Essays on the Role of Informed Trading in Stock Markets

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Declaration

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Essays on the Role of Informed Trading in Stock Markets

Abstract

The first essay, Chapter 3, shows that uninformed investors require a price discount to hold the stock because they perceive a new information uncertainty risk when short-sale constraints are binding and informed trading is absent. Stock prices become less informative when short-sale constraints keep informed investors out of the market. The less informative prices create a new information uncertainty risk for uninformed investors because uninformed investors are unable to figure out the true value of the stock without knowing the private information of informed investors. The new information uncertainty risk effect becomes greater if stocks have greater information uncertainty, which reflects the convenience of learning fundamental news.

The second essay, Chapter 4, examines two special new information uncertainty risk effects by controlling for trading volume. When volume is large, uninformed investors observe high buying pressure but cannot distinguish noise demand from information-based buying. They confront this new information uncertainty risk and demand premium to buy stock. Thus, overvaluation caused by short-sale constraints is reduced. When volume is small, uninformed investors convince that informed investors have negative information but do not know how bad the information is. They will not hold the stock under this new information uncertainty risk and therefore future return will becomes worse.

The third essay, Chapter 5, studies the impact of informed trading to the momentum effect. It proposes that if momentum is a result of underreaction and if informed trading identifies stocks with underreaction, the presence of informed trading predicts future momentum effect. Consistently, the empirical results show that momentum effect arises when informed trading is present. Greater informed trading leads to greater momentum effect. Although information uncertainty is related to both informed trading and momentum, the identified relationship between informed trading and momentum is robust after controlling for uncertainty.

Keywords: informed trading; information uncertainty; short-sale constraints; trading volume; momentum.

Chapter 1

Introduction

This thesis contains three essays on the role of informed trading in stock markets. Informed trading is the trading behaviour of informed investors who trade on their superior information. Informed investors have superior information because they either have private information or have excellent skills to analyse public information. Informed trading is important because informed traders move prices towards the full informational efficiency, which, however, is not continuously attainable because at least information itself changes over time. Therefore, the influence of informed trading in financial market should not be neglected.

The first two essays, Chapter 3 and Chapter 4, consider a new information uncertainty risk as perceived by uninformed investors when (1) short-sale constraints are binding; and (2) informed trading is absent. This new information uncertainty risk is motivated by three theoretical papers: Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008). They study the asset pricing implications of short-sale constraints in an asymmetric information setting. In contrast to prior literature that focuses on the overvaluation effect of short-sale constraints, they suggest that asset price becomes less informative when informed investors are constrained by short-sale constraints. The less informative prices create a new information uncertainty risk for uninformed investors, since uninformed investors are unable to figure out the true value of the stock without knowing the private information of informed investors.

Specifically, Chapter 3 examines the general impact of the new information uncertainty risk on stock returns. That is, the new information uncertainty risk causes stock prices to decline when uninformed investors perceive the new information uncertainty risk because they are reluctant to hold the stock unless there is a price discount. Moreover, Chapter 3 further suggests the new information uncertainty risk effect can be affected by stock's information uncertainty condition, which reflects the convenience of learning the fundamental value of stock. Accordingly, the level of stock's information uncertainty is negatively related to the level of price's informative condition. Therefore, chapter 3 proposes three testable hypotheses. First, stocks will have lower future returns if the level of informed trading is lower and when short-sale constraints are binding. Second, when information uncertainty is high, the new information uncertainty risk effect presented in the first hypothesis is strong. When information uncertainty is low, this effect rarely arises. Third, when information uncertainty is low and short-sale constraints are not binding, this new information uncertainty risk effect will not emerge. All these hypotheses are confirmed by the empirical results.

Chapter 4, the second essay, further examines two special new information uncertainty risk effects. The three theoretical papers of Yuan (2006), Bai, Chang, and Wang (2006), and Marin and Olivier (2008) are actually focusing on two different kinds of new information uncertainty risk effect. In particular, short-sale constraints are likely to bind when prices are high in Yuan (2006), which captures the overvaluation situation. In this case, new uncertainty dampens the upward price movement because uninformed investors are reluctant to hold asset because they cannot distinguish high noise demand from information-based buying. Hence, the first kind of new information uncertainty risk reduces the level of overvaluation. By contrast, Marin and Olivier (2008) and Bai, Chang, and Wang (2006) argue that short-sale constraints are likely to bind when asset prices are low. Without a high noise demand in the market, uninformed investors can only infer that informed investors are in possession of bad news since otherwise informed buying activities can be observed. Uninformed investors become aware of a new information uncertainty risk as they could not find out how negative the information really is. Thus, the second kind of new information uncertainty risk exacerbates downward price movement as uninformed investors demand an information-disadvantage premium to hold the stock.

Chapter 4 confirms the two kinds of effects after controlling for trading volume. Firstly, the scenario in Yuan (2006) is captured by the high level of trading activities. Since short-sale constraints can create overvaluation, high level of trading activities combined with overvaluation represent high noise demand and buying pressure in the market. The empirical evidence shows that stock should have higher future return if the level of informed trading is lower when (1) the level of trading activities is high;

(2) short-sale constraints are binding. Secondly, the scenario suggested by Bai, Chang, and Wang (2006) and Marin and Olivier (2008) can be captured by the low level of trading activities. The low levels of trading activities and informed trading would convince uninformed investors that majority of investors hold downward beliefs and informed investors hold negative private information. This is because not only informed investors but also most of investors in the market stop buying stock. The empirical evidence also reports that stock will have lower future returns if the level of informed trading is lower and when (1) the level of trading activities is low; and (2) short-sale constraints are binding.

The third essay, Chapter 5, concentrates on the impact of informed trading to the momentum effect. It proposes that if momentum is a result of underreaction and if informed trading identifies stocks with underreaction, the presence of informed trading predicts future momentum effect. Consistently, the empirical results show that momentum effect arises when informed trading is present. Greater informed trading leads to greater momentum effect. Although information uncertainty is related to both informed trading and momentum, the identified relationship between informed trading and momentum is robust after controlling for uncertainty.

Nevertheless, information uncertainty still has influence on informed trading as high uncertainty tends to contribute to the predictability of informed trading, which is consistent with Hong, Lim and Stein (2000)'s information diffusion theory about information uncertainty. Chapter 5 also sheds light on the information uncertainty effect on momentum. It reexamines Zhang (2006)'s findings by controlling for informed trading. The empirical findings, however, provide many contrary evidence to Zhang (2006)'s findings. High level of information uncertainty does not produce momentum unless the level of informed trading is relatively high. Furthermore, past winners with higher uncertainty could earn lower future returns when the level of informed trading is low. These findings suggest the reported relationship between information uncertainty and momentum requires careful interpretations.

The three essays use the sample of NYSE and AMEX stocks during the period from January 1983 to December 2001. They also share one common proxy for informed trading: probability of information-based trade (PIN). The change in breadth of ownership (ΔBREADTH) is used to measure the short-sale constraints in Chapter 3 and Chapter 4. Chapter 3 and Chapter 5 adopt analyst coverage (COV), firm age (AGE), and firm size (MV) as the proxies for information uncertainty. Chapter 4 uses trading volume (VOL), the total number of shares traded at each month t, to measure the level of trading activities. The past 11-month stock returns $RET_{t-11,\, t-1}$ are used to examine price momentum strategies in Chapter 5

The original frequency of PIN is yearly because the data of PIN is obtained from the 1983 – 2001 annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The original frequency of ΔBREADTH is quarterly as quarterly datasets of mutual funds holdings are used to calculate ΔBREADTH (CDA/Spectrum s12 in the Thomson Reuters). All the original frequencies of COV, AGE, MV, VOL, and stock returns are monthly. COV is calculated based on the raw detail forecast data unadjusted for stock splits in I/B/E/S, and it is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month. AGE is measured as the number of years since the firm was first covered by CRSP. The CRSP monthly tape provides data on firm age, firm size, and monthly returns.

Since all the portfolios in the empirical tests are monthly rebalanced, the annual PIN data and quarterly ΔBREADTH data are adjusted into monthly frequency. The value of PIN at month t takes the value of PIN in that year. The value of $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T. Although these monthly frequency values are the best approximate measures to their true values, they can introduce crucial flaws into the empirical findings in this thesis. For instance, the value of PIN in each month t will be always high if the annual value of PIN is high in the same year. However, the real monthly value of PIN should not be constant during the same year. When stocks are sorted into portfolios by the level of PIN, stocks are classified by their average value of PIN during that year but not their actual value of PIN at that month. The portfolios of PIN will contain the same stocks throughout the year. In addition, if portfolios are constructed by three-way sorting, for example, by COV, ΔBREADTH and PIN, then the obtained portfolios cannot represent the precise values for the three variables.

Therefore, the possible frequency mismatches may not lead to accurate results for the monthly portfolio analysis.

The empirical examinations in this thesis are based on monthly rebalancing of portfolio analysis. This is because the focus of this thesis is the role of informed trading in price discovery, which emphasizes the price adjustment to the full information level. Since information always changes rapidly and informed trading can be restricted sometimes, the monthly rebalanced portfolio analysis should be more suitable for examining the role of informed trading in stock markets. If portfolios are not monthly rebalanced, the findings in this thesis are very likely to change. For example, the focus of Chapter 3 and Chapter 4 is the new information uncertainty risk, which is encountered by uninformed investors when prices become less informative. When portfolios are quarterly or yearly rebalanced, then the time window for uninformed investors to understand the true value of stocks become longer. Moreover, the level of informed trading and information about stocks will also change dramatically in the longer period. As a result, uninformed investors may absorb more information and become less uncertain about the true value of stocks. Thus, the new information uncertainty risk may not arise. Similarly, the documented relationship between informed trading and momentum in Chapter 5 also depends on the monthly rebalanced portfolio analysis. When portfolios are quarterly or yearly rebalanced, then the level of informed trading during one quarter or one year cannot precisely indentify stocks with underreaction. As a result, the presence of informed trading may not lead to momentum. This is because during the period of one quarter or one year, prices may have adjusted to fundamental news with the help of informed trading and the following trading by uninformed investors.

This thesis also has other limitations. Although each essay has presented robustness checks like subperiod analysis, the empirical results can still be sample specific or because of the specific proxy variables used. Duarte and Young (2009) show that the PIN component related to illiquidity is priced. They suggest that liquidity effects unrelated to information asymmetry explain the relation between PIN and the cross-section of expected returns. Chen, Hong, and Stein (2002) also suggest that the changes in breadth might not really reflect binding short-sale constraints, but represent the superior stock-picking skill of mutual fund managers who are smarter than individuals. While this thesis yields several predications that expected returns should be increasing (or decreasing) with the level of informed trading under certain some conditions, Patton and Timmermann (2009) suggest that the full set of monotonicity in expected returns should be exploited. They propose new and simple ways to test for Monotonicity in financial variables and compare the proposed tests with extant alternatives such as *t*-tests, Bonferroni bounds and multivariate inequality tests through empirical applications and simulations.

The rest of this thesis is organized as follows. Chapter 2 provides an overall literature review about previous studies that are related to this thesis. Chapter 3 presents the first essay on informed trading, short-sale constraints, and information uncertainty. Chapter 4 gives the second essay on informed trading, short-sale constraints, and trading volume. Chapter 5 demonstrates the third essay on informed trading, information uncertainty, and momentum. Chapter 6 concludes this thesis.

Chapter 2

Literature Review

2.1. The Efficiency of Financial Markets

Economics is the science of how to satisfy unlimited requirements with limited resources. Since market facilitates the allocation of resources, economists introduced the concept of "efficiency" to assess the market performance.

In the case of financial economists, a market is efficient if it is "informationally efficient". Asset prices are informational efficient if they fully and correctly reflect the relevant information. The Efficient Markets Hypothesis (EMH) is intended to provide a benchmark for assessing the performance of financial markets according to the concept of informational efficiency.

The EMH became the central proposition of finance during the 1970s. Fama (1970, 1976) assembles a comprehensive review on market efficiency. He defines an efficient financial market as one in which prices always reflect the available information. In other words, the financial market is efficient if stock prices adjust instantaneously to new information.

Obviously, the stock prices of efficient market would provide unbiased signals for optimal resource allocation. Thus, the market truly performs well if the EMH holds. In order to examine whether the EMH holds, enormous empirical and theoretical studies have been developed. At first, a vast array of findings supports the EMH in early decades. However, more and more empirical evidence shows that the EMH has been challenged since 1980.

Economists have developed theoretical idea to understand these financial phenomena. In particular, behavioural finance emerges. As a new approach to financial markets, behavioural finance assumes that some agents are not fully rational. Shleifer (2000) presents that behavioural finance theory rests on two foundations: “limits to arbitrage”, which show that arbitrage in real-world financial markets is far from perfect; “investor sentiment”, which focuses on how irrational investors actually form their beliefs, preferences and valuations, and more generally their demands for securities.

2.1.1. The Challenges to the EMH

Behavioural finance challenges the EMH with both empirical and theoretical evidence.

The Empirical Challenges

In general, the EMH provides two broad categories of empirical predictions. First, when the news about the fundamental value of an asset emerges in the markets, its price should react and incorporate this news both quickly and correctly. Second, since the asset price must be consistent to its fundamental value, price should not move without any news about the value of this asset.

The principal hypothesis following from quick and accurate reaction of prices to new information is that people cannot earn superior risk-adjusted profits from the stale information. Fama (1970) distinguishes between three types of stale information based on the three forms of the EMH. For the weak form, stale information is past prices and returns. The semi-strong form means that any publicly available information is stale. The strong form states that even the private information could be stale quickly. To be fair, most evaluations of the EMH have focused on weak and semi-strong form efficiency.

During the period between 1960 and 1980, the empirical evidence appears almost universally confirms the predictions of the EHM. However, empirical evidence sustains the challenge to the EMH since 1980. Shiller (1981) provides an early important one on stock market volatility, which shows that stock market prices are far more volatile than could be justified by asset pricing models. Empirical finding like this is called as anomaly, which seems to be inconsistent with the EMH. Impressively, Anomalies have been claimed using data from financial markets all over the world.

Firstly, the weak form EMH suffers from anomalies such as contrarian and momentum that imply investor can make excess profits using past price information. De Bondt and Thaler (1985) find that a long-term contrarian strategy, which consists in buying losers and selling winners based on a performance observed two to five years earlier, could generate positive returns in the following years. Momentum, first presented by Jegadeesh and Titman (1993), is much more significant. They show that movements in individual stock prices over the period of six to twelve months tend to predict future movements in the same direction. That is, while contrarian refers to the long-term trends, momentum reveals that the short-term trends persist. Subsequently, even Fama (1991) admits that stock returns are predictable from past returns.

Secondly, the semi-strong form EMH has not fared better. It is challenged by many variables that predict future returns. At the beginning, the size and January effects are best known anomalies, which show a tendency of small firms to provide positive risk-adjusted returns, particularly in January and especially at the turn of the year (Banz 1981, Keim 1983). More recently, value and growth effects are widely documented. In general, value investing selects stocks with high ratios of dividend yield (D/P), book to market (B/M), earnings to price (E/P), or cash flow to price (C/P). In contrast, growth investing attempts to find stocks with low ratios of D/P, B/M, E/P or C/P. Most studies have convincingly presented that value stocks outperform growth stocks around the world (Lakonishok, Shleifer and Vishny 1994, Fama and French

1998, Davis, Fama and French 2000).

Finally, empirical results also show that stock prices could react to non-information. In fact, many sharp changes in stock prices do not appear to accompany significant news. Cutler, Poterba and Summers (1991) report that the 50 largest day stock price movements came on days of no major announcements. Roll (1984, 1988) point out that shocks other than news appear to move security prices, in contrast to the EMH. Wurgler and Zhuravskaya (2002) find that the inclusion in the S&P500 generates a substantial uninformed demand for the shares of the company.

The Theoretical Challenges

Following to the empirical challenges to the EMH, financial economists begin to criticize three theoretical foundations of the EMH.

At first, the EMH assumes that investors are rational and hence they would value assets rationally. However, it is difficult to support the case that people in general, and investors specifically, are fully rational. Kahneman and Riepe (1998) indicate that the irrationality of investors is pervasive and systematic. Apart from the psychological evidence, it is well-known that many investors react to irrelevant information and trade on noise rather than information. Kyle (1985) and Black (1986) define these irrational investors as the "noise traders".

Second, the EMH claims that even if some investors are not fully rational, markets could still be efficient as long as they trade randomly and hence their trades would cancel each other. This implies that the correlation in the strategies of the irrational investors is limited. In contrast, Kahneman and Tversky (1973) reveal that investor sentiment typically determines the common judgment errors made by a substantial number of investors. Shiller (1984) argues that the mistakes would become more severe when the noise traders behave socially and follow each others. Empirical studies also confirm that the aggregate trading of noise traders could be systematically correlated. Barber, Odean, and Zhu (2006a) demonstrate that the trading of individual investors is surprisingly systematic using trading records in U.S. stock markets. Barber, Odean, and Zhu (2006b) argue that noise traders indeed move the markets because they find that noise trader can affect stock prices using eighteen years of tick-by-tick transactional data for U.S. stocks. Finally, Shleifer (2000) presents that professional managers of pension and mutual funds are subject to the same biases as individual investors.

At last, the EMH still can be achieved if rational investors could quickly undo any dislocation by the correlated trading of irrational investors. This situation claimed by Friedman (1953) and Fama (1965) implies two assertions. First, as soon as there is a deviation from the fundament value – in other words, a mispricing occurs - an arbitrage opportunity is created. Second, rational traders will immediately snap up this opportunity, thereby correcting the mispricing. Ross (2004) defines an arbitrage opportunity as an investment strategy that guarantees a positive payoff in some contingency with on possibility of a negative payoff and with no initial net investment. Thus, rational investors in the EMH are typically referred to as “arbitrageurs” because of the belief that a mispriced asset immediately creates an opportunity for riskless profits.

Unfortunately, there could be limits to the ability of arbitrageurs to correct the mispricing. This is known as “limits to arbitrage” in behavioural finance. Firstly, Barberis and Taler (2003) show that arbitrage can be risky and costly due to fundamental risk, implementation costs, and noise trader risk. As a result, the mispricing can remain unchallenged. Arbitrageurs have to bear fundamental risk since substitute securities are often highly imperfect. Implementation costs, such as transaction costs, short-sale constraints and borrowing constraints, can make it less attractive to exploit a mispricing. Noise trader risk, introduced by De Long, Shleifer, Summers, and Waldmann (1990a), is the risk that the mispricing being exploited by the arbitrageur worsens in the short run. While the security and its substitute security would converge ultimately, the price gap between them may become large temporarily. In addition, Shleifer and Vishny (1997) emphasize that noise trader risk matters is extremely important for the arbitrageurs because of their agency feature. In real world, most arbitrageurs are professional portfolio managers, who are not managing their own money, but rather managing other investors’ money. If a mispricing that the arbitrageur is trying to exploit worsens in the short run, generating negative returns, investors may withdraw their funds. Then the arbitrageur will be forced to liquidate position prematurely. Moreover, many arbitrageurs borrow money and securities from intermediaries to take advantage of mispricing. They have to pay interest and also face the risk of liquidation. After poor short-term returns, lenders will call their loans seeing the value of their collateral erode.

Secondly, under some circumstances, arbitrageurs may prefer to trade in the same direction as the noise traders, thereby exacerbating the mispricing, rather than against them. Shleifer and Summers (1990) indicate that some speculators indeed believe that exacerbating the mispricing with noise traders is the way to beat them. De Long, Shleifer, Summers, and Waldmann (1990b) show that if noise traders follow positive feedback strategies, arbitrageurs may prefer to trade in the same direction as the noise traders. Although eventually arbitrageurs help prices return to fundamentals, in short run they feed the mispricing rather than help it to dissolve. Abreu and Brunnermeier (2002) present that arbitrageurs could face synchronization risk as well, which derives from arbitrageurs' uncertainty about when other arbitrageurs will start exploring an arbitrage opportunity. In the equilibrium of their model, the combination of synchronization risk and holding costs causes arbitrageurs time the market rather than correct mispricing right away. This leads to delayed arbitrage. As a consequence, mispricing can remain unchallenged and persist in growing over short or even intermediate period.

2.1.2. The Defence of the EMH

While the EMH encounters seriously attacks, its advocators strike back as well.

Anomalies and Market Efficiency

Some financial economics argue that anomalies do not necessarily mean the death of EMH. At first, since every appraisal of market efficiency depends upon an asset pricing model, the test must assume an equilibrium model that defines normal security returns. If efficiency is rejected, this could be the case that market is truly inefficient, or because an incorrect equilibrium model has been assumed. Hence, Campbell, Lo and Mackinlay (1997) suggest that this joint hypothesis problem implies that market efficiency as such can never be rejected.

In addition, the economic relevance of a presumed anomaly is also important. Jensen (1978) emphasizes the importance of trading profitability in assessing market efficiency. If anomalous return is not definitive enough for investors to make money trading on it, then it is not economically significant and hence market is still efficient. This definition of market efficiency highlights the practical respect and the importance of market microstructure issues such as transaction costs.

Finally, some researchers have found that anomalies often seem to disappear, reverse, or attenuate. Schwert (2003) indicates that most anomalies are more apparent than real in his survey on anomalies and market efficiency. Even if the anomalies existed in the sample period in which they were first identified, the practitioners who would take advantage of anomalies and consequently cause them to disappear.

The Challenges to Behavioural Finance

Neoclassical and behavioural finance are two revolutions in financial economics that came at different periods and largely from different people. The efficient market theory and traditional asset pricing framework stem from neoclassical finance, in which agents are fully rational. In contrast, assuming agents are not fully rational, behavioural finance claims that it explains the evidence that appears anomalous from the EMH and generates new predications that have been supported in empirical results. However, proponents of neoclassical finance also argue that behavioural finance remains controversial.

Ross (2004) points out that at present, behavioural finance seems more defined by what it does not like about neoclassical finance than what it has to offer as an alternative. First, the anomalies are considered affronts to neoclassical or "rational finance", and explanations are sought elsewhere. Second, sufficient noise and risk are introduced into the models in which arbitrageurs cannot enforce the correction of mispricing induced by irrational traders.

It is true that most of the people usually indeed misbehave as the suggestion from behavioural finance. To cope with this, the neoclassical theories rely on the abilities and motivations of some smart and well-financed investors. Meanwhile, the well-developed normative neoclassical portfolio theories also assist individual investors when they are tempted to stray from rationality. Thus, the theoretical need for the average investor to be rational is a straw man. Given the effort neoclassical finance has made to distance itself from preference assumptions and rely on the stronger principle of no arbitrage, Ross (2004) argues that the behavioural critique is ironic.

Although neoclassical and behavioural finance are often seemed to be incompatible, Shiller (2006) suggests that the two approaches in fact have always been intertwined, and some of the most important applications of their insights will require the use of both approaches.

2.1.3. Are Financial Markets Efficient?

While financial markets efficiency is controversial, two well-known predictions of the EMH provide some ideas about whether markets are efficient and the directions for further research. The first statement is “prices are right”, which means that prices are set and maintained by rational agents. The second statement is “no free lunch”, which implies that no investment strategy could earn excess risk-adjusted returns.

These two propositions are important because they guide financial economists to investigate the market efficiency. Since both of them are true in an efficient market, many researchers take it for granted that they are the same. However, Barberis and Taler (2003) argue that they are not equivalent. If prices are right, then there is indeed no free lunch. But the absence of free lunch does not necessarily mean that prices are right. The rationale is that even if mispricing exists, arbitrageurs could not eliminate it away definitely. In the view of behavioural finance, the arbitrage can be limited. Thus, no free lunch can also be true in an inefficient market. In other words, the evidence that no one could beat the markets does not necessarily mean that the market is efficient.

This distinction is crucial for evaluating the ongoing debate on market efficiency. First, many economists use the inability of professional money managers to beat the markets as strong evidence of efficiency. But, if the absence of free lunch does not implies prices are right, the performance of money managers tells little about whether prices reflect fundamental value. Second, although some researchers think the debate should focus on there is no free lunch, many economists believe that the emphasis should be whether prices are right. The ultimate concern of economists is that capital be allocated to the most promising investment opportunities. This depends much more on whether prices are right than on whether there is any free lunch for taking.

Considering this distinction, Shiller (2003) concludes that researchers should not expect market efficiency to be so egregiously wrong that immediate profits should be continually available. But market efficiency can be egregiously wrong in other senses such as it could not interpret sock market bubbles. Indeed, mispricing always emerges and even persists in financial markets. Therefore, the innovations of asset pricing theory are required.

2.2 Momentum Literature

The studies on momentum are always popular because it is the strongest challenge to EMH and economists try to explain it in all kinds of approaches.

2.2.1. The Form of Momentum

Generally, momentum refers to the tendency of stock prices to continue moving in the same direction for several months after an initial impulse. The most basic form of momentum is price momentum, where the initial impulse is simply a change in the price itself. Price momentum was found in aggregate US stock prices in late 1980's (Poterba and Summers 1988), in individual US stock prices in the early 1990's (Jegadeesh and Titman 1993), and in international markets in the later 1990's

(Rouwenhorst 1998, 1999). Other forms of momentum have been measured using different initial impulses. Post-earnings-announcement drift is momentum following a surprise earnings announcement (Ball and Brown 1968, Bernard and Thomas 1989, 1990), while earnings momentum is momentum following a revision in analysts' earnings forecasts (Chan, Jegadeesh, and Lakonishok 1996).

2.2.2. Overreaction and Underreaction

Traditional asset pricing model requires high returns to compensate for some kind of risk, but stocks that have superior performance recently, or have had positive earnings surprises, typically seem to have lower risk, not higher risk. Therefore, momentum cannot be explained by measures of risk (Grundy and Martin 2001, Griffin, Ji, and Martin 2003). In contrast, momentum arises more naturally under behavioural asset pricing model.

Generally, behavioural explanations of momentum can be divided into two main categories. The first category, called as overreaction, stresses that irrational investors may overreact to stories of doubtful or intangible information (see, e.g., Daniel and Titman 2006). If overreaction develops gradually, then stock prices may display momentum for a period of time but will eventually reverse and return to fundamental value. For instance, herding phenomenon is one kind of overreaction. Sirri and Tufano (1998) show that individual investors are attracted to funds, fund categories, and fund families that have performed well recently, consistent with the herding hypothesis. However, there is less evidence that herding generates short-run momentum that eventually reverses. Brunnermeier and Nagel (2004) present one closely related result. They show that hedge funds rode the technology bubble through the late 1990's even after technology stocks are regarded to be overpriced by any conventional measure. These funds appeared to believe that positive short-term momentum would overcome poor long-term value, and their strategy was quite successful.

Instead, the evidence for momentum generated by underreaction to fundamentals, which belongs to the second category, is stronger than the evidence for momentum generated by overreaction. This set of underreaction theories emphasizes a process of gradual adjustment to news (see, e.g., Chan, Jegadeesh, and Lakonishok 1996). Stock prices initially underreact to the news, and then adjust over time so that the long-term response is the appropriate rational one. Moreover, underreaction theories suggest some potential mechanisms about how underreaction works. In Barberis, Shleifer, and Vishny (1998), there is a representative investor, who suffers from a conservatism bias, does not update beliefs sufficiently when new public information emerges. In Hong and Stein (1999), the emphasis is the heterogeneities across investors, who observe different pieces of private information at different times but fail to extract information from prices. If information diffuses gradually across the population, prices underreact in the short run.

2.2.3. Empirical Evidence

Empirical studies test implications of behavioural theories and provide many interesting findings. First, momentum should be stronger when fundamental news is less obvious and harder to analyse. Zhang (2006) confirms that momentum is stronger in stocks that are hard to value such as young stocks, small stocks, stocks that are covered by relatively few analysts, stocks with widely dispersed analyst earnings forecasts, and stocks with volatile returns and cash flows. Hong, Lim and Stein (2000) show that momentum is greater when fundamental news is bad and hence not publicized by firm management. Grinblatt and Moskowitz (2004) also present that momentum is stronger when news comes out slowly over several months than when there is a large disclosure that is obvious even to inattentive investors. Furthermore, momentum effects exist not only within stocks but across stocks, particularly from large-cap and high-volume stocks to small-cap low-volume stocks, and from stocks in one industry to their suppliers and customers (Chordia and Swaminathan 2000, Lo and MacKinlay 1990, Menzly and Ozbas 2006).

Second, Grinblatt and Moskowitz (2004) further demonstrate that momentum should be stronger when some behavioural forces push in the same direction. Since many individual taxable investors delay tax-loss selling until the end of the year, they are particularly likely to sell past losers and hold onto past winners at year-end. This effect strengthens momentum in December and weakens it in January.

Third, momentum should be stronger when rational investors face high transactions costs in their arbitrage trading. Johnson and Schwartz (2000) find that during the 1990's, earnings momentum and post-earnings-announcement drift weakened in liquid markets such as the US and the UK, but remained stronger in less liquid international markets.

Finally, arbitrageurs could exploit the underreaction phenomenon. Cohen, Gompers, and Vuolteenaho (2003) study the aggregate holdings of US institutional investors and confirm that institutions buy shares from individuals in response to good cash-flow news. However, institutions are not simply following price momentum strategies as they sell shares to individuals when price goes up in the absence of positive cash-flow news.

2.3. Short-Sale Constraints Literature

Neoclassical asset pricing theories rely on the assumption that market participants can buy, sell and short sell securities at no cost. In practice, short selling a security is not as straightforward as simple selling or buying. There are various costs as well as legal and institutional restrictions that impose constraints on short selling. Although short-sale constraints have been attributed as an important factor in determining asset prices (see, e.g., survey by Rubinstein 2004), the nature and the significance of their impact remain inconclusive. Note that although this thesis focuses on short-sale constraints in the stock market, their importance is recognized in other markets as well such as the fixed-income market (Krishnamurthy 2002).

Generally, theoretical models in literature use the holding of assets to measure the condition of short-sale constraints. If the holding of assets cannot be less than zero, the short-sale constraints of assets are binding tightly. In this case, investors who want to reduce their holdings can only exit the market at most as they cannot take any short position. As a result, the selling pressure on the assets will be relieved by the binding short-sale constraints. According to Bai, Chang, and Wang (2006), short-sale constraints could limit two types of trades: (1) trade to share risk; and (2) trade to speculate on private information. Thus, binding short-sale constraints can reduce the allocational and informational efficiency of the market. When binding short-sale constraints limit risk-sharing trades, they shift the demand for the asset upwards and consequently its price. This is the most typical case in the market, and it is the spirit of Miller (1977). Bai, Chang, and Wang (2006) suggest that in the presence of information asymmetry, limiting short sales driven by private information increases the uncertainty about the asset as perceived by uninformed investors, which reduces the demand for the asset. When this information effect dominates, short-sale constraints actually cause asset prices to decrease and price volatility to increase. In addition, short-sale constraints can give rise to discrete price drops accompanied by increases in volatility when the uncertainty perceived by uninformed investors surges in certain states.

2.3.1. The Source of Short-Sale Constraints

The Frictional Securities Lending Market

At first, there are short-sale constraints that stem from the mechanics of shorting. To be able to sell a stock short, one must borrow it first. In order to borrow shares, an investor needs to find an institution or individual willing to lend shares. Financial institutions, such as mutual funds, trusts, or asset managers, typically do much of this lending. These lenders receive a fee in the form of interest payments generated by the short-sale proceeds, minus any interest rebate that the lenders return to the borrowers.

This rebate rate is the fee that the lender of the stock must pay back to the borrower of that stock. This fee arises because in order to sell a stock short, an investor must borrow shares from an investor who owns them and is willing to lend them. The short seller must leave collateral with the lender in order to borrow the shares; in turn, the lender pays the short-seller interest—the “rebate” rate—on this collateral. Retail borrowers typically receive no interest on their proceeds, so the situation described above applies mainly to institutional short sellers. The difference or spread between the interest rate on cash funds and the rebate rate is a direct cost to the short seller, and is often referred to as the loan fee. The rebate rate serves to equilibrate supply and demand in the stock lending market, much like the “repo” rate in the fixed income market. Obviously, if every investor were willing and able to lend shares in a competitive market, the lending fee would be close to zero. However, as Duffie (1996) and Krishnamurthy (2002) show, if some investors who are willing to hold overpriced assets do not lend, a strictly positive fee can arise.

Apparently, rebates create costs for establishing a short position in a security. In addition, short sellers incur searching costs since the fact that security owners and those wishing to short have to find each other. This is because the security lending market is not a centralized market with a market-clearing price, and hence rebates only partially equilibrate supply and demand. While individual retail investors are particularly likely to be unable to short, there is also extensive evidence of institutional investors unable to short no matter how much they are willing to pay for borrowing shares.

Even though short sellers establish their short positions successfully, they still face risks like recall risk. Once a short seller has initiated a position by borrowing stock, the borrowed stock may be recalled at any time by the lender. If the short seller is unable to find another lender, he is forced to close his position. There are several reasons that a shareholder might refuse to lend stock, or might withdraw his shares from the stock lending market. First, if the lender sells his stock, he must recall his stock loan so that he can deliver his shares to the buyer. Second, shareholders may refuse to lend their stock because they fear that by helping short sellers, they will be helping drive stock prices down. Third, for individual investors, brokers typically only have the ability to lend out of margin accounts, not cash accounts. Fourth, some institutions do not have stock lending programs at all, perhaps because they feel their holdings are too small and the income generated by lending would not be enough to compensate for the fixed cost of setting up a lending program.

Generally, it is easy and cheap to borrow most large cap stocks, but it can be difficult to borrow stocks which are small, have low institutional ownership, or which are in high demand for borrowing. A somewhat paradoxical description of the stock lending market is that it usually works very well, except when you want to use it, in which case it works terribly. In particular, it can be difficult or expensive to short stocks that many people want to short.

Other Frictions for Short Selling

In addition to the problems in the stock lending market, there are a variety of other frictions for short selling. Firstly, short selling is restricted by all kinds of regulations. For example, the SEC, the Federal Reserve, the various stock exchanges, underwriters, and individual brokerage firms in US impede short shelling by administer regulations and procedures, including the additional collateral requirement (Federal Reserve Regulation T), the up-tick rule (Securities and Exchange Commission [SEC] Rule

10a-1), a higher tax rate on profits on short sales (which are treated as short-term capital gain), the risk of short squeeze, and others. Many institutions set up to encourage individuals to buy stocks, but few institutions set up to encourage them to short. For some institutional investors, short selling is prohibited by their charters. Almazan, Brown, Carlson, and Chapman (2002) report that about 70% of mutual funds explicitly state (in Form N-SAR they file with the SEC) that they are not permitted to sell short.

Secondly, short sellers also face hostility from governments and society. Policy makers and the general public seem to have an instinctive reaction that short selling is morally wrong. In particular, short sellers are blamed in times of crisis or following major price declines. The general idea seems to be that short selling is bad, and when bad things happen, such as war, it probably involves short sellers in some way. For example, the New York Stock Exchange imposed special short selling regulations during World War I, in response to both a substantial market decline and a fear that enemy agents would drive down stock prices. Short sellers were extremely unpopular in 1930 as well because many politicians, journalists, and investors blamed them for the stock market crash. More recently, the SEC and various other regulatory authorities investigated whether terrorists had shorted stocks or had bought puts, armed with foreknowledge of the attacks, although there is no evidence of terrorist shorting activities. Following the dot-com bubbles in the early 2000's, governments start to limit short selling. The authorities in Britain and Japan have sought to discourage shorting and securities lending. A major lender of European stocks announced it was ceasing securities lending and urged others to do the same.

Thirdly, short sellers also face hostility from the firms they short. Managers of firms do not like people who short sell their stock, especially if the short sellers are accusing the firms of fraud and even more especially when the fraud accusations are true. Consequently, sometimes companies will fight with their short sellers.

Note that derivatives, such as options and futures, could provide alternative ways to take a short position in a security. However, derivatives trading has its own costs and restrictions (Ofek and Richardson 2003).

2.3.2. The Overvaluation Effect of Short-Sale Constraints

Extensive literature studies the overpricing impact of short-sale constraints. In particular, the combination of differences of opinion among market participants and short-sale constraints could deliver overvaluation to securities.

The Source of Heterogeneous Beliefs

First of all, it is important to know the possible sources of heterogeneous beliefs because short-sale constraints are supposed to restrict the pessimistic opinions. It seems that asymmetric information might cause differences of opinion. The presence of private information suggests that investors could use it to trade and make a profit. However, Tirole (1982) and Milgrom and Stokey (1982) use no-trade theorem to rule out this possibility. They show that rational investors who share the same prior beliefs cannot expect to profit from speculating against each other based on differences in information. In particular, Tirole (1982) demonstrates that the no-trade theorem holds in dynamic Rational Expectations Equilibrium (REE). In his model, the resale options suggested by Harrison and Kreps (1978) cannot arise in asset prices even if short-sale constraints are imposed.

Scheinkman and Xiong (2003a) summarized the approaches to avoid the no-trade result. First, the presence of traders, who trade for no-speculative reasons such as diversification or liquidity, would make the trading among speculators a positive-sum game. Several market microstructure models such as Grossman and Stiglitz (1980), Kyle (1985), and Wang (1993) adopt this approach with asymmetric information. The second option is to relax the assumption that agents share the same prior beliefs. This approach is pursued by Morris (1996), Biais and Bossaerts (1998), and Brav and Heaton (2002). Finally, the way out can be agents have behavioural biases that preclude full rationality. Hirshleier (2001) and Barberis and Thaler (2003) review various behavioural biases suggested by the psychology. In particular, some behavioural biases may generate heterogeneity of beliefs. For example, Brunnermeier and Parker (2003) present that heterogeneous beliefs can arise if agents gain utility from adopting certain beliefs. Nevertheless, Overconfidence is the most well documented behavioural bias that can generate heterogeneous beliefs.

