HITOTSUBASHI UNIVERSITY

Three Essays on Empirical Tests of Market Efficiency

A DISSERTATION

SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

for the degree

DOCTOR OF PHILOSOPHY

Field of Finance

By

Hidetomo Takahashi

KUNITACHI, TOKYO

ABSTRACT

Three Essays on Empirical Tests of Market Efficiency

Hidetomo Takahashi

This dissertation provides empirical evidence that the notion of market efficiency is not consistent with the real world and explains how market efficiency is violated. In the first essay, entitled "The influence of academic interactions on stock selection and performance: Evidence from Japan", I examine whether academic interactions between fund managers and board members improve fund performance. I find that mutual fund managers are more likely to hold academically related stocks. Furthermore, performance tests provide empirical evidence that academic interactions increase fund profits. However, mutual fund managers appear to miss profitable investment opportunities that take advantage of academic interactions because of their investment styles. Overall, the essay provides evidence that mutual fund managers appear to take advantage of academic interactions to earn greater profits. This empirical evidence is consistent with the milder form of market efficiency that security prices reflect information up to the point where the marginal benefit of acting on the information does not exceed the marginal cost of collecting it, as suggested by Grossman and Stiglitz (1980).

The second essay, entitled "Short-sale inflow and stock returns: Evidence from Japan", examines the relationship between shorting demand and subsequent stock price movements, using a ten-year panel of flow-based information on stock borrowings and a flow-based measure for shorting demand in Japan. I find that the least heavily shorted stocks tend to outperform the most heavily shorted stocks in the following month and that this outperformance persists for up to three months. In addition, I find that this outperformance is not confined to stocks with high information asymmetry. This provides evidence that short sellers act as skillful investors in order to detect stock price deviations rather than as informed investors. I also find that this outperformance persists over longer periods among firms with stronger short-sale constraints. These findings suggest that there are skillful investors who are able to detect when a stock price has deviated from its fundamental value and take advantage of trading restrictions to generate such profitable opportunities.

The third essay, entitled "Individual investor flows and cross-section of stock returns: Evidence from Japan", examines whether the trading patterns of individual investors generate cross-sectional differences in future stock returns. I find that stocks that are heavily sold by individual investors outperform stocks that are heavily purchased. Additionally, this relationship is more pronounced among firms with stronger limits on arbitraging. These findings are consistent with the predictions of noise trader models in which the systematic activities of noise traders affect stock returns when they trade in concert and there are limitations to the activities of rational arbitrageurs.

Overall, this dissertation provides empirical evidence that the traditional form of market efficiency is, in some cases, inconsistent with the real world and suggests that researchers in finance should define a version of the efficient markets hypothesis that is milder or more adaptive than the traditional form.

Acknowledgements

This dissertation is the product of years of research, discussion, feedback, and revision in addition to being the culmination of many years of education. There are many people to whom I want to express my appreciation. I have most directly benefited from the advice of many faculty members and fellow students during my six years as a Ph.D. candidate at the Graduate School of Commerce and Management, Hitotsubashi University. In particular, I would like to thank Masaya Ishikawa, Takashi Misumi (principal advisor), Chikafumi Nakamura, Eiji Okano, Eiji Ogawa (co-advisor), Takeshi Osada, and Taiyo Yoshimi for all of their invaluable help throughout the process of writing this dissertation. I also would like to thank my many other close friends and my family (particularly Akiko and Aoi) for all of their help during this period. I never would have achieved this without them.

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CHAPTER 1

Introduction

A half century ago, finance was merely a descriptive field. Since a few researchers in economics suggest some questions, it has become the most dominant subfield of economics. The first hypothesis that researchers in finance suggested was the idea of market efficiency. The notion of market efficiency is that asset prices in asset markets are set conditional on all available information. This notion makes a number of predictions that have been empirically examined for decades. In this dissertation, I focus on the two predictions that still remain unsolved. The first prediction is that no market participant can persistently outperform the market average. The second prediction focuses on why security prices deviate from the rationally discounted value of expected cash flows. By testing these two predictions, this thesis explores the notion of market efficiency and contributes to the understanding of this notion. Before presenting empirical analyses of market efficiency, I begin this chapter by reviewing the notion of market efficiency and its premises in this chapter.

1.1. The efficient market hypothesis

The efficient markets hypothesis (EMH) is the proposition that current stock prices fully reflect all available information about the value of the firm, a concept originally introduced by Fama (1965). The EMH can be tested empirically from at least two different standpoints. One test determines whether security prices incorporate all available information. The other test determines whether security prices equal the prices that incorporate all available information. This section presents empirical studies from these two varying standpoints.

