mature markets. Since the emerging markets are commonly subject to poor market developments, the impact of information asymmetry should be more strong in these market and offset the premium effect of uncertainty. The results of portfolio analysis are further confirmed by cross-sectional regressions and robustness tests.

The chapter 5 addresses the question that how information uncertainty affects corporate financing decisions, and analyzes the behavior of seasoned equity offerings to answer this question. The results indicate that firms with greater information uncertainty tend to issue more SEOs than firms with low information uncertainty. The probability of SEOs issuance is positively associated with information uncertainty, even controlling the prior or post stock valuation. Our findings confirm the market timing behavioral of equity issuance documented in the literature (Loughran and Ritter, 1995, 1997). Moreover, as suggested by behavioral corporate finance theory, stock market overpricing is one major motivation for equity financing. Our evidence is consistent with this point of view that firms with higher prior stock valuation and lower post performance have a greater probability of equity issuance. This study links the literature of behavioral corporate finance and information uncertainty research, and provides value ambiguity being another indicator of stock mispricing. Using stock price as proxy for stock valuation is under critique from neoclassic finance theory. Loughran and Ritter (2000) and Eckbo, Masulis, and Norli (2000) suggest that the estimation of mispricing from stock price performance would be improper for equity financing research, as the issuers' risk bearing varies during the offering process. Our study provides three proxies unrelated to stock price and supports the mispricing interpretation on market timing behavior.

6.0.2 Implication, Limitation And Potential Future Research

This thesis has implications for the investors as well as corporate managers. First, it shows that the stock prices would suffer more misvaluation when the recent news to the market is hard to interpret. Therefore, investors should avoid investing in the underlying firms until the uncertainty is resolved by new information which has more precise indications of firm's fundamental value. Also, this work suggests the increased arbitrage risk for institutional investors who may have better knowledge of firm's value. The misvaluation or arbitrage opportunity of stocks with information uncertainty is related to the investor's psychological biases. As Hirshleifer (2001) argues, the noise traders who beliefs in their personal evaluation could 'arbitrage away the arbitrageur' even without the knowledge of firm's true value. As long as the force of investors' biases is strong enough to impact the stock price, arbitrageurs should be cautioned to choose the right time of trading against the misvaluation. A proper indicator for arbitrageur to assess the misvaluation persistence could be idiosyncratic volatility or dispersions among analyst forecasts. Moreover, corporate managers should be aware that information uncertainty imposes the cost of equity issuance in addition to adverse selection cost. The announcement effect is more negative for firms with larger information uncertainty which may offset the benefits from selling overpriced stocks. Previous research shows that adverse selection cost could be lowered by disclosing more information to the market. However, information uncertainty could not be efficiently mitigated from the corporate side as it partially stems from the nature of business.

This thesis, inevitably, has some limitations and requires further research on information uncertainty. Our study adopts several proxies for information uncertainty because there is no one universally agreed proxy in the literature. Each proxy we use may capture other firm's characteristics. For example, the idiosyncratic volatility is the main proxy in all three empirical chapters. This proxy has been widely used to measure price synchronicity in the study of corporate governance. Although each proxy alone may be questioned for appropriation, they jointly would undoubtedly provide enough explanation power to indicate the influence of information uncertainty. Also, we are aware that in the international study, we use only two proxies, less than proxies used in chapters 3 and 5. The reason is that the data of international stock market in DataStream is limited to form other proxies, and some proxies, such as firm ages, are not comparable across the markets. Surely, with more understanding on the characteristics of information uncertainty, we may find one proper and unique proxy to test this issue in the future.

Another potential limitation in this study is that we carry out the empirical tests in different markets. Chapter 3 uses UK stock market to test the influence of information uncertainty in stock price continuation, while in Chapter 5 we provide the empirical evidence based on US equity market. Both of these two markets are mature and well developed that the difference between them would be trivial. The reason for using US market in Chapter 5 is simply because the equity market has more issuance volume that gives us greater statistics power. We have no doubt that the impact of information uncertainty would be similar in the UK as in the US.

Along the line of this study, future research could use the proxies in this study and test more specific misvaluation from investors' biases. Our study provides the empirical evidence that the information uncertainty amplifies the effect of psychological biases, but does not focus on any specific type of psychological biases. For example, the research on retail investors could use information uncertainty as an indicator to distinguish the investors' biases and rational behavior. If the trading of retail investors is motivated by overconfidence or narrow framing, then one should observe more such trading behavior on the firms with higher information uncertainty.

Secondly, We have not explicitly distinguish information uncertainty and information asymmetry. A theoretical study in the context of cognitive process as well as rational reaction is required to clarify the different impacts of information uncertainty and asymmetry. The potential in this orientation is considerable in both expanding our understanding and practicing in real market. More disclosure of information would certainty lower the information asymmetry, while on the other hand, it may fill the market up with noise that increase the estimation costs and risks.

Furthermore, our research shows corporate managers tend to issue more equity when previous information uncertainty is high and market valuation is high. The behavioral corporate finance suggests that the market timing phenomenon could be due to either irrational market traders, or irrational managers' decisions. By comparing the usage of SEO proceeds between issuers with high and low information uncertainty, one may tell whether the market timing behavior can be explained by irrational managers or not. If managers observe the overpricing and knowingly sell overpriced stocks, they should not use the proceeds to do investment because the true cost of equity is high. On the other hand, if managers believe that high market valuation indicates the low cost of equity or good corporate outlook, they may overinvest the proceeds to non-profitable opportunities.

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