Overconfidence is the tendency of people to overestimate the precision of their knowledge. Psychology studies, such as Alpert and Raiffa (1982), Brenner, Koehler, Liberman, and Tversky (1996), suggest that people are overconfident. Camerer (1995) argues that even experts can display overconfidence. Financial economists have developed theoretical models to analyse the implications of overconfidence on financial markets. Kyle and Wang (1997) adopt overconfidence as a commitment device over competitors to improve one's welfare. Daniel, Hirshleifer, and Subrahmanyam (1998) use overconfidence to explain the predictable returns of financial assets. Odean (1998) demonstrates that overconfidence can cause excessive trading. Bernardo and Welch (2001) discuss the benefits of overconfidence to entrepreneurs through the reduced tendency to herd. In these studies, overconfidence is modelled as overestimation of the precision of one's information. Scheinkman and Xiong (2003b) exploit the consequences of this overestimation in a dynamic model of pricing and trading. They regard overconfidence as a convenient way to generate a parameterized model of heterogeneous beliefs. Since overconfident investors believe more strongly in their own assessments of an asset's value than in the assessment of others, heterogeneous beliefs arise.

Theoretical Studies

In an earlier paper, Miller (1977) theorizes that in the presence of short-sale constraints, security prices tend to reflect a more optimistic valuation than the average opinion of potential investors and thus tend to be upward biased. This overvaluation argument is based on two conditions: (1) A security's short sales are either prohibited or costly, and (2) investors have heterogeneous beliefs or information about the security's value. The underlying intuition is quite straightforward. Pessimistic investors are forced to sit out of the market when short sales are not available, and thus some negative information is not reflected in prices, enabling enthusiastic buyers to bid prices above the level that average investors perceive as fair.

Jarrow (1980) and Figlewski (1981) are among the first to model Miller's (1977) idea rigorously in a static capital asset pricing model (CAPM) framework. In his general equilibrium analysis, Jarrow (1980) shows that the total effect of prohibiting short sales may be quite complex, owing to the substitution effect among stocks. When two equivalent markets that differ only with respect to short-sale restrictions are compared, the price of an individual risky asset under short-sale restrictions can be either higher or lower than the price of the same asset in the other market. Figlewski (1981) adopts a standard one-period model to show that when investors with unfavourable information are constrained from selling short, excess demand exists and equilibrium prices exceed the market-clearing price that would obtain if short-sale constraints did not exist. Figlewski's (1981) conclusion is consistent with Miller's (1977) intuition.

Chen, Hong, and Stein (2002) obtain a similar result in their model that allows for risk aversion—stocks with short-sale constraints reflect optimistic beliefs and thus realize lower future returns.

While the above static models analyse the overvaluation generated by optimistic beliefs, other studies adopt dynamic models to show that the price can be higher than the valuation of all investors because of the opportunity to speculate that arises when short selling is prohibited. In their dynamic model, Harrison and Kreps (1978) consider the trading dynamics of heterogeneous investors. They call that investors exhibit speculative behaviour if the right to resell an asset makes them willing to pay more for it than they would pay if obliged to hold it forever. They attribute this speculation to Keynes (1936), who finds that a trader speculate if his most interest is in cashing in capital gains rather than enjoying a future dividend stream. The speculation is particularly compelling when agents are risk-neutral since in this case no risk-sharing benefits arise from trading. Furthermore, short sales must be costly in order to make the resale option valuable in speculation. They show that speculative behaviour arises in the model under the assumptions that heterogeneous investors are risk-neutral and short sales are not possible. Thus, differences of opinions generate trading and speculation.

Morris (1996) considers a special case of the model of Harrison and Kreps, where traders' heterogeneous prior beliefs are updated rationally as information arrives. He shows that even if traders' posterior beliefs are converging to the true fundamental value, the speculative premium never disappears. As traders learn about the true distribution of some asset's dividends, a speculative premium occurs as each trader anticipates the possibility of reselling the asset to another trader before complete learning has occurred. The speculative premium depends on differences in beliefs at all possible future contingencies.

Duffie, Garleanu, and Pedersen (2002) present a dynamic model to show that the prospect of lending fees may push the initial price of a stock above even the most optimistic buyer's valuation. This happens because the optimistic investors not only expect returns from capital gains and from dividends, but also they expect to get extra fees from lending their stocks to short-sellers. This added benefit is of greatest significance when differences of opinion are particularly strong.

Not only overpricing but also bubble can emerge when investors face short-sale constraints. Allen, Morris, and Postlewaite (1993) show it is possible for short-sale constraints to generate finite bubbles. They distinguish between "expected" and "strong bubbles". If each agent's expected value of the asset is lower than the asset price, an expected bubble occurs. A strong bubble occurs if all agents know that the price is higher than the value of any possible dividend stream outcome. They show that the two conditions are necessary for an expected bubble to occur. First, the initial allocation must be interim Pareto inefficiency. Otherwise, no one will have the incentive to buy the asset. This statement is analogous to the zero-sum argument in the proof of the no-trade theorem. In other words, this condition implies that there have to be gains from trade or at least some investors have to think that there might be gains from trade. Second, each agent must be short-sale constrained at some period in the future with positive probability. If an investor assigns positive probability to being short-sale constrained at some future contingency, he might like to hold on to an asset, even if the price is strictly higher than his marginal valuation of the asset. These two conditions above are necessary for expected bubbles as well as for strong bubbles because any strong bubble is also an expected bubble. Allen, Morris, and Postlewaite derive an additional necessary condition for strong bubbles. If a strong bubble occurs, everybody knows that no possible dividend realization can justify the price. To make this happen in equilibrium, traders must believe that the other traders do not know this fact. Therefore, strong bubbles can only occur if each trader has private information. This condition implies that strong bubbles can never arise in a market setting where net trades of all agents are common knowledge.

Speculative bubble can arise under short-sale constraints if traders have heterogeneous beliefs. Hong, Scheinkman, and Xiong (2006) indicate that the price of an asset exceeds fundamental value for two reasons. First, the price is biased upward because of heterogeneous initial beliefs. If these initial beliefs are sufficiently different, price only reflects the beliefs of the optimistic group as the pessimistic group simply sits out of the markets because of short-sale constraints. This is the "optimism effect" (see, e.g., Miller 1977, Chen, Hong, and Stein 2002). Second, speculations can arise in the dynamics of trading. Investors pay prices that exceed their own valuation of future dividends as they anticipate find a buyer willing to pay even more in the future. This is the "resale option effect" (see, e.g., Harrison and Kreps 1978, Scheinkman and Xiong (2003b).

Scheinkman and Xiong (2003b) explore the speculative bubble with a continuous-time equilibrium model of speculative trading, which provides a flexible framework to analyse links between asset prices, trading volume, and price volatility. They use overconfident to generate heterogeneous beliefs among agents regarding asset fundamentals. There are three signals including dividend at each instant available to all agents for detecting fundamental value. According to their different interpretation of the signals, agents are divided into two groups. Each group overestimates the informativeness of a different signal and knows that its forecast differ from the other group's. As information flows, the forecasts by agents of the two groups oscillate, and one group that is relatively more optimistic at one instant may become less optimistic than other group in the future. These fluctuations in relative beliefs generate trade. When evaluating the asset, agents consider not only their own view of fundamentals but also the fact that the owner of the asset has an option to sell it in the future to agents in other group. This option will be sent one by one. These characteristics make the option "American" and give it a recursive structure. The difference between the current owner's demand price and his fundamental valuation, which is exactly the resale option value, can be reasonably called a bubble. Fluctuations in the value of the bubble contribute an extra component to price volatility. Scheinkman and Xiong emphasize that the bubble is a consequence of the divergence of opinions generated by the overestimation of informativeness of the distinct signals. On average, agents in their model are neither optimists nor pessimists.

Apart from bubbles, market crashes could occur under short-sale constraints as well. Hong and Stein (2003) develop a theory of market crashes based on differences of opinion among investors. Because of short-sale constraints, bearish investors do not initially participate in the market and their information is not revealed in prices. However, if other previously bullish investors bail out of the market, the originally bearish group may become the marginal "support buyers", and more will be learned about their signals. Therefore, accumulated hidden information comes out during market declines.

Empirical Studies

Most empirical tests are carried out to test whether more short-sale constrained firms are overvalued. Cohen, Diether, and Malloy (2007) present that one strand of the literature employs proxies for shorting demand or shorting supply. The idea behind looking at shorting demand is that some investors may want to short a stock but may be impeded by constraints; if one can measure the size of this group of investors, then one can measure the extent of overpricing or the extent of private information left out of the market. The idea behind looking at shorting supply is that shorting a stock requires that one first borrow the shares, and thus a low supply of lendable shares may indicate that short-sale constraints are binding tightly.

The oldest empirical literature on short-selling focuses on short interest ratios (shares sold short divided by shares outstanding) as a proxy for shorting demand. Figlewski (1981) examines the relationship between the level of short interest and subsequent stock returns. His tests assume that short interest proxies for the level of shares that would be sold short if short-sale constraints were nonexistent, and therefore, the amount of adverse information that was excluded from the market price. He provides some evidence that more heavily shorted firms underperform less heavily shorted firms. Note that his findings is not strong because while the least shorted firms produced positive abnormal returns with high statistical significance, the most shorted deciles did not produce statistically significant negative abnormal returns.

Some papers also find statistically significant subsequent underperformance for heavily shorted firms. For example, Asquith and Meulbroek (1995) and Desai, Ramesh, Thiagarajan, and Balachandran (2002) find significant abnormal returns for stocks with high short interest on, respectively, the NYSE and NASDAQ exchanges for 1976 to 1993 and 1988 to 1994. Note that the methodologies used in these two papers were not designed to provide a test of Miller (1977)'s overpricing story.

However, other papers, including Woolridge and Dickson (1994), Brent, Morse and Stice (1990), and Figlewski and Webb (1993), find little or no relation between the level of short interest and subsequent returns. Desai, Ramesh, Thiagarajan, and Balachandran (2002) argue that this could be due to the problematic nature of short interest. For example, a low level of short interest may not indicate low shorting demand: Stocks that are impossible to short could have a huge shorting demand, yet the level of short interest is zero. The weak results could also be due to the typical focus on levels of short interest, rather than changes. Alternatively, they argue that the weak results could be due to the use of small and/or biased samples in these early studies.

Chen, Hong, and Stein (2002) also claim that short interest proxy suffers limitations. They argue that variations in short interest may reflect variations in the transactions costs of selling short rather than in suppressed negative information. Thus, a stock with a low or zero value of short interest may simply be difficult or costly to sell short, which could potentially translate into more, rather than less, negative information being held from the market. They argue further that no clear-cut interpretation of the relationship between short interest and subsequent returns may exist because of D'Avolio (2002)'s finding. D'Avolio shows that for stock deciles sorted by short interest, neither the mean loan fee nor the percentage of stocks with high loan fees in the portfolio is monotonic in the actual short interest.

A variety of studies offer alternative approaches to measure the short-sale constraints by exploiting the fact that an unwillingness or inability to short may limit the revelation of negative opinions. For example, institutional or cultural norms may limit shorting. Almazan, Brown, Carlson, and Chapman (2002) find that only about 30% of mutual funds are allowed by their charters to sell short and only 2% actually do sell short. Chen, Hong, and Stein (2002) use this fact to motivate their choice of breadth of mutual fund ownership as an indicator of the extent to which negative valuations are not expressed in prices. They find that reductions in breadth, which signal an increase in the amount of negative information withheld from the market, lead to negative subsequent abnormal returns on average during the sample period, 1979 to 1998.

Similarly, Nagel (2005) uses residual institutional ownership as a proxy for shorting demand by assuming low residual institutional ownership signals that negative information is being withheld from stock prices. He finds that underperformance in growth stocks and high dispersion stocks is concentrated among stocks with low institutional ownership. However, when he combines his sample period with that in Chen, Hong, and Stein (2002), there is no longer a reliable pattern during the 1980 to 2003 period between breadth of mutual fund ownership and future returns. Residual institutional ownership may also proxy for shorting supply, since low institutional ownership restricts the supply of available shares on loan. As in Chen, Hong, and

Stein (2002), it is not clear which channel (shorting demand or shorting supply) drives the results. Mutual fund and institutional investment, aside from representing only a portion of the investing universe, are also driven by nonshorting considerations such as investment style.

Asquith, Pathak, and Ritter (2005), one of the few papers that explicitly recognizes the competing effects of shorting supply and shorting demand, argue that stocks with high shorting demand and low shorting supply are the most likely to face binding short-sale constraints. They show that stocks in the highest percentile of short interest (their proxy for shorting demand) and the lowest third of institutional ownership (their proxy for shorting supply) underperform by 215 basis points per month during the 1988 to 2002 period on an equal-weight basis. Note that they also face the same interpretation problems mentioned above since they proxy for shorting supply and demand using institutional ownership and short interest.

While Asquith, Pathak, and Ritter (2005) do not disentangle the individual effects of shorting supply and shorting demand, Cohen, Diether, and Malloy (2007) is the first paper to examine the link between the shorting market and stock prices by isolating shifts in the supply and demand for shorting. Their paper is unique because they are able to use actual data on loan fees and loan amounts (not proxies) from a large institutional investor to decompose the effect on stock prices into the part that is due to shorting demand, and the part that is due to shorting supply. They find that shorting demand is an important predictor of future stock returns: an increase in shorting demand leads to negative abnormal returns of 2.98% in the following month. Furthermore, they show that the results are stronger in environments with less public information flow, suggesting that the shorting market is an important mechanism for private information revelation.

Another empirical approach tries to obtain data on the direct costs of shorting from the stock loan market, which provides a measure of the constraints on short selling. The most commonly used metric is the rebate rate, in particular, the spread between the rebate rate and the market interest rate. The existing evidence on rebate rates has generally been limited to proprietary databases over short time periods. Using a database from a single lender from April 2000 through September 2001, D'Avolio (2002) reports that only 9% of the stocks in his sample are "on special" (defined here as a loan fee greater than 1% per annum) on a typical day. The other 91% typically have loan fees around 20 basis points per annum. In other words, the rebate rate is typically about 20 basis points less than the Federal Funds rate. He does find that stocks on special have higher short interest.

Using a sample of rebate rates from a single lender from November 1998 through October 1999, Geczy, Musto, and Reed (2002) conclude that short-sale constraints are unable to explain anomalous patterns in stock returns. Meanwhile, using proprietary data from July 1999 to December 2001, Ofek, Richardson, and Whitelaw (2004) document that stocks that violate put-call parity are more likely to underperform. Finally, using a small database of rebate rates hand-collected from the Wall Street Journal from 1926 to 1933, Jones and Lamont (2002) find that stocks with low rebate rates (high loan fees) experience low subsequent returns. However, the effect is modest. They only find large negative size-adjusted returns (−2.52% in the following month) among stocks that are both expensive to short and new to the loan crowd (another proxy for high shorting demand).

Since derivatives such as option could provide alternative ways to take a short position in a security, one empirical approach considers the link between short-sale constraints and stock prices in the context of option introductions. For example, Danielsen and Sorescu (2001) focus on abnormal stock returns following option listings. Since traded put and call options arguably offer a low-cost way of establishing a short position, the listing of options can be viewed as the de facto alleviation of short-sale constraints. Danielsen and Sorescu (2001) find that post-1980 option introductions are associated with negative abnormal returns in underlying stocks. Similarly, Ofek and Richardson (2003) use data on DotComs and show that short-sale constraints, in the form of stock option lockups, have a considerable and persistent negative impact on subsequent stock returns. However, these papers have limitations. Danielsen and Sorescu (2001) only analyses optionable stocks, which tend to be large, while Ofek and Richardson (2003) only explores Internet IPOs. In addition, Mayhew and Mihov (2005) find no evidence that investors take disproportionately bearish positions in newly listed options. This may serve to weaken the causal link between a relaxation of short-sale constraints and stock prices in the context of option introductions.

While the above empirical tests of the overpricing hypothesis examine the impact of short-sale constraints on stock prices, a different approach focuses on the degree of divergence in opinions. For example, Diether, Malloy, and Scherbina (2002) use the dispersion of analysts' earnings forecasts to measure the dispersion of investor opinions and show that stocks with higher dispersion earn lower future returns than otherwise similar stocks. However, Boehme, Danielsen, and Sorescu (2006) argue that these pervious tests are imperfect because Miller (1977)'s hypothesis implies that both the dispersion of investors opinion and the short-sale constraints are necessary to stock price overvaluation. They examine the valuation effects of the interaction between these two conditions and show that high dispersion of investor opinions and short-sale constraints are both required to produce overvaluation. Mohanaraman (2003) also combine the two conditions to test the Miller (1977) story. He finds that high short interest stocks have lower returns the greater the dispersion in analysts' forecasts.

Another paper also examines the overvaluation effect of short-sale constraints based on the combination of two factors. Henry (2006) considers the effect of informed trading on the returns to stocks with high levels of short interest. Portfolios in his paper that constructed by interacting short-sale constraint metrics with informed trade metrics produce more negative returns than portfolios constructed along only one dimension. Among highly shorted firms, portfolios with high levels of informed trading generally underperform but those with low levels of informed trading do not. The results suggest that the underperformance of high short interest stocks is driven by firms that have high levels of informed trading. However, this negative relationship between informed trading and returns is reversed for stocks with low to moderate short interest levels.

2.3.3. Short-Sale Constraints under Asymmetric Information

Nonetheless, whether short-sale constraints will always lead to overpricing is far from certain. While most of studies do not explore the short-sale constraints effects in an asymmetric information setting, some papers consider the asymmetric information setting. Diamond and Verrecchia (1987) show that sort-sale constraints do not necessarily lead to overvaluation. They examine the effects of short-sale constraints in a rational expectations framework. In their model, short-sale constraints reduce the adjustment speed of prices to private information, especially to bad news, since investors with negative information are prohibited from shorting. However, short-sale constraints do not lead to an upward bias in prices in their model. This is because when investors forming their own beliefs, they could rationally take into account the fact that negative information may be not reflected in trading prices. In contrast to

Miller (1977) and other optimism models, Diamond and Verrecchia's (1987) work is more in the efficient markets tradition. However, they make a strong assumption by introducing a risk-neutral market maker who has perfect knowledge of the economic environment and can perform Bayesian updating in the short period between two consecutive trades.

More recently, three studies including Bai, Chang, and Wang (2006), Marin and Olivier (2008), and Yuan (2006) also focus on the asymmetric information setting and provide new insights on asset pricing under short-sale constraints. Firstly, Marin and Olivier (2006) provide an explanation to one puzzle that the price of individual stocks sometimes crashes without the arrival of fundamental news. They attribute this to one hypothesis that crashes may be caused by the absence of insider trading. Their theory indicates that rational uninformed investors may react more strongly to the absence of insider sales than to their presence (the "dog that did not bark" effect). Their empirical evidence supports this because they find that at the individual stock level insiders sales peak many months before a large drop in the stock price, while insiders purchases peak only the month before a large jump.

Secondly, Bai, Chang, and Wang (2006) study how short-sale constraints affect asset price and market efficiency. They consider a fully rational expectations equilibrium model, in which investors trade to share risk and to speculate on private information in the presence of short-sale constraints. Short-sale constraints limit both types of trades, and thus reduce the allocational and informational efficiency of the market. Limiting short sales driven by risk-sharing simply shifts the demand for the asset upwards and consequently its price. However, limiting short sales driven by private information increases the uncertainty about the asset as perceived by less informed investors, which reduces their demand for the asset. When this information effect dominates, short-sale constraints actually cause asset prices to decrease and price volatility to increase. Moreover, they show that short-sale constraints can give rise to discrete price drops accompanied by a sharp rise in volatility when prices fail to be informative and the uncertainty perceived by uninformed investors surges.

Thirdly, Yuan (2006) argue that short-sale constraints when combined with information asymmetry dampen the upward price movement and thus make bubbles difficult to form. Her theory considers the situation that when a high level of noise demand increases the price, informed investors may be constrained out of the market due to short-sale restrictions. In this scenario, informed investors' private information is not embedded in the market clearing price, resulting a noisy price. Uninformed investors are less willing to purchase the asset since they cannot distinguish noise demand from information-based buying. Their demand becomes more elastic as the price increases, inducing a dampening effect. Hence, large upward price movements become less likely.

Note that Yuan (2006) captures different market phenomenon from Marin and Olivier

(2008), and Bai, Chang, and Wang (2006). The differences are due to choice of model setup. In the model of Yuan (2006), there is a noisy demand or supply shock so that prices do not fully reveal private information, similar to the noisy rational expectations equilibrium (REE) model that used by Hellwig (1980). Instead of this independent noise trading, the latter two studies introduce noise trading through informed investor hedging need on their non-tradable asset. Following Bhattacharya and Spiegel (1991), Marin and Olivier (2008) extend the Grossman and Stiglitz (1980) model by substituting noise trading with rational trading driven by stochastic hedging needs. In addition, they introduce a simple constraint on asset holdings. Bai, Chang, and Wang (2006) also extend Grossman and Stiglitz's (1980) framework with differently informed investors. They consider fully rational expectations equilibrium model, in which investors trade to share risk and to speculate on private information in the presence of short-sale constraints.

Grossman and Stiglitz's (1980) model was developed to address the partial information transmission role of prices. That is, prices perform a role in conveying information from informed investors to uninformed investors. Informed investors possess superior information because they have bought an identical signal of the risky asset's private information. In addition, the aggregate supply of the risky asset is set to be random. Uninformed investors can only partially infer the private signal from the prices because they cannot disentangle the price change due to the noise aggregate supply from the change which is due to the informed trading. On the other hand, Hellwig's model (1980) captures the information aggregation role of prices. If there is not only one piece of private information but there are many informed investors with different pieces of private information, the equilibrium price corresponds to some aggregate of all the pieces of private information. In this case, the aggregation of private information through price depends on investors' preferences. Intuitively, the price impact of investor *i*'s private information should depend on the reaction of investor *i* to this information, which in turn should depend on investor *i*'s preference. Hellwig study the aggregation of information in a large market, in which individual investors have no influence on the price. In particular, the relative importance of the information available to investor *i* depends on his preferences. His information is relatively the more important, the less risk averse he is. Furthermore, the equilibrium price will reflect only those components of information that are common to a large number of informed investors. In other words, the market is a good aggregator of information, if there are many informed investors with many independent sources of private information. In this case, the "noise" in the information available to any individual investor is filtered out and does not affect the price.

This modelling difference causes several significant differences in results. In particular, short-sale constraints are likely to bind when prices are high in Yuan (2006), which captures the phenomenon that informed investors are short-sale constrained when the high asset price is caused by a high level of noise demand, a scenario similar to the "tech" bubble. A decrease in price informativeness in this case lowers the likelihood of bubbles but will not cause crashes. By contrast, in Marin and Olivier (2008), and Bai, Chang, and Wang (2006), short-sale constraints are likely to bind when asset prices are low. This is because informed investors are endowed with excess non-traded risky assets. To hedge this non-traded risk, they have to short-sell the traded asset that is positively correlated with the non-traded asset. Consequently, the sharp drop of price informativeness due to short-sale constraints causes a crash in the price of the traded asset. Therefore, they capture a different set of market conditions.

Furthermore, the source of uncertainty in Yuan (2006) is also different from that identified in these two studies. In Marin and Olivier (2008), and Bai, Chang, and Wang (2006), at a given price, informed investors' demand can be inferred and so is their constraint status. By comparison, in Yuan (2006), informed investors' constraint status cannot be inferred with certainty since the high price could be caused either by a high realization of private signals or by a high level of noise trading. This introduces an additional source of perceived uncertainty to uninformed investors and causes equilibrium price more skewed and more volatile.

2.4. Asymmetric Information Literature

Financial markets are driven by news and information. Although standard asset pricing theory assumes that all market participants possess the same information, different investors hold different information in reality.

2.4.1. The Importance of Information

The fact that information matters in financial markets is because of the close relationship between information and price. First, information could have significant impact on prices. Since asset entails uncertain future payments, asset prices are driven by expectations about these future payoffs. In order to make trading decisions, traders evaluate their expectations based on their information. Thus, their information could affect their trading activity and, hence the asset prices. Second, investors can learn information from price system. Since the actions of informed traders are driven by their information set, uninformed traders can infer part of the private information held by informed traders from the current movement of an asset's price. Thus, Brunnermeier (2001) presents that prices have a dual role: an index of scarcity or bargaining power and a conveyor of information.

Information asymmetry typically occurs when some investors have better or more timely information than others. The source of this asymmetry can simply be the superior knowledge that informed traders obtain both private and public information but uninformed traders only have public information. Secondly, even if all traders received the same news, they still might interpret it differently. Typically one has to make use of other information to figure out the impact of this news on the asset's value. Hence, traders with different background information might draw different conclusions from the same news.

Finally, the impossibility of perfect information efficiency enhances the impact of asymmetric information. Grossman and Stiglitz (1980) argue that market prices cannot fully reveal all relevant information since, if they did, no one would have an incentive to spend resources on gathering information in the first place. Traders who collect information must make extra profit from doing that. Consequently, the competitive equilibrium with costly, endogenous information acquisition does not exist if markets are perfect informationally efficient. This is known as the "Grossman-Stiglitz paradox".

Therefore, financial markets cannot be well understood without considering asymmetric information. As a result, the study of asset pricing under asymmetric information arises.

2.4.2. No-Trade Theorem and Partially Revealing Equilibrium

There are huge trading activities in financial markets. The high trading volume is often attributed to the speculation of investors. Investors might speculate if they hold different opinions about the value of assets, which might be due to different information among traders. However, counter to this intuition, asymmetric information alone cannot explain the high trading volume in financial markets.

No-trade theorem shows that asymmetry in information will not lead to trade if it is common knowledge that all traders are rational and the current allocation is ex ante Pareto efficient (Milgrom and Stokey 1982, Tirole 1982). An event is common knowledge in a certain state if all agents know that the true sate lies in this event and all know that all know this and so on, ad infinitum. Note that the no-trade theorem goes further than market efficiency and argues that even if you do know something that others do not, you still cannot profit from that knowledge. Ross (2004) explains that the key to this result is that the method by which people acquire information is common knowledge, which roughly means that while someone else does not know what you know, they do know that you might know something useful and that you know that they know it, and so on. As a result, trader will have the idea that why should I trade with others since if they want to trade with me, they must think they can make money at my expense.

Currently, the preferred way to rule out the no-trade theorem is by positing a noisy rational expectations equilibrium model. Following Grossman and Stiglitz (1980), most models exogenously introduce noise in order to make the equilibrium price only partially revealing.

Brunnermeier (2001) defines an equilibrium that is partially revealing if less informed traders cannot determine whether the unexpected price changes are due to others' information of common interest or information of their private interest. The literature refers to trade due to information of common interest as informational trading, whereas trade due to information of private interest is called uninformed trading or noise/liquidity trading.

Thus, investors receive different information in partially revealing equilibrium. Consequently, they will have different beliefs and hence, trade for holding different assets.

2.4.3. Asset Pricing under Asymmetric Information

Since the traditional asset pricing theory abstracts from the trading mechanics, O'Hara (2003) argues that it ignores the central fact that market microstructure literature focuses: Asset prices evolve in markets. Much of market microstructure analyses differences in information between investors, and how the flows of differential information generate trade, spreads and price changes (O'Hara 1995, Madhavan 2000, Harris 2003). Therefore, Easley and O'Hara (2003) suggest that a junction of traditional asset pricing and market microstructure paradigms would be beneficial for asset pricing under asymmetric information.

O'Hara (2003) provides an elegant interpretation for why asymmetric information could affect prices. In the standard story, with an infinite number of assets and an infinite number of agents with the same information, diversification can remove any asset-specific risk. In particular, if risks are uncorrelated across assets, then diversifying makes the risk totally vanish, and hence investor could simply hold one share of every asset. If the risks are correlated, then only market risk remains, this is the CAPM story. Thus, in either case, the idiosyncratic risk attaching to individual assets is not important.

However, she suggests that, this is not the case if there is differential information. Information creates a risk for uninformed traders as the trading gains of the informed come from the trading losses of the uninformed. Unfortunately, the uninformed are unable to diversify the risk that the informed are making their profit. Thus, unless prices are fully revealing, or public information is perfect, this kind of non-diversifiable risk remains.

So, why the uninformed investors continue to trade? She argues that they recognize risk and they demand compensation for bearing it. Uninformed investors know they will lose to better informed investors, but they have portfolio choices to make. These choices allow them to choose assets in which their risk of losing to better informed investors is lower. Therefore, this risk should be compensated in equilibrium. Traders demand extra returns to induce them to hold assets in which information risk is great.

Theoretical Evidence

Akerlof (1970) suggests that the asymmetric information among traders creates an "adverse selection problem" (or "lemon's problem"): uninformed traders cannot discern the extent to which the price change is due to informed or uninformed demand. This problem triggers the substantial research on how asymmetric information affects asset prices. In particular, the literature on partially revealing rational expectations shows how differential information affects asset prices.

Grossman and Stiglitz (1980) consider a noisy Rational Expectations Equilibrium (REE) in which investors are competitive price takers who learn from prices. In equilibrium, while some investors refrain from collecting information, others incur cost in gathering information and get compensated in the form of superior expected investment performance such that the two groups of investors have the same overall expected utility.

Grossman and Stiglitz's model captures the partial information transmission role of prices, but does not illustrate the information aggregation role of prices. This is because information is not dispersed among the traders in their model. This additional aspect is analysed by Hellwig (1980) and Diamond and Verrecchia (1981).

Moreover, Hellwig raises another problem: traders behave "schizophrenically" in a competitive REE. On the one hand, each trader takes the equilibrium price as given when making his trading decision. On the other hand, he tries to infer information from the price, which means that he thinks that private information is reflected in the price. To deal with this problem, Admati (1985) extends Hellwig's setting to a model with multiple risky assets and infinitely many traders. Thus in this "large market" model each informed trader becomes "small" in an appropriate sense. In this model, her analysis shows how investors face different risk-return tradeoffs when differential information is not fully revealed in equilibrium.

Wang (1993) presents a two-asset, dynamic REE model that asymmetric information has three effects on asset prices. First, uninformed investors require a risk premium to compensate them for the adverse selection problem. Second, informed trading also makes prices more informative, thereby reducing the risk for the uninformed and lowering the risk premium. Third, the increasing asymmetry in information among investors can cause price volatility to increase because the adverse selection problem becomes more severe. Moreover, the optimal investment strategy of the informed investors depends not only on the value of the underlying true state variables but also on the reaction of uninformed investors. At last, he suggests that it can be optimal for less informed traders to chase the trend.

Brennan and Cao (1997) use a similar idea to explain how superior information about home country assets can help explain international equity flows. They show that when domestic investors possess a cumulative information advantage over foreign investors about their domestic market, investors tend to purchase foreign assets in periods when the return on foreign assets is high and to sell when the return is low.

Jones and Slezak (1999) construct a multi-asset dynamic rational expectations model to investigate the implications of asymmetric information on both cross-sectional and dynamic properties of asset returns. They demonstrate that the model is capable of generating a variety of behaviour, some of which are roughly consistent with well-established empirical regularities, including (1) the size effect, (2) the asymmetric lead-lag between the returns on large and small firms over short horizons, (3) the weak relationship between beta (from CAPM) and expected return, and (4) the success of other variables (e.g., book-to-market) at explaining the cross section of expected returns.

Easley and O'Hara (2004) build a multi-asset partially revealing REE model to examine the role of information in affecting a firm's cost of capital. They show that if information about an asset is private, rather than public, then uninformed investors demand a higher rate of return on the asset to compensate for the risk of trading with better informed traders. In equilibrium, the quantity and quality of information affect asset prices.

Empirical Evidence

Despite that information, particularly private information, is not directly observable, the microstructure literature provides ways for empirical research. Firstly, Kyle (1985) provides Kyle λ, which measures the responsiveness of prices to signed order flow. It can be estimated by regressing price changes on signed order flow. This measure is developed based on the idea that liquidity suppliers in securities markets are always aware that other traders may have better information. In particular, Kyle (1985) models the behaviour of a single market maker who sets a "break-even" price in response to the net combined order flow of informed and uninformed traders. The market maker's price sensitivity to order flow, also called the "price impact", is set to balance the market maker's losses from trades with the informed against gains from trades with the uninformed. Thus, the price impact is a function of the degree of asymmetric information in the market.

Secondly, the probability of information-based trade (PIN), from Easley, Kiefer and O'Hara (1997b), refers to the measure of the importance of private information in a microstructure setting. PIN, which can be estimated from data on trades, measures the fraction of orders that arise from informed traders. The PIN measure is a private information measure because it is a function of abnormal order flow. The underlying assumption is that public information is directly incorporated into prices without the need of trading activity, whereas private information is reflected in excess buying or excess selling pressure (abnormal order flow). In other words, order flow captures information that is not common knowledge because, if it were common knowledge, the specialist would have automatically moved prices to the appropriate level and there would not have been any trading activity.

There is a substantial literature adopts the above two measures to test the impact of asymmetric information on prices. For the papers on the Kyle λ measure, for example, see Glosten and Harris (1988), Hasbrouck (1991), Foster and Viswanathan (1993), Brennan and Subrahmanyam (1996), and Amihud (2002). The papers on PIN measure include, for instance, Easley, Kiefer and O'Hara (1996, 1997a, b), Easley, Kiefer, O'Hara and Paperman (1996), and Easley, Hvidkjaer and O'Hara (2002).

All these papers provide evidence that asymmetric information affects asset prices. For instance, Brennan and Subrahmanyam (1996) and Amihud (2002) argue that stocks with high λ are less attractive to uninformed investors. Easley, Hvidkjaer and O'Hara (2002) use a structural microstructure model to estimate the probability of information-based trade in each NYSE common stock yearly for the period 1983 to 1998. They show that stocks with higher rates of return require higher rates of return. This result suggests that the risk of informed trading is priced.

While models of adverse selection risk in literature generally assume that market makers offset expected losses to informed traders with expected gains from the uninformed, Odders-White and Ready (2008) suggest that focusing only on the expected loss to informed traders provides an incomplete picture. They recognize that measures of the expected loss capture a combination of two effects: (1) the probability of a private information event, and (2) the likely magnitude of the information. Thus, they develop a method of separately estimating the probability and magnitude of private information using returns and trade imbalances. Their findings suggest that firms with similar expected losses can have markedly different probabilities and magnitudes of private information events. For example, large firms have smaller, more frequent information events, while small firms experience larger, less frequent events. These differences cannot be observed by simply studying adverse selection costs (e.g., spreads or price impacts). They suggest that their separation on the probability and magnitude of information events is important and their estimation method is a reasonable alternative when the PIN estimation cannot be used.

More recently, Duarte and Young (2009) examine whether PIN is priced because of information asymmetry or because of other liquidity effects that are unrelated to information asymmetry. They find that the original PIN model of Easley, Kiefer and O'Hara (1997b) cannot match the pervasive positive correlation between buy and sell order flow or the relatively large variances of buy and sell order flow. They develop an extension of the PIN model to accommodate these mismatch problems by allowing for simultaneous positive shocks to both buy and sell order flow. This extension model can be used to compute a new measure of asymmetric information, AdjPIN. Since AdjPIN is orthogonal to expected returns in a Fama-MacBeth (1973) regression, PIN is not priced because it is a proxy for information asymmetry. They further use the extended model to develop a measure of illiquidity unrelated to information asymmetry, PSOS (probability of symmetric order-flow shock). In addition to being related to illiquidity, PSOS is strongly correlated with PIN while the correlation between PSOS and AdjPIN is relatively low. Thus, PSOS is the component of PIN that proxies for illiquidity unrelated to asymmetric information. Since the estimated relation between expected returns and PSOS is strong, the relation between PIN and expected returns is due to the fact that PIN is also a proxy of illiquidity not related to private information. They therefore conclude that liquidity effects unrelated to information asymmetry explain the relation between PIN and the cross-section of expected returns.

2.5. Information Uncertainty Literature

Although it seems that information uncertainty is closely related to asymmetric information, they can be very different from each other. The essence of asymmetric information means that different people hold different information, while information uncertainty focuses on the information environment of firms which determines the convenience of acquiring and studying information.

2.5.1. The Concept of Information Uncertainty

In the prior literature, information uncertainty is often modelled as the information asymmetry component of the cost of capital (e.g., Diamond and Verrecchia 1991, Easley and O'Hara 2001, Verrecchia 2001) or estimation risk (e.g., Barry and Brown 1985, Coles and Loewenstein 1988, Klein and Bawa 1976). More recently, Jiang, Lee, and Zhang (2005) and Zhang (2006) propose that information uncertainty means the ambiguity with respect to the implications of new information for a firm's value, which potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information. Specifically, they argue that information asymmetry means some agents know more about a firm's value than others, while information uncertainty refers to the value ambiguity, or the degree to which a firm's value can be reasonably estimated by even the most knowledgeable investors at reasonable costs. High uncertainty firms, for example, are companies whose expected cash flows are less knowable, perhaps because of the nature of their business or operation environment. These firms associated with higher information acquisition costs, and estimates of their fundamental values are inherently less reliable and more volatile.