1.1.1. Empirical test of informational market efficiency

The first testable hypothesis directly examines whether security prices reflect all available information (in this dissertation, I call this "informational market efficiency"). When researchers test this hypothesis, the natural first question is "what constitutes all available information?". Fama (1970, 1991) suggests an explicit perspective. According to his view, there are three types of "available information": (a) past prices – weak form, (b) all public information – semi-strong form, (c) all information, including insider information – strong form. Previous empirical studies have taken different approaches to test the three types of informational market efficiency. This subsection explains how the three types of informational market efficiency have been empirically examined.

1.1.1.1. Weak form. Under the weak form of informational market efficiency, the current price fully incorporates information of historical prices only. That is, nobody can detect mispriced securities and outperform the market solely by analyzing past prices. The weak form of informational market efficiency has become famous for two reasons: (a) security prices are arguably the most public and readily available pieces of information and (b) some security analysts actually use information on historical prices to predict future prices, a process called "technical analysis". When reseachers examine the weak form of informational market efficiency, they test the random walk hypothesis.

In tests of the random walk hypothesis, researchers test whether successive price movements are independent. The first test of the random walk hypothesis is performed by Cowles and Jones (1937), which compare the frequency of sequence reversals in historical stock returns. These sequences consist of two groups: one containing pairs of consecutive returns with the same sign and another containing pairs of consecutive returns with opposite signs. Cootner (1962; 1964), Fama (1963; 1965), Fama and Blume (1966), and Osborne (1959) perform random walk tests and provide empirical support for the weak form of informational market efficiency.

More recently, some studies have suggested that the weak form of informational market efficiency is violated. Campbell, Lo, and MacKinlay (1997) assert that various studies of the U.S. stock market report evidence that equity returns display positive serial correlation at horizons shorter than one year (Lo and MacKinlay, 1988) and negative serial correlation at longer horizons (Fama and French, 1988; Poterba and Summers, 1988). However, both in the short-run and the long-run, the degree of predictability is generally small compared to the high variability of returns. Overall, the aggregated empirical evidence suggests that the weak form of informational market efficiency is at least approximately true.

1.1.1.2. Semi-strong form. The semi-strong form of informational market efficiency states that share prices fully reflect all relevant, publicly available information. Publicly available information includes not only past price movements but also earnings and dividend announcements, rights issues, technological breakthroughs, resignations of directors, audited financial statements, and other information made public by the company. The semi-strong form of efficiency implies that there is no advantage in analyzing publicly available information after it has been released because the market has already incorporated that information into the stock price.

To test the semi-strong form of informational market efficiency, Fama (1991) suggests event studies that test how stock prices react to newly released information. Fama et al. (1969) generally find this pattern of price adjustment following major events, such as mergers, stock splits, or changes in a firm's dividend policy. However, Fama (1998) discover that stock prices do not adjust instantaneously to earnings announcements. Instead, a firm's share price generally continues to rise (or fall) for a substantial period after the announcement of an unexpectedly high (or low) profit. This anomaly, which is called post-earnings announcement drift (PEAD), appears to be quite consistent across different sample periods and research methodologies (Ball and Brown 1968; Chan, Jegadeesh and Lakonishok 1996; Fama 1998). Empirical studies lend support for the semi-strong form of informational market efficiency except in the case of PEAD.

1.1.1.3. Strong form. The strong form of informational market efficiency claims that security prices incorporate all available information, including private information. Under this form of market efficiency, obtaining non-public information would not be beneficial as no market participant, including investors with valuable private information, can outperform the market. To test this notion, most empirical studies examine the performance of mutual funds that are considered to be more informed and sophisticated than other market participants.

Early studies on mutual funds (Jensen, 1968; Sharpe, 1966) support the efficient market hypothesis. In other words, mutual funds cannot outperform the market. However, recent studies (see, for example, Grinblatt and Titman, 1992; Elton, Gruber, Das, and

Hlavka, 1993; Hendricks, Patel, and Zeckhauser, 1993; Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996; Wermers, 1999) find compelling evidence that mutual funds, on average, generate negative abnormal returns and that relative performance persists. That is, some mutual funds yield positive abnormal returns and, as a result, outperform the market. More recently, Carhart (1997) demonstrate that the superior performance of top performing funds is a result of the momentum effect explained by Jegadeesh and Titman (1993). On the other hand, Bollen and Busse (2005) find that performance persists over short quarterly holding periods, even after controlling for momentum. From a series of mutual fund performance tests, it appears that the evidence for the superior performance of mutual funds is mixed.