2.5.2. Asset Pricing under Information Uncertainty

The empirical findings on information uncertainty are normally difficult to reconcile with traditional asset pricing models. Specifically, prior studies have found that younger firms (Zhang 2006), firms with higher volatility (Ang, Hodrick, Xing, and

Zhang 2003), higher volume (or turnover) (Lee and Swaminathan 2000), greater expected growth (LaPorta 1996), higher price-to-book (PB) ratios (Fama and French 1992), wider dispersion in analyst earnings forecast (Diether, Malloy, and Scherbina 2002), and longer implied duration in their future cash flows (DeChow, Sloan, and Soliman 2003), all earn lower subsequent returns.

These empirical results are puzzling because in standard asset pricing models, non-systematic risk is not priced, and various information uncertainty proxies should have no ability to predict future returns. More recently, Easley and O'Hara (2003) examine information risk in asset pricing. However, this kind of model focuses on information asymmetry and predicts that higher information uncertainty should be associated with higher information risk or greater information acquisition costs and hence higher (not lower) expected returns.

While the rational framework under asymmetric information could not provide explanations for empirical evidence of information uncertainty, behavioural finance establishes the approach. Hirshleifer (2001) posits that greater uncertainty about a set of stocks leave more room for psychological biases. Therefore, the misvaluation effects of almost any mistaken-beliefs model should be strongest among firms about which there is high uncertainty and poor information. For example, Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) show that return predictability should be stronger in firms with greater uncertainty because investors tend to be more overconfident when firms' businesses are hard to value.

Thus, Jiang, Lee, and Zhang (2005) argue that when information uncertainty of firms is higher, investors' individual valuations are more diffused and solid feedback on the quality of their private signal is more difficult to obtain. Thus, investors in high-uncertainty firms tend to overweight their private signals, and place too little weight on public news and news about firm fundamentals. Using several different proxies for information uncertainty, Jiang, Lee, and Zhang (2005) show that high uncertainty firms tend to be overpriced and hence earn lower future returns. Furthermore, high uncertainty firms will exhibit greater price and earnings momentum effects.

Jiang, Lee, and Zhang (2005) argue that another important feature of a high uncertainty environment is the ability to constrain arbitrage. With greater value ambiguity, rational traders face elevated information acquisition costs and greater information risk associated with noisy value estimates. Perhaps even more importantly, they confront the increased likelihood of informational cascades. For instance, Bikchandani, Hirshleifer, and Welch (1992) show that when each individual receives a noisy private signal, it is often optimal to follow the behaviour of the preceding traders without regard of his own information. Thus, Jiang, Lee, and Zhang (2005) argue that when firm value is highly uncertain, rational investors will adapt by relying more heavily on the recent actions of others than on their own signals. An important consequence of this behaviour is that rational forces can actually exacerbate, rather than correct, deviations of price from fundamental value. Therefore, the increased likelihood of informational cascades also contributes to greater price and earnings momentum effects among high uncertainty firms.

2.5.3. Information Uncertainty and Information Disclosure

Hong, Lim, and Stein (2000) also adopt information uncertainty as the measure of information diffusion speed. They consider analyst coverage as proxy for rate of information flow. Thus, information uncertainty is closely related information disclosure. Plenty of accounting studies have documented the effect of information disclosure on returns. Verrecchia (2001) provide a survey of the theoretical work, and Healy and Palepu (2001) give a survey of the empirical work. These reports show that while the theoretical argument that accounting disclosure can reduce information uncertainty and cost of capital is appealing, but the overall empirical evidence is mixed. More recently, Zhang (2006) show that the effects of information uncertainty on future returns following good and bad news offset each other in unsigned analysis might explain why previous studies often find an insignificant effect of accounting disclosure. He also suggests a potential additional role for accounting disclosure. That is, more transparent disclosure might reduce information uncertainty and speed the absorption of new information into the stock prices.

Chapter 3

Informed Trading, Short-Sale Constraints, and Information Uncertainty

3.1. Introduction

It is puzzling that the prices of individual stocks sometimes decline without the arrival of fundamental news. There are many possible answers to this phenomenon. In contrast with the traditional asset pricing models (such as CAPM, APT of Ross 1977, and representative agent asset-pricing model of Lucas 1978), recent studies that focus on various market frictions provide fresh views. This chapter empirically examines one possible explanation that based on the combination impact of short-sale constraints and information asymmetry on stock prices. According to three key papers including Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008), the unusual declines of stock prices can be due to the reaction of uninformed investors to a new information uncertainty risk. In particular, uninformed investors will require a price discount to hold the stock because they will perceive a new information uncertainty risk when short-sale constraints are binding and informed trading is absent.

The theory behind this new information uncertainty risk effect is that the trading activities of informed investors help their private information gets incorporated into stocks prices and hence prices adjust to the fundamental value continuously. Thus, stock prices become less informative when binding short-sale constraints keep informed investors from trading on their private information. The less informative prices create a new information uncertainty risk for uninformed investors, since uninformed investors are unable to figure out the true value of the stock without knowing the private information held by informed investors. Because of this new information uncertainty risk, uninformed investors are reluctant to hold the stock unless there is a price discount. While the three key papers concentrate on asset pricing implications of short-sale constraints in an asymmetric information setting, this chapter focuses on the role of informed trading in this new information uncertainty risk effect and proposes the following hypothesis.

Hypothesis 1: *Stocks will have lower future returns if the level of informed trading is lower and when short-sale constraints are binding.*

In addition, this chapter argues that the new information uncertainty risk effect can be affected by stock's information uncertainty condition. Information uncertainty here, as presented in Zhang (2006), means the ambiguity with respect to the implications of new information for a firm's value. It potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information. In other words, information uncertainty reflects the convenience of learning the fundamental value of stock. Accordingly, the level of stock's information uncertainty is negatively related to the level of price's informative condition. If stock has greater information uncertainty, the new information uncertainty risk perceived by uninformed investors will be stronger because (1) they would find it is harder to study the true value of stock; (2) they have to rely more on informed investors' private information. If stock has lower information uncertainty, the new information uncertainty risk perceived by uninformed investors will be smaller because (1) they could learn the true value of stock easier; (2) they will not be eager to acquire informed investors' private information. Therefore, the impact of information uncertainty on the new information uncertainty risk effect is represented by the following hypothesis.

Hypothesis 2: *Hypothesis 1 is mostly valid when information uncertainty is high. When information uncertainty is low, stocks with low level of informed trading and binding short-sale constraints rarely experience lower future returns.*

According to the above analysis, the new information uncertainty risk effect should not arise when information uncertainty is low and short-sale constraints are not binding. This is because, in this scenario, uninformed investors understand that it is not very hard to learn the true value of stock and the lack of informed trading generally mean the absence of private information. Hence, the case that the new information uncertainty risk effect will not emerge is summarized by the following hypothesis.

Hypothesis 3: *Low level of informed trading will not affect future stocks returns when information uncertainty is low and short-sale constraints are not binding.*

The empirical results in this chapter confirm the three hypotheses using monthly data on NYSE- and AMEX-listed stocks from 1983 to 2001. Specifically, the existence of informed trading is measured by the probability of information-based trade (PIN). The binding short-sale constraints are defined as the reductive changes in breadth of ownership (ΔBREADTH). Analyst coverage (COV), firm age (AGE), and firm size (MV) are used as the proxies for the information uncertainty of stocks. Different portfolios are formed to test the three hypotheses.

The empirical results confirm the existence of new information uncertainty risk effect. Firstly, Hypothesis 1 is supported by the evidence that high-minus-low PIN hedging portfolio earns significant positive return among stocks with binding short-sale constraints (negative low-ΔBREADTH). Secondly, Hypothesis 2 and Hypothesis 3 are verified by the portfolio returns under the three-way sorting by information uncertainty, short-sale constraints and informed trading proxies. When information uncertainty is high (low-COV, low-AGE, or low-MV) and short-sale constraints are binding, low-PIN stocks always underperform high-PIN stocks. When information uncertainty is low (high-COV, high-AGE, or high-MV) and short-sale constraints are binding, low-PIN stocks rarely underperform high-PIN stocks. When information uncertainty is low and short-sale constraints are not binding, low-PIN stocks do not underperform high-PIN stocks.

However, the information risk theory proposed by Easley, Hvidkjaer, and O'Hara (2002) can also explain the evidence that supports Hypothesis 1. The information risk theory argues that stocks with more information asymmetry have higher expected returns. Thus, Hypothesis 1 alone cannot fully support the new information uncertainty risk effect. Comfortingly, the results that support Hypothesis 2 and Hypothesis 3 can show some distinct features of the new information uncertainty risk effect. Since these features cannot be explained by the information risk theory, the new information uncertainty risk effect can be further justified. The performances of three-way sorting portfolios show that when information uncertainty is low, high-PIN stocks generally do not perform better than low-PIN stocks no matter short-sale constraints are binding or not. In addition, when information uncertainty is low, the case that low-PIN stocks underperform high-PIN stocks is possible only if short-sale constraints are binding. While these findings cannot be rationalized with the information risk theory, they coincide perfectly with the new information uncertainty risk effect.

Chapter 3 contributes to the literature in several ways. First, it is the first study that empirically verifies the existence of the new information uncertainty risk effect created by the presence of short-sale constraints and the absence of informed trading.

Thus, Chapter 3 establishes a possible explanation for stock price decreasing without the arrival of any fundamental news. Second, it further explores the link between information uncertainty and the new information uncertainty risk. According to the findings, one efficient way to eliminate the new information uncertainty risk is to reduce the level of information uncertainty. Third, previous literature mainly considers the existence of informed trading as a signal of asymmetric information. Chapter 3 suggests that the nonexistence of informed trading is also important. Finally, previous literature generally focuses on how short-sale constraints influence the relation between investors' expectations and asset prices. Chapter 3 implies that short-sale constraints can also influence the risk as perceived by investors.

The remainder of this chapter is outlined as follows. Section 3.2 reviews related literature. Section 3.3 constructs the sample and describes the data characteristics. Section 3.4 discusses empirical results from the portfolio analysis. Section 3.5 concludes this chapter.

3.2. Related Literature

Literature generally shows that short-sale constrains can cause overpricing because of two reasons. First, short-sale constraints keep more pessimistic investors out of the market and hence prices tend to reflect a more optimistic valuation than they otherwise would. This is the "optimism effect" (see, e.g., Miller 1977, Chen, Hong, and Stein 2002). Second, speculations can arise in the dynamics of trading under short-sale constraints. That is, investors pay prices that exceed their own valuation of future dividends as they anticipate find a buyer willing to pay even more in the future. This is the "resale option effect" (see, e.g., Harrison and Kreps 1978 and Scheinkman and Xiong 2003b). Although most empirical studies suggest that short-sale constrained firms are overvalued, financial economists pursue more appropriate measure of short-sale constraints all the time. Since the level of short-sale constraints cannot be directly observed, different kinds of proxies are proposed.

Three are several categories of measures of short-sale constraints. Firstly, the old-fashion papers use high short interest ratios (shares sold short divided by shares outstanding) as a proxy for shorting demand (e.g., Figlewski 1981, Figlewski and Webb 1993, Desai, Ramesh, Thiagarajan, and Balachandran 2002). However, the short interest proxy suffers limitations. For instance, Chen, Hong, and Stein (2002) argue that variations in short interest may reflect variations in the transactions costs of selling short rather than in suppressed negative information. The second literature category instead focuses on the fact that short sales depend on stock ownership by mutual funds and institutions because of the assumption that most lendable shares are from institutional owners (Chen, Hong, and Stein 2002, Nagel 2005). The third category recognizes the competing effects of shorting supply and shorting demand, and argues that stocks with high shorting demand and low shorting supply are the most likely to face binding short-sale constraints (Asquith, Pathak, and Ritter 2005).

Cohen, Diether, and Malloy (2007) disentangle the individual effects of shorting supply and shorting demand and find that shorting demand is an important predictor of future stock returns. Fourthly, another empirical approach tries to obtain data on the direct costs of shorting from the stock loan market. They generally look at the rebate rate on borrowed stock (D'Avolio 2002, Geczy, Musto, and Reed 2002, Ofek, Richardson, and Whitelaw 2004, Jones and Lamont 2002). Fifthly, some papers consider the link between short-sale constraints and stock prices in the context of option introductions. This is because derivatives such as option could provide alternative ways to take a short position in a security (Danielsen and Sorescu 2001, Ofek and Richardson 2003). Finally, Boehme, Danielsen, and Sorescu (2006) examine the valuation effects of the interaction between dispersion of investor opinions and short-sale constraints. They argue that most of pervious tests are imperfect because Miller (1977)'s hypothesis implies that both the dispersion of investors opinion and the short-sale constraints are necessary to stock price overvaluation.

By contrast, some papers consider the asymmetric information setting and suggest that short-sale constraints do not necessarily cause overvaluation. Using a rational expectations model, Diamond and Verrecchia (1987) provide an alternative view by modelling the effects of short-sale constraints in a rational expectations framework. They show that the price of a stock with binding short-sale constraints adjusts more slowly to unfavourable private information than it does to favourable private information. But they argue that in a rational market, traders will recognize the existence of short-sale constraints and will adjust their beliefs such that no overpricing of securities will exist, on average. More recently, Bai, Chang, and Wang (2006), Marin and Olivier (2008), and Yuan (2006) argue that the lack of informed trading could lead to a new information uncertainty risk to uninformed investors when short-sale constraints are binding. When the degree of information asymmetry is significant, short-sale constraints can affect stock prices.

Specifically, in the fully rational expectations equilibrium model of Bai, Chang, and Wang (2006), investors trade for sharing risk or/and speculating on private information. Short-sale constraints limit both types of trades. Limiting short sales driven by risk-sharing shifts the demand for the asset upwards. Limiting short sales driven by private information increases the uncertainty about the asset as perceived by uninformed investors and hence reduces the demand for the asset. When this information effect dominates, short-sale constraints actually cause asset prices to decrease and price volatility to increase.

Marin and Olivier (2008) also suggest uninformed investors may react more strongly to the absence of insider sales (informed trading) than to their presence. In their noisy rational expectations model, once insiders' holdings reach the floor set by the constraints like short-sale constraints, insiders can no longer deliver bad news into prices. Thus, uninformed investors can only infer that insiders are in possession of bad news but not how bad the news really is. This results in a crash in price since uninformed investors' beliefs decrease and their perceived level of uncertainty increases.

In Yuan (2006)'s noisy rational expectations equilibrium model, uninformed investors are uncertain whether trading constraints restrict informed investors from transmitting information to prices, and thus they demand an information-disadvantaged premium in holding stocks. This creates a large price decline. However, she focuses on the scenario in which information asymmetry combined with short-sale constraints dampens the upward price movement.

While asymmetric information is helpful for discovering new role of short-sale constraints, theoretical literature, including Grossman and Stiglitiz (1980), Admati (1985), Wang (1993), Jones and Slezak (1999), and Easley and O'Hara (2000), suggests that asymmetric information alone can affect asset returns. Easley and O'Hara (2004) show that uninformed investors understand they will lose to the informed investors who know private information, and so requires a greater expected return to hold the asset with more information risk. Easley and O'Hara (2004) show that assets with more private and less public information should have greater expected returns. Despite that information, particularly private information, is not directly observable, the microstructure literature provides ways for empirical research. Firstly, Kyle (1985) provides Kyle λ, which measures the responsiveness of prices to signed order flow. It can be estimated by regressing price changes on signed order flow.

Secondly, the probability of information-based trade (PIN), from Easley, Kiefer and O'Hara (1997b), refers to the measure of the importance of private information in a microstructure setting. PIN, which can be estimated from data on trades, measures the fraction of orders that arise from informed traders. Moreover, Vega (2006) shows that PIN is not exclusively an insider trading measure as it also captures informed trading by investors who are particularly skillful in analysing public news.

In the prior literature, information uncertainty is often modelled as the information asymmetry component of the cost of capital (e.g., Diamond and Verrecchia 1991, Easley and O'Hara 2001, Verrecchia 2001) or estimation risk (e.g., Barry and Brown 1985, Coles and Loewenstein 1988, Klein and Bawa 1976) and therefore increases expected stock returns. However, recent studies, including Jiang, Lee, and Zhang (2005) and Zhang (2006), do not equal information uncertainty to information asymmetry. They argue that information asymmetry means some agents know more about a firm's value than others, while information uncertainty refers to the value ambiguity, or the degree to which a firm's value can be reasonably estimated by even the most knowledgeable investors at reasonable costs. High uncertainty firms are companies whose expected cash flows are less knowable, perhaps because of the nature of their business or operation environment. These firms associated with higher information acquisition costs, and estimates of their fundamental values are inherently less reliable and more volatile.

3.3. Data and Sample

The sample of Chapter 3 is restricted by the data resources of Cass Business School of City University London (CASS). Wharton Research Data Services (WRDS) is the databases for this chapter but CASS only subscribed limited datasets. Thus, the choices of proxies for informed trading, short-sale constraints and information uncertainty depend on the available datasets at CASS.

3.3.1. Informed Trading Proxy

The level of informed trading is measured by the probability of information-based trade (PIN). There are other popular proxies like bid-ask spread and price impact that are used to measure the degree of asymmetric information. However, the degree of asymmetric information does not necessarily capture the level of informed trading since informed investors may not fully trade on their private information because of limitations like short-sale constraints. Instead, PIN can directly measure the level of informed trading as it is a function of abnormal order flow. However, PIN is a controversial proxy for information asymmetry. Easley, Hvidkjaer, and O'Hara (2002) find that PIN is an important determinant of cross-section of expected returns. Mohanram and Rajgopal (2007) find that PIN is not priced beyond Easley, Hvidkjaer, and O'Hara (2002)'s sample period of 1984 - 1988. Duarte and Young (2009) show that the PIN component related to illiquidity is priced. They suggest that liquidity effects unrelated to information asymmetry explain the relation between PIN and the cross-section of expected returns. Nevertheless, the focus of this chapter is not the information asymmetry effect but the joint effect of short-sale constraints and informed trading. Thus, PIN is still a suitable informed trading proxy for this chapter as informed trading can be identified by abnormal order flow imbalance.

Easley and O'Hara (1992) define PIN as the estimated arrival rate of informed trades divided by the estimated arrival rate of all trades during a pre-specified period of time. Formally, the Institute for the Study of Security Markets (ISSM) and NYSE Trade and Quote (NYSE TAQ) datasets are required to estimate PIN. However, CASS has not subscribed ISSM dataset and only subscribed NYSE TAQ dataset from 2004. Although the datasets for estimating PIN are not available, the annual PIN data estimated in Easley, Hvidkjaer, and O'Hara (2005) can be obtained from Soeren Hvidkjaer's website. Because the frequency of portfolio is monthly in this chapter, the value of PIN in each month t takes the value of PIN in that year.

Easley, Hvidkjaer, and O'Hara (2005) estimate the annual PIN for the sample of all ordinary common stocks listed on the NYSE and the AMEX for the years 1983 - 2001 because the market microstructure of NYSE and AMEX are most closely consistent to that of their PIN model. Thus, this chapter also focuses on NYSE- and AMEX-listed stocks during the period of 1983 to 2001. They exclude REITs (Real Estate Investment Trusts), stocks of companies incorporated outside of the U.S, and closed-end funds. They also exclude a stock in any year in which it did not have at least 60 days with quotes or trades, as they cannot estimate their trade model reliably for such stocks. In addition, since they form portfolios based on year-end firm size, they exclude stocks for which this information is not available. In addition, they eliminate stocks with a year-end price below $1.

Their final sample of PIN estimates includes 1863 to 2414 stocks in the years 1983 - 2001. In particular, among nearly 40,000 stock-years, they were able to obtain PIN estimates for all but 475. These failures were generally because of the days of extremely high trading volume in last six years of the sample, which caused computational underflow in the optimization program. In addition, this occurs almost exclusively for the largest stocks rather than for smaller stocks. For example, while only 47 of the 2037 stocks (3.6%) in the 2001 year-sample do not obtain PIN estimates, these stocks account for 23.7% of the total market capitalization in the 2001 year-sample. This limitation suggests interpreting the results for large stocks with caution. Appendix 3.1 provides the basic information of the PIN estimates in Easley, Hvidkjaer, and O'Hara (2005).

3.3.2. Short-Sale Constraints Proxy

According to the data availability at CASS, the only choice for short-sale constraints proxy is the change in breadth of ownership proposed by Chen, Hong, and Stein

(2002). This is because CASS does not have datasets for estimating other common short-sale constraints measures such as short interest and institutional ownership. Breadth is defined roughly as the number of owners with long positions in a particular stock. If the owners cannot take a short position, when they have information suggesting they should short, they will at least reduce their holdings to zero. Thus, a reduction in the number of owners is evidence of more investors who are sitting on the sidelines with their pessimistic valuations not registered in the stock's price. Since Chen, Hong, and Stein (2002) assume that the amount of negative information withheld from the market can represent the level of tightly binding short-sale constraints, the reductions in breadth should mean short-sale constraints are binding and forecast lower subsequent returns. Because Chen, Hong, and Stein (2002) do not have comprehensive ownership data, they look at quarterly data on mutual fund ownership instead of a more complete measure of breadth of ownership. Moreover, since mutual funds rarely take short positions, mutual funds that do not have long positions can represent that these funds sitting on the sidelines, i.e., having no position at all.

However, the breadth of mutual fund ownership proxy has drawbacks. Because ownership data do not cover all potential investors subject to short-sale constraints, the breadth of mutual fund ownership is part influenced by movements in the relative holdings of mutual fund versus other classes of investors. The reduction in breadth that means tightly binding short-sale constraints should capture the scenario in which the aggregate holdings of the mutual fund sector are unchanged, but the shares are less broadly held within the mutual fund sector. However, a reduction in breadth could be the case that shares have net moved out of the mutual fund sector and into other class of investors, for example, the hands of individuals. Thus, the changes in breadth might not really reflect binding short-sale constraints, but represent the superior stock-picking skill of mutual fund managers who are smarter than individuals. In addition, the market movements can also affect the changes in breadth. During market downturn times, stocks generally suffer poor performance and mutual funds managers cannot take too much risk, and hence mutual funds managers are very likely to reduce their holdings in stocks. Therefore, reductions in breadth of ownership may not really reflect binding short-sales constraints, but rather because of stock market downturn. Similarly, stock market boom can lead to increases in breadth of ownership, and hence the increases in breadth do not necessarily mean that short-sale constraints are not binding.

The datasets of Mutual Funds Holdings (CDA/Spectrum s12) in the Thomson Reuters databases are used to compute the change in breadth of ownership. This database contains information on quarterly equity holdings of mutual funds based in the United States from 1982 to 2002. Mutual funds are required by SEC regulation N30-D to disclose their portfolio holdings twice a year. CDA/Spectrum collects data from these filings and supplements the data through voluntary quarterly reports published by the mutual funds for their shareholders. None of the funds is excluded according to its investment objectives. According to Chen, Hong, and Stein (2002), the calculation of the change in breadth of ownership requires the mutual funds to be in both quarter T and quarter T-1. From this group, the change in the breadth of ownership for a stock in quarter T, denoted as $\Delta BREADTH_T$, is the number of funds who hold the stock at quarter T minus the number of funds who hold the stock at quarter T-1 and divide by the total number of funds in the sample at quarter T-1. Finally, since the frequency of portfolio is monthly in this chapter, $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T.

3.3.3. Information Uncertainty Proxy

Since individual proxy may capture other things except information uncertainty, this chapter adopts three proxies for information uncertainty: analyst coverage (COV), firm age (AGE), and firm size (MV). This is because they are closely related to firm's information environment and they are easily and directly observed by uninformed investors. Another advantage is that they can keep the sample size consistent as each firm can have fully available information for all three proxies.

Firstly, analyst coverage, measured as the number of analyst following the firm in the previous year, can determine the amount of available information on the firm for investors. Analysts collect, digest, and distribute information about the fundamental news of firm. Firms with higher analyst coverage means a larger number of analysts provide the relevant information, which implies less information uncertainty about the firm. The Institutional Brokers Estimates System (I/B/E/S) provides consensus and detail forecasts from security analysts. Following Zhang (2006), analyst coverage (COV) is calculated based on the raw detail forecast data unadjusted for stock splits in I/B/E/S. Specifically, COV is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month.

Secondly, firm age can measure information uncertainty because firms with a longer history would provide more available information to the market (Barry and Brown 1985). Thus, young firms with short history have higher uncertainty. Following Zhang (2006), firm age is measured as the number of years since the firm was first covered by Center for Research in Securities Prices (CRSP).

Thirdly, one natural information uncertainty measure is firm size, which can be calculated as the market capitalization based on data in CRSP. Small firms tend to be unique and less diversified. They may also have fewer scales of running conditions such as the number of suppliers, customers, shareholders and products. Therefore, less information on small firms could be available to the market and it might costs investors more to collect small firms' information. The CRSP monthly tape in WRDS also provides data on monthly returns.

There are all kinds of proxies for information uncertainty in literature. For example, Jiang, Lee, and Zhang (2005) summarize that stocks with high information uncertainty refer to firms with higher volatility (Ang, Hodrick, Xing, and Zhang 2003), higher volume (or turnover) (Lee and Swaminathan 2000), greater expected growth (LaPorta 1996), higher price-to-book (PB) ratios (Fama and French 1992), wider dispersion in analyst earnings forecast (Diether, Malloy, and Scherbina 2002), and longer implied duration in their future cash flows (DeChow, Sloan, and Soliman 2003). In addition, these high-uncertainty stocks are observed to earn lower future returns. This is because many of these variables are related to other features such as differences of opinion. Previous studies generally use dispersion in analyst forecasts to examine the overvaluation effect (Miller 1977). Deither, Malloy, and Scherbina (2002) find that as the degree of overpricing increases as the dispersion of valuations rises. In addition, turnover is also used to measure differences of opinion among investors. Hong and Stein (2007) indicate that dynamic models with disagreement among investors and short-sale constraints imply a positive correlation exists between trading volume and the degree of overpricing. Therefore, many information uncertainty proxies may introduce unnecessary biases into the empirical results, specially, the proxies for dispersion of opinion. By contrast, analyst coverage alone does not have significant price impact. Moreover, the computation of dispersion requires each firm has at least two analyst forecasts, and hence dispersion will have smaller sample size than analyst coverage.

3.3.4. Sample Selection Criteria

Finally, a stock has to satisfy the following criteria to be included in the sample. First, stocks with a price less than \$5 are excluded to minimize the problem of bid-ask bounces and extreme illiquidity of small stocks (Jegadeesh and Titman 2001). Second, this chapter requires all grouping variables are jointly available at end month t as portfolios are rebalanced monthly. These grouping variables include three information uncertainty proxies (MV_t, AGE_t, and COV_t), short-sale constraints proxy ($\Delta BREADTH_t$) and informed trading proxy (PIN_t). Stocks without firm size have been excluded. Since PIN is the key variable, stocks are excluded if they have missing value of PIN. Following Aslan, Easley, Hvidkjaer, and O'Hara (2007), the missing value of COV_t or $\Delta BREADTH_t$ takes value of zero.

3.3.5. Risk-adjusted Returns

To achieve precise conclusion for the empirical tests, this chapter takes common risk factors into account. Fama and French (1996) argue that many of the CAPM average-return anomalies are related, and that they are captured by the three-factor model in Fama and French (1993). In the three-factor model, R_M - R_F is the excess return on a proxy for the market portfolio, SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return on a portfolio comprised of high book-to-market stocks and the return on a portfolio comprised of low book-to-market stocks. The variable HML represents the value premium; high book-to-market stocks are value stocks, and low book-to-market stocks are growth stocks. Similarly, the variable SMB represents the size premium. However, the three-factor model does not explain the returns to momentum portfolios (see Jegadeesh and Titman 1993, Grundy and Martin 2001). Carhart (1997) suggests adding a factor-mimicking portfolio based on momentum (UMD), i.e. the returns on a diversified portfolio long in recent winners and short in recent losers, to the three factor model.

This chapter adjusts high-minus-low PIN hedging portfolio returns for common risk factors. In particular, the returns of high-minus-low PIN hedging portfolios are adjusted by the three factors:

$$R_i = \alpha_i + \beta_i (R_M - R_{F)} + s_iSMB + h_iHML + e_{i.},$$

and four-factor model:

$$R_i = \alpha_i + \beta_i (R_M - R_{F)} + s_iSMB + h_iHML + m_iUMD + e_{i.}.$$

All the four factors are downloaded from Kenneth French’s website. According to Fama and French (1993) and the descriptions on Kenneth French’s website, the following details provide the procedures that construct the four factors.

(1) The Fama-French Three Factors

The Fama-French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market. The 6 size/book-to-market portfolios, which are constructed at the end of each June, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in t-1 divided by ME for December of t-1. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. SMB and HML for July of year t to June of year t+1 include all NYSE, AMEX, and NASDAQ stocks that have market equity data for December of year t-1 and June of year t, and (positive) book equity data for year t-1.

SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios,

SMB =1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth).

HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios,

HML =1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).

Rm-Rf, the excess return on the market, is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates).

(2) The Momentum Factor

Fama and French use six value-weight portfolios formed on size and prior (2-12) returns to construct UMD factor. The six value-weight portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles.

UMD is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios,

UMD =1/2 (Small High + Big High) - 1/2(Small Low + Big Low).

The six portfolios used to construct UMD each month include NYSE, AMEX, and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of the month t-1), a stock must have a price for the end of month t-13 and a good return for t-2. In addition, any missing returns from t-12 to t-3 must be -99.0, CRSP's code for a missing price. Each included stock also must have ME for the end of t-1.

3.3.6. Summary Statistics

Table 3.1 provides the summary statistics of the sample in this chapter. Panel A contains mean monthly statistics for the firm-month observations by year. The sample contains on average 1,750 firms per month from 1983 to 2001. The unusual decrease in the number of firms from 1999 is because the sample size is determined by the number of PIN estimations. Easley, Hvidkjaer, and O'Hara (2005) indicate that the extremely high daily trading volume in later years could cause failures for estimating PIN. Furthermore, they present that this occurs almost exclusively for the largest stocks rather than for smaller stocks. As it is shown in Panel A, firm size keeps increasing from 1983 to 2001. The average number of analyst coverage is around 8, and the average firm age is about 22 in each year. The monthly mean of the change in breadth of ownership changes from year to year without a consistent pattern. The monthly mean of PIN in the sample is 0.199, and its approximate trend is decreasing from 1983 to 2001.

Panel B shows the correlation matrix. The Pearson and Spearman correlations for these five variables are quite similar. The correlations between ΔBREADTH and the other four variables are all weak, suggesting that short-sale constraints are straightforward to all kinds of firms. Consistent with Aslan, Easley, Hvidkjaer, and O'Hara (2007), three variables including firm size, analyst coverage, and firm age are positively correlated with each other, and all of them are negatively correlated with PIN. In addition, these correlations are generally strong. These results are not surprising because firms with high information uncertainty such as small firms, young firms, and firms with low analyst following are typically subject to high degree of private information.

Panel C provides a close look at the relationship between firm size and other four variables. Following Chen, Hong, and Stein (2002), firms are assigned into size quintiles, determined by NYSE market capitalization breakpoints (obtained from Kenneth French's website). The mean value of ΔBREADTH is closely related to firm size, ranging from 0.01% for stocks in the bottom-size quintile, to 0.19% for stocks in the top-size quintile. Meanwhile, the standard deviations of ΔBREADTH show similar patterns with respect to firm size. More importantly, the mean values and standard deviations show that there is much more variation in ΔBREADTH across large stocks comparing with small stocks. This pattern, empathized by Chen, Hong, and Stein (2002), implies that the bottom- and top-ΔBREADTH will be dominated by large firms. Similarly, analyst coverage suffers the same problem. However, both firm age and PIN avoid this problem. Although their mean values and standard deviations are also closely related to firm size, they still have meaningful variations in both small and large firms.

3.4. Empirical Results

To investigate the new information uncertainty risk effect empirically, stocks are assigned to portfolios based on certain characteristics. This standard approach in asset pricing, pioneered by Jegadeesh and Titman (1993), reduces the variability in returns.

3.4.1. Portfolio Returns Sorted by One Variable

Table 3.2 examines the individual impact of analyst coverage (COV), firm age (AGE), firm size (MV), short-sale constraints (ΔBREADTH) and the probability of information-based trading (PIN) on stock returns. In particular, at each month t, stocks are assigned into five classes of analyst coverage (COV_t), with the class breakpoints determined separately within each size (MV_t) quintile in the same month. The COV_t classes are then recombined across the five MV_t quintiles, and hence five COV_t groups obtained. This procedure ensures that within each COV_t group, stocks do not have roughly the same size. The procedure is necessary because, as it is shown in Panel C of Table 3.1, there is much more variation in COV across large stocks. If it was an unconditional ranking on COV independent of MV, then the extreme (lowest or highest COV) groups would be dominated by large stocks. Because the change in breadth of ownership (ΔBREADTH) suffers the same problem as COV, stocks are sorted into ΔBREADTH groups by following the above steps as well. For the other three variables (MV, AGE, and PIN), stocks are simply sorted into five groups at each month t based on the value level of variable at that month. Equally weighted portfolios are formed within each subgroup, and portfolios are held for one month.

Table 3.2 reports the average monthly portfolio returns. At first, higher uncertainty (low-MV, low-COV, or low-AGE) stocks forecast lower returns but only high-minus-low COV hedging portfolio yields positive return of 0.19% at 10% significance level. Thus, as Zhang (2006) suggests, information uncertainty is not a cross-sectional risk factor. Second, hedging portfolio that longs high-ΔBREADTH stocks and shorts low-ΔBREADTH stocks earns a positive return of 1.05% at 1% significance level. This is consistent to the finding of Chen, Hong, and Stein (2002), who present that reductions in breadth should forecast lower returns. Finally, the information risk theory in Easley, Hvidkjaer, and O'Hara (2002) is confirmed because stocks with higher probabilities of information-based trading have higher rates of return. The return of high-minus-low PIN hedging portfolio is 0.31% at 10% significance level.

3.4.2. Portfolio Returns Sorted by Information Uncertainty Proxy and PIN

Table 3.3 examines the interaction of PIN and information uncertainty variable. Stocks are classified into five categories based on information uncertainty proxy at each month. The sorting method for COV is special. At each month t, stocks are assigned into quintile classes of COV_t, with the quintile breakpoints determined separately within each MV_t quintile. The COV_t quintiles are then recombined across MV_t classes. Within each uncertainty category, stocks are then sorted into five quintiles by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and their one-month-ahead returns are reported in Table 3.3. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively.

Table 3.3 shows that stocks with high level of informed trading generally have superior performance when information uncertainty is high. Firstly, all three panels show that when information uncertainty is small there is barely a difference between high-PIN and low-PIN stocks. The return differentials between high-PIN and low-PIN firms are 0.06% within high-COV category, 0.06% within high-AGE category, and 0.16% within high-MV category, which are very small and not statistically significant. Secondly, two of three panels have strong statistically significant positive high-minus-low PIN hedging portfolio returns within high information uncertainty category (0.49% within low-AGE group and 0.85% within low-COV group).

These findings are consistent with the information risk theory. If information uncertainty is low, there is hardly any private information in this transparent information environment. Hence, the overall information risk is small and high-PIN stocks will not outperform low-PIN stocks. If stocks have high information uncertainty, they also tend to have high degree of private information. As a result, stocks with higher level of informed trading should have higher future returns. Therefore, information uncertainty has an impact on informed trading. Based on the strong correlation between information uncertainty variables and PIN in Panel B of

Table 3.1 and other firm-specific variables related to PIN, Aslan, Easley, Hvidkjaer, and O'Hara (2007) use data of market and accounting characteristics including firm size, firm age, and analyst coverage to develop a proxy for PIN, denoted as PPIN. They find that information risk as captured by PPIN is both statistically and economically significant for asset prices.

Informed trading, on the other hand, can also affect information uncertainty of stocks. Because informed trading moves prices toward the full information levels, low level of informed trading leads to less informative prices and hence the uncertainty of stocks increases. High informed trading improves information efficiency and thereby reducing information uncertainty (Wang 1993). Finally, the new information uncertainty risk proposed in this chapter is also introduced by the absence of informed trading combined with binding short-sale constraints.

The above analysis underlines that the investigation on the new information uncertainty risk effect should take information uncertainty into account.

3.4.3. Portfolio Returns Sorted by Short-Sale Constraints Proxy and PIN

In order to examine Hypothesis 1, Table 3.4 assigns stocks into portfolios based on short-sale constraints proxy and informed trading proxy. At each month t, stocks are sorted into five classes of the change in breadth of ownership $\Delta BREADTH_t$, with the class breakpoints determined separately within each firm size MV_t quintile. The $\Delta BREADTH_t$ classes are then recombined across MV_t quintiles. Within each $\Delta BREADTH_t$ category, stocks are then sorted into five groups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month.

In Table 3.4, high-minus-low PIN hedging portfolio only produces significant positive return if stocks are subject to lowest or highest level of ΔBREADTH. These two hedging portfolios have similar statistically significant positive returns. Thus, stocks with higher PIN could earn higher returns when short-sale constraints are binding tightly or not binding at all. The information risk theory could fit with either case as trading on private information is always profitable. Note that both low-PIN and high-PIN stocks have higher returns in high-ΔBREADTH subgroup than low-ΔBREADTH subgroup. To a great extent, this can be due to the fact that higher ΔBREADTH stocks have higher subsequent returns. More importantly, Hypothesis 1 is verified since stocks with binding short-sale constraints (low-ΔBREADTH) with low level of informed trading (low-PIN) have lower future returns. However, Hypothesis 1 alone is not enough for confirming the existence of the new information uncertainty risk effect as the information risk theory could interpret its evidence as well. Therefore, it is important to examine the unique features of the new information uncertainty risk effect by controlling for information uncertainty.

3.4.4. Portfolio Returns under Three-Way Sorting

Table 3.5 uses a three-way sort by information uncertainty, short-sale constraints, and informed trading proxies to analyse the new information uncertainty effect under different levels of information uncertainty.

Each month t, stocks are firstly classified into three information uncertainty groups based on the level of uncertainty. In order to ensure that within each analyst coverage (COV_t) subgroup, stocks do not have roughly the same size, the sorting method on COV_t in Panel A is special as before. Stocks are assigned into three COV_t classes, with the class breakpoints determined separately within each size (MV_t) quintile. The COV_t classes are then recombined across the five MV_t quintiles, and hence three COV_t groups obtained. The sorting method on firm age (AGE) in Panel B and firm size (MV) in Panel C is normal as stocks are simply sorted into three categories by the level of uncertainty at month t. For each information uncertainty group, stocks are then sorted into three groups based on the level of the change of breadth of ownership ($\Delta BREADTH_t$). For each uncertainty and the change of breadth subgroup, stocks are further sorted into three divisions by the level of informed trading (PIN_t). This three-way sort classifies stocks into 27 portfolios. Portfolios are equally weighted and their performances are tracked over one-month head. Table 3.5 reports the raw and risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks.

First of all, the first columns of three panels in Table 3.5 present the similar performances for stocks with binding short-sale constraints (low-ΔBREADTH) and high information uncertainty (low-COV, low-AGE, or low-MV). That is, these stocks have lower subsequent returns if the level of informed trading is lower. The raw return differential between high- and low-PIN of these stocks is significantly positive in Panel B and Panel C except Panel A. Moreover, the Fama-French three-factor and the four-factor risk-adjusted returns of all hedging portfolios that long high-PIN and short low-PIN stocks are strong significantly positive in all there panels. These results obviously confirm the first part of Hypothesis 2 that Hypothesis 1 is mostly valid when information uncertainty is high.

Table 3.5 also reports supporting evidence for the second part of Hypothesis 2 that when information uncertainty is low, stocks with low level of informed trading and binding short-sale constraints rarely experience lower future returns. Both Panel A and Panel C show that within high-uncertainty (low-COV, or low-MV) and low-ΔBREADTH groups, the raw and risk-adjusted returns of high-minus-low hedging portfolios are not statistically significant different from zero. Only Panel B shows that within high-AGE and low-ΔBREADTH group, this hedging portfolio earns significant positive raw return (0.32% t = 1.85) and the four-factor risk-adjusted return (0.31% t = 1.79). These results are consistent with the new information uncertainty risk effect. Although low information uncertainty helps uninformed investors to understand the true value of stock, it cannot completely eliminate the potential new information uncertainty risk since uninformed investors can perceive that risk as long as short-sale constraints are binding and informed trading is absent.

Finally, all three panels of Table 3.5 justify Hypothesis 3 as well because none of the raw, the three-factor and the four-factor risk-adjusted returns are statistically significant different from zero for all high-minus-low PIN hedging portfolios within low-uncertainty (high-COV, high-AGE, or high-MV) and high-ΔBREADTH groups. When short-sale constraints are not binding (high-ΔBREADTH), uninformed investors generally do not believe that informed investors are kept from trading on their private information. In addition, low information uncertainty implies that it is convenient to obtain information about the fundamental value of stock. Thus, the absence of informed trading will not introduce the new information uncertainty risk about stock to uninformed investors.

While the above findings support the new information uncertainty risk effect, it is important to see whether the information risk theory interpret these findings. Similar to Hypothesis 1 in Table 3.4, the information risk theory can explain the superior performance of high-PIN stocks with high information uncertainty and binding short-sale constraints. However, the results provided by stocks with low information uncertainty present challenges to the information risk theory. Table 3.3 has shown that the information risk effect does not arise when information uncertainty is low. By contrast, Panel B of Table 3.5 shows that high-PIN stocks outperform low-PIN stocks when information uncertainty is low (high-AGE) and short-sale constraints are binding (low-ΔBREADTH). More importantly, among stocks with long history, high-PIN stocks only outperform when short-sale constraints are binding. This importance of short-sale constraints cannot be explained by the information risk theory either.

The intuition behind Hypothesis 2 and Hypothesis 3, however, can explain these results well. Short-sale constraints are important because binding short-sale constraints keep informed investors from trading on private information, and hence prices become less informative and uninformed investors understand there is unexposed important private information. Thus, uninformed investors still have a chance to perceive a new information uncertainty risk even though stocks have transparent information environment (low information uncertainty). If short-sale constraints are not binding, informed investors can trade on private information and enrich the informativeness of prices without limitation, and uninformed investors will not believe the absence of informed trading means the unexposed important private information. Therefore, the new information uncertainty risk will not arise, especially when information uncertainty is low.

According to the above analysis, Hypothesis 2 and Hypothesis 3 are vital for the valid of the new information uncertainty risk effect. This is because they not only directly present additional supports for the new information uncertainty risk effect, but also provide a way to distinguish the new information uncertainty risk theory from the information risk theory.

3.4.5. Subperiod Analysis

Table 3.6 provides the subperiod analysis for Hypothesis 2 and Hypothesis 3, which are relatively much more curial than Hypothesis 1. This robustness check can examine if the new information uncertainty risk effect is time-specific. The two subperiods include 1983 to 1992 and 1993 to 2002. The results of three-way sort by information uncertainty, short-sale constraints, and informed trading proxies are presented in Panel A for analyst coverage, Panel B for firm age, and Panel C for firm size respectively. These results only include the raw and risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks. Overall, Table 3.6 confirms Hypothesis 2 and Hypothesis 3 again. When information uncertainty is great and short-sale constraints are binding, low-PIN stocks generally underperform in either subperiod. When information uncertainty is small and short-sale constraints are binding, hedging portfolios only have significant positive return in the subperiod 1983 to 1992. When information uncertainty is small and short-sale constraints are not binding, all hedging portfolios do not earn significant positive four-factor risk-adjusted returns in either subperiod.

3.4.6. Comments on Robustness

To ascertain that the new information uncertainty risk effect documented here is not caused by specific sample, specific proxies or an obvious explanation, this chapter has employed several ways to demonstrate robustness.

Firstly, this chapter proposes Hypothesis 2 and Hypothesis 3 to explore the role of information uncertainty in the new information uncertainty risk effect. On the one hand, information uncertainty is important because it is naturally related to the new information uncertainty risk. Uninformed investors perceive the new information uncertainty risk because they are extremely uncertain about the true value of stock. Since information uncertainty of stock has an influence on uninformed investors' judgments about the true value of stock, information uncertainty can affect the information uncertainty risk. On the other hand, information uncertainty should be taken into account because it can be used to distinguish the new information uncertainty risk effect from the information risk effect. According to Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008), Hypothesis 1 is developed to capture the new information uncertainty risk effect. Although Table 3.4 provides supporting evidence to Hypothesis 1, the information risk theory could also explain the results in Table 3.4. Nevertheless, information uncertainty can be used to identify the unique features of the new information uncertainty risk effect. As it is shown in Section 3.4.4, the information risk theory fails to interpret the importance of binding short-sale constraints to the poor performance of stocks with low level of informed trading.

Secondly, this chapter tries to adopt alternative proxies to examine the new information uncertainty risk effect. Due to data limitation, the only proxy of informed trading is probability of information-based trading (PIN), and the only proxy of short-sale constraints is the change in breadth of ownership (ΔBREADTH). While the primary proxy of information uncertainty is analyst coverage (COV), this chapter also uses firm age (AGE) and firm size (MV) to measure information uncertainty. The three kinds of information uncertainty proxies in Panel A, Panel B, and Panel C of Table 3.5 lead to similar results for Hypothesis 2 and Hypothesis 3.

Finally, this chapter provides subperiod analysis in Section 3.4.5. The two subperiods include 1983 to 1992 and 1993 to 2002. The subperiod analysis shows that Hypothesis 1, Hypothesis 2 and Hypothesis 3 are valid in each subperiod.

3.5. Conclusion

This chapter empirically examines a new information uncertainty risk effect, which can provide possible explanation for the phenomenon that the prices of individual stocks sometimes decline without the arrival of fundamental news. According to Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008), which study asset pricing under short-sale constraints in an information asymmetry setting, this chapter proposes that uninformed investors perceive a new information uncertainty risk when short-sale constraints are binding and informed trading is absent. As a result, uninformed investors require a price discount to hold the stock.

This new information uncertainty risk effect arises because prices become less informative when short-sale constraints stop informed investors from trading on private information. Hence, uninformed investors become more uncertain about the true value of stocks without the unexposed private information held by informed investors. In addition, this chapter further suggests that information uncertainty of stocks can affect this new information uncertainty risk effect because information uncertainty of stock represents the convenience of learning the fundamental value of stock.

The empirical findings confirm this new information uncertainty effect as stocks with higher level of informed trading will have lower future returns when short-sale constraints are binding. Moreover, this effect is strong when information uncertainty is high, and it rarely arises when information uncertainty is low. When information uncertainty is low and short-sale constraints are not binding, this new information uncertainty risk effect will not emerge. Although the information risk theory can also explain that stocks with low informed trading have lower subsequent returns, it cannot explain the important impact of short-sale constraints to the performance of these stocks when information uncertainty is low, which is the unique feature of the new information uncertainty risk effect.

Appendix 3.1: Summary Statistics of PIN Estimates in Easley, Hvidkjaer, and O'Hara (2005)

This table provides the basic information on the yearly PIN estimates in Easley, Hvidkjaer, and O'Hara (2005). The source of these information is Panel A of Table 1 in Easley, Hvidkjaer, and O'Hara (2005). nEst is the number of stocks for which pin estimates were obtained, while nNotEst is the number of stocks for which estimates could not be obtained. fracCap is the total year-end the market value of the stocks for which pin estimates were not obtained divided by the total market value of the sample.

Year	nEst.	nNotEst.	fracCap
1983	2,094	4	0.000
1984	2,038	5	0.001
1985	1,993	3	0.000
1986	1,914	5	0.001
1987	1,974	7	0.001
1988	1,956	4	0.019
1989	1,900	9	0.007
1990	1,858	5	0.000
1991	1,945	14	0.002
1992	2,008	20	0.032
1993	2,151	11	0.013
1994	2,209	6	0.001
1995	2,219	20	0.007
1996	2,246	64	0.119
1997	2,320	67	0.234
1998	2,371	43	0.187
1999	2,228	66	0.252
2000	2,099	75	0.311
2001	1,990	47	0.237

Table 3.1 Summary Statistics

This table provides the summary statistics for NYSE and AMEX stocks during the period 1983 - 2001. Panel A reports the mean monthly statistics for all stocks. Panel B shows the correlation matrix, in which the Pearson's correlations are shown above the diagonal with Spearman's correlation below. Panel C demonstrates the mean and standard deviation values by NYSE Market Capitalization quintiles. No. of firms per month is the monthly average number of firms in the sample. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month. $\Delta BREADTH_T$ is the change in breadth of ownership from the end of quarter T-1 to quarter T. The breadth of ownership in quarter T is the fraction of all mutual funds long the stock at the end of quarter T. $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero.

Panel A: Mean Monthly Statistics by Year

Year	No.of Firms per Month	MV per Month	COV per Month	AGE per Month	ΔBREADTH per Month	PIN per Month
1983	1,920	754	7	22	0.13%	0.222
1984	1,832	777	8	22	0.03%	0.208
1985	1,759	931	9	23	0.04%	0.216
1986	1,706	1,178	9	23	0.04%	0.216
1987	1,706	1,362	9	22	0.09%	0.217
1988	1,630	1,293	8	22	0.01%	0.216
1989	1,573	1,580	9	22	0.08%	0.213
1990	1,424	1,692	9	23	0.06%	0.215
1991	1,474	1,934	8	23	0.07%	0.214
1992	1,609	1,946	7	22	0.08%	0.209
1993	1,756	2,079	8	22	0.12%	0.199
1994	1,844	2,085	8	22	0.10%	0.198
1995	1,882	2,386	7	22	-0.01%	0.196
1996	1,932	2,578	7	21	0.05%	0.192
1997	2,038	2,723	7	21	0.03%	0.181
1998	2,048	3,552	7	21	0.04%	0.171
1999	1,880	4,059	8	21	0.07%	0.169
2000	1,680	4,124	8	22	0.08%	0.171
2001	1,549	4,719	9	23	0.03%	0.180
Total	1,750	2,209	8	22	0.06%	0.199

Table 3.1—*Continued*

Panel B: Correlation Matrix (Pearson Correlations Are Shown above the Diagonal with Spearman Below)					
	MV	COV	AGE	ΔBREADTH	PIN
MV	1	0.318	0.240	0.114	-0.291
COV	0.528	1	0.228	0.098	-0.383
AGE	0.301	0.150	1	0.042	-0.240
ΔBREADTH	0.042	0.043	0.008	1	-0.057
PIN	-0.693	-0.390	-0.250	-0.021	1

Panel C: Means and Standard Deviations by NYSE Market Capitalization Quintiles

		All Firms	Quintile 1 Firms (Smallest)	Quintile 2 Firms	Quintile 3 Firms	Quintile 4 Firms	Quintile 5 Firms (Largest)
MV	Mean	2,209	67	261	651	1,686	10,382
	Std.Dev.	7,554	50	126	282	832	16,151
COV	Mean	8	1	5	8	12	19
	Std.Dev.	10	3	5	7	10	14
AGE	Mean	22	16	17	20	26	35
	Std.Dev.	18	12	14	17	18	21
ΔBREADTH	Mean	0.06%	0.01%	0.02%	0.04%	0.07%	0.19%
	Std.Dev.	0.61%	0.12%	0.23%	0.33%	0.51%	1.32%
PIN	Mean	0.199	0.262	0.212	0.185	0.164	0.133
	Std.Dev.	0.077	0.084	0.058	0.053	0.048	0.040

Table 3.2 Portfolio Returns Sorted by One Variable

This table reports average monthly portfolio returns sorted by one variable only. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Analyst coverage (COV) is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month. Firm age (AGE) is the number of years since the firm was first covered by CRSP. $\Delta BREADTH_T$ is the change in breadth of ownership from the end of quarter T-1 to quarter T. The breadth of ownership in quarter T is the fraction of all mutual funds long the stock at the end of quarter T. $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. At each month t, stocks are assigned into five classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. Stocks are sorted into $\Delta BREADTH_t$ quintiles by following the above steps as COV_t. For the other three variables, each month stocks are simply sorted into five groups based on the value level of variable at that month. Stocks are held for one month and portfolio returns are equally weighted. Stocks with a price less than $5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	MV	COV	AGE	ΔBREADTH	PIN
Q1 (Low)	0.0099	0.0103	0.0100	0.0081	0.0115
	3.21	3.63	2.92	2.40	4.14
Q2	0.0121	0.0108	0.0114	0.0091	0.0112
	3.60	3.79	3.46	3.07	3.53
Q3	0.0124	0.0138	0.0126	0.0111	0.0103
	3.75	4.47	4.06	3.89	3.14
Q4	0.0122	0.0124	0.0127	0.0128	0.0117
	3.91	3.97	4.42	4.43	3.52
Q5 (High)	0.0127	0.0122	0.0125	0.0186	0.0146
	4.47	3.53	4.75	5.74	5.00
Q5 - Q1	0.0028	**0.0019***	0.0024	**0.0105*****	**0.0031***
	1.29	1.74	1.51	8.59	1.73

Table 3.3 Portfolio Returns Sorted by Information Uncertainty and PIN

This table reports average monthly portfolio returns based on information uncertainty proxy and the probability of information-based trade proxy (PIN). Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Stocks are first classified into five categories based on information uncertainty proxy at each month. The sorting method for COV is special. At each month t, stocks are assigned into five classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. Within each uncertainty category, stocks are then sorted into five groups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by COV and PIN

PIN	COV				
	C1 (Low)	C2	C3	C4	C5 (High)
P1 (Low)	0.0114	0.0085	0.0118	0.0121	0.0131
	4.29	2.86	3.88	4.17	4.33
P2	0.0103	0.0091	0.0123	0.0121	0.0125
	3.6	2.86	3.8	3.67	3.40
P3	0.0086	0.0098	0.0137	0.0115	0.0103
	2.77	3.01	4.11	3.33	2.68
P4	0.0092	0.0123	0.0140	0.0116	0.0114
	2.87	3.99	4.29	3.31	2.98
P5 (High)	0.0120	0.0144	0.0171	0.0149	0.0137
	3.82	5.51	5.34	4.54	3.68
P5 - P1	0.0006	**0.0060*** **	**0.0053*** **	0.0028	0.0006
	0.29	3.16	2.79	1.42	0.23

Table 3.3—*Continued*

PIN	AGE				
	A1 (Low)	A1 (Low)	A1 (Low)	A1 (Low)	A1 (Low)
Panel B: Portfolios Formed by AGE and PIN					
P1 (Low)	0.0098	0.0105	0.0119	0.0117	0.0126
	2.94	3.10	3.73	3.91	5.03
P2	0.0077	0.0089	0.0110	0.0122	0.0114
	2.09	2.42	3.18	3.86	4.22
P3	0.0081	0.0109	0.0111	0.0116	0.0124
	2.12	2.92	3.38	3.73	4.50
P4	0.0099	0.0134	0.0142	0.0128	0.0125
	2.66	3.83	4.23	4.15	4.21
P5 (High)	0.0146	0.0136	0.0147	0.0151	0.0133
	4.41	4.48	4.95	5.38	4.63
P5 - P1	**0.0049*****	0.0031	0.0028	**0.0035***	0.0006
	2.65	1.50	1.34	1.66	0.31

Panel C: Portfolios Formed by MV and PIN

PIN	MV				
	M1 (Low)	M2	M3	M4	M5 (High)
P1 (Low)	0.0052	0.0093	0.0115	0.0128	0.0126
	1.46	2.59	3.54	4.22	4.61
P2	0.0083	0.0095	0.0114	0.0111	0.0118
	2.32	2.65	3.26	3.41	4.12
P3	0.0091	0.0124	0.0121	0.0125	0.0118
	2.65	3.45	3.43	3.67	3.97
P4	0.0134	0.0131	0.0117	0.0101	0.0131
	4.24	3.73	3.43	3.10	4.34
P5 (High)	0.0137	0.0163	0.0154	0.0144	0.0141
	5.22	5.07	4.55	4.69	4.68
P5 - P1	**0.0085*****	**0.0070*****	**0.0039****	0.0016	0.0016
	3.93	3.81	2.46	1.05	1.12

Table 3.4 Portfolio Returns Sorted by Short-Sale Constraints and PIN

This table reports average monthly portfolio returns based on short-sale constraints proxy (the change of breadth of ownership ΔBREADTH) and the probability of information-based trade proxy (PIN). At each month t, stocks are assigned into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each MV_t quintile. The $\Delta BREADTH_t$ classes are then recombined across MV_t quintiles. Within each $\Delta BREADTH_t$ category, stocks are then sorted into five groups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

PIN	ΔBREADTH				
	B1 (Low)	B2	B3	B4	B5 (High)
P1 (Low)	0.0083	0.0093	0.0105	0.0130	0.0163
	2.70	3.27	3.76	4.75	5.38
P2	0.0071	0.0093	0.0101	0.0129	0.0172
	1.92	2.81	3.28	4.18	5.04
P3	0.0047	0.0073	0.0096	0.0119	0.0183
	1.26	2.22	3.06	3.78	5.18
P4	0.0077	0.0094	0.0121	0.0113	0.0207
	2.10	2.81	3.74	3.40	5.67
P5 (High)	0.0126	0.0105	0.0133	0.0150	0.0204
	3.65	3.56	4.69	4.87	6.04
P5 - P1	**0.0042***	0.0012	0.0028	0.0020	**0.0041***
	1.90	0.61	1.43	0.97	1.81

Table 3.5 Portfolio Returns Sorted by Information Uncertainty, Short-Sale Constraints, and PIN

This table reports average monthly portfolio returns using three-way sorting. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Stocks are first classified into three information uncertainty categories at each month. Within each uncertainty category, stocks are then sorted into three levels of the change in breadth of ownership ($\Delta BREADTH_t$). For each uncertainty and the change of breadth subgroup, stocks are further sorted into three divisions by the level of probability of information-based trade (PIN_t). The sorting method for COV is special. At each month t, stocks are assigned into three classes of COV_t, with the class breakpoints determined separately within each MV_t quintile, the COV_t classes are then recombined across MV_t quintiles. For the resulting 27 subgroups, equally weighted portfolios are constructed and held for one month. All three panels report the Fama-French three-factor and the four-factor risk-adjusted returns for all high-minus-low PIN hedging portfolios. Stocks with a price less than $5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by COV, ΔBREADTH and PIN

PIN	Low COV			Medium COV			High COV		
	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0088	0.0112	0.0103	0.0103	0.0106	0.0136	0.0094	0.0116	0.0159
	2.61	4.10	3.19	3.29	3.60	4.45	2.94	3.36	5.00
Medium	0.0073	0.0091	0.0133	0.0113	0.0107	0.0148	0.0069	0.0092	0.0150
	2.01	3.00	3.96	3.40	3.32	4.39	1.88	2.44	4.34
High	0.0125	0.0105	0.0179	0.0120	0.0144	0.0173	0.0103	0.0152	0.0171
	4.03	3.68	5.48	3.78	4.30	4.95	2.78	3.87	4.75
H – L (Raw)	0.0038	-0.0007	**0.0076*** **	0.0017	**0.0038*** **	**0.0037** **	0.0009	**0.0035***	0.0012
	1.57	-0.40	3.29	1.00	2.60	2.20	0.45	1.90	0.64
H – L (3-Factor)	**0.0060** **	-0.0005	**0.0084*** **	0.0017	**0.0035** **	**0.0035** **	-0.0009	0.0023	0.0007
	2.56	-0.29	3.90	1.03	2.49	2.21	-0.48	1.37	0.41
H – L (4-Factor)	**0.0057** **	-0.0007	**0.0069*** **	0.0012	**0.0035** **	**0.0031***	-0.0005	0.0017	0.0009
	2.36	-0.37	3.20	0.72	2.48	1.89	-0.25	0.98	0.47

Table 3.5—*Continued*

Panel B: Portfolios Formed by AGE, ΔBREADTH and PIN									
	Low AGE			Medium AGE			High AGE		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0061	0.0082	0.0146	0.0092	0.0095	0.0144	0.0107	0.0124	0.0137
	1.74	2.43	4.11	2.74	3.06	4.40	3.91	4.87	4.87
Medium	0.0044	0.0090	0.0139	0.0101	0.0101	0.0165	0.0103	0.0109	0.0128
	1.13	2.45	3.51	2.84	3.16	4.94	3.34	3.80	4.31
High	0.0098	0.0125	0.0181	0.0127	0.0126	0.0175	0.0140	0.0127	0.0155
	2.69	3.84	4.78	3.79	4.17	5.28	4.45	4.22	5.07
H – L (Raw)	**0.0036****	**0.0044****	**0.0035***	**0.0035***	**0.0031***	0.0032	**0.0032***	0.0003	0.0018
	1.99	2.45	1.70	1.93	1.83	1.63	1.85	0.15	1.02
H – L (3-Factor)	**0.0038****	**0.0042****	**0.0032***	**0.0038****	**0.0038****	**0.0047*****	0.0025	-0.0005	0.0018
	2.04	2.39	1.66	2.20	2.38	2.83	1.50	-0.28	1.23
H – L (4-Factor)	**0.0038****	0.0024	0.0008	**0.0039****	**0.0031***	**0.0034****	**0.0031***	-0.0001	0.0014
	2.03	1.39	0.44	2.23	1.88	2.05	1.79	-0.04	0.95

Table 3.5—*Continued*

Panel C: Portfolios Formed by MV, ΔBREADTH and PIN									
	Low MV			Medium MV			High MV		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0036	0.0068	0.0121	0.0089	0.0094	0.0151	0.0099	0.0123	0.0158
	0.94	2.04	3.26	2.42	3.09	4.41	3.47	4.42	5.41
Medium	0.0085	0.0086	0.0153	0.0063	0.0106	0.0180	0.0087	0.0128	0.0138
	2.27	2.61	4.16	1.71	3.21	5.04	2.71	4.23	4.41
High	0.0127	0.0120	0.0182	0.0107	0.0136	0.0186	0.0100	0.0121	0.0175
	3.85	4.13	5.61	3.00	4.30	5.23	3.10	3.88	5.26
H – L (Raw)	**0.0091***	**0.0053***	**0.0061***	0.0018	**0.0042***	**0.0035**	0.00003	-0.0001	0.0018
	4.04	2.94	3.06	1.10	2.97	2.00	0.02	-0.10	1.26
H – L (3-Factor)	**0.0104***	**0.0057***	**0.0068***	0.0027	**0.0044***	**0.0042**	-0.0005	-0.0006	0.0010
	4.67	3.31	3.37	1.60	3.14	2.50	-0.35	-0.45	0.86
H – L (4-Factor)	**0.0089***	**0.0048***	**0.0053***	0.0016	**0.0029**	0.0024	-0.0009	-0.0011	0.0001
	3.97	2.71	2.60	0.95	2.10	1.46	-0.62	-0.84	0.08

Table 3.6 Subperiod Analysis

This table reports the average monthly returns of high-minus-low PIN hedging portfolios in two subperiods 1983 - 1992 and 1993 - 2002. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. The 9 hedging portfolios in each panel are constructed following the procedures in Table 3.5. All three panels report the Fama-French three-factor and the four-factor risk-adjusted returns for all high-minus-low PIN hedging portfolios. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV or PIN are excluded, and the missing value of COV or ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by COV, ΔBREADTH and PIN

PIN	Low COV			Medium COV			High COV		
	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	0.0042	-0.0009	0.0053	**0.0044*****	**0.0057******	0.0013	0.0001	**0.0041****	0.0021
	1.12	-0.45	1.62	1.96	2.84	0.59	0.02	1.77	0.96
H – L (3-Factor)	**0.0064****	-0.000004	0.0046	**0.0057******	**0.0059******	**0.0030****	-0.0001	**0.0044*****	**0.0028****
	1.67	-0.00	1.42	2.95	3.01	1.71	-0.04	2.02	1.66
H – L (4-Factor)	**0.0067****	0.000047	0.0048	**0.0052******	**0.0049*****	0.0028	-0.0007	**0.0039****	0.0025
	1.69	0.03	1.44	2.65	2.47	1.52	-0.32	1.76	1.45
1993 - 2002									
H – L (Raw)	0.0033	-0.0005	**0.0102******	-0.0012	0.0018	**0.0064*****	0.0018	0.0030	0.0003
	1.14	-0.15	3.08	-0.45	0.84	2.50	0.61	0.99	0.08
H – L (3-Factor)	**0.0059*****	0.0022	**0.0114******	-0.0016	0.0007	**0.0058*****	0.0001	0.0001	0.0001
	2.28	0.75	4.22	-0.57	0.38	2.28	0.02	0.05	0.03
H – L (4-Factor)	**0.0052****	0.0017	**0.0087******	-0.0027	0.0014	**0.0049****	0.0007	-0.0009	0.0005
	1.94	0.57	3.41	-0.99	0.68	1.90	0.25	-0.32	0.15

Table 3.6—*Continued*

Panel B: Portfolios Formed by AGE, ΔBREADTH and PIN									
	Low AGE			Medium AGE			High AGE		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0028***	**0.0075***	**-0.0013***	**0.0037***	**0.0049***	**0.0030***	**0.0039***	**-0.0002***	**0.0019***
	1.16	3.45	-0.53	1.50	2.34	1.51	1.56	-0.06	0.86
H – L (3-Factor)	0.0031	**0.0075***	-0.0026	**0.0045**	**0.0067***	**0.0054***	**0.0044**	0.0006	**0.0034**
	1.23	3.46	-1.11	2.12	3.55	3.26	2.02	0.28	1.98
H – L (4-Factor)	0.0029	**0.0063***	-0.0035	**0.0040***	**0.0054***	**0.0054***	**0.0038***	0.0007	0.0027
	1.13	2.92	-1.48	1.82	2.91	3.16	1.70	0.32	1.53
1993 - 2002									
H – L (Raw)	0.0045	0.0010	**0.0087***	0.0034	0.0011	0.0034	0.0025	0.0008	0.0016
	1.64	0.34	2.69	1.22	0.40	0.98	1.03	0.30	0.59
H – L (3-Factor)	**0.0048***	0.0020	**0.0106***	0.0037	0.0024	0.0044	0.0020	0.0003	0.0014
	1.73	0.73	3.50	1.35	0.96	1.46	0.79	0.11	0.61
H – L (4-Factor)	**0.0051***	-0.0005	**0.0071**	0.0039	0.0017	0.0021	0.0029	0.0005	0.0011
	1.76	-0.20	2.55	1.41	0.66	0.71	1.15	0.21	0.47

Table 3.6—*Continued*

Panel C: Portfolios Formed by MV, ΔBREADTH and PIN									
PIN	Low MV			Medium MV			High MV		
	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0108*****	**0.0086*****	**0.0096*****	**0.0030*****	**0.0041*****	**0.0026*****	**0.0033*****	**-0.0026*****	**0.0002*****
	3.38	4.43	3.69	1.36	2.24	1.30	1.87	-1.41	0.12
H – L (3-Factor)	**0.0117*****	**0.0084*****	**0.0092*****	0.0032	**0.0049*****	0.0022	**0.0042****	-0.0017	-0.0001
	3.55	4.12	3.43	1.37	2.81	1.06	2.47	-1.04	-0.04
H – L (4-Factor)	**0.0112*****	**0.0075*****	**0.0089*****	0.0027	**0.0035****	0.0015	**0.0037****	-0.0017	-0.0004
	3.30	3.66	3.23	1.14	2.10	0.72	2.11	-1.00	-0.24
1993 - 2002									
H – L (Raw)	**0.0072****	0.0017	0.0024	0.0005	**0.0042***	0.0044	-0.0036	0.0025	0.0035
	2.28	0.56	0.78	0.20	1.97	1.52	-1.46	1.28	1.58
H – L (3-Factor)	**0.0102*****	0.0042	0.0046	0.0023	**0.0049****	**0.0054****	**-0.0056****	0.0015	0.0025
	3.42	1.52	1.53	0.94	2.26	2.10	-2.38	0.77	1.42
H – L (4-Factor)	**0.0078*****	0.0030	0.0020	0.0005	0.0030	0.0030	**-0.0063*****	0.0004	0.0012
	2.67	1.06	0.68	0.20	1.44	1.20	-2.62	0.21	0.66

Chapter 4

Informed Trading, Short-Sale Constraints, and Trading Volume

4.1. Introduction

The prior literature often documents that short-sale constraints cause overpricing. However, whether short-sale constraints will always lead to overpricing is far from certain. For example, Diamond and Verrecchia (1987) show that the presence of short sales constraints reduces the informational efficiency of prices but does not bias them upward in a rational expectations model. Chapter 3 demonstrates that when short-sale constraints are binding tightly and informed trading is absent, prices will decrease because uninformed investors confront a new information uncertainty risk and hence they are reluctant to hold the stock. While this new information uncertainty risk is the central theme of Yuan (2006), Bai, Chang, and Wang (2006), and Marin and Olivier (2008), the three theoretical papers are actually focusing on two different kinds of new information uncertainty risk effect.

In particular, the combination of binding short-sale constraints and the absence of informed trading would affect stock prices in two distinct ways under two special conditions. Firstly, Yuan (2006) argues that short-sale constraints combined with information asymmetry dampen the upward price movement and thus make bubbles difficult to form. In the model of Yuan (2006), there is a noisy demand or supply shock so that prices do not fully reveal private information, similar to the noisy rational expectations equilibrium (REE) model that used by Hellwig (1980) and Grossman and Stiglitz (1980). She considers the situation in which high stock prices are driven by a high level of noise demand, and informed investors are kept out of the market due to short-sale constraints. In this scenario, informed investors' private information is not embedded in the market clearing price, resulting a noisy price. Uninformed investors face a new information uncertainty risk as they cannot distinguish noise demand from informed buying. Thus, upward price movement will be dampened since uninformed investors demand an information-disadvantage premium to hold the stock. Hence, the first kind of new information uncertainty risk reduces the level of overvaluation.

Secondly, Bai, Chang, and Wang (2006) and Marin and Olivier (2008) suggest that short-sale constraints combined with information asymmetry would cause crash of asset prices. Bai, Chang, and Wang (2006) extend Grossman-Stiglitz (1980)'s framework with differently informed investors. They consider fully rational expectations equilibrium model with binding short-sale constraints. Investors in that model trade for sharing risk or speculating on private information. Following Bhattacharya and Spiegel (1991), Marin and Olivier (2008) also extend the Grossman and Stiglitz (1980) model by substituting noise trading with rational trading driven by stochastic hedging needs. In addition, they introduce a simple constraint on asset holdings. Therefore, both Bai, Chang, and Wang (2006) and Marin and Olivier (2008) introduce noise trading through informed investors' hedging need on their non-tradable asset so that prices do not fully reveal private information. They consider the scenario in which stock prices are likely to be low when short-sale constraints are binding. When the binding short-sale constraints keep informed investors from trading on private information, prices become less informative. In this case, without a high noise demand in the market, uninformed investors can only infer that informed investors are in possession of bad news since otherwise informed buying activities can be observed. Uninformed investors become aware of a new information uncertainty risk as they could not find out how negative the information really is. Thus, the second kind of new information uncertainty risk exacerbates downward price movement as uninformed investors demand an information-disadvantage premium to hold the stock.

While the above three papers concentrate on the role of short-sale constraints in an asymmetric information setting, the purpose of this chapter is the relation between informed trading and future stock returns under two special conditions. To examine the two kinds of new information uncertainty risk effect, this chapter proposes that different levels of trading activities in the market combined with binding short-sale constraints and low informed trading can be used to capture the two kinds of market scenarios. This is because Lee and Swaminathan (2000) suggest that volume provides information about the extent to which investor sentiment favours a stock at a point in time. While uninformed investors perceive a new information uncertainty risk when short-sale constraints are binding and informed trading is absent, different levels of trading activities shape their feelings about the new uncertainty risk. On the one hand, the scenario in Yuan (2006) is captured by the high level of trading activities. Since short-sale constraints can create overvaluation, high level of trading activities combined with overvaluation represent high noise demand and buying pressure in the market. Thus, uninformed investors could not distinguish noise demand from informed buying. The first kind of new information uncertainty effect can be presented by the following hypotheses.

Hypothesis 1: *Stock should have higher future return if the level of informed trading is lower when (1) the level of trading activities is high; (2) short-sale constraints are binding.*

On the other hand, the scenario suggested by Bai, Chang, and Wang (2006) and Marin and Olivier (2008) can be captured by the low level of trading activities. The low levels of trading activities and informed trading would convince uninformed investors that the majority of investors hold downward beliefs and informed investors hold negative private information, since not only informed investors but also most of investors in the market stop buying stock. Therefore, uninformed investors become aware of the potential bad news but they do not know how bad the information really is. The following hypothesis describes the second kind of new information uncertainty effect.

Hypothesis 2: *Stock will have lower future returns if the level of informed trading is lower and when (1) the level of trading activities is low; and (2) short-sale constraints are binding.*

The empirical results in this chapter confirm these two hypotheses using monthly data on NYSE- and AMEX-listed stocks from 1983 to 2001. Specifically, trading volume (VOL) is used to measure the trading activity of stocks. The existence of informed trading is measured by the probability of information-based trade (PIN). The stocks with binding short-sale constraints are defined as stocks with reductive change in breadth of ownership (ΔBREADTH). Moreover, stocks with negative and low ΔBREADTH (tightly binding short-sale constraints) are attributed to be overvalued. The analysis based on the performance of different portfolios constructed by these variables provides supporting evidence to the two hypotheses. Hypothesis 1 is supported by the evidence that high-minus-low PIN strategy produces significant negative return among stocks with high-VOL and negative low-ΔBREADTH. In other words, when trading activity is great, short-sale constrained stocks with low level of informed trading are subject to less overpricing comparing to short-sale constrained stocks with high level of informed trading. On the other hand, when the level of VOL is low and ΔBREADTH is low and negative, high-minus-low PIN hedging portfolio earns significant positive return. Hence, Hypothesis 2 is verified as short-sale constrained stocks with lower informed trading underperform when trading activity is low.

The information risk theory also suggests that higher informed trading stocks earn higher subsequent returns as information is a risk factor (see, e.g., Easley, Hvidkjaer, and O'Hara 2002). Hence, it seems that the prediction of Hypothesis 2 can be explained by the information risk theory as well. However, within low-VOL group, high-PIN stocks outperform low-PIN stocks only when short-sale constraints are binding tightly. The information risk theory cannot interpret the importance of short-sale constraints. In contrast, the new uncertainty risk theory can explain it well because uninformed investors only perceive the new information uncertainty risk when short-sale constraints are binding, which are assumed to keep informed investors from trading on private information. Furthermore, the empirical evidence of Hypothesis 1 shows that high-PIN stocks should underperform than low-PIN stocks when short-sale constraints are binding and trading volume is intense, which is contrary to the information risk theory

This chapter contributes to the literature in several ways. First, Chapter 4 is the first study that empirically examines and supports the two theories proposed by Yuan (2006) as well as Bai, Chang, and Wang (2006) and Marin and Olivier (2008). Chapter 4 not only confirms the new information uncertainty risk once again but also verifies that there can be two different kinds of new information uncertainty risk effect. Second, previous literature mainly focuses on the close relationship between short-sale constraints and overvaluation. Chapter 4 shows that short-sale constraints can actually dampen the degree of overvaluation under certain conditions. Finally, while previous literature normally uses trading volume to measure heterogeneous beliefs, Chapter 4 suggests that trading volume can also influence the uncertainty risk as perceived by uninformed investors.

The remainder of this chapter is organized as follows. Section 4.2 reviews related literature. Section 4.3 presents the data and sample. Section 4.4 discusses empirical results from the portfolio analysis. Section 4.5 concludes this chapter.

4.2. Related Literature

Because Chapter 2 and Chapter 3 have reviewed related literature about short-sale constraints and asymmetric information (informed trading), this chapter focuses on the details of three key papers including Yuan (2006), Bai, Chang, and Wang (2006), and Marin and Olivier (2008).

Yuan (2006) argues that short-sale constraints when combined with information asymmetry dampen the upward price movement and thus make bubbles difficult to form. Her theory considers the situation that when a high level of noise demand increases the price, informed investors may be constrained out of the market due to short-sale restrictions. In this scenario, informed investors' private information is not embedded in the market clearing price, resulting a noisy price. Uninformed investors are less willing to purchase the asset since they cannot distinguish noise demand from information-based buying. Their demand becomes more elastic as the price increases, inducing a dampening effect. Hence, large upward price movements become less likely.

Bai, Chang, and Wang (2006) study how short-sale constraints affect asset price and market efficiency. They consider a fully rational expectations equilibrium model, in which investors start to trade to share risk or to speculate on private information in the presence of short-sale constraints. Short-sale constraints limit both types of trades, and thus reduce the allocational and informational efficiency of the market. Limiting short sales driven by risk-sharing simply shifts the demand for the asset upwards and consequently its price. However, limiting short sales driven by private information increases the uncertainty about the asset as perceived by less informed investors, which reduces their demand for the asset. When this information effect dominates, short-sale constraints actually cause asset prices to decrease and price volatility to increase. Moreover, they show that short-sale constraints can give rise to discrete price drops accompanied by a sharp rise in volatility when prices fail to be informative and the uncertainty perceived by uninformed investors surges.

Marin and Olivier (2008) document that at the individual stock level, sales of insiders peak many months before a large drop in the stock price, while purchases of insiders peak only the month before a large jump. They provide a theoretical explanation for this phenomenon based on asset pricing under trading constraints and asymmetric information. The key feature of their theory is that uninformed investors may react more strongly to the absence of insider sales than to their presence. They attribute this as the “dog that did not bark” effect. They also empirically test their hypothesis and find it is still robust after examining competing stories such as patterns of insider trading driven by earnings announcement dates, or insiders timing their trades to evade prosecution.

The three key papers share one common insight that short-sale constrained informed trading creates an additional information uncertainty as perceived by uninformed investors, which has been analysed in Chapter 3. However, the three papers have many differences either.

Firstly, although all of them build noisy rational expectation equilibrium models to analyse the new information uncertainty risk, their models have different features. In the model of Yuan (2006), there is a noisy demand or supply shock so that prices do not fully reveal private information, similar to the noisy rational expectations equilibrium (REE) model that used by Hellwig (1980) and Grossman and Stiglitz (1980). Bai, Chang, and Wang (2006) extend Grossman-Stiglitz (1980)’s framework with differently informed investors. They consider fully rational expectations equilibrium model with binding short-sale constraints. Investors in that model trade for sharing risk or speculating on private information. Following Bhattacharya and Spiegel (1991), Marin and Olivier (2008) also extend the Grossman and Stiglitz (1980) model by substituting noise trading with rational trading driven by stochastic hedging needs. In addition, they introduce a simple constraint on asset holdings. Therefore, both Bai, Chang, and Wang (2006) and Marin and Olivier (2008) introduce noise trading through informed investors' hedging need on their non-tradable asset so that prices do not fully reveal private information.

Secondly, since they introduce noisy into models differently, their models capture different market conditions. The model of Yuan (2006) captures the phenomenon that informed investors are short-sale constrained when the high stock price is caused by a high level of noise demand, a scenario similar to the "dot-com bubble". Thus, she suggests that short-sale constraints are likely to bind when prices are high. By contrast, in the models of Bai, Chang, and Wang (2006) and Marin and Olivier (2008), short-sale constraints are likely to bind when asset prices are low. Without the high noise demand in the market, uninformed investors can only infer that informed investors are in possession of bad news since otherwise informed buying activities can be observed.

Thirdly, according to these different market scenarios, their models have different predictions. In the model of Yuan (2006), uninformed investors cannot infer private information from the noisy prices because binding short-sale constraints keep informed investors from trading on private information. According to the high buying pressure generated by high noise demand and the overvaluation effect of short-sale constraints, uninformed investors face a new information uncertainty risk as they cannot distinguish noise demand from informed buying. Thus, upward price movement will be dampened since uninformed investors demand an information-disadvantage premium to hold the stock. Hence, the first kind of new information uncertainty risk reduces the level of overvaluation. By contrast, in the models of Bai, Chang, and Wang (2006) and Marin and Olivier (2008), since there is no high noise demand in the market, uninformed investors can only infer that informed investors are in possession of bad news since otherwise informed buying activities can be observed. Uninformed investors become aware of a new information uncertainty risk as they could not find out how negative the information really is. Thus, the second kind of new information uncertainty risk exacerbates downward price movement as uninformed investors demand an information-disadvantage premium to hold the stock.

Fourthly, while the focus of Bai, Chang, and Wang (2006) is short-sale constraints, Marin and Olivier (2008) consider the general trading constraints including short-sale constraints. Moreover, the study of Marin and Olivier (2008) is motivated by the evidence of insider trading and crashes in asset prices. They also empirically confirm their hypothesis by using insider trading data in the US market. The other two papers are pure theoretical.

Finally, Yuan (2006) also explores how general trading constraints affect asset prices in the presence of asymmetric information. She suggests that prices play an important role in shaping uninformed investor expectation in an asymmetric information environment. Accordingly, uninformed investors are uncertain whether trading constraints restrict informed investors from transmitting information to prices, and thus they demand an information-disadvantage premium in holding stocks. This effect creates a large price decline. Apart from the effect of information asymmetry combined with short-sale constraints, she also sheds light on the role of borrowing constraints as she argues that information asymmetry combined with borrowing constraints intensifies the downward price movement. In addition, the source of uncertainty in Yuan (2006) is different from that in Bai, Chang, and Wang (2006) and Marin and Olivier (2008). In the latter two studies, at a given price, informed investors' demand can be inferred and so is their constraint status. By contrast, in Yuan (2006), informed investors' constraint status cannot be inferred with certainty since the high price could be caused either by a high realization of private signals or by a high level of noise trading. This introduces an additional source of perceived uncertainty to uninformed investors and causes equilibrium price more skewed and more volatile.

Although this chapter employs trading volume to capture certain market scenarios, trading volume is often attributed to differences of opinion among investors in literature. Many studies including Diether, Malloy, and Scherbina (2002) and Boehme, Danielsen, and Sorescu (2006) use turnover to measure dispersion of opinions. Hong and Stein (2007) suggest that trading volume appears to be an indicator of sentiment. They call one particular class of heterogeneous-agent models as "disagreement" models. These models underline the importance of differences in the beliefs of investors, which can be due to (1) gradual information flow; (2) limited attention; (3) heterogeneous priors. The most compelling attractive feature of these models is that they directly address the joint behaviour of stock prices and trading volume. Cao and Ou-Yang (2009) argue that it is differences of opinion regarding public information that determines the dynamics of trading volume in stocks and options. Their model suggests that four kinds of disagreements lead to trading in stock markets: (1) disagreements about the mean of the current public information; (2) disagreements about the precision of the current public information; (3) disagreements about the mean of the next-period public information; and (4) disagreements about the precision of past public information. Only two kinds of disagreements lead to trading in option markets: disagreements about the precisions of the current- and next-period public information. Their results show that stock trading starts at the public event date and decays slowly, whereas options trading are clustered before and during the public event date. Furthermore, they develop a multiple-stock model and indicate that trading volume of a stock depends not only on disagreements about this stock's payoff, but also on disagreements about the payoffs of other correlated stocks. Even if there are no disagreements or no signals about a stock's payoff, there may still be trading in that stock due to disagreements about the payoffs of other related stocks.

4.3. Data and Sample

This chapter uses probability of information-based trade (PIN) as the informed trading proxy and the change in breadth of ownership (ΔBREADTH) as the short-sale constraints proxy, which is consistent with Chapter 3. The monthly PIN data is obtained from the 1983 – 2001 annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. Easley, Hvidkjaer, and O'Hara (2005) argue that the market microstructure of NYSE and AMEX are most closely consistent to that of their PIN model, therefore this chapter also focuses on the NYSE- and AMEX-listed stocks during the period of 1983 - 2001. Since short-sale constraints also serve as proxy for overvaluation, stocks with negative and low ΔBREADTH in this chapter are regarded as overpriced. The datasets of Mutual Funds Holdings (CDA/Spectrum s12) in the Thomson Reuters databases are used to compute the change in breadth of ownership. Similar to Chapter 3, the value of $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T.

The extent of trading activity is measured by trading volume (VOL). Volume is the total number of shares traded in the market. While raw trading volume is unscaled and hence is likely to be highly correlated with firm size, most recent studies have used turnover as a measure of the trading volume in a stock. Generally, turnover is defined as the total number of shares traded divided by the total number of shares outstanding. However, raw volume has several advantages than turnover in the context of this chapter. Obviously, volume describes the extent of trading activity more directly. The level of volume is merely the total number of shares traded, but the level of turnover also depends on the total number of shares outstanding. Thus, it can be the case that one stock A has higher volume than stock B but A has lower turnover than B because A has much larger shares outstanding than B. Since this chapter concentrates on the reaction of uninformed investors to different level of trading activity in the market, volume is a more suitable measure than turnover. Moreover, turnover has missing value if the total number of shares outstanding is zero despite the level of volume. Thus, volume would introduce larger sample size than turnover. The CRSP monthly tape in WRDS provides the data for trading volume as well as firm size (MV) and monthly returns.

At last, the sample in this chapter has two requirements. Firstly, following Jegadeesh and Titman (2001), stocks with a price less than $5 are excluded to minimize the problem of bid-ask bounces and extreme illiquidity of small stocks. Secondly, this chapter requires all grouping variables are jointly available at each month t. These grouping variables include firm size (MV_t), volume (VOL_t), short-sale constraints ($\Delta BREADTH_t$) and the probability of informed trading (PIN_t). Therefore, stocks with missing value of firm size will be excluded. Since both VOL_t and PIN_t are primary variables, stocks are excluded if they do not have valid information on any of the variable at month t. Following Aslan, Easley, Hvidkjaer, and O'Hara (2007), $\Delta BREADTH_t$ takes value of zero if it has missing value at month t.

This chapter adjusts high-minus-low PIN hedging portfolio returns for common risk factors. In particular, the returns of high-minus-low PIN hedging portfolios are adjusted by the three factors:

$$R_i = \alpha_i + \beta_i (R_M - R_F) + s_i SMB + h_i HML + e_i,$$

and four factors:

$$R_i = \alpha_i + \beta_i (R_M - R_F) + s_i SMB + h_i HML + m_i UMD + e_i.$$

All the four factors are downloaded from Kenneth French's website.

Table 4.1 provides the summary statistics of the sample in this chapter. Panel A contains mean monthly statistics for the firm-month observations by year. These observations are those that will be used to form portfolios in later sections. The sample contains on average 1,745 firms per month from 1983 to 2001. The unusual decrease in the number of firms from 1999 is because the sample size is determined by the availability of probability of information-based trade (PIN). Easley, Hvidkjaer, and O'Hara (2005) indicate that the extremely high daily trading volume in late 1990s could cause failures for estimating PIN. Furthermore, they present that this occurs almost exclusively for the largest stocks rather than for smaller stocks. The monthly mean of PIN in the sample is 0.199, and its general trend is decreasing from 1983 (0.222) to 2001 (0.180). Panel A also confirms that trading volume becomes relative large since the late 1990s. While the average monthly volume in whole sample is 37,994, it continues to increasing from 1994 (10,579) to 2001 (117,578). Firm size (MV) is also strict increasing from 1983 to 2001, and the monthly mean of the change in breadth of ownership (ΔBREADTH) changes from year to year without a consistent pattern.

Panel B demonstrates the correlation matrix. The Pearson and Spearman correlations for these four variables are quite similar. Larger firms tend to have larger trading volume because of the strong positive relations between MV and VOL in both Pearson and Spearman matrix. Smaller firms are likely to have higher probability of information-based trade since MV is highly negatively correlated with PIN (Pearson = -0.291 and Spearman = -0.694). The negative correlation between volume and PIN is strong as well (Pearson = -0.348 and Spearman = -0.684). However, none of the Pearson and Spearman correlations between ΔBREADTH and any of other three variables is strong. Thus, short-sale constraints apply to all kinds of firms.

Finally, Panel C provides a close look at the relationship between firm size and other three variables by assigning firms into size quintiles, which are determined by NYSE market capitalization breakpoints (obtained from Kenneth French's website). The mean value of ΔBREADTH is closely related to firm size, ranging from 0.01% for stocks in the bottom-size quintile, to 0.19% for stocks in the top-size quintile. The standard deviations of ΔBREADTH show a similar pattern with respect to firm size. According to this pattern that there is much more variation in ΔBREADTH across large stocks comparing with small stocks, Chen, Hong, and Stein (2002) indicate that small firms will not have enough meaningful variation in ΔBREADTH. However, VOL and PIN do not suffer this problem since their bottom- and top-ranking groups will not be dominated by large firms as ΔBREADTH's. Although the mean and standard deviation values of VOL are also closely related to firm size, these values in the bottom-size quintile are still large enough to guarantee meaningful variation in VOL across smallest firms. Similarly, the mean and standard deviation values in the top-size quintile ensure significant variation in PIN across largest firms.

4.4. Empirical Results

To empirically investigate the two hypotheses, stocks are assigned to portfolios based on certain characteristics. This standard approach in asset pricing, pioneered by Jegadeesh and Titman (1993), reduces the variability in returns.

4.4.1. Portfolio Returns Sorted by One Variable

The first step is to review the individual impact of trading volume (VOL), short-sale constraints (ΔBREADTH) and the probability of informed trading (PIN) on stock returns. These independent effects of variables give a baseline against which to compare their jointly effects in later tests. In Table 4.2, stocks are classified into five groups based on the level of each variable at each month.

The sorting method is special for the change in breadth of ownership (ΔBREADTH). At each month t, stocks are assigned into five classes of $\Delta BREADTH_t$ at that month, with the class breakpoints determined separately within each size (MV_t) quintile in the same month. The $\Delta BREADTH_t$ classes are then recombined across the five MV_t quintiles, and hence five $\Delta BREADTH_t$ groups obtained. This procedure ensures that within each $\Delta BREADTH_t$ quintile, stocks do not have roughly the same size. The procedure is necessary because, as it is shown in Panel C of Table 4.1, there is much more variation in ΔBREADTH across large stocks. If it was an unconditional ranking on ΔBREADTH independent of MV, then the lowest ΔBREADTH and the highest ΔBREADTH groups would be dominated by large stocks. For the other two variables (VOL and PIN) that do not have this problem, stocks are simply sorted into five groups at each month t based on the value level of variable at that month. Equally weighted portfolios are formed within each subgroup, and portfolios are held for one month.

Table 4.2 presents the average monthly portfolio returns. First of all, although high volume stocks perform better than low volume stocks, hedging portfolio that longs high-VOL and shorts low-VOL stocks does not generate significant return (0.21%

with t = 1.08). Thus, volume in this chapter does not capture the overpricing effect as the evidence in literature. Second, hedging portfolio that longs high-ΔBREADTH and shorts low-ΔBREADTH stocks earns significant positive return (1.07% with t = 8.53). Hence, the short-sale constrained stocks do perform worse than otherwise stocks. At last, the positive relationship between PIN and subsequent returns in information risk theory is confirmed since the return of high-minus-low PIN hedging portfolio is 0.31% at 10% significance level.

4.4.2. The Interaction between Trading Volume and Short Sale Constraints

Table 4.3 examines the price impact of the interaction between trading volume and short sale constraints. Panel A of Table 4.3 shows the independent sorting portfolio results. Stocks are sorted into five groups based on VOL_t at each month t. Meanwhile, stocks are also assigned into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each firm size (MV_t) quintile. The $\Delta BREADTH_t$ classes are then recombined across five MV_t quintiles. The combination of the independent rankings on ΔBREADTH and VOL gives 25 groups at each month t. Table 4.3 also provides dependent sorting portfolio results of ΔBREADTH under VOL in Panel B and VOL under ΔBREADTH in Panel C, respectively. In Panel B, stocks are classified into five VOL_t groups, and within each VOL group stocks are further divided into five $\Delta BREADTH_t$ subgroups. In contrast, stocks in Panel C are sorted into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each firm size (MV_t) quintile. The $\Delta BREADTH_t$ classes are then recombined across five MV_t quintiles. For each the obtained five groups of $\Delta BREADTH_t$, stocks are then sorted into five volume subgroups based on the level of VOL_t. All the resulting 25 portfolios in three panels are equal-weighted and held for one month. Table 4.3 provides the average monthly portfolio returns.

The independent and dependent sorting evidence are the basically same. On the one hand, the change in breadth of ownership effect is confirmed in all three panels. Moreover, hedging portfolios that long high-ΔBREADTH stocks and short low-ΔBREADTH stocks earn largest significant positive returns within high-VOL groups. Therefore, the overvaluation effect of short-sale constraints is stronger if the level of trading volume is higher. On the other hand, all three panels show that stocks with higher trading volume only have higher future returns when short-sale constraints are not binding. While the returns of high-minus-low VOL hedging portfolios within the high-ΔBREADTH groups are significant positive, the performance of high-minus-low VOL hedging portfolios within the low-ΔBREADTH groups are negative but not statistically significant different from zero. Overall, Table 4.3 presents that short-sale constrained stocks tend underperform more if they have higher trading volume. This is consistent with the literature that overvaluation is often accompanied by intense trading activities (Hong and Stein 2007). Thus, the implication is that high-minus-low ΔBREADTH strategy generates higher subsequent return if trading volume is greater.

4.4.3. The Interaction between Trading Volume and PIN

Table 4.4 examines the interaction between trading volume and informed trading. In particular, stocks are assigned into 25 portfolios based on dependent sorting by VOL and PIN. At each month t, stocks are sorted into five VOL_t classes first. Within each VOL_t class, stocks are then sorted into five subgroups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Table 4.4 provides the average monthly portfolio returns.

Table 4.4 shows that low informed trading stocks have lower subsequent returns when volume is small but tend to earn higher subsequent returns when volume is large. However, the performance of high informed trading stocks does not change significantly with the level of volume. Therefore, high-minus-low PIN hedging portfolio within low-VOL group generates significant positive return (0.34% t = 2.36), but the return of the same hedging portfolio within high-VOL group is not statistically significant different from zero (-0.25% t = -1.12).

On the other hand, low-VOL stocks also have lower subsequent returns when informed trading is low but have higher subsequent returns when informed trading is high. The performance of high-VOL stocks does not change significantly with the level of informed trading. Thus, high-minus-low VOL hedging portfolio within low-PIN quintile generates significant positive return (0.42% t=1.92), but the return of the same hedging portfolio within high-PIN quintile is not statistically significant different from zero (-0.18% t = -0.65).

According to the performance of above hedging portfolios, the significant positive returns are mainly contributed by shorting stocks with low level of informed trading and low level of volume. The relative poor performance of stocks with low-PIN and low-VOL can be due to that both informed and uninformed investors are not interested in holding these stocks. Note that high-VOL and high-PIN stocks do not have great performance as well, which might be due to the fact that high volume stocks are associated with the arrival rate of both informed and uninformed investors. Panel B of Table 4.1 has presented that volume is negatively related to PIN, which is consistent with the notion that stocks with greater trading activity tend to have more uninformed order flow. Therefore, in order to differentiate between VOL and PIN, the best way is to examine the level of informed order flow and the level of uninformed order flow.

4.4.4. The Interaction between Short-Sale Constraints and PIN

Table 4.5 reviews the interaction between short-sale constraints (ΔBREADTH) and informed trading (PIN). At each month t, stocks are assigned into five classes of the change in breadth of ownership $\Delta BREADTH_t$, with the class breakpoints determined separately within each MV_t quintile. The $\Delta BREADTH_t$ classes are then recombined across MV_t quintiles. Within each $\Delta BREADTH_t$ category obtained, stocks are then sorted into five quintiles by PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Table 4.5 provides the average monthly portfolio returns.

The results of Table 4.5 are basically the same as that of Table 3.4 in Chapter 3. High-minus-low PIN hedging portfolio produces significant positive return if stocks are subject to lowest or highest level of ΔBREADTH. Therefore, stocks with higher level of informed trading could earn higher returns when short-sale constraints are binding tightly or not binding at all. While the new information uncertainty risk effect documented in Chapter 3 can explain the case with binding short-sale constraints, the information risk theory can explain either case that short-sale constraints are binding tightly or not binding at all. On the other hand, high-minus-low ΔBREADTH hedging portfolios always earn significant positive returns regardless of the level of informed trading, although their performance within low-PIN group is not different from the result within high-PIN group. Therefore, informed trading alone cannot change the fact that short-sale constrained stocks always underperform stocks without binding short-sale constraints. Nevertheless, short-sale constrained stocks with low-PIN have the lowest subsequent returns, which is consistent with the new information uncertainty risk effect documented in Chapter 3. When short-sale constraints are not binding, stocks with high level of informed trading have the largest subsequent returns, which is consistent with the information risk theory.

4.4.5. Portfolio Returns under Three-Way Sorting

The investigation of the two hypotheses requires a three-way sort by trading activity, short-sale constraints, and informed trading proxies. Three kinds of three-way sorting methods are used to obtain robust results. In Panel A of Table 4.6, stocks are assigned into three trading volume (VOL_t) categories at month t. Within each volume category, stocks are then sorted into three groups based on the level of the change in breadth of ownership ($\Delta BREADTH_t$). Finally, for each volume and the change in breadth subgroup, stocks are further sorted into three divisions by the level of probability of information-based trade (PIN_t). Thus, Panel A focuses on stocks with different level of trading volume.

By contrast, Panel B of Table 4.6 concentrates on short-sale constrained stocks. At each month t, stocks are sorted into three $\Delta BREADTH_t$ classes, with the class breakpoints determined separately within each size (MV_t) quintile in the same month. The $\Delta BREADTH_t$ classes are then recombined across the five MV_t quintiles, and hence three the change in breadth groups obtained. This procedure ensures that within each $\Delta BREADTH_t$ group, stocks do not have roughly the same size. Stocks in each $\Delta BREADTH_t$ group are then assigned into three VOL_t divisions, and each $\Delta BREADTH_t$ and VOL_t group is further sorted into three PIN_t subgroups.

In order to show that the results in Panel A and Panel B are not depending on specific sorting methods, Panel C of Table 4.6 uses independent sorting to examine stocks with different levels trading volumes and short-sale constraints. At the beginning, stocks are assigned into three VOL_t groups and three $\Delta BREADTH_t$ groups separately at each month t. The combination of the independent rankings on VOL_t and $\Delta BREADTH_t$ gives 9 groups at each month t. For stocks within each VOL_t and $\Delta BREADTH_t$ group, they are further assigned into three PIN_t subgroups.

All the above three-way sorts classify stocks into 27 portfolios, portfolios are equally weighted and their performances are tracked over one-month head. Apart from raw portfolio returns, Table 4.7 also reports the Fama-French three-factor and the four-factor risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks.

Firstly, Table 4.6 confirms the first kind of new information uncertainty risk effect presented by Hypothesis 1 because when trading volume is high, stocks with binding short-sale constraints will have higher future returns if informed trading is lower. All three panels of Table 4.6 show that all high-minus-low PIN hedging portfolios within high-VOL and low-ΔBREADTH subgroup have significant negative risk-adjusted returns. Furthermore, the return differential between high-PIN stocks and low-PIN stocks within high-VOL and low-ΔBREADTH subgroup in Panel B is the largest comparing to other two panels. This can be due to the fact that Panel B concentrates on the overvaluation effect of short-sale constrained stocks. It is also important to note that, when trading volume is high but short-sale constraints are not binding, the positive risk-adjusted return differential between high-PIN stocks and low-PIN stocks becomes statistically insignificant. Therefore, the binding short-sale constraints are crucial for the less overpricing effect. This is consistent to the first kind of new information uncertainty risk effect, which suggests that the absence of informed trading only creates a new information uncertainty risk as perceived by uninformed investors when short-sale constraints are binding tightly. Overall, the above findings suggest that when stocks have intense trading activity, short-sale constrained stocks have less overvaluation if the level of informed trading is lower.

Secondly, Table 4.6 verifies Hypothesis 2 because when trading volume is low and short-sale constraints are binding, low-PIN stocks underperform high-PIN stocks. All three panels of Table 4.6 show that hedging portfolios based on high-minus-low PIN strategy yield significant positive returns within low-VOL and low-ΔBREADTH subgroups. Specially, this hedging portfolio has the largest positive return in Panel A. This is because Panel A concentrates on stocks with different level of trading volume. Therefore, the second kind of new information uncertainty risk effect is confirmed.

Finally, Table 4.6 can also provide evidence to distinguish Hypothesis 2 from the information risk theory, which can also explain the evidence of Hypothesis 2. The information risk theory, presented by Easley, Hvidkjaer, and O'Hara (2002), argues that high-PIN stocks have high information risk and hence leads to high subsequent returns. Table 4.4 has presented high-PIN stocks with higher future returns than low-PIN stocks within low-VOL group. Table 4.5 also shows that high-PIN stocks outperform low-PIN stocks within low-ΔBREADTH group or high-ΔBREADTH group. According to the information risk theory and these findings, short-sale constraints should not make any difference to the performance of high-minus-low PIN hedging portfolio within low-VOL subgroup. However, the results in Table 4.6 underline the importance of short-sale constraints. Pane A and C provide the evidence of statistically insignificant raw and risk-adjusted return of this hedging portfolio when short-sale constraints are not binding. However, all three panels show that this hedging portfolio earns significant positive return within low-VOL when short-sale constraints are binding.

Although the information risk theory cannot explain the role of the binding short-sale constraints, the second kind of new information uncertainty risk effect presented by Hypothesis 2 can interpret it well. When short-sale constraints are binding and the level informed trading is low, uninformed investors find the prices less informative because binding short-sale constraints keep informed investors from trading on private information. Since the levels of volume and informed trading are both low, uninformed investors would believe that the private information is negative because otherwise positive news would lead to buying activities in the market. In this case, uninformed investors face a new information uncertainty risk because they are not sure how bad the information is. As a result, they are reluctant to hold stocks and hence stock prices are forced to decrease to attract marginal buyers. This explains the results found in low-VOL and low-ΔBREADTH subgroup. On the other hand, when short-sale constraints are not binding, informed investors can trade on their private information without limitation. Thus, uninformed investors do not believe the absence of informed trading implies the unrevealed private information. As a result, uninformed investors will not face the new information uncertainty risk.

4.4.6. Subperiod Analysis

Table 4.7 provides the subperiod analysis to see if the results that support the two hypotheses are time-specific. The subperiods include 1983 to 1992 and 1993 to 2002. The sorting methods of portfolios in Panel A, B, and C of Table 4.7 correspond to Panel A, B, and C of Table 4.6, respectively. The results here only include the raw returns, the Fama-French three-factor and the four-factor risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks.

According to the results in Table 4.7, Hypothesis 1 is confirmed by evidence in subperiod of 1993 to 2002 while Hypothesis 2 is supported by evidence in subperiod of 1983 to 1992. When stocks have high trading volume and short-sale constraints are binding, hedging portfolios only generate strong significant negative risk-adjusted returns in latter subperiod as none of their returns in earlier subperiod is significantly different from zero. By contrast, when stocks have low trading volume and short-sale constraints are binding, hedging portfolios generally earn significant positive raw and risk-adjusted returns in earlier subperiod, and most of their positive raw and risk-adjusted returns are no longer statistically significant in latter subperiod.

Although these findings might imply that two hypotheses are time-specific, they are more likely to be explained by the feature of the trading volume time series. Panel A in Table 4.1 has shown that the monthly trading volume keeps increasing from 1983 to 2001. In addition, the increasing speed grows more rapidly in period of 1993 to 2001 than in period of 1983 to 1992. Actually, the average monthly volume in period of 1983 to 1992 is 19,932 while the average monthly volume in period of 1993 to 2001 is 58,116. Since Hypothesis 1 captures the scenario of intense trading activity and Hypothesis 2 represents the situation with low trading activity, it is natural that Hypothesis 1 works better in subperiod of 1993 to 2002 and Hypothesis 2 is more effective in subperiod of 1983 to 1992.

4.4.7. Comments on Robustness

Although Section 4.4.6 provides one robustness check of subperiod analysis, it is too early to say that the empirical findings in this chapter are robust. Because of data limitation, there are no alternative proxies for informed trading and short-sale constraints. Despite the fact that the results may not hold in general, this chapter has used three kinds of three-way sorting methods to examine the robustness of the two different new information uncertainty risk effects.

Panel A of Table 4.6 adopts the three-way nonindependent sort by volume and then by short-sale constraints and finally by informed trading. In this way, stocks within low-VOL low-ΔBREADTH and low-PIN subgroup are subject to low or absent buying activities, and hence they match the market scenario suggested by Bai, Chang, and Wang (2006) and Marin and Olivier (2008). Therefore, Panel A of Table 4.6 is designed to examine the crash of prices effect in Hypothesis 2.

Panel B of Table 4.6 employs another three-way nonindependent sort by short-sale constraints and then by volume and finally by informed trading, which can accurately examine the overvaluation effect of short-sale constrained stocks. Stocks within low-ΔBREADTH low-VOL and low-PIN subgroup are subject to high buying pressure and noise demand, which is the market scenario in Yuan (2006). Therefore, Panel B of Table 4.6 can be used to examine the reduction of overvaluation effect in Hypothesis 1.

In order to demonstrate the findings are not determined by specific sorting methods, Panel C of Table 4.6 assigns stocks into three volume and three short-sale constraints groups independently. For stocks within each volume and short-sale constraints group, they are then classified into three informed trading subgroups.

The empirical findings in Table 4.6 show that the two different new information uncertainty risk effects can be verified by each of the three sorting methods. Furthermore, like the case in Chapter 3, the prediction of Hypothesis 2 can be explained by the information risk theory. Nevertheless, the information risk theory is controversial in Table 4.6 as it cannot explain why low-VOL and low-PIN stocks no longer underperform low-VOL and high-PIN stocks when short-sale constraints are not binding.

4.5. Conclusion

This chapter examines two kinds of new information uncertainty risk effects proposed by Yuan (2006), and Bai, Chang, and Wang (2006) and Marin and Olivier (2008). They all study asset pricing theories under short-sale constraints in an asymmetric information setting, but their models capture two kinds of market scenarios. Firstly, short-sale constraints are likely to bind when prices are high in Yuan (2006), which captures the overvaluation effect. In this case, the sharp drop of price informativeness that due to the binding short-sale constraints and absent informed trading could produce a new information uncertainty risk to uninformed investors. The first kind of new uncertainty risk dampens the upward price movement because uninformed investors cannot distinguish high noise demand from information-based buying and hence they are reluctant to hold the stock. Secondly, Bai, Chang, and Wang (2006) and Marin and Olivier (2008) suggest that short-sale constraints are likely to bind when asset prices are low. In this case, a new information uncertainty risk also arises when short-sale constraints are binding and informed trading is absent. The second kind of new information uncertainty risk will cause decline in the price or even crash since uninformed investors believe there is negative private information and they are not sure how negative it is.

This chapter use two extreme levels of trading volume to estimate the two market condition of the above two predictions. On the one hand, high trading volume combined with binding short-sale constraints could cause overpricing with high noise demand. This captures the scenario of the first kind of new information uncertainty risk effect. On the other hand, the low levels of trading volume and informed trading could convince uninformed investors that most investors have downward beliefs and informed investors hold negative information. This captures the scenario of the second kind of new information uncertainty risk effect.

Using monthly data on NYSE- and AMEX-listed stocks from 1983 to 2001, this chapter provides supporting evidence to these two kinds of effect. For the first kind of new information uncertainty risk effect, stocks with lower level of informed trading have higher future returns when short-sale constraints are binding and trading volume is high. For the second kind of new information uncertainty risk effect, stocks with lower level of informed trading have lower future returns when short-sale constraints are binding and trading volume is low. Moreover, this second new uncertainty risk effect does not arise when short-sale constraints are not binding. Therefore, the information risk theory that predicts stocks with higher informed trading will perform better cannot fully explain these findings.

Table 4.1 Summary Statistics

This table provides the summary statistics for NYSE and AMEX stocks during the period from January 1983 through December 2001. Panel A reports the mean monthly statistics for all stocks. Panel B shows the correlation matrix, in which the Pearson's correlations are shown above the diagonal with Spearman's correlation below. Panel C demonstrates the mean and standard deviation values by NYSE Market Capitalization quintiles. No. of firms per month is the monthly average number of firms in the sample. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Trading volume (VOL) is the total number of shares traded at each month t. $\Delta BREADTH_T$ is the change in breadth of ownership from the end of quarter T-1 to quarter T. The breadth of ownership in quarter T is the fraction of all mutual funds long the stock at the end of quarter T. $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero.

Panel A: Mean Monthly Statistics by Year

Year	No.of Firms per Month	MV per Month	VOL per Month	ΔBREADTH per Month	PIN per Month
1983	1,918	754	10,579	0.13%	0.222
1984	1,830	776	11,758	0.03%	0.208
1985	1,757	931	14,743	0.04%	0.216
1986	1,703	1,180	19,144	0.04%	0.216
1987	1,700	1,365	24,689	0.09%	0.217
1988	1,627	1,295	21,338	0.01%	0.216
1989	1,570	1,581	22,518	0.08%	0.213
1990	1,421	1,694	22,877	0.06%	0.215
1991	1,471	1,937	25,461	0.07%	0.214
1992	1,604	1,951	26,210	0.08%	0.209
1993	1,750	2,083	30,894	0.12%	0.199
1994	1,839	2,089	32,548	0.10%	0.198
1995	1,877	2,391	37,648	-0.01%	0.195
1996	1,924	2,586	38,424	0.05%	0.192
1997	2,032	2,730	43,765	0.03%	0.181
1998	2,040	3,561	58,077	0.04%	0.171
1999	1,875	4,063	70,624	0.07%	0.169
2000	1,676	4,130	93,484	0.08%	0.171
2001	1,546	4,720	117,578	0.03%	0.180
Total	1,745	2,213	37,994	0.06%	0.199

Table 4.1—*Continued*

Panel B: Correlation Matrix (Pearson Correlations Are Shown above the Diagonal with Spearman Below)				
	MV	VOL	ΔBREADTH	PIN
MV	1	0.679	0.114	-0.291
VOL	0.837	1	0.082	-0.348
ΔBREADTH	0.042	0.031	1	-0.057
PIN	-0.694	-0.684	-0.021	1

Panel C: Means and Standard Deviations by NYSE Market Capitalization Quintiles

		All Firms	Quintile 1 Firms (Smallest)	Quintile 2 Firms	Quintile 3 Firms	Quintile 4 Firms	Quintile 5 Firms (Largest)
MV	Mean	2,213	67	261	651	1,686	10,383
	Std.Dev.	7,561	50	126	282	832	16,155
VOL	Mean	37,994	3,040	10,486	22,336	48,456	135,138
	Std.Dev.	93,138	6,571	17,099	33,562	71,230	179,889
ΔBREADTH	Mean	0.06%	0.01%	0.02%	0.04%	0.06%	0.19%
	Std.Dev.	0.61%	0.12%	0.23%	0.33%	0.51%	1.31%
PIN	Mean	0.199	0.262	0.211	0.185	0.164	0.133
	Std.Dev.	0.077	0.084	0.058	0.053	0.048	0.040

Table 4.2 Portfolio Returns Sorted by One Variable

This table reports average monthly portfolio returns sorted by one variable only. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Trading volume (VOL) is the total number of shares traded at each month t. $\Delta BREADTH_T$ is the change in breadth of ownership from the end of quarter T-1 to quarter T. The breadth of ownership in quarter T is the fraction of all mutual funds long the stock at the end of quarter T. $\Delta BREADTH_t$ at month t is equal to the value of $\Delta BREADTH_T$ in quarter T if month t belongs to quarter T. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. At each month t, stocks are assigned into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each MV_t quintile. The $\Delta BREADTH_t$ classes are then recombined across MV_t quintiles. For the other two variables VOL and PIN, each month t stocks are simply sorted into five groups based on the value level of variable at that month. Stocks are held for one month and portfolio returns are equally weighted. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	VOL	ΔBREADTH	PIN
Q1 (Low)	0.0102	0.0079	0.0115
	3.92	2.36	4.15
Q2	0.0124	0.0093	0.0112
	4.01	3.12	3.53
Q3	0.0121	0.0111	0.0103
	3.62	3.89	3.15
Q4	0.0123	0.0129	0.0117
	3.70	4.41	3.52
Q5 (High)	0.0123	0.0186	0.0146
	3.89	5.75	5.01
Q5 - Q1	0.0021	**0.0107*** **	**0.0031***
	1.08	8.53	1.73

Table 4.3 Portfolio Returns Sorted by Trading Volume and Short-Sale Constraints

This table reports average monthly portfolio returns by sorting the change in breadth of ownership (ΔBREADTH) and trading volume (VOL). Panel A uses independent sorting. Stocks are sorted into five groups based on VOL_t at each month t. Stocks are then assigned into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each firm size (MV_t) quintile. The $\Delta BREADTH_t$ classes are then recombined across five MV_t quintiles. The combination of the independent rankings on ΔBREADTH and VOL gives 25 groups at each month t. Panel B and C adopt dependent sorting of ΔBREADTH under VOL and VOL under ΔBREADTH, respectively. In Panel B, stocks are classified into five VOL_t groups, and each VOL_t group is further divided into five $\Delta BREADTH_t$ subgroups. In contrast, stocks in Panel C are sorted into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each firm size (MV_t) quintile. The $\Delta BREADTH_t$ classes are then recombined across five MV_t quintiles. For each of the five $\Delta BREADTH_t$ groups obtained, stocks are then sorted into five VOL_t subgroups. All these portfolios are equal-weighted and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios by VOL and ΔBREADTH Independently

ΔBREADTH	VOL					
	V1 (Low)	V2	V3	V4	V5 (High)	V5 - V1
B1 (Low)	0.0074	0.0096	0.0079	0.0066	0.0069	-0.0005
	2.48	2.80	2.10	1.71	1.96	-0.22
B2	0.0082	0.0095	0.0081	0.0099	0.0093	0.0008
	2.69	3.11	2.39	2.82	2.89	0.28
B3	0.0101	0.0116	0.0105	0.0108	0.0108	0.0007
	3.77	3.7	3.30	3.49	3.38	0.31
B4	0.0097	0.0131	0.0134	0.0134	0.0156	**0.0064***
	2.67	4.16	4.06	4.08	4.77	1.93
B5 (High)	0.0140	0.0188	0.0204	0.0199	0.0191	**0.0051****
	4.99	5.37	5.47	5.52	5.79	2.16
B5 - B1	**0.0066*****	**0.0093*****	**0.0125*****	**0.0133*****	**0.0123*****	
	3.79	5.31	6.61	6.66	6.98	

Table 4.3—*Continued*

Panel B: Portfolios by ΔBREADTH under VOL						
ΔBREADTH	VOL					
	V1 (Low)	V2	V3	V4	V5 (High)	V5 - V1
B1 (Low)	0.0074	0.0105	0.0089	0.0077	0.0073	-0.0001
	2.55	3.25	2.45	2.21	2.13	-0.04
B2	0.0092	0.0072	0.0080	0.0106	0.0096	0.0009
	3.21	2.04	2.10	2.82	2.83	0.29
B3	0.0096	0.0120	0.0118	0.0128	0.0111	0.0012
	3.27	3.39	3.29	3.73	3.15	0.49
B4	0.0081	0.0146	0.0150	0.0138	0.0151	**0.0071****
	2.70	4.28	4.53	3.92	4.67	2.13
B5 (High)	0.0130	0.0178	0.0182	0.0175	0.0194	**0.0063*****
	4.74	5.33	5.14	5.19	5.76	2.63
B5 - B1	**0.0056*****	**0.0072*****	**0.0093*****	**0.0098*****	**0.0121*****	
	3.49	4.10	4.80	5.48	5.87	

Panel C: Portfolios by VOL under ΔBREADTH						
VOL	ΔBREADTH					
	B1 (Low)	B2	B3	B4	B5 (High)	B5 - B1
V1 (Low)	0.0083	0.0088	0.0103	0.0099	0.0146	**0.0063*****
	2.73	3.16	3.97	3.75	4.97	4.18
V2	0.0095	0.0096	0.0123	0.0135	0.0200	**0.0105*****
	2.65	3.19	3.98	4.36	5.53	5.62
V3	0.0069	0.0091	0.0116	0.0124	0.0192	**0.0122*****
	1.80	2.66	3.59	3.73	5.19	6.11
V4	0.0080	0.0098	0.0103	0.0135	0.0201	**0.0121*****
	2.13	2.87	3.38	4.06	5.66	6.40
V5 (High)	0.0069	0.0092	0.0110	0.0150	0.0190	**0.0121*****
	2.01	2.88	3.51	4.81	5.80	6.82
V5 - V1	-0.0014	0.0005	0.0007	**0.0051****	**0.0044***	
	-0.62	0.21	0.32	2.25	1.91	

Table 4.4 Portfolio Returns Sorted by Trading Volume and PIN

This table reports average monthly portfolio returns based on trading activity proxy (trading volume, VOL) and the probability of information-based trade proxy (PIN). At each month t, stocks are assigned into five categories of VOL_t first. Within each VOL_t category, stocks are then sorted into five quintiles by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

PIN	VOL					
	V1 (Low)	V2	V3	V4	V5 (High)	V5 - V1
P1 (Low)	0.0092	0.0077	0.0098	0.0119	0.0133	**0.0042***
	3.59	2.91	3.46	4.00	4.71	1.92
P2	0.0084	0.0105	0.0092	0.0124	0.0126	**0.0042***
	2.92	3.31	2.71	3.71	4.21	1.90
P3	0.0095	0.0119	0.0122	0.0118	0.0118	0.0024
	3.29	3.55	3.41	3.45	3.69	1.09
P4	0.0113	0.0137	0.0110	0.0113	0.0127	0.0014
	4.05	4.03	3.12	3.14	3.54	0.57
P5 (High)	0.0126	0.0184	0.0181	0.0143	0.0108	-0.0018
	5.05	5.25	4.61	3.68	2.86	-0.65
P5 - P1	**0.0034****	**0.0106*****	**0.0082*****	0.0024	-0.0025	
	2.36	5.91	3.96	1.15	-1.12	

Table 4.5 Portfolio Returns Sorted by Short-Sale Constraints and PIN

This table reports average monthly portfolio returns based on short-sale constraints proxy (the change of breadth of ownership ΔBREADTH) and the probability of information-based trade proxy (PIN). At each month t, stocks are assigned into five classes of $\Delta BREADTH_t$, with the class breakpoints determined separately within each MV_t quintile. The $\Delta BREADTH_t$ classes are then recombined across MV_t quintiles. Within each $\Delta BREADTH_t$ group obtained, stocks are then sorted into five subgroups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

PIN	ΔBREADTH					
	B1 (Low)	B2	B3	B4	B5 (High)	B5 - B1
P1 (Low)	0.0084	0.0094	0.0106	0.0131	0.0164	**0.0081*** **
	2.70	3.34	3.79	4.77	5.45	5.13
P2	0.0071	0.0091	0.0102	0.0128	0.0172	**0.0100*** **
	1.93	2.76	3.32	4.1	5.02	5.71
P3	0.0045	0.0075	0.0095	0.0117	0.0182	**0.0137*** **
	1.21	2.27	3.01	3.71	5.18	8.06
P4	0.0075	0.0097	0.0121	0.0121	0.0209	**0.0134*** **
	2.05	2.89	3.77	3.62	5.68	7.39
P5 (High)	0.0123	0.0108	0.0132	0.0147	0.0203	**0.0080*** **
	3.57	3.65	4.64	4.77	6.05	4.24
P5 - P1	**0.0039***	0.0014	0.0026	0.0016	**0.0038***	
	1.76	0.69	1.36	0.81	1.72	

Table 4.6 Portfolio Returns under Three-Way Sorting

This table reports average monthly portfolio returns using three-way sorting on trading volume (VOL), the change in breadth of ownership ($\Delta BREADTH_t$), and probability of information-based trade (PIN_t) at each month t. In Panel A, stocks are assigned into three trading volume (VOL_t) categories at month t. Within each volume category, stocks are sorted into three the change of breadth of ownership groups based on the level of $\Delta BREADTH_t$. Then for each volume and the change of breadth subgroup, stocks are further sorted into three divisions by the level of probability of information-based trade (PIN_t). Panel B classifies stocks into three $\Delta BREADTH_t$ classes, with the class breakpoints determined separately within each size (MV_t) quintile. The $\Delta BREADTH_t$ classes are then recombined across the five MV_t quintiles, and hence three the change of breadth groups obtained. Stocks in each $\Delta BREADTH_t$ group are then assigned into three VOL_t divisions, and each $\Delta BREADTH_t$ and VOL_t group is further sorted into three PIN_t subgroups. In Panel C, stocks are assigned into three VOL_t groups and three $\Delta BREADTH_t$ groups separately at each month t. The combination of the independent rankings on VOL_t and $\Delta BREADTH_t$ gives 9 groups at each month t. Then for stocks within each VOL_t and $\Delta BREADTH_t$ group, they are further assigned into three PIN_t subgroups. All three-way sorts classify stocks into 27 portfolios, which are equally weighted and are held for one-month head. Apart from raw portfolio returns, Table 4.7 also reports the Fama-French three-factor and the four-factor risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of $\Delta BREADTH$ takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4.6—*Continued*

Panel A: Portfolios Formed by PIN within ΔBREADTH under VOL									
	Low VOL			Medium VOL			High VOL		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0076	0.0093	0.0124	0.0086	0.0097	0.0127	0.0104	0.0123	0.0159
	2.57	3.30	4.25	2.64	3.36	4.12	3.46	4.22	5.25
Medium	0.0087	0.0097	0.0145	0.0079	0.0087	0.0161	0.0086	0.0124	0.0142
	2.82	3.22	4.57	2.19	2.57	4.54	2.44	3.65	4.13
High	0.0120	0.0120	0.0150	0.0118	0.0163	0.0202	0.0073	0.0112	0.0187
	3.90	4.26	5.10	3.07	4.31	5.08	1.93	2.95	4.93
H – L (Raw)	**0.0043****	**0.0027***	0.0026	**0.0033***	**0.0066*****	**0.0075*****	-0.0031	-0.0011	0.0028
	2.49	1.79	1.64	1.77	3.67	3.64	-1.60	-0.58	1.52
H – L (3-Factor)	**0.0043****	**0.0028***	**0.0031***	**0.0032***	**0.0050*****	**0.0072*****	**-0.0044*****	**-0.0029***	0.0015
	2.40	1.85	1.93	1.88	3.35	4.50	-2.61	-1.80	1.11
H – L (4-Factor)	**0.0041****	0.0023	0.0021	**0.0035****	**0.0045*****	**0.0054*****	**-0.0036****	**-0.0029***	0.0011
	2.23	1.46	1.28	2.05	2.98	3.48	-2.13	-1.75	0.76

Table 4.6—*Continued*

Panel B: Portfolios Formed by PIN within VOL under ΔBREADTH									
	Low ΔBREADTH			Medium ΔBREADTH			High ΔBREADTH		
PIN	VOL			VOL			VOL		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0065	0.0082	0.0095	0.0084	0.0089	0.0118	0.0125	0.0149	0.0169
	2.15	2.39	3.18	3.09	3.15	4.09	4.26	4.61	5.75
Medium	0.0099	0.0083	0.0083	0.0103	0.0094	0.0110	0.0148	0.0152	0.0160
	3.01	2.27	2.35	3.46	2.93	3.45	4.48	4.25	4.78
High	0.0103	0.0105	0.0062	0.0126	0.0146	0.0098	0.0156	0.0226	0.0197
	3.42	2.69	1.59	4.78	4.06	2.84	5.22	5.68	5.11
H – L (Raw)	**0.0038****	0.0023	-0.0033	**0.0042*****	**0.0057*****	-0.0020	**0.0030****	**0.0077*****	0.0028
	2.52	1.26	-1.59	2.90	3.21	-1.12	1.97	3.91	1.36
H – L (3-Factor)	**0.0041*****	0.0027	**-0.0050*****	**0.0049*****	**0.0048*****	**-0.0025***	**0.0030***	**0.0070*****	0.0014
	2.65	1.63	-2.79	3.32	3.45	-1.67	1.91	4.71	1.04
H – L (4-Factor)	**0.0036****	**0.0036****	**-0.0043****	**0.0044*****	**0.0039*****	**-0.0027***	**0.0028***	**0.0060*****	0.0011
	2.29	2.14	-2.35	2.91	2.83	-1.74	1.74	4.01	0.77

Table 4.6—*Continued*

Panel C: Portfolios Formed by PIN under VOL and ΔBREADTH									
	Low VOL			Medium VOL			High VOL		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0069	0.0086	0.0131	0.0072	0.0097	0.0135	0.0091	0.0119	0.0165
	2.31	3.10	4.46	2.19	3.39	4.32	3.03	4.09	5.56
Medium	0.0084	0.0105	0.0151	0.0077	0.0094	0.0163	0.0083	0.0120	0.0167
	2.67	3.49	4.74	2.09	2.92	4.54	2.30	3.76	4.94
High	0.0105	0.0125	0.0149	0.0112	0.0137	0.0212	0.0069	0.0093	0.0203
	3.44	4.67	5.09	2.95	3.79	5.23	1.75	2.65	5.25
H – L (Raw)	**0.0036****	**0.0040*****	0.0018	**0.0041****	**0.0039****	**0.0077*****	-0.0022	-0.0026	**0.0038***
	2.10	2.77	1.07	2.36	2.28	3.82	-1.12	-1.33	1.88
H – L (3-Factor)	**0.0038****	**0.0048*****	0.0023	**0.0039****	**0.0031****	**0.0068*****	**-0.0039****	**-0.0030***	0.0021
	2.17	3.25	1.36	2.43	2.33	4.16	-2.36	-1.80	1.62
H – L (4-Factor)	**0.0036****	**0.0045*****	0.0022	**0.0045*****	**0.0025***	**0.0056*****	**-0.0032***	**-0.0030***	0.0021
	1.98	2.98	1.27	2.79	1.88	3.42	-1.88	-1.77	1.57

Table 4.7 Subperiod Analysis

This table reports the average monthly returns of hedging portfolios based on PIN strategy in two subperiods 1983 to 1992 and 1993 to 2002. VOL is trading volume. ΔBREADTH is the change in breadth of ownership. PIN is probability of information-based trade. The sorting methods of portfolios in Panel A, B, and C correspond to Panel A, B, and C of Table 4.6, respectively. The results here only include the raw returns, and the Fama-French three-factor and the four-factor risk-adjusted returns for all hedging portfolios that long high-PIN stocks and short low-PIN stocks. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, VOL or PIN are excluded, and the missing value of ΔBREADTH takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by PIN within ΔBREADTH under VOL									
	Low VOL			Medium VOL			High VOL		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0057****	**0.0044*****	0.0031	0.0031	**0.0046***	**0.0049****	-0.0014	-0.0033	0.0029
	2.09	2.65	1.57	1.27	1.88	2.15	-0.63	-1.36	1.27
H – L (3-Factor)	**0.0053***	**0.0040****	**0.0040***	0.0030	**0.0039****	**0.0047****	-0.0007	-0.0030	0.0024
	1.86	2.35	1.97	1.29	2.08	2.29	-0.37	-1.56	1.28
H – L (4-Factor)	**0.0051***	**0.0030***	0.0030	0.0037	**0.0033***	**0.0043****	-0.0011	-0.0031	0.0020
	1.75	1.79	1.49	1.55	1.72	2.06	-0.57	-1.55	1.06
1993 - 2002									
H – L (Raw)	0.0028	0.0007	0.0020	0.0035	**0.0087*****	**0.0103*****	-0.0049	0.0012	0.0026
	1.36	0.30	0.80	1.22	3.32	2.94	-1.54	0.41	0.90
H – L (3-Factor)	0.0036	0.0030	0.0028	0.0035	**0.0072*****	**0.0095*****	**-0.0079*****	-0.0020	0.0007
	1.65	1.26	1.08	1.42	3.15	3.78	-2.91	-0.80	0.36
H – L (4-Factor)	0.0032	0.0024	0.0014	0.0036	**0.0069*****	**0.0068*****	**-0.0068****	-0.0021	0.0001
	1.45	0.99	0.52	1.40	2.91	2.90	-2.44	-0.80	0.03

Table 4.7—*Continued*

Panel B: Portfolios Formed by PIN within VOL under ΔBREADTH									
	Low ΔBREADTH			Medium ΔBREADTH			High ΔBREADTH		
PIN	VOL			VOL			VOL		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0052*****	0.0021	-0.0012	**0.0058*****	**0.0055****	-0.0028	**0.0036****	**0.0038***	0.0016
	2.41	0.97	-0.44	3.74	2.36	-1.30	2.00	1.73	0.68
H – L (3-Factor)	**0.0049****	0.0027	-0.0004	**0.0057*****	**0.0053*****	-0.0018	**0.0037****	**0.0039****	0.0009
	2.21	1.29	-0.16	3.50	2.88	-1.13	2.02	2.00	0.47
H – L (4-Factor)	**0.0049****	0.0031	-0.0006	**0.0052*****	**0.0049****	-0.0018	0.0030	**0.0036***	0.0007
	2.14	1.47	-0.25	3.13	2.56	-1.07	1.60	1.79	0.39
1993 - 2002									
H – L (Raw)	0.0022	0.0026	**-0.0056***	0.0024	**0.0059****	-0.0012	0.0024	**0.0119*****	0.0041
	1.08	0.84	-1.74	0.96	2.17	-0.40	0.93	3.61	1.19
H – L (3-Factor)	**0.0039***	0.0027	**-0.0097*****	**0.0045***	**0.0048****	-0.0024	0.0039	**0.0101*****	0.0016
	1.86	1.01	-3.76	1.81	2.29	-0.94	1.51	4.39	0.81
H – L (4-Factor)	0.0030	0.0038	**-0.0088*****	0.0041	**0.0035***	-0.0029	0.0038	**0.0086*****	0.0013
	1.40	1.41	-3.33	1.61	1.70	-1.09	1.45	3.75	0.62

Table 4.7—*Continued*

Panel C: Portfolios Formed by PIN under VOL and ΔBREADTH									
	Low VOL			Medium VOL			High VOL		
PIN	ΔBREADTH			ΔBREADTH			ΔBREADTH		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0045***	**0.0054*****	0.0028	**0.0044****	**0.0041***	**0.0050****	0.0002	**-0.0041***	0.0033
	1.76	3.71	1.41	2.07	1.85	2.07	0.10	-1.69	1.42
H – L (3-Factor)	0.0043	**0.0056*****	**0.0035***	**0.0044****	**0.0037****	**0.0046****	0.0009	-0.0030	0.0026
	1.63	3.71	1.73	2.18	2.20	2.19	0.46	-1.48	1.41
H – L (4-Factor)	**0.0048***	**0.0050*****	0.0028	**0.0047****	**0.0037****	**0.0041***	0.0002	-0.0028	0.0023
	1.79	3.27	1.37	2.26	2.18	1.90	0.09	-1.37	1.22
1993 - 2002									
H – L (Raw)	0.0026	0.0023	0.0006	0.0037	0.0037	**0.0107*****	-0.0049	-0.0010	0.0043
	1.16	0.93	0.22	1.34	1.39	3.25	-1.51	-0.32	1.29
H – L (3-Factor)	**0.0039***	**0.0048***	0.0021	0.0035	0.0032	**0.0092*****	**-0.0088*****	-0.0023	0.0013
	1.70	1.91	0.76	1.39	1.56	3.59	-3.38	-0.86	0.66
H – L (4-Factor)	0.0030	**0.0047***	0.0022	**0.0044***	0.0022	**0.0075*****	**-0.0074*****	-0.0025	0.0015
	1.27	1.79	0.77	1.70	1.05	2.95	-2.83	-0.91	0.75

Chapter 5

Informed Trading, Information Uncertainty, and Momentum

5.1. Introduction

Previous literature has recognized the momentum phenomenon as one of the biggest challenges to asset pricing. Although traditional asset pricing models fail to explain the high abnormal returns generated by momentum strategies (see, e.g., Grundy and Martin 2001, Griffin, Ji, and Martin 2003), some have suggested that momentum arises more naturally within behavioural asset pricing models (see, e.g., Barberis, Shleifer, and Vishny 1998, Daniel, Hirshleifer, and Subrahmanyam 1998). In particular, one popular category stresses that momentum is a symptom of underreaction: prices adjust too slowly to news (see, e.g., Chan, Jegadeesh, and Lakonishok 1996, Hong and Stein 1999). Hong, Lim and Stein (2000) empirically find that momentum reflects the gradual diffusion of firm-specific information. They also quote one recent paper's empirical finding as saying that momentum at least in part reflects the adjustment of stock prices to the sort of information that is not made publicly available to all investors simultaneously.

The market microstructure literature suggests another way to investigate momentum. O'Hara (2003) argues that anomalies such as momentum highlight the need to incorporate market microstructure approaches into asset pricing. In particular, market microstructure focuses on price discovery – asset prices evolve in markets. Informed investors who have superior private information will move prices toward the full information levels. Uninformed investors make inferences about this information from prices and follow informed trading. However, continuously attaining the full information levels is not credible. Thus, trading activities of informed and uninformed investors are crucial for better understanding the adjustment of prices to the full information values. Recently, Hvidkjaer (2006) provides a trade-based analysis of momentum. He finds the evidence of both initial underreaction and delayed reaction among small traders, who are typically uninformed investors. By contrast, initial selling pressure for losers and buying pressure for winners exist among large trades, which are typically informed trading. Thus, large traders show not evidence of underreaction and they engage in (early-stage) momentum trading.

According to the above literature, this chapter investigates the impact of informed trading to the momentum effect. The main proposition is that if momentum is a result of underreaction and if informed trading identifies stocks with underreaction, the presence of informed trading predicts future momentum effect. Since informed investors have private information and hence understand the true value of stock, their trading implies that price has not adjusted to the full information level. In other words, the presence of informed trading suggests there is an underreaction. Because informed trading moves price to the full information level, uninformed investors can gradually learn informed investors' private information from the price movements. As a result, uninformed investors will follow the earlier informed trading eventually and prices continue to adjusting until reaching the full information level. Therefore, the momentum effect (price continuation) arises following informed trading. Accordingly, the main hypothesis is the following.

Main Hypothesis: *The momentum effect arises when informed trading is present. Higher level of informed trading leads to stronger momentum effect.*

However, the robustness of informed trading's predictability on momentum requires taking the information uncertainty effect into account. This is because information uncertainty is closely related to both momentum and informed trading. Information uncertainty means the ambiguity with respect to the implications of new information for a firm's value (Zhang 2006). Hong, Lim and Stein (2000) show that momentum strategies perform better among stocks with low analyst coverage (high information uncertainty). They attribute information uncertainty to a measure of information diffusion speed. In addition, previous studies have documented that information uncertainty alone can forecast momentum. Zhang (2006) attributes information uncertainty like analyst coverage to a measure of behavioural biases, which are responsible for underreaction according to behavioural finance. He shows that greater information uncertainty produces higher returns following good news and lower returns following bad news. As a result, greater information uncertainty should lead to stronger momentum. It is thus important to see whether information uncertainty affects the predictive power of informed trading on momentum. Moreover, it is also interesting to check Zhang's findings by controlling for informed trading as Wang (1993) indicates that the presence of informed trading improves information efficiency and thereby reducing information uncertainty. Therefore, this chapter further examines the following questions.

Question 1: *Does the predictability of informed trading on momentum remain robust after controlling for information uncertainty?*

Question 2: *Does the predictability of information uncertainty on momentum remain robust after controlling for informed trading?*

Question 3: *How can information uncertainty forecast momentum? In other words, considering the information diffusion theory proposed by Hong, Lim and Stein (2000) and the behavioural biases theory proposed by Zhang (2006), which theory is more robust?*

Using monthly data on NYSE- and AMEX-listed stocks from 1983 to 2001, this chapter examines the main hypothesis and the three further questions. Specifically, price momentum is measured with past 11-month stock returns as Zhang (2006). Past winners refer to good news and past losers refer to bad news. The probability of information-based trade (PIN), proposed by Easley, Kiefer and O'Hara (1997), is used to measure informed trading. Analyst coverage (COV), firm age (AGE), and firm size (MV) are used as the proxies for the information uncertainty of stocks. The empirical investigations provide several major findings.

First, momentum strategy has significant positive returns when the level of PIN is equal or above average. Stocks with higher level of PIN have stronger momentum, while momentum disappears when the level of PIN is below average (Main Hypothesis). Second, after controlling for information uncertainty, momentum is again observed in most high-PIN portfolios (Question 1). Third, the predictive power on momentum by information uncertainty is determined by informed trading. High level of information uncertainty will not lead to momentum if the level of PIN is low (Question 2). Fourth, the empirical results support Hong, Lim and Stein (2000)'s theory but reject Zhang (2006)'s (Question 3). After controlling for information uncertainty, high information uncertainty tends to contribute the momentum effect introduced by informed trading. Stocks with high level of PIN exhibit stronger momentum if information uncertainty is greater. Stocks with medium level of PIN only exhibit momentum if information uncertainty is high. These findings are consistent with the information diffusion theory. This is because when the level of informed trading is large enough, informed trading can move prices toward the full information levels. Since the fundamental news spread slowly when information uncertainty is high, uninformed investors also learn the fundamental news from the price movements gradually. Hence, uninformed investors follow informed trading gradually and momentum (the slow price adjustment) emerges. After controlling for informed trading, high level of information uncertainty does not lead to momentum unless the level of informed trading is relatively high. Moreover, past winners with higher uncertainty could earn lower future returns when the level of PIN is low. All these results are opposite to Zhang (2006)'s findings.

Therefore, the above findings show that informed trading holds better predictive power to momentum than information uncertainty. While information uncertainty does not work in the way suggested by Zhang (2006) after controlling informed trading, it can nonetheless still influence the degree of predictability of informed trading. The connection between information uncertainty and informed trading is not surprising according to Hong, Lim and Stein (2000)'s theory about information diffusion. Moreover, Aslan, Easley, Hvidkjaer, and O'Hara (2007) also report that PIN is negatively related to information uncertainty.

Hameed, Hong, and Warachka (2008), one most relevant work to this chapter, also document that firm-specific informed trading is an important determinant of momentum. In addition, they show that the relation between informed trading and momentum cannot explained by liquidity and uncertainty proxies such as analyst forecast dispersion, analyst coverage, idiosyncratic return volatility, and size. However, the central theme of their paper is different from this chapter. Their analysis is motivated by Wang (1994), who suggests that informed investors trade either because of private information or investment needs that lead to uninformed trades. Thus, they argue that if turnover is motivated by private information, uninformed investors gradually become informed and influence prices in a manner that causes return continuation. Conversely, turnover without private information leads to subsequent reversals. They find that high turnover stocks with high PIN exhibiting return continuation; high turnover stocks with low PIN exhibit return reversals. Therefore, their focus is the combination effect of turnover and informed trading.

The central theme of this chapter, however, only depends on the important role of informed trading played in price discovery. That is, if momentum is due to the process that price continuously and gradually adjusts to the full information level after an initial underreaction to information, informed investors identifies stocks with underreaction and their trading activities deliver private information to uninformed investors, who will follow informed trading gradually. Since this proposition depends on the speed of information diffusion that measured by information uncertainty, this chapter also examines the interaction among informed trading, information uncertainty, and momentum.

This chapter makes several potential contributions. First, it finds that informed trading plays an important role in explaining the well-documented momentum phenomenon. It stresses that price discovery, emphasized by market microstructure, is crucial for better understanding of the momentum effect. Second, it presents that information uncertainty can also contribute to the momentum effect, though it is not the determinant factor as informed trading. Finally, it suggests that the reported relationship between information uncertainty and momentum requires careful interpretations. The findings in this chapter imply that the predictive power of information uncertainty on momentum is not due to the linkage between uncertainty and behavioural biases, but because of the relation between uncertainty and information diffusion.

The rest of this chapter is organized as follows. Section 5.2 reviews related literature. Section 5.3 constructs the sample and describes the data characteristics. Section 5.4 reports empirical results from the portfolio analysis and provides dissection. Section 5.5 concludes.

5.2. Related Literature

Momentum refers to the tendency of stock prices to continue moving in the same direction for several months after an initial impulse. At first, Jegadeesh and Titman (1993) show that stocks with high recent performance continue to earn higher returns over the next three to twelve months than stocks with low recent performance. The momentum effect has also been documented in international markets (Rouwenhorst 1998), industry portfolios (Moskowitz and Grinblatt 1999), and size and book-to-market portfolios (Lewellen 2002). Jegadeesh and Titman (2001) find that momentum remains strong in the post-1993 sample. Lee and Swaminathan (2000) indicate that momentum is more prevalent in stocks with high trading volume. Hong, Lim, and Stein (2000) report that small firms with low analyst coverage display great momentum. Avramov, Chordia, Jostova, and Philipov (2007) find that momentum profits are large and significant among firms with low-grade credit ratings but are nonexistent among firms with high-grade credit ratings. Jiang, Lee, and Zhang (2005) and Zhang (2006) report that momentum effect are greater among firms with higher information uncertainty that can be measured by size, age, return volatility, cash flow volatility, and analyst coverage, dispersion in analyst forecasts.

Many studies report that high abnormal returns generated by momentum strategies cannot be explained by measures of risk. Jegadeesh and Titman (1993) document that momentum cannot be explained by market risk. Fama and French (1996) show that Fama-French three-factor model cannot explain momentum. Grundy and Martin (2001) and Avramov and Chordia (2006) find that controlling for time-varying exposures to common risk factors does not affect momentum profits.

Since many empirical studies in literature have failed to document direct evidence of risk that might drive momentum, behavioural theories based on some kind of bounded rationality of investors such as overconfidence or underreaction to information have been developed to explain the momentum effect (see, e.g., Barberis, Shleifer, and

Vishny 1998, Daniel, Hirshleifer, and Subrahmanyam 1998, and Hong and Stein 1999).

Nevertheless, many papers still try to explore risk explanations of momentum. Conrad and Kaul (1998) argue that cross-sectional variations in the mean returns of individual securities can potentially drive momentum. Ahn, Conrad, and Dittmar (2003) suggest that their nonparametric risk adjustment can account for about half of momentum profits. Bansal, Dittmar, and Lundblad (2005) show that the consumption risk embodied in cash flows can explain the momentum effect. Chen and Zhang (2008) find that winner-minus-loser portfolios have positive exposures on a low-minus-high investment factor, which can be motivated from neoclassical reasoning. Although Griffin, Ji, and Martin (2003) show that the model of Chen, Roll, Ross (1986) does not provide any evidence that macroeconomic risk variables can explain momentum, Liu and Zhang (2008) report that macroeconomic risk can actually drive momentum. Liu and Zhang (2008) show that recent winners have temporarily higher loadings than recent losers on the growth rate of industrial production (MP), which is a common risk factor motivated by Chen, Roll, and Ross (1996). The loading spread derives mostly from the positive loadings of winners. Because this macroeconomic risk factor explains more than half of momentum profits in many tests, they conclude that risk plays an important role in driving momentum profits.

Several other papers consider whether liquidity risk factor can account for momentum profits. At first, some papers examine whether strategies that constructed to exploit the momentum effect can be profitable after taking transaction costs into account. Moskowitz and Grinblatt (1999) and Grundy and Martin (2001) find the implementation of momentum strategies involves high portfolio turnover. Thus, the strategies that attempt to exploit potentially profitable momentum are likely to involve relatively high transaction costs. Lesmond, Schill, and Zhou (2004) examine transaction costs for extreme past winner stocks and loser stocks, and find little evidence that trading costs for the standard momentum strategies are below 1.5% per trade. They therefore suggest that the profits are largely "illusive" for the standard momentum strategies. Korajczyk and Sadka (2004) also find that the typical momentum strategies are less likely to be profitable for large investment funds. Since the profitability of momentum strategies are strongly related to transaction costs, it is an open question that whether the returns of momentum strategies can be related to the time variation of liquidity. Pastor and Stambaugh (2003) present that a liquidity risk factor accounts for half of the profits to a winner-loser momentum portfolio. Thus, the abnormal returns of momentum can be viewed as compensation for liquidity risk as they are sensitive to unexpected changes in systematic liquidity. Sadka (2006) also shows that unexpected systematic (market-wide) variations of the variable component rather than the fixed component of liquidity are shown to be priced within the context of momentum portfolio returns.

It is important to note that informed trading (or information asymmetry) and liquidity are related despite they are not the same. Liquidity basically refers to the matching of buyers and sellers. Pastor and Stambaugh (2003) indicate that liquidity is a broad and elusive concept that generally denotes the ability to trade large quantities of asset quickly, at low cost, and without moving the price. More specifically, there are two kinds of liquidity in literature. Firstly, many papers focus on the firm-specific liquidity (the liquidity level), which is often contributed by information asymmetry. Most of these studies that investigate the relation between liquidity and asset prices focus on the level of liquidity as a characteristic of a stock. They argue that investors holding illiquid assets are compensated by higher future returns. For example, Amihud and Mendelson (1986) argue that investors demand a premium for relatively low liquidity stocks (measured by using bid-ask spreads). Similarly, Brennan and Subrahmanyam (1996) find that stocks with higher price impacts earn higher future returns. Easley, Hvidjaker, and O'Hara (2002) find that the level of liquidity, measured as PIN, carries a positive premium in asset prices. Secondly, another strand of literature concentrates on the systematic component of liquidity (liquidity risk) rather than on the actual idiosyncratic level of liquidity (firm-specific). These studies document the fact that while firm-specific liquidity fluctuates over time, there is a systematic or market-wide component to these liquidity fluctuations (see, e.g., Chordia, Roll, and Subrahmanyam 2000, Huberman and Halka 2001, Amihud 2002). Pastor and Stambaugh (2003) develop a measure of aggregate (market-wide) liquidity based on daily price reversals and show that assets whose returns highly covary with this aggregate liquidity measure earn higher expected returns than do assets whose returns exhibit low covariation with aggregate liquidity. Hence, systematic liquidity risk is a priced risk factor. Acharya and Pedersen (2005) build a liquidity adjusted capital asset pricing model to provide a unified framework for understanding how liquidity risk may affect asset prices. In their model, the require return of stock depends on its expected liquidity and on the covariances of its own return and liquidity with the market return and liquidity.

Herding behaviour is often associated with a group of investors trading in the same direction over a period of time. Since most herding models suggest that investors follow some common signal, it is possible that momentum is because of herding as past returns are likely to be a simple and important signal on which investors focus. On the one hand, many papers focus on institutional investors, who would engage in herding as a result of superior private information, security characteristics, fads, or agency problems. Grinblatt, Titman, and Wermers (1995) find that 77% of the mutual funds were momentum investors, buying stocks that were past winners. However, most mutual funds did not systematically sell past losers. Similar to Lakonishok, Shleifer, and Vishny (1992), they also document weak evidence that institutional herding impacts prices. Although Nofsinger and Sias (1999) report that institutional herding is positively correlated with lag returns and appears to be related to stock return momentum, they are unable to infer whether institutional herding contributes to momentum. Finally, Cohen, Gompers, and Vuolteenaho (2003) study the aggregate holdings of US institutional investors and confirm that institutions buy shares from individuals in response to good cash-flow news. However, institutions are not simply following price momentum strategies as they sell shares to individuals when price goes up in the absence of positive cash-flow news.

On the other hand, plenty of studies suggest that individual investors, who are regarded as noise or uninformed investors, often engage in herding because of irrational but systematic responses to fads or sentiment. Grinblatt and Moskowitz (2004) find that many individual taxable investors delay tax-loss selling until the end of the year. At the end of the year, they are particularly likely to sell poor performers and hold onto good performers. Thus, momentum tends to be strong in December and weak in January. Hvidkjaer (2006) provides a trade-based analysis of momentum. He finds initial underreaction followed by delayed reaction among small traders and no evidence of underreaction among large traders. While large-trade imbalances have little impact on subsequent returns, small-trade imbalances during formation period significantly affect momentum returns, suggesting that underreaction among small traders contribute to the momentum effect.

5.3. Data and Sample

In the line with Chapter 3 and Chapter 4, this chapter also uses probability of information-based trade (PIN) as the informed trading proxy. This chapter also adopts analyst coverage (COV), firm age (AGE), and firm size (MV) as the proxies for information uncertainty as Chapter 3. Momentum is constructed by the past 11-month stocks returns following Zhang (2006).

The monthly PIN data is obtained from the 1983 – 2001 annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The PIN value of stock in each month t takes the PIN value in that year. Since Easley, Hvidkjaer, and O'Hara (2005) argue that the market microstructure of NYSE and AMEX are most closely consistent to that of their PIN model, this chapter also focuses on NYSE- and AMEX-listed stocks during the period of 1983 to 2001.

Following Zhang (2006), analyst coverage (COV) is calculated based on the raw detail forecast data unadjusted for stock splits in I/B/E/S. Specifically, COV is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month.

The CRSP monthly tape in WRDS provides data on firm age, firm size, and monthly returns. Firm size (MV) is the market capitalization (in millions of dollars). Firm age (AGE) can be measured as the number of years since the firm was first covered by CRSP. Moreover, stocks are required to have past 11-month returns $RET_{t-11,\, t-1}$ for examining price momentum strategies. $RET_{t-11,\, t-1}$ is accumulated returns from month t - 11 to t - 1. This 1-month lag between the momentum measure and portfolio formation month is consistent with Fama and French (1996) since skipping the portfolio formation month reduces bias from bid-ask bounce.

Finally, a stock has to satisfy the following criteria to be included in the sample. First, following Jegadeesh and Titman (2001), stocks with a share price below \$5 at the portfolio formation date are eliminated to make sure that the results are not driven by small, illiquid stocks or by the bid–ask bounce. Second, this chapter requires all grouping variables are jointly available at each month t. These grouping variables include three information uncertainty proxies (MV_t, AGE_t and COV_t), past 11-month returns ($RET_{t-11,\ t-1}$) and informed trading proxy (PIN_t). Therefore, stocks without valid values of firm size and past 11-month returns are excluded. Since PIN is the primary variable, stocks are excluded if they do not have data on PIN. After the above filtration, following Aslan, Easley, Hvidkjaer, and O'Hara (2007), COV_t takes value of zero if it is missing at month t.

This chapter also adjusts hedging portfolio returns for common risk factors. The returns of hedging portfolios in following sections are adjusted by the three factors:

$$R_i = \alpha_i + \beta_i (R_M - R_F) + s_i SMB + h_i HML + e_i,$$

and four-factor model:

$$R_i = \alpha_i + \beta_i (R_M - R_F) + s_i SMB + h_i HML + m_i UMD + e_i.$$

All the four factors are downloaded from Kenneth French's website.

Table 5.1 gives the summary statistics of the sample in this chapter. Panel A contains mean monthly statistics for the firm-month observations by year. These observations will be used to form portfolios in following sections. The sample contains on average 1,680 firms per month from 1983 to 2001. The unusual drop in the number of firms from 1999 is because the sample size is determined by the number of PIN estimations. Easley, Hvidkjaer, and O'Hara (2005) indicate that the extremely high daily trading volume in later years could cause failures for estimating PIN. They present that this occurs almost exclusively for the largest stocks rather than for smaller stocks. As it is shown in Panel A, firm size keeps increasing from 1983 to 2001. The average number of analyst coverage is around 8, and the average firm age is about 23 in each year. However, the monthly mean of the past 11-month returns $RET_{t-11,\, t-1}$ changes from year to year without a consistent pattern. The monthly mean of $RET_{t-11,\, t-1}$ only turns to be negative in 1988 (-0.24%), which should be due to the 1987 Stock Market Crash. Since stocks generally have poor performance during market downturn time, it is not surprise that after the 1987 Stock Market Crash, the monthly mean of the past 11-month returns in 1988 tends to be negative. The monthly mean of PIN in the sample is 0.198, and its approximate trend is decreasing from 1983 to 2001.

Panel B shows the correlation matrix. The Pearson and Spearman correlations for these five variables are quite similar. Firm size is strong positively correlated with firm age and analyst coverage but strong negatively correlated with PIN. Thus, small firms tend to have short history, less information transparent, and high probability of informed trading. New firms also tend to have less analysts and high probability of informed trading as AGE and COV are positively correlated and both of them are negatively correlated to PIN. At last, all the correlations between past 11-month returns and the other four variables are weak. The Pearson (Spearman) correlation between $RET_{t-11, t-1}$ and MV_t is 0.014 (0.097), which is consistent with that correlation in Zhang (2006).

Panel C provides a close look at the relationship between firm size and other four variables by assigning stocks into NYSE capitalization breakpoints (obtained from Kenneth French's website). The purpose is to emphasize that there is much more variation in the level of analyst coverage across large stocks comparing with small stocks. Without controlling for firm size, the independent sorting on COV will let bottom- and top-COV groups dominate by large firms. This pattern is firstly proposed by Chen, Hong, and Stein (2002) for the variable breadth of ownership. The rest variables AGE, $RET_{t-11, t-1}$ and PIN will not encounter this problem because their means and standard deviations guarantee enough variations in both small and large firms.

5.4. Empirical Results

In this section, stocks are assigned to portfolios based on certain characteristics in order to draw conclusions about the average returns for different test. This standard approach in asset pricing, pioneered by Jegadeesh and Titman (1993), reduces the variability in returns.

5.4.1. Portfolio Sorted by One Variable

Table 5.2 provides an initial look at the momentum effect and the individual impact of analyst coverage (COV), firm age (AGE), firm size (MV) and the probability of information-based trading (PIN) on stock returns. At each month t, stocks are assigned into five classes of analyst coverage (COV_t) at that month, with the class breakpoints determined separately within each size (MV_t) quintile in the same month. The COV_t classes are then recombined across the five MV_t quintiles, and hence five COV_t categories obtained. This procedure ensures that within each COV_t category, stocks do not have roughly the same size. This procedure is necessary because, as it is shown in Panel C of Table 5.1, there is much more variation in COV across large stocks. If it was an unconditional ranking on COV independent of MV, then the extreme (lowest or highest COV) categories would be dominated by large stocks. For the other four variables (MV, AGE, $RET_{t-11,\, t-1,}$ and PIN), stocks are simply sorted into five groups at each month t based on the value level of the variable at that month. For each of the resulting groups, equally weighted portfolios are formed and are held for one month.

Table 5.2 reports the average monthly portfolio returns. At first, higher uncertainty (low-MV, low-COV, or low-AGE) stocks forecast lower returns. Except for firm size, hedging portfolios on other two uncertainty variables that long high-quintile stocks and short low-quintile stocks generate significant positive returns. Second, the momentum effect is confirmed in this sample as past winners outperform past losers by 1.02% (t = 4.32). Third, the results of PIN confirm the information risk proposed by Easley, Hvidkjaer, and O'Hara (2002) because hedging portfolio that long high-PIN stocks and short low-PIN stocks earns a return of 0.31% at 10% significance level.

5.4.2. Portfolio Sorted by Momentum and Information Uncertainty

Table 5.3 reviews the interaction between momentum and information uncertainty documented by Zhang (2006). At each month t, stocks are first classified into five categories based on past returns from t - 11 to t - 1. For each momentum category, stocks are further sorted into five groups by the level of information uncertainty. For the resulting 25 subgroups, equally weighted portfolios are constructed and their one-month-ahead returns are reported in Table 5.3. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively.

All three panels in Table 5.3 show that greater information uncertainty leads to relatively lower future returns for past losers. In each panel, hedging strategy that longs high-uncertainty and shorts low-uncertainty stocks yields significant negative return within group of past losers. However, the evidence that relatively higher future returns for past winners when information uncertainty is greater is weak here. Among past winner stocks, high-minus-low hedging portfolio on uncertainty only obtains significant positive return in Panel C.

Nevertheless, information uncertainty still has a significant impact on momentum. Table 5.3 shows that momentum is much stronger for high-uncertainty firms than low-uncertainty firms, although it does not measure the momentum effect within each uncertainty group. The return from a trading strategy with a long position in past winner and a short position in past losers increases strictly with increasing information uncertainty, which is consistent with Zhang (2006).

5.4.3. Portfolio Sorted by Information Uncertainty and PIN

Table 5.4 examines the interactions of PIN and information uncertainty variables. Stocks are simply classified into five categories based on information uncertainty proxy at each month, and the sorting method for analyst coverage is special. At each month t, stocks are assigned into five classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. Within each uncertainty category, stocks are then sorted into five groups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and their one-month-ahead returns are reported in Table 5.4. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively.

Firstly, higher informed trading only generates higher returns when information uncertainty is large enough. When information uncertainty is relative high, i.e., stocks have above middle level uncertainty, high-minus-low PIN hedging portfolio has strong statistically significant positive returns in all three panels. One exception is hedging portfolio on low-COV stocks in Panel A. Thus, informed investors always make profits from trading on private information under great uncertainty environment. In contrast, all three panels show that there is barely a difference between high-PIN and low-PIN stocks when information uncertainty is small. The return differentials between high-PIN and low-PIN firms in all three panels are not statistically significant different from zero. The can be due to the fact that there is hardly any private information that can exist long if firm's information environment is more transparent, and hence trading on private information will not lead to huge profit.

Secondly, information uncertainty only affects stock prices when the level of informed trading is low. All three panels show that high-uncertainty stocks perform worse than low-uncertainty stocks within low-PIN groups. When the level of PIN is above average, none of high-minus-low quintile hedging portfolios on uncertainty proxy can earn significant negative returns. This confirms the proposition that informed trading enhances the information efficiency of prices, and hence reducing information uncertainty.

5.4.4. Portfolio Sorted by PIN and Momentum

In order to test the main hypothesis, Table 5.5 examines the momentum effect under different level of informed trading. At each month t, stocks are first assigned into five groups of PIN_t. Within each group of PIN_t, stocks are then sorted into five divisions based on past returns from t – 11 to t – 1. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Apart from the raw returns, Table 5.5 also gives the Fama-French three-factor and the four-factor risk-adjusted returns for momentum hedging portfolios that long past winners and short past losers.

Following high level of informed trading, momentum strategy earns abnormal positive return. The raw and risk-adjusted return differentials between past winners and past losers are significant positive for stocks with middle level and above middle level of PIN. In addition, the return differential increases strictly from middle-PIN group to high-PIN group. By contrast, stocks with less than the middle level of PIN do not have significant positive returns for momentum strategies. Furthermore, their momentum strategies even yield significant negative four-factor risk-adjusted returns. Overall, Table 5.5 confirms the main hypothesis because the momentum effect is only observed when the level of informed trading is large enough and the higher level of informed trading the stronger the momentum effect.

5.4.5. Portfolio under Three-Way Sorting

To find answers for the three questions in Section 5.1, three kinds of three-way sorting methods are used for comparing the predictability of informed trading and information uncertainty on momentum.

(1) Predictability of Informed Trading after Controlling for Information Uncertainty

The first portfolio strategy in Table 5.6 is to examine whether information uncertainty can affect the predictive power of informed trading on the momentum effect. This strategy focuses on the momentum effect within each PIN group under three levels of uncertainty. Each month stocks are sorted into three groups based on the level of information uncertainty at that month. Each uncertainty group is then sorted into three PIN groups. Each uncertainty and PIN group is further sorted into three momentum divisions. Note that the sorting method for analyst coverage is special as before. At each month t, stocks are assigned into three classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. Stocks are held for one-month-ahead and portfolio returns are equal-weighted. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively. Table 5.6 reports the raw and risk-adjusted returns for momentum hedging portfolios that long past winners and short past losers.

The evidence in Table 5.6 suggests that the predictability of informed trading on momentum is unchallenged. No matter what the level of information uncertainty is like (low, middle, or high), high level of informed trading generally leads to significant positive raw and risk-adjusted returns for momentum strategies. The only one exception is the result of high-MV group in Panel C. Nevertheless, there is a connection between informed uncertainty and informed trading. Panel B and Panel C show that among high-PIN groups, momentum is stronger if uncertainty is greater. Furthermore, momentum arises within medium-PIN groups when uncertainty is large. Finally, one interesting finding is that momentum strategy earns significant positive return within low-MV and low-PIN group, although other two panels do not exhibit similar findings within high-uncertainty and low-PIN groups.

(2) Predictability of Information Uncertainty after Controlling for Informed Trading

In order to examine whether greater information uncertainty can predict greater momentum when the level of informed trading is low, Table 5.7 further investigates the information uncertainty effect on momentum documented in Zhang (2006) by controlling for the level of informed trading.

First of all, Table 5.7 shows the momentum effect within each uncertainty group under three levels of PIN. This strategy can examine if the predictive power of uncertainty remains after controlling for the level of informed trading. Each month stocks are sorted into three groups based on the level of PIN at that month. Each PIN group is then sorted into three information uncertainty groups. Each PIN and uncertainty group is further sorted into three momentum divisions. Stocks are held for one-month-ahead and portfolio returns are equal-weighted. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively. Table 5.7 reports the raw and risk-adjusted returns for momentum hedging portfolios.

The results of Table 5.7 are striking. High information uncertainty does not lead to momentum unless PIN is relatively high. Within the low-PIN groups of all three panels, the raw and risk-adjusted returns of momentum hedging portfolios are not significant positive, and 8 of 9 momentum hedging portfolios even generate strong significant negative returns. Thus, no matter how large the uncertainty is like, the lack of informed trading means that momentum will not emerge. Moreover, all the raw and risk-adjusted returns of momentum hedging portfolios are strong significant positive within high-PIN groups regardless the level of uncertainty (low, medium, or high). Therefore, it is not information uncertainty but informed trading determines the momentum effect. Similar to Table 5.6, information uncertainty still has influence on predictability of informed trading. Panel B and Panel C show that among high-PIN groups, momentum is stronger if uncertainty is greater. Among medium-PIN groups, high-uncertainty stocks present the evidence of momentum as well.

To examine Zhang (2006)'s proposition more thoroughly, Table 5.8 examines the impact of information uncertainty on bad news (past losers) and good news (past winners). The strategy in Table 5.8 concentrates on the information uncertainty effect within each PIN group under different momentum groups. Each month t stocks are sorted into three momentum groups based on the level of past returns from t – 11 to t - 1. Each momentum group is then sorted into three PIN groups. Each momentum and PIN group is further sorted into three uncertainty divisions. Stocks are held for one-month-ahead and portfolio returns are equal-weighted. Information uncertainty proxy refers to COV, AGE, and MV in Panel A, B, and C respectively. Table 5.8 reports the raw and risk-adjusted returns for hedging portfolios that long low-uncertainty stocks and short high-uncertainty stocks.

Zhang (2006) suggests that higher expected stock returns following good news but lower expected stock returns following bad news relative to the returns of stocks with less information uncertainty. Table 5.8 provides results for information uncertainty effect on bad news and good news. On the one hand, information uncertainty effect on bad news seems to be more effective when the level of informed trading is low. The low-PIN groups in Panel B and C support that greater information uncertainty produces lower returns following bad news. Only Panel B confirms this with evidence of high-PIN group. On the other hand, results from past winners reject the predicted information uncertainty effect on good news. All three panels present that neither the results in high-PIN groups nor the results in low-PIN groups support the prediction that greater uncertainty leads to higher returns following good news. In addition, Panel A and Panel C actually show that lower information uncertainty leads to higher returns following good news within low-PIN groups, which is completely opposite to Zhang (2006)'s findings.

(3) General Remarks

According to the findings in Table 5.6, Table 5.7 and Table 5.8, the comparison between the predictive power of informed trading and information uncertainty on momentum becomes clear.

First, considering Question 1, the above results show that high level of informed trading can predict the momentum effect regardless the level of information uncertainty. Moreover, the momentum effect generally does not exist if the level informed trading is low. Thus, the impact of informed trading on momentum is determinant.

Second, considering Question 2, the empirical findings demonstrate that the information uncertainty effect documented by Zhang (2006) is out of order after controlling informed trading. High information uncertainty does not lead to momentum unless the level of informed trading is low. Therefore, the predictive power on momentum by information uncertainty is determined by informed trading.

Third, considering Question 3, the above analysis provides supporting evidence to Hong, Lim and Stein (2000)'s information diffusion theory but presents contrary evidence to Zhang (2006)'s behavioural biases theory. In particular, after controlling for information uncertainty, high information uncertainty tends to contribute the momentum effect introduced by informed trading. When the level informed trading is high, momentum is stronger if uncertainty is larger. When the level of informed trading is moderate, momentum only arises with high information uncertainty. These findings are consistent with the information diffusion theory. This is because high information uncertainty implies that the fundamental news spread slowly. Thus, when the level of informed trading is large enough, informed trading can move prices toward the full information levels. The price movements will help uninformed investors to learn the fundamental news and hence follow informed trading gradually. Consequently, a slow price adjustment, i.e., price continuation, emerges. On the other hand, there are opposite results to Zhang (2006)'s findings. After controlling for informed trading, high level of information uncertainty does not lead to momentum unless the level of informed trading is relatively high. Moreover, past winners with higher uncertainty could earn lower future returns when the level of PIN is low.

5.4.6. Subperiod Analysis

Table 5.9 provides the subperiod analysis. This robustness check examines whether previous results are time-specific. The subperiods include 1983 to 1992 and 1993 to 2002. Firstly, Panel A reexamines the momentum effect within different level of informed trading (Table 5.5). Secondly, Panel B1, B2, and B3 review the predictability of informed trading on momentum under different level of information uncertainty (Table 5.6). Thirdly, Panel C1, C2, and C3 review the predictability of information uncertainty on momentum under different level of informed trading (Table 5.7). Finally, Panel D1, D2, and D3 investigate the information uncertainty effect on past losers and winners again (Table 5.8). All the portfolio construction methods are the same as previous related tables. All panels only report the one-month-ahead raw and the Fama-French three-factor and the four-factor risk-adjusted returns for the relevant hedging portfolios. Overall, Table 5.9 provides consistent results to previous related tables.

5.4.7. Comments on Robustness

This chapter has established several robustness checks, although it cannot fully rule out the informed trading's predictability on momentum here is not because of specific sample, specific proxies, or other explanation.

The first and important robustness check is to examine the influence of information uncertainty on the relationship between informed trading and momentum. This is because not only momentum but also informed trading is closely related to information uncertainty. Table 5.6 uses the three-way nonindependent sort by information uncertainty and then by informed trading and finally by momentum. The results indicate that high level of informed trading generally leads to momentum effect regardless the level of information uncertainty. Thus, the predictability of informed trading on momentum is unchallenged.

This chapter also investigates how information uncertainty contributes to momentum effect. Table 5.7 employs the three-way nonindependent sort by informed trading and then by information uncertainty and finally by momentum. It demonstrates that high level of information uncertainty does not lead to momentum unless the level of informed trading is relatively high. When the level of informed trading is high, momentum is stronger if uncertainty is greater. When the level of informed trading is moderate, momentum emerges if uncertainty is large. Therefore, it is not information uncertainty but informed trading determines the momentum effect. In addition, these findings suggest that the impact of information uncertainty on momentum should be due to Hong, Lim and Stein (2000)'s information diffusion theory but not Zhang (2006)'s behavioural biases theory.

To further examine Zhang (2006)'s behavioural biases theory, Table 5.8 adopts the three-way nonindependent sort by momentum and then by informed trading and finally by information uncertainty. The evidence that past winners with higher information uncertainty could earn lower future returns when the level of informed trading is low is contrast to the behavioural biases theory.

Although there is no alternative choice of informed trading proxy, this chapter uses two alternative measures of information uncertainty including firm age and firm size. The robustness tests with the alternative proxies have similar results as the primary proxy analyst coverage.

At last, subperiod analysis in Section 5.4.6, the final robustness check, presents that the identified relationship between informed trading and momentum is valid in each subperiod of 1983 – 1992 and 1993 – 2002.

5.5. Conclusion

This chapter analyses the role of informed trading in the momentum effect from two perspectives. First, it proposes that if momentum is a result of underreaction and if informed trading identifies stocks with underreaction, the presence of informed trading forecasts future momentum effect. The empirical findings show that high probability of informed trading forecasts momentum effect and momentum will not arise if the level of informed trading is relatively low. Furthermore, the momentum effect is greater if the level of informed trading is higher.

Second, this chapter further questions whether information uncertainty can change the predicative power of informed trading because information uncertainty means the speed of information diffusion which affects the adjustment of price to the fundamental news. Moreover, Zhang (2006) shows that great information uncertainty alone can lead to momentum. The empirical results in this chapter indicate that the identified relationship between informed trading and momentum is robust after controlling for uncertainty proxy such as analyst coverage, firm age, and size. High probability of informed trading leads to momentum regardless the level of uncertainty. Nevertheless, information uncertainty still has influence on informed trading as high uncertainty tends to contribute the predictability of informed trading, which is consistent with Hong, Lim and Stein (2000)'s information diffusion theory about information uncertainty.

This chapter also sheds light on the information uncertainty effect on momentum. It reexamines Zhang (2006)'s findings by controlling for informed trading. The empirical findings, however, provide many contrary evidence to Zhang (2006)'s findings. High level of information uncertainty does not produce momentum unless the level of informed trading is relatively high. Furthermore, past winners with higher uncertainty could earn lower future returns when the level of informed trading is low. These findings suggest the reported relationship between information uncertainty and momentum requires careful interpretations.

Table 5.1 Summary Statistics

This table provides the summary statistics for NYSE and AMEX stocks during the period 1983 - 2001. Panel A reports the mean monthly statistics for all stocks. Panel B shows the correlation matrix, in which the Pearson's correlations are shown above the diagonal with Spearman's correlation below. Panel C demonstrates the mean and standard deviation values by NYSE Market Capitalization quintiles. No. of firms per month is the monthly average number of firms in the sample. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month. $RET_{t-11,\,t-1}$ is accumulated returns from month t – 11 to t – 1. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The value of PIN in each month t takes the PIN value in that year. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV, $RET_{t-11,\,t-1}$ or PIN are excluded, and the missing value of COV takes value of zero.

Panel A: Mean Monthly Statistics by Year

Year	No.of Firms per Month	MV_t per Month	COV_t per Month	AGE_t per Month	$RET_{t-11,\,t-1}$ per Month	PIN_t per Month
1983	1,889	760	7	22	64.27%	0.221
1984	1,781	768	9	23	3.68%	0.208
1985	1,718	946	9	23	20.73%	0.214
1986	1,657	1,203	9	23	30.25%	0.216
1987	1,616	1,418	9	23	16.05%	0.215
1988	1,584	1,320	8	23	-0.24%	0.215
1989	1,531	1,608	9	23	22.53%	0.212
1990	1,380	1,730	10	24	0.39%	0.215
1991	1,430	1,974	8	24	22.16%	0.214
1992	1,529	2,018	8	24	22.17%	0.208
1993	1,669	2,153	8	23	25.94%	0.198
1994	1,749	2,163	8	23	11.41%	0.196
1995	1,805	2,464	8	23	15.33%	0.194
1996	1,817	2,680	7	23	25.36%	0.190
1997	1,914	2,844	7	22	26.61%	0.179
1998	1,922	3,728	8	22	16.71%	0.169
1999	1,812	4,117	8	22	2.84%	0.169
2000	1,614	4,205	9	23	10.07%	0.169
2001	1,505	4,787	9	23	22.72%	0.179
Total	1,680	2,265	8	23	19.36%	0.198

Table 5.1—*Continued*

Panel B: Correlation Matrix

(Pearson Correlations Are Shown above the Diagonal with Spearman Below)

	MV_t	COV_t	AGE_t	$RET_{t-11, t-1}$	PIN_t
MV_t	1	0.316	0.240	0.014	-0.292
COV_t	0.529	1	0.210	-0.042	-0.383
AGE_t	0.307	0.125	1	-0.042	-0.238
$RET_{t-11, t-1}$	0.097	-0.019	0.004	1	0.066
PIN_t	-0.698	-0.388	-0.246	0.036	1

Panel C: Means and Standard Deviations by NYSE Market Capitalization Quintiles

		All Firms	Quintile 1 Firms (Smallest)	Quintile 2 Firms	Quintile 3 Firms	Quintile 4 Firms	Quintile 5 Firms (Largest)
MV_t	Mean	2,265	67	260	650	1,684	10,411
	Std.Dev.	7,683	50	126	282	833	16,220
COV_t	Mean	8	2	5	8	12	19
	Std.Dev.	10	3	5	7	10	14
AGE_t	Mean	23	17	18	21	27	35
	Std.Dev.	17	12	14	17	18	21
$RET_{t-11, t-1}$	Mean	19.36%	18.00%	18.69%	19.82%	19.65%	21.55%
	Std.Dev.	50.68%	62.29%	55.53%	47.41%	41.03%	33.52%
PIN_t	Mean	0.198	0.262	0.211	0.184	0.163	0.133
	Std.Dev.	0.077	0.084	0.058	0.052	0.047	0.040

Table 5.2 Portfolio Returns Sorted by One Variable

This table reports average monthly portfolio returns sorted by one variable only. Firm size (MV) is the market capitalization at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts providing annual FY1 earnings estimates lagged 12 months from the end of the month. $RET_{t-11,\ t-1}$ is accumulated returns from month t – 11 to t – 1. The probability of information-based trade (PIN) is obtained from the annual PIN data in Easley, Hvidkjaer, and O'Hara (2005). The value of PIN in each month t takes the PIN value in that year. At each month t, stocks are assigned into five classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. For the rest four variables, each month stocks are simply sorted into five groups based on the value level of variable at that month. Stocks are held for one month and portfolio returns are equally weighted. Stocks with a price less than \$5 are excluded. Stocks with missing value of MV, $RET_{t-11,\ t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	MV	COV	AGE	$RET_{t-11,\ t-1}$	PIN
Q1 (Low)	0.0103	0.0101	0.0097	0.0064	0.0117
	3.35	3.64	2.90	1.74	4.20
Q2	0.0122	0.0111	0.0120	0.0113	0.0113
	3.64	3.95	3.65	3.88	3.59
Q3	0.0122	0.0135	0.0126	0.0122	0.0101
	3.72	4.39	4.11	4.43	3.11
Q4	0.0123	0.0126	0.0128	0.0132	0.0117
	3.99	4.03	4.48	4.67	3.57
Q5 (High)	0.0126	0.0123	0.0125	0.0165	0.0147
	4.45	3.56	4.75	4.84	5.11
Q5 - Q1	0.0024	**0.0022***	**0.0027***	**0.0102*****	**0.0031***
	1.10	1.90	1.78	4.32	1.73

Table 5.3 Portfolio Returns Sorted by Momentum and Information Uncertainty

This table reports average monthly portfolio returns based on momentum and information uncertainty proxy. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. At each month t, stocks are first classified into five categories based on past returns from t - 11 to t – 1 ($RET_{t-11,\ t-1}$). For each momentum category, stocks are further sorted into five groups by information uncertainty level. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11,\ t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by Momentum and COV

COV	Momentum					
	M1 (Losers)	M2	M3	M4	M5 (Winners)	M5 - M1
C1 (Low)	0.0065	0.0089	0.0107	0.0108	0.0156	0.0120
	1.89	3.25	4.06	3.69	4.10	4.17
C2	0.0044	0.0119	0.0115	0.0132	0.0174	0.0134
	1.12	4.19	3.62	4.22	4.20	4.04
C3	0.0054	0.0125	0.0133	0.0134	0.0181	0.0128
	1.37	3.83	4.40	4.24	4.83	4.92
C4	0.0083	0.0122	0.0127	0.0139	0.0155	0.0072
	2.03	3.63	3.94	4.40	4.30	2.75
C5 (High)	0.0089	0.0125	0.0121	0.0136	0.0168	0.0078
	2.08	3.95	3.97	4.51	4.74	2.36
C1 – C5	**-0.0049****	**-0.0034****	-0.0015	**-0.0027***	-0.0019	
	-2.02	-2.04	-0.92	-1.66	-0.88	

Table 5.3—*Continued*

Panel B: Portfolios Formed by Momentum and AGE						
	Momentum					
AGE	M1 (Losers)	M2	M3	M4	M5 (Winners)	M5 - M1
A1 (Low)	0.0013	0.0089	0.0112	0.0137	0.0164	0.0151
	0.31	2.77	3.53	4.26	4.23	5.37
A2	0.0041	0.0106	0.0127	0.0131	0.0181	0.0140
	1.02	3.38	4.19	4.26	4.79	5.13
A3	0.0074	0.0120	0.0124	0.0133	0.0178	0.0104
	1.91	3.86	4.37	4.43	4.84	3.63
A4	0.0100	0.0116	0.0124	0.0133	0.0161	0.0061
	2.76	4.13	4.67	4.82	4.84	2.36
A5 (High)	0.0097	0.0134	0.0124	0.0129	0.0137	0.0040
	2.80	4.67	4.70	4.85	4.32	1.46
A1 – A5	**-0.0084*** **	**-0.0045** **	-0.0012	0.0008	0.0027	
	-3.98	-2.51	-0.72	0.44	1.39	

Panel C: Portfolios Formed by Momentum and MV						
	Momentum					
MV	M1 (Losers)	M2	M3	M4	M5 (Winners)	M5 - M1
V1 (Low)	0.0045	0.0092	0.0124	0.0140	0.0193	0.0148
	1.28	3.15	4.21	4.59	5.36	6.27
V2	0.0035	0.0116	0.0129	0.0122	0.0183	0.0148
	0.89	3.57	4.07	3.89	4.82	5.70
V3	0.0060	0.0116	0.0129	0.0136	0.0160	0.0099
	1.47	3.55	4.51	4.41	4.22	3.60
V4	0.0075	0.0123	0.0120	0.0131	0.0147	0.0071
	1.85	3.8	4.01	4.39	4.13	2.39
V5 (High)	0.0102	0.0117	0.0111	0.0131	0.0144	0.0042
	2.65	3.92	3.83	4.54	4.31	1.27
V1 – V5	**-0.0057** **	-0.0026	0.0013	0.0009	**0.0049***	
	-2.04	-1.03	0.55	0.36	1.95	

Table 5.4 Portfolio Returns Sorted by Information Uncertainty and PIN

This table reports average monthly portfolio returns based on information uncertainty proxy and the probability of information-based trade proxy (PIN). Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Stocks are first classified into five categories based on information uncertainty proxy at each month. The sorting method for COV is special. At each month t, stocks are assigned into five classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. Within each uncertainty category, stocks are then sorted into five groups by the level of PIN_t. For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11, t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by and COV and PIN

PIN	COV					
	C1 (Low)	C2	C3	C4	C5 (High)	C5 - C1
P1 (Low)	0.0112	0.0080	0.0118	0.0123	0.0136	0.0024
	4.26	2.76	3.83	4.24	4.51	1.75
P2	0.0103	0.0094	0.0122	0.0119	0.0119	0.0015
	3.58	3.01	3.80	3.64	3.21	0.92
P3	0.0084	0.0106	0.0138	0.0110	0.0108	0.0024
	2.74	3.32	4.14	3.23	2.76	1.48
P4	0.0094	0.0124	0.0135	0.0125	0.0116	0.0023
	2.95	4.06	4.1	3.61	3.04	1.23
P5 (High)	0.0115	0.0151	0.0164	0.0151	0.0137	0.0023
	3.83	5.77	5.14	4.56	3.70	1.32
P5 - P1	0.0002	**0.0071*** **	**0.0047** **	0.0028	0.0001	
	0.12	3.77	2.41	1.34	0.05	

Table 5.4—*Continued*

Panel B: Portfolios Formed by AGE and PIN						
PIN	AGE					
	A1 (Low)	A2	A3	A4	A5 (High)	A5 - A1
P1 (Low)	0.0092	0.0110	0.0118	0.0119	0.0125	0.0033
	2.8	3.26	3.73	4.01	4.96	1.74
P2	0.0080	0.0093	0.0108	0.0124	0.0114	0.0034
	2.17	2.56	3.14	3.95	4.23	1.57
P3	0.0072	0.0116	0.0118	0.0114	0.0124	0.0051
	1.96	3.14	3.63	3.70	4.47	2.46
P4	0.0100	0.0137	0.0140	0.0127	0.0124	0.0024
	2.73	3.89	4.18	4.14	4.16	1.16
P5 (High)	0.0143	0.0146	0.0147	0.0154	0.0136	-0.0007
	4.44	4.82	5.00	5.47	4.71	-0.44
P5 - P1	**0.0051*****	**0.0036***	0.0029	**0.0036***	0.0011	
	2.63	1.77	1.37	1.66	0.53	

Panel C: Portfolios Formed by and MV and PIN						
PIN	MV					
	V1 (Low)	V2	V3	V4	V5 (High)	V5 - V1
P1 (Low)	0.0063	0.0099	0.0118	0.0127	0.0126	0.0063
	1.78	2.80	3.66	4.27	4.60	2.27
P2	0.0080	0.0091	0.0107	0.0110	0.0120	0.0039
	2.26	2.53	3.10	3.39	4.15	1.44
P3	0.0092	0.0119	0.0119	0.0129	0.0118	0.0026
	2.70	3.36	3.35	3.82	3.99	1.05
P4	0.0142	0.0132	0.0120	0.0106	0.0130	-0.0012
	4.55	3.78	3.57	3.28	4.34	-0.53
P5 (High)	0.0137	0.0167	0.0146	0.0144	0.0139	0.0002
	5.26	5.25	4.38	4.71	4.61	0.09
P5 - P1	**0.0074*****	**0.0068*****	**0.0028***	0.0017	0.0013	
	3.39	3.85	1.72	1.08	0.98	

Table 5.5 Portfolio Returns Sorted by PIN and Momentum

This table reports average monthly portfolio returns based on the probability of information-based trade proxy (PIN) and momentum. At each month t, stocks are first assigned into five groups based on the level of PIN_t. Within each group of PIN_t, stocks are then sorted into five divisions based on past returns from t – 11 to t – 1($RET_{t-11,\ t-1}$). For the resulting 25 subgroups, equally weighted portfolios are constructed and held for one month. The Fama-French three-factor and the four-factor risk-adjusted returns are reported for momentum strategies. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11,\ t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Momentum	PIN				
	P1 (Low)	P2	P3	P4	P5 (High)
M1 (Losers)	0.0105	0.0086	0.0029	0.0032	0.0065
	2.96	2.10	0.70	0.79	1.94
M2	0.0113	0.0118	0.0096	0.0115	0.0114
	3.98	3.56	2.98	3.50	3.96
M3	0.0104	0.0120	0.0113	0.0127	0.0161
	3.88	4.08	3.67	4.06	5.80
M4	0.0120	0.0111	0.0128	0.0142	0.0170
	4.40	3.60	4.04	4.53	6.03
M5 (Winners)	0.0141	0.0130	0.0141	0.0171	0.0228
	4.40	3.78	3.72	4.44	6.27
M5 – M1	0.0035	0.0044	**0.0112*** **	**0.0140*** **	**0.0163*** **
(Raw)	1.27	1.50	3.99	5.23	6.23
M5 – M1	0.0042	**0.0051***	**0.0122*** **	**0.0154*** **	**0.0175*** **
(3-Factor)	1.44	1.67	4.20	5.70	6.79
M5 – M1	**-0.0045*** **	**-0.0036** **	**0.0046** **	**0.0090*** **	**0.0122*** **
(4-Factor)	-3.03	-1.97	2.38	4.48	5.76

Table 5.6 Portfolio Returns Sorted by Information Uncertainty, PIN and Momentum

This table reports average monthly portfolio returns using three-way sorting by information uncertainty proxy, probability of information-based trade (PIN), and momentum. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Each month t stocks are sorted into three groups based on the level of information uncertainty at that month. Each uncertainty group is then sorted into three groups by the level of PIN_t. Each uncertainty and PIN_t group is further sorted into three momentum divisions based on past returns from t – 11 to t – 1 ($RET_{t-11, t-1}$). Note that the sorting method for analyst coverage is special. At each month t, stocks are assigned into three classes of COV_t, with the class breakpoints determined separately within each MV_t quintile. The COV_t classes are then recombined across MV_t quintiles. For the resulting 27 subgroups, equally weighted portfolios are constructed and held for one month. All three panels report the Fama-French three-factor and the four-factor risk-adjusted returns for all momentum strategies. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11, t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by COV, PIN, and Momentum

Momentum	Low COV			Medium COV			High COV		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0097	0.0036	0.0075	0.0105	0.0103	0.0082	0.0123	0.0065	0.0057
	3.07	1.05	2.54	3.13	2.94	2.46	3.30	1.51	1.44
Medium	0.0101	0.0112	0.0126	0.0110	0.0123	0.0162	0.0114	0.0117	0.0144
	3.91	4.06	4.73	3.84	3.98	5.58	3.82	3.36	4.35
High (Winners)	0.0108	0.0124	0.0177	0.0122	0.0150	0.0202	0.0142	0.0150	0.0202
	3.69	3.67	5.52	3.83	4.24	5.69	4.42	4.24	5.39
H – L (Raw)	0.0011	**0.0088*** **	**0.0102*** **	0.0017	**0.0047** **	**0.0120*** **	0.0020	**0.0085*** **	**0.0145*** **
	0.46	3.71	4.86	0.86	2.18	5.60	0.76	3.44	6.33
H – L (3-Factor)	0.0012	**0.0098*** **	**0.0109*** **	0.0024	**0.0048** **	**0.0126*** **	0.0030	**0.0094*** **	**0.0154*** **
	0.49	4.07	5.21	1.15	2.17	5.78	1.13	3.73	6.50
H – L (4-Factor)	**-0.0057*** **	**0.0039** **	**0.0069*** **	**-0.0030** **	-0.0007	**0.0081*** **	**-0.0048*** **	**0.0034* **	**0.0107*** **
	-4.08	2.24	3.86	-2.24	-0.44	4.52	-3.20	1.80	5.38

Table 5.6—*Continued*

Panel B: Portfolios Formed by AGE, PIN, and Momentum									
Momentum	Low AGE			Medium AGE			High AGE		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0065	0.0003	0.0060	0.0098	0.0096	0.0086	0.0124	0.0118	0.0099
	1.67	0.06	1.68	2.59	2.61	2.74	4.22	3.50	3.04
Medium	0.0093	0.0116	0.0152	0.0110	0.0120	0.0141	0.0105	0.0128	0.0142
	2.90	3.41	5.04	3.53	3.90	4.94	4.07	4.71	5.23
High (Winners)	0.0123	0.0153	0.0199	0.0141	0.0146	0.0188	0.0129	0.0117	0.0169
	3.35	3.97	5.49	4.35	4.24	5.59	4.44	3.93	5.49
H – L (Raw)	**0.0057****	**0.0151*****	**0.0139*****	**0.0043***	**0.0050****	**0.0102*****	0.0005	-0.0001	**0.0070*****
	2.30	5.74	5.90	1.66	2.35	4.88	0.21	-0.04	3.25
H – L (3-Factor)	**0.0057****	**0.0161*****	**0.0149*****	**0.0052***	**0.0059*****	**0.0106*****	0.0006	0.0013	**0.0082*****
	2.20	5.95	6.20	1.90	2.74	5.05	0.27	0.55	3.73
H – L (4-Factor)	-0.0012	**0.0095*****	**0.0103*****	**-0.0029****	0.00064	**0.0061*****	**-0.0051*****	**-0.0046*****	**0.0040****
	-0.70	4.85	5.03	-2.07	0.41	3.61	-3.35	-2.86	2.12

Table 5.6—*Continued*

Panel C: Portfolios Formed by MV, PIN, and Momentum									
Momentum	Low MV			Medium MV			High MV		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0022	0.0050	0.0074	0.0102	0.0084	0.0084	0.0117	0.0120	0.0105
	0.54	1.32	2.41	2.60	2.16	2.44	3.72	3.48	3.02
Medium	0.0082	0.0126	0.0143	0.0121	0.0111	0.0154	0.0113	0.0122	0.0133
	2.62	3.97	5.17	4.06	3.48	5.16	4.05	4.13	4.42
High (Winners)	0.0132	0.0171	0.0196	0.0116	0.0141	0.0177	0.0137	0.0130	0.0154
	3.72	4.63	6.29	3.43	3.90	4.84	4.63	4.02	4.58
H – L (Raw)	**0.0110*** **	**0.0122*** **	**0.0122*** **	0.0015	**0.0058** **	**0.0093*** **	0.0020	0.0009	**0.0049* **
	4.65	5.47	6.23	0.57	2.53	4.26	0.89	0.39	1.87
H – L (3-Factor)	**0.0116*** **	**0.0138*** **	**0.0129*** **	0.0014	**0.0065*** **	**0.0096*** **	0.0028	0.0019	**0.0071*** **
	4.73	6.09	6.47	0.51	2.72	4.35	1.21	0.77	2.68
H – L (4-Factor)	**0.0067*** **	**0.0095*** **	**0.0103*** **	**-0.0053*** **	0.0006	**0.0046*** **	**-0.0038*** **	**-0.0051*** **	-0.0004
	3.28	4.89	5.43	-2.73	0.38	2.70	-2.77	-3.68	-0.23

Table 5.7 Portfolio Returns Sorted by PIN, Information Uncertainty and Momentum

This table reports average monthly portfolio returns using three-way sorting by probability of information-based trade (PIN), information uncertainty, and momentum. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Each month t stocks are sorted into three groups based on the level of PIN_t. Each PIN_t group is then sorted into three information uncertainty groups. Each PIN_t and uncertainty group is further sorted into three momentum divisions based on past returns from t – 11 to t – 1 ($RET_{t-11, t-1}$). For the resulting 27 subgroups, equally weighted portfolios are constructed and held for one month. All three panels report the Fama-French three-factor and the four-factor risk-adjusted returns for all momentum strategies. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11, t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by PIN, COV, and Momentum

Momentum	Low PIN			Medium PIN			High PIN		
	COV			COV			COV		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0101	0.0101	0.0124	0.0022	0.0075	0.0082	0.0075	0.0064	0.0081
	3.20	2.65	3.51	0.60	1.99	2.07	2.42	1.84	2.13
Medium	0.0101	0.0114	0.0122	0.0098	0.0128	0.0131	0.0126	0.0143	0.0162
	3.99	3.79	4.08	3.46	4.01	3.97	4.80	4.85	5.00
High (Winners)	0.0108	0.0118	0.0149	0.0123	0.0140	0.0146	0.0164	0.0190	0.0228
	3.63	3.61	4.68	3.57	3.85	4.19	5.07	5.44	5.98
H – L (Raw)	0.0007	0.0017	0.0025	**0.0101*** **	**0.0065*** **	**0.0064** **	**0.0089*** **	**0.0126*** **	**0.0147*** **
	0.31	0.73	0.99	3.99	2.84	2.47	4.46	5.48	5.58
H – L (3-Factor)	0.0005	0.0029	0.0035	**0.0105*** **	**0.0070*** **	**0.0077*** **	**0.0099*** **	**0.0135*** **	**0.0157*** **
	0.21	1.21	1.32	3.99	2.96	2.91	4.97	5.67	5.84
H – L (4-Factor)	**-0.0058*** **	**-0.0037** **	**-0.0043*** **	**0.0041** **	0.0015	0.0010	**0.0062*** **	**0.0099*** **	**0.0101*** **
	-3.83	-2.43	-3.00	2.14	0.85	0.53	3.60	4.54	4.59

Table 5.7—*Continued*

Panel B: Portfolios Formed by PIN, AGE, and Momentum									
Momentum	Low PIN			Medium PIN			High PIN		
	AGE			AGE			AGE		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0084	0.0116	0.0135	0.0012	0.0087	0.0097	0.0044	0.0082	0.0100
	2.18	3.35	4.54	0.29	2.23	2.88	1.19	2.51	3.16
Medium	0.0100	0.0111	0.0111	0.0101	0.0112	0.0129	0.0144	0.0145	0.0147
	3.24	3.79	4.24	2.97	3.52	4.47	4.65	4.93	5.53
High (Winners)	0.0137	0.0127	0.0123	0.0133	0.0140	0.0132	0.0192	0.0198	0.0175
	3.90	4.08	4.37	3.42	4.06	4.18	5.10	5.57	5.79
H – L (Raw)	**0.0053****	0.0011	-0.0012	**0.0121*****	**0.0054****	0.0035	**0.0148*****	**0.0117*****	**0.0075*****
	2.05	0.48	-0.55	4.55	2.21	1.58	6.18	5.00	3.88
H – L (3-Factor)	**0.0054****	0.0020	-0.0007	**0.0123*****	**0.0065*****	**0.0044***	**0.0162*****	**0.0118*****	**0.0088*****
	2.02	0.85	-0.31	4.46	2.63	1.93	6.69	4.95	4.52
H – L (4-Factor)	-0.0023	**-0.0049*****	**-0.0062*****	**0.0057*****	0.0004	-0.0013	**0.0108*****	**0.0068*****	**0.0056*****
	-1.56	-3.57	-3.84	2.80	0.21	-0.78	5.69	3.50	3.20

Table 5.7—*Continued*

Panel C: Portfolios Formed by PIN, MV, and Momentum									
	Low PIN			Medium PIN			High PIN		
Momentum	MV			MV			MV		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low (Losers)	0.0096	0.0117	0.0119	0.0029	0.0070	0.0100	0.0056	0.0084	0.0093
	2.50	3.27	3.92	0.72	1.81	2.85	1.66	2.32	2.73
Medium	0.0111	0.0115	0.0114	0.0091	0.0125	0.0120	0.0124	0.0144	0.0163
	3.82	3.95	3.99	2.80	3.94	3.96	4.40	4.72	5.52
High (Winners)	0.0100	0.0130	0.0138	0.0143	0.0137	0.0132	0.0169	0.0195	0.0204
	3.04	4.11	4.55	3.82	3.80	3.89	5.17	5.48	5.52
H – L (Raw)	0.0003	0.0014	0.0019	**0.0114*** **	**0.0067*** **	0.0032	**0.0113*** **	**0.0111*** **	**0.0111*** **
	0.14	0.57	0.87	5.00	2.99	1.27	5.60	5.07	4.62
H – L (3-Factor)	0.0003	0.0021	0.0028	**0.0112*** **	**0.0076*** **	**0.0047* **	**0.0125*** **	**0.0122*** **	**0.0121*** **
	0.12	0.83	1.22	4.75	3.26	1.83	6.01	5.44	4.97
H – L (4-Factor)	**-0.0062*** **	**-0.0050*** **	**-0.0038*** **	**0.0068*** **	0.0019	-0.0024	**0.0100*** **	**0.0077*** **	**0.0065*** **
	-3.50	-3.19	-2.98	3.33	1.12	-1.53	4.99	4.12	3.50

Table 5.8 Portfolio Returns Sorted by Momentum, PIN and Information Uncertainty

This table reports average monthly portfolio returns using three-way sorting by momentum, probability of information-based trade (PIN), and information uncertainty. Information uncertainty proxies include analyst coverage (COV), firm age (AGE) and firm size (MV) in Panel A, B, and C respectively. Each month t stocks are sorted into three momentum groups based on the level of past returns from t – 11 to t – 1 ($RET_{t-11,\,t-1}$). Each momentum group is then sorted into three PIN_t groups. Each momentum and PIN_t group is further sorted into three uncertainty divisions. For the resulting 27 subgroups, equally weighted portfolios are constructed and held for one month. All three panels report the Fama-French three-factor and the four-factor risk-adjusted returns for low-minus-high group hedging portfolios on uncertainty. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11,\,t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by Momentum, PIN, and COV

COV	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0088	0.0021	0.0077	0.0105	0.0096	0.0124	0.0103	0.0129	0.0167
	2.78	0.57	2.52	3.96	3.48	4.60	3.36	3.77	5.21
Medium	0.0112	0.0079	0.0060	0.0110	0.0126	0.0153	0.0120	0.0137	0.0192
	2.96	2.07	1.76	3.72	3.96	5.27	3.60	3.80	5.43
High	0.0115	0.0082	0.0083	0.0116	0.0124	0.0161	0.0152	0.0153	0.0224
	3.12	2.05	2.17	3.84	3.86	4.96	4.83	4.42	6.04
H – L (Raw)	**0.0027***	**0.0061*****	0.0005	0.0011	**0.0028****	**0.0038****	**0.0050*****	0.0024	**0.0057*****
	1.68	3.41	0.25	0.80	2.08	2.34	3.74	1.51	2.87
H – L (3-Factor)	0.0009	**0.0047*****	-0.0020	0.0005	0.0016	0.0018	**0.0054*****	0.0021	**0.0037***
	0.58	2.72	-1.13	0.44	1.28	1.19	4.37	1.27	1.90
H – L (4-Factor)	0.0018	**0.0050*****	-0.0006	0.0012	**0.0022***	0.0019	**0.0052*****	0.0022	0.0027
	1.18	2.81	-0.35	0.96	1.74	1.20	4.07	1.32	1.33

Table 5.8—*Continued*

Panel B: Portfolios Formed by Momentum, PIN, and AGE									
	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
AGE	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0076	0.0007	0.0052	0.0105	0.0098	0.0150	0.0125	0.0144	0.0196
	2.01	0.17	1.42	3.45	2.94	4.85	3.54	3.86	5.43
Medium	0.0114	0.0077	0.0083	0.0107	0.0122	0.0140	0.0129	0.0138	0.0202
	3.16	2.00	2.52	3.72	3.99	4.75	4.12	3.93	5.80
High	0.0127	0.0095	0.0103	0.0119	0.0130	0.0143	0.0121	0.0136	0.0177
	4.00	2.76	3.29	4.43	4.68	5.34	4.24	4.19	5.76
H – L (Raw)	**0.0051*****	**0.0087*****	**0.0051*****	0.0014	**0.0033****	-0.0006	-0.0004	-0.0008	-0.0019
	2.85	4.59	2.99	0.98	2.18	-0.48	-0.24	-0.50	-1.08
H – L (3-Factor)	**0.0056*****	**0.0090*****	**0.0063*****	0.0019	**0.0036*****	0.0004	0.0002	-0.0007	-0.0008
	3.57	4.99	3.76	1.51	2.70	0.31	0.19	-0.43	-0.46
H – L (4-Factor)	**0.0048*****	**0.0077*****	**0.0055*****	0.0010	**0.0024***	0.0003	0.0004	-0.0013	-0.0001
	2.84	4.23	3.22	0.79	1.80	0.25	0.27	-0.79	-0.03

Table 5.8—*Continued*

Panel C: Portfolios Formed by Momentum, PIN, and MV									
MV	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.0087	0.0032	0.0061	0.0106	0.0101	0.0138	0.0113	0.0151	0.0181
	2.34	0.81	1.99	3.70	3.14	4.72	3.32	4.05	5.49
Medium	0.0117	0.0059	0.0087	0.0113	0.0126	0.0146	0.0133	0.0131	0.0195
	3.20	1.53	2.42	3.88	4.13	4.76	4.19	3.70	5.38
High	0.0112	0.0089	0.0088	0.0113	0.0120	0.0150	0.0130	0.0136	0.0203
	3.38	2.38	2.51	3.88	3.97	5.15	4.30	4.13	5.95
H – L (Raw)	0.0025	**0.0057****	0.0026	0.0007	0.0018	0.0012	0.0018	-0.0015	0.0022
	1.17	2.53	1.33	0.46	0.99	0.60	0.98	-0.75	1.03
H – L (3-Factor)	**0.0030***	**0.0053*****	0.0008	0.0009	0.0017	0.0010	**0.0036****	0.00003	0.0012
	1.74	2.62	0.40	0.74	1.22	0.50	2.46	0.02	0.56
H – L (4-Factor)	**0.0031***	**0.0061*****	0.0020	0.0005	0.0009	0.0005	**0.0026***	-0.0021	-0.0004
	1.70	2.99	1.00	0.39	0.62	0.23	1.79	-1.23	-0.19

Table 5.9 Subperiod Analysis

This table provides subperiod analysis for Table 5.5 – Table 5.8. Two subperiods are 1983 - 1992 and 1993 - 2002. Panel A refers to Table 5.5 - Portfolio Returns Sorted by PIN and Momentum. Panel B1, B2, and B3 refer to Table 5.6 - Portfolio Returns Sorted by Information Uncertainty, PIN and Momentum. Panel C1, C2, and C3 refer to Table 5.7 - Portfolio Returns Sorted by PIN, Information Uncertainty and Momentum. Panel D1, D2, and D3 refer to Table 5.8 - Portfolio Returns Sorted by Momentum, PIN and Information Uncertainty. All hedging portfolios are constructed as previous related tables. All panels report one-month-ahead raw returns and the Fama-French three-factor and the four-factor risk-adjusted returns for the relevant hedging portfolios. Stocks with a price less than $5 are excluded. Stocks with missing value of MV, $RET_{t-11, t-1}$ or PIN are excluded, and the missing value of COV takes value of zero. The sample period is 1983 - 2001. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Formed by PIN and Momentum

Momentum	PIN				
	P1 (Low)	P2	P3	P4	P5 (High)
			1983 - 1992		
M5 – M1	0.0025	0.0059	**0.0127*** **	**0.0116*** **	**0.0117*** **
(Raw)	0.75	1.65	3.64	3.50	3.52
M5 – M1	0.0019	0.0052	**0.0132*** **	**0.0130*** **	**0.0138*** **
(3-Factor)	0.55	1.41	3.71	3.93	4.10
M5 – M1	**-0.0051*** **	-0.0023	**0.0066*** **	**0.0072*** **	**0.0087*** **
(4-Factor)	-2.85	-1.20	2.90	3.17	3.27
			1993 - 2002		
M5 – M1	0.0046	0.0029	**0.0096** **	**0.0165*** **	**0.0214*** **
(Raw)	1.02	0.59	2.13	3.88	5.26
M5 – M1	0.0068	0.0054	**0.0118** **	**0.0186*** **	**0.0208*** **
(3-Factor)	1.44	1.07	2.51	4.19	5.30
M5 – M1	-0.0036	**-0.0050* **	0.0028	**0.0110*** **	**0.0148*** **
(4-Factor)	-1.56	-1.70	0.90	3.30	4.62

Table 5.9—*Continued*

Panel B1: Portfolios Formed by COV, PIN, and Momentum									
Momentum	Low COV			Medium COV			High COV		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	0.0007	**0.0102*** **	**0.0103*** **	0.0029	**0.0067** **	**0.0089*** **	0.0012	**0.0062** **	**0.0112*** **
	0.23	3.19	3.55	1.12	2.51	3.22	0.39	2.21	3.98
H – L (3-Factor)	-0.0007	**0.0111*** **	**0.0110*** **	0.0025	**0.0061** **	**0.0100*** **	0.0015	**0.0062** **	**0.0125*** **
	-0.22	3.39	3.64	0.94	2.23	3.53	0.49	2.18	4.35
H – L (4-Factor)	**-0.0071*** **	**0.0051** **	**0.0067*** **	-0.0024	0.0018	**0.0058** **	**-0.0047** **	0.0014	**0.0085*** **
	-4.24	2.40	2.70	-1.38	0.87	2.55	-2.56	0.69	3.56
1993 - 2002									
H – L (Raw)	0.0015	**0.0072** **	**0.0101*** **	0.0004	0.0026	**0.0154*** **	0.0028	**0.0110*** **	**0.0181*** **
	0.42	2.06	3.31	0.14	0.74	4.67	0.66	2.64	4.94
H – L (3-Factor)	0.0035	**0.0077** **	**0.0100*** **	0.0020	0.0035	**0.0156*** **	0.0045	**0.0133*** **	**0.0192*** **
	0.97	2.11	3.43	0.64	0.98	4.59	1.02	3.13	4.94
H – L (4-Factor)	**-0.0042** **	0.0010	**0.0058** **	**-0.0042** **	-0.0036	**0.0103*** **	**-0.0050** **	**0.0060* **	**0.0135*** **
	-2.14	0.41	2.35	-2.05	-1.55	3.76	-2.08	1.89	4.15

Table 5.9—*Continued*

Panel B2: Portfolios Formed by AGE, PIN, and Momentum									
	Low AGE			Medium AGE			High AGE		
Momentum	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0066****	**0.0170*****	**0.0113*****	**0.0048***	0.0038	**0.0067*****	-0.0005	0.0015	**0.0051***
	2.12	5.01	3.42	1.67	1.61	2.62	-0.18	0.49	1.79
H – L (3-Factor)	0.0049	**0.0176*****	**0.0136*****	0.0046	**0.0044***	**0.0071*****	-0.0014	0.0018	**0.0050***
	1.55	5.26	3.99	1.53	1.80	2.73	-0.48	0.57	1.69
H – L (4-Factor)	-0.0008	**0.0120*****	**0.0086*****	-0.0014	0.0004	0.0034	**-0.0072*****	**-0.0040***	0.0006
	-0.37	4.96	3.13	-0.83	0.21	1.57	-4.19	-1.93	0.25
1993 - 2002									
H – L (Raw)	0.0048	**0.0129*****	**0.0166*****	0.0038	**0.0062***	**0.0140*****	0.0015	-0.0018	**0.0090*****
	1.21	3.19	5.00	0.85	1.73	4.2	0.48	-0.58	2.79
H – L (3-Factor)	0.0066	**0.0150*****	**0.0165*****	0.0051	**0.0078****	**0.0141*****	0.0034	0.0007	**0.0107*****
	1.57	3.53	4.78	1.08	2.09	4.19	1.01	0.20	3.25
H – L (4-Factor)	-0.0017	**0.0073****	**0.0113*****	**-0.0052****	0.0009	**0.0086*****	-0.0028	**-0.0056****	**0.0063****
	-0.65	2.42	3.96	-2.20	0.36	3.27	-1.18	-2.58	2.19

Table 5.9—*Continued*

Panel B3: Portfolios Formed by MV, PIN, and Momentum									
Momentum	Low MV			Medium MV			High MV		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0107*** **	**0.0106*** **	**0.0114*** **	0.0039	**0.0066** **	**0.0060** **	-0.0002	0.0008	0.0043
	3.71	3.54	3.88	1.13	2.45	2.17	-0.09	0.24	1.52
H – L (3-Factor)	**0.0104*** **	**0.0122*** **	**0.0138*** **	0.0026	**0.0071** **	**0.0051* **	-0.0003	0.0011	**0.0058** **
	3.49	3.95	4.58	0.71	2.52	1.83	-0.10	0.32	2.00
H – L (4-Factor)	**0.0058** **	**0.0085*** **	**0.0100*** **	**-0.0042* **	0.0020	-0.0002	**-0.0059*** **	**-0.0056*** **	0.0003
	2.49	3.11	3.82	-1.86	1.08	-0.10	-4.13	-3.37	0.19
1993 - 2002									
H – L (Raw)	**0.0113*** **	**0.0139*** **	**0.0130*** **	-0.0012	0.0049	**0.0129*** **	0.0045	0.0011	0.0057
	2.95	4.18	5.14	-0.32	1.29	3.79	1.22	0.31	1.23
H – L (3-Factor)	**0.0128*** **	**0.0155*** **	**0.0119*** **	0.0001	0.0062	**0.0142*** **	**0.0066* **	0.0027	**0.0085* **
	3.25	4.54	4.66	0.02	1.57	4.08	1.73	0.73	1.82
H – L (4-Factor)	**0.0076** **	**0.0103*** **	**0.0095*** **	**-0.0070** **	-0.0007	**0.0091*** **	-0.0012	**-0.0052** **	-0.0013
	2.20	3.69	3.89	-2.43	-0.25	3.13	-0.51	-2.56	-0.50

Table 5.9—*Continued*

Momentum	Low PIN			Medium PIN			High PIN		
	COV			COV			COV		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Panel C1: Portfolios Formed by PIN, COV, and Momentum									
1983 - 1992									
H – L (Raw)	0.0017	0.0013	0.0014	**0.0127*** **	**0.0097*** **	**0.0048***	**0.0088*** **	**0.0111*** **	**0.0091*** **
	0.54	0.42	0.47	3.54	3.59	1.71	3.29	3.07	3.30
H – L (3-Factor)	0.0002	0.0009	0.0020	**0.0127*** **	**0.0095*** **	**0.0052***	**0.0100*** **	**0.0117*** **	**0.0099*** **
	0.05	0.27	0.70	3.50	3.40	1.82	3.67	3.09	3.48
H – L (4-Factor)	**-0.0061*** **	**-0.0053*** **	**-0.0036** **	**0.0061** **	**0.0052** **	0.00003	**0.0063*** **	**0.0076** **	**0.0055** **
	-3.62	-2.77	-2.09	2.57	2.38	0.02	2.75	2.24	2.49
1993 - 2002									
H – L (Raw)	-0.0004	0.0022	0.0038	**0.0073** **	0.0029	**0.0081***	**0.0090*** **	**0.0142*** **	**0.0208*** **
	-0.11	0.61	0.88	2.03	0.79	1.81	3.01	5.11	4.57
H – L (3-Factor)	0.0012	0.0046	0.0049	**0.0085** **	0.0043	**0.0111** **	**0.0092*** **	**0.0151*** **	**0.0216*** **
	0.34	1.23	1.07	2.26	1.10	2.41	3.12	5.25	4.57
H – L (4-Factor)	**-0.0056** **	-0.0029	**-0.0050** **	0.0017	-0.0027	0.0026	**0.0052** **	**0.0116*** **	**0.0145*** **
	-2.48	-1.31	-2.12	0.64	-0.94	0.81	2.02	4.47	3.72

Table 5.9—*Continued*

Momentum	Low PIN			Medium PIN			High PIN		
	AGE			AGE			AGE		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Panel C2: Portfolios Formed by PIN, AGE, and Momentum									
1983 - 1992									
H – L (Raw)	0.0045	0.0015	-0.0026	**0.0144*****	**0.0068*****	0.0030	**0.0128*****	**0.0079*****	**0.0053****
	1.56	0.49	-0.90	4.13	2.80	0.99	3.94	2.71	2.01
H – L (3-Factor)	0.0035	0.0013	-0.0031	**0.0138*****	**0.0075*****	0.0033	**0.0146*****	**0.0089*****	**0.0053***
	1.19	0.42	-1.02	3.88	2.97	1.07	4.41	3.00	1.92
H – L (4-Factor)	-0.0022	**-0.0052*****	**-0.0090*****	**0.0076*****	**0.0029***	-0.0020	**0.0095*****	**0.0044***	0.0020
	-1.30	-3.02	-5.22	3.06	1.75	-0.95	3.68	1.89	0.83
1993 - 2002									
H – L (Raw)	0.0061	0.0007	0.0004	**0.0095****	0.0038	0.0041	**0.0169*****	**0.0157*****	**0.0098*****
	1.40	0.19	0.13	2.35	0.87	1.24	4.79	4.30	3.50
H – L (3-Factor)	0.0072	0.0026	0.0024	**0.0114*****	0.0064	0.0052	**0.0174*****	**0.0150*****	**0.0119*****
	1.55	0.71	0.73	2.73	1.42	1.51	4.84	3.93	4.31
H – L (4-Factor)	-0.0026	**-0.0053*****	-0.0032	0.0042	-0.0018	-0.0011	**0.0114*****	**0.0090*****	**0.0085*****
	-1.03	-2.77	-1.26	1.34	-0.57	-0.48	4.14	2.94	3.42

Table 5.9—*Continued*

Panel C3: Portfolios Formed by PIN, MV, and Momentum									
	Low PIN			Medium PIN			High PIN		
Momentum	MV			MV			MV		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	0.0020	0.0009	-0.0014	**0.0124*** **	**0.0080*** **	0.0029	**0.0105*** **	**0.0104*** **	**0.0070** **
	0.63	0.28	-0.54	4.24	2.84	0.94	3.53	3.53	2.57
H – L (3-Factor)	0.0010	0.0006	-0.0010	**0.0115*** **	**0.0087*** **	0.0037	**0.0128*** **	**0.0111*** **	**0.0071** **
	0.30	0.17	-0.38	3.81	2.96	1.16	4.22	3.61	2.50
H – L (4-Factor)	**-0.0053** **	**-0.0063*** **	**-0.0060*** **	**0.0070*** **	**0.0035* **	-0.0023	**0.0092*** **	**0.0068*** **	0.0021
	-2.49	-3.54	-4.05	2.90	1.75	-1.17	3.41	2.67	1.07
1993 - 2002									
H – L (Raw)	-0.0015	0.0019	0.0055	**0.0102*** **	0.0053	0.0036	**0.0122*** **	**0.0118*** **	**0.0156*** **
	-0.39	0.51	1.47	2.89	1.50	0.86	4.48	3.62	3.88
H – L (3-Factor)	-0.0004	0.0039	**0.0066* **	**0.0112*** **	**0.0074** **	0.0058	**0.0124*** **	**0.0130*** **	**0.0169*** **
	-0.11	1.01	1.71	3.03	2.00	1.37	4.33	3.88	4.17
H – L (4-Factor)	**-0.0077*** **	-0.0038	-0.0016	**0.0065** **	0.0007	-0.0029	**0.0102*** **	**0.0080*** **	**0.0103*** **
	-2.82	-1.64	-0.77	1.98	0.28	-1.20	3.62	2.88	3.24

Table 5.9—*Continued*

Panel D1: Portfolios Formed by Momentum, PIN, and COV									
	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
COV	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	0.0035	**0.0084*** **	0.0017	0.0001	0.0012	**0.0056*** **	**0.0037** **	0.0009	0.0019
	1.58	3.47	0.69	0.05	0.63	2.61	1.99	0.40	0.95
H – L (3-Factor)	0.0005	**0.0065*** **	0.0008	-0.0011	0.0003	**0.0047** **	**0.0040** **	-0.0001	0.0009
	0.23	2.75	0.31	-0.68	0.17	2.27	2.35	-0.04	0.45
H – L (4-Factor)	0.0010	**0.0062** **	0.0015	-0.0007	0.0003	**0.0054** **	**0.0053*** **	0.0011	0.0011
	0.48	2.57	0.63	-0.40	0.16	2.57	3.20	0.47	0.55
1993 - 2002									
H – L (Raw)	0.0019	0.0036	-0.0009	0.0022	0.0046b	0.0017	**0.0064*** **	**0.0042***	**0.0096*** **
	0.79	1.35	-0.31	1.08	2.32	0.72	3.34	1.72	2.80
H – L (3-Factor)	0.0025	0.0022	**-0.0052** **	**0.0032***	**0.0035***	-0.0013	**0.0074*** **	**0.0045***	**0.0069** **
	1.11	0.85	-1.99	1.93	1.84	-0.55	4.13	1.93	1.99
H – L (4-Factor)	**0.0041***	0.0030	-0.0031	**0.0041** **	**0.0048** **	-0.0016	**0.0063*** **	0.0039	0.0049
	1.80	1.13	-1.23	2.49	2.53	-0.69	3.52	1.61	1.41

Table 5.9—*Continued*

Panel D2: Portfolios Formed by Momentum, PIN, and AGE

AGE	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0073*****	**0.0098*****	**0.0061****	0.0022	0.0019	-0.0017	0.0015	-0.0026	-0.0016
	3.13	4.17	2.54	1.35	0.91	-0.95	0.79	-1.06	-0.68
H – L (3-Factor)	**0.0064*****	**0.0088*****	**0.0075*****	0.0013	0.0007	-0.0008	0.0006	**-0.0038***	-0.0022
	3.39	3.85	3.20	0.94	0.40	-0.45	0.40	-1.70	-0.92
H – L (4-Factor)	**0.0071*****	**0.0079*****	**0.0069*****	0.0011	-0.0004	-0.0011	0.0004	**-0.0040***	-0.0019
	3.69	3.44	2.89	0.76	-0.23	-0.58	0.24	-1.77	-0.78
1993 - 2002									
H – L (Raw)	0.0026	**0.0076****	0.0039	0.0005	**0.0047****	0.0005	-0.0024	0.0011	-0.0022
	0.97	2.49	1.64	0.20	2.21	0.26	-0.88	0.47	-0.85
H – L (3-Factor)	0.0035	**0.0091*****	**0.0045***	0.0021	**0.0059*****	0.0015	-0.0006	0.0011	0.0003
	1.40	3.17	1.85	1.07	3.11	0.73	-0.25	0.46	0.10
H – L (4-Factor)	0.0012	**0.0075****	0.0034	0.0012	**0.0047****	0.0016	0.0001	0.0004	0.0015
	0.51	2.60	1.35	0.58	2.48	0.78	0.06	0.15	0.55

Table 5.9—*Continued*

Panel D3: Portfolios Formed by Momentum, PIN, and MV									
	Low Momentum (Losers)			Medium Momentum			High Momentum (Winners)		
MV	PIN			PIN			PIN		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
1983 - 1992									
H – L (Raw)	**0.0065****	**0.0092*****	0.0017	0.0015	0.0015	0.0017	0.0019	-0.0016	-0.0009
	2.36	2.96	0.64	0.70	0.62	0.63	0.80	-0.65	-0.36
H – L (3-Factor)	**0.0048****	**0.0073*****	0.0018	-0.0005	0.0005	0.0018	0.0019	-0.0015	-0.0022
	2.12	2.68	0.66	-0.34	0.26	0.76	1.13	-0.73	-0.86
H – L (4-Factor)	**0.0058****	**0.0090*****	0.0026	-0.0002	0.0001	0.0021	0.0022	-0.0017	-0.0024
	2.52	3.33	0.95	-0.15	0.08	0.90	1.31	-0.81	-0.89
1993 - 2002									
H – L (Raw)	-0.0019	0.0019	0.0037	-0.0001	0.0023	0.0007	0.0017	-0.0013	0.0056
	-0.58	0.58	1.22	-0.03	0.78	0.24	0.59	-0.43	1.60
H – L (3-Factor)	0.0002	0.0018	-0.0006	0.0016	0.0024	-0.0013	**0.0045***	0.0009	0.0036
	0.09	0.63	-0.19	0.84	1.07	-0.42	1.90	0.32	1.03
H – L (4-Factor)	-0.0002	0.0026	0.0013	0.0011	0.0013	-0.0020	0.0030	-0.0025	0.0008
	-0.07	0.85	0.43	0.54	0.59	-0.63	1.26	-0.96	0.24

Chapter 6

General Conclusion

The literature on asymmetric information and market microstructure mainly focus on two roles of informed trading. On the one hand, the presence of informed trading implies the existence of private information. On the other hand, informed trading improves information efficiency because informed investors move price towards the full information level. According to these two insights, this thesis demonstrates that informed trading might have two interesting implications in stock markets. First, the absence of informed trading combined with short-sale constraints can lead to declines in prices (Chapter 3 and Chapter 4). Second, the presence of informed trading can lead to momentum effect (Chapter 5).

Chapter 3, the first essay, empirically shows that stocks will have lower future returns if the level of informed trading is lower and when short-sale constraints are binding. This effect is because of a new information uncertainty risk as perceived by uninformed investors. Specifically, stock prices become less informative when binding short-sale constraints keep informed investors from trading on their private information. The less informative prices create a new information uncertainty risk for uninformed investors, since uninformed investors are unable to figure out the true value of the stock without knowing the private information held by informed investors.

Because of this new information uncertainty risk, uninformed investors are reluctant to hold the stock unless there is a price discount. This new information uncertainty risk effect is the central theme of three theoretical papers including Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008). In addition, Chapter 3 suggests that this new information uncertainty risk effect can be affected by stock's information uncertainty condition, which reflects the convenience of learning the fundamental value of stock. The empirical results show that this new information uncertainty risk effect becomes strong if information uncertainty is high, and it rarely arises if information uncertainty is low. When information uncertainty is low and short-sale constraints are not binding, this new information uncertainty risk effect does not emerge.

Chapter 4, the second essay, demonstrates low level of informed trading combined with binding short-sale constraints can introduce two special new information uncertainty risk effects under certain market conditions. In particular, Chapter 4 uses trading volume to capture two different market scenarios. The first kind of new information uncertainty risk dampens the upward price movement, which is predicted by the model of Yuan (2006). When volume is great, uninformed investors observe high buying pressure as binding short-sale constraints lead to overvaluation and large volume represents high noise demand. Since prices become less informative when the level of informed trading is low and short-sale constraints are binding, uninformed investors cannot distinguish noise demand from information-based buying. They will demand an information-disadvantage premium to hold the stock, and therefore overvaluation caused by short-sale constraints will be reduced. The second kind of new information uncertainty risk exacerbates downward price movement, which is predicted by the models of Bai, Chang, and Wang (2006), and Marin and Olivier (2008). When volume is small, uninformed investors convince that informed investors have negative information as both most of investors in the market and informed investors stop buying. Because prices become less informative when the level of informed trading is low and short-sale constraints are binding, uninformed investors do not know how bad the information is. They will not hold the stock without an information-disadvantage premium, and hence future return becomes worse.

While both Chapter 3 and Chapter 4 highlight the absence of informed trading, Chapter 5, the third essay, stresses the presence of informed trading can lead to momentum effect. It proposes that if momentum is a result of underreaction and if informed trading identifies stocks with underreaction, the presence of informed trading predicts future momentum effect. This is because informed trading identifies underreaction and moves price towards the full information level, uninformed investors can gradually learn informed investors' private information from the price movements. As a result, uninformed investors will follow the earlier informed trading eventually and prices continue to adjusting until reaching the full information level. Therefore, the momentum effect (price continuation) arises following informed trading.

Consistently, the empirical results show that momentum effect arises when informed trading is present. Moreover, higher informed trading leads to greater momentum effect. Although information uncertainty is related to both informed trading and momentum, the identified relationship between informed trading and momentum is robust after controlling for information uncertainty. The behavioural biases theory proposed by Zhang (2006) suggests that information uncertainty measures the degree of behavioural biases, which are responsible for momentum because behavioural biases lead to underreaction according to behavioural finance. However, Chapter 5 provides contrary evidence to the behavioural biases theory. High level of information uncertainty does not produce momentum unless the level of informed trading is relatively high. Furthermore, past winners with higher uncertainty could earn lower future returns when the level of informed trading is low. According to the role of informed trading played in momentum effect, the empirical findings in Chapter 5 suggest that the documented relationship between information uncertainty and momentum should be due to the information diffusion theory proposed by Hong, Lim and Stein (2000). That is, information uncertainty reflects the speed of price adjustment to the full information level.

This thesis has several potential contributions. First, Chapter 3 and Chapter 4 confirm that a new information uncertainty risk can arise when short-sale constraints are binding and the level of informed trading is low. Moreover, Chapter 3 presents the general new information uncertainty risk effect and Chapter 4 demonstrates two special new information uncertainty risk effects. Therefore, the new information uncertainty risk that proposed by Bai, Chang, and Wang (2006), Yuan (2006), and Marin and Olivier (2008) is verified. Second, Chapter 3 and Chapter 4 imply that short-sale constraints can influence the risk as perceived by uninformed investors, although previous literature generally focuses on how short-sale constraints influence the relation between investors' expectations and asset prices. Third, Chapter 5 emphasizes the importance of price discovery for understanding momentum effect by presenting that informed trading plays an important role in momentum. Finally, the empirical findings in Chapter 3, Chapter 4, and Chapter 5 shed light on the interaction between informed trading and information uncertainty. They suggest that informed trading has relative stronger impact on stock returns, although information uncertainty can contribute to the price impact of informed trading.

Nevertheless, the three essays in this thesis also have important limitations. First, because of data limitation, the robustness checks are not enough to fully ascertain that the empirical findings are not caused by specific sample, specific proxies or other obvious explanations. Second, since the original frequencies of informed trading and short-sale constraints are not monthly, the results of the monthly portfolio analysis suffer frequency mismatch problems and hence will not absolutely accurate. Finally, because the empirical results in this thesis are completely based on monthly rebalancing of portfolio analysis, other rebalancing methods can yield different outcomes. These limitations suggest that the findings documented in this thesis require careful caution for their robustness.

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