There are different approaches for testing whether any market participant can outperform the market. Using shareholding or trading data of individual investors, some studies test whether an individual can persistently outperform the market. At first glance, it appears unlikely that researchers would be able to find individual investors who yield consistently superior performance because individual investors are regarded as noise traders in most theoretical models. However, Barber and Odean (2000) and Coval, Hirshleifer, and Shumway (2005) find that some individual investors do outperform the market. Another approach to test the strong for m of market efficiency focuses on the measurable characteristics of mutual funds. Chevalier and Ellison (1999) investigate biographical data on managers and find that fund managers from undergraduate institutions with higher average SAT scores earn higher average returns. Other evidence from manager-level data indicates that fund managers tend to overweight nearby companies (Coval and Moskowitz, 1999) and earn higher returns on their local holdings (Coval and Moskowitz, 2001), suggesting a link between geographic proximity and information transmission. Furthermore, Cohen, Frazzini, and Malloy (2008) find that portfolio managers place larger bets on firms they are connected to through academic ties and perform significantly better on these holdings relative to their non-connected holdings. These studies that focus on measurable characteristics of mutual funds suggest that mutual funds achieve superior performance when the fund managers invest in firms where they have more or better information. That is, as noted in Grossman and Stiglitz (1980), security prices reflect information up to the point where the marginal benefit of acting on the information does not exceed the marginal cost of collecting it. As a result, security prices do not always reflect all available information as costly private information is just partly reflected in security prices.

1.1.2. Stock return anomalies

Another prediction made by the EMH is that the current price of a stock closely reflects the rationally discounted value of expected cash flows, where the cross-section of expected returns depends only on the cross-section of systematic risks. This prediction arises from the question on why security prices should incorporate all available information. If prices do not reflect all available information, there would be arbitrage opportunities. In other words, there would be particular strategies to yield positive abnormal returns or net present values.

Earlier studies report some strategies that yield abnormal returns, as measured by the CAPM. Value effects (Lakonishok, Shleifer, and Vishny, 1994), size anomalies (Banz, 1981; Chan and Chen, 1991), reversal effects (DeBondt and Thaler, 1985), momentum effects

(Jegadeesh and Titman, 1993), and post-earnings announcement drifts (Chan, Jegadeesh, and Lakonishok, 1996) are the most well-known phenomenon that are inconsistent with the traditional EMH. Based on these findings, some researchers claim that stock market participants do not always make rational decisions, thereby affecting stock returns and violating the EMH. However, Fama (1998) points out that these anomalies are sensitive to the research methodology employed and diminish if researchers apply the appropriate technique. Fama (1998) asserts that these anomalies, with the exception of post-earnings announcement drifts and momentum effects, are largely explained by a multifactor model that includes systematic risk components other than the market risk. In addition, it should be noted that the positive abnormal returns generated by a strategy that exploits these anomalies are frequently slim and can be easily eclipsed by transaction costs and taxes. Therefore, even if researchers conclude that a particular anomaly exists, it does not necessarily follow that the EMH is violated.

While it is true that these observed anomalies do not necessarily disprove the EMH, it remains unclear why some strategies yield positive abnormal returns or net present values. Some researchers insist that stock return anomalies support the view that securities can be mispriced because of frictions in the stock market. As long as there are limits on investors' ability to arbitrage, mispriced securities will exist. De Long et al. (1990) and Shleifer and Vishny (1997) introduce the idea of noise trader risk. Noise trader risk, which is faced by rational traders, is the risk that irrational noise traders may not only cause an asset to be mispriced but also may cause the mispricing to widen rather than narrow. The effect of noise trading persists because noise traders behave unpredictably. Therefore, the random trading of the noise traders presents rational traders with a unique, non-diversifiable risk that deters rational traders from fully and immediately arbitraging the mispricings generated by noise trading. Furthermore, implementation costs such as commissions, bid-ask spreads, price impacts, taxes, and short-sale constraints can make it less attractive to exploit a mispricing. In particular, as Miller (1977) notes, in the presence of short-sale constraints, security prices tend to reflect a more optimistic valuation than the average opinion of potential investors and, as a result, tend to be upward biased.

Recently, some empirical studies provide supportive evidence for the effects of limits on arbitraging, such as noise trader risk and implementation costs, on stock prices. Hvidkjaer (2008), Barber, Odean, and Zhu (2006), and Frazzini and Lamont (2008) find that trading behaviors of individual investors, who are likely to be regarded as noise traders, predict negative subsequent stock returns. In addition, Barber, Odean, and Zhu (2006) assert that return predictability is stronger among firms with stronger short-sale constraints. Some empirical studies have found that financial anomalies are more pronounced among firms with higher idiosyncratic risks (Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2005) and stricter short-sale constraints (Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Jones and Lamont, 2002; Lamont, 2004; Ofek, Richardson, and Whitelaw, 2004; Reed, 2003; Nagel, 2005). These empirical studies lend support to the theory that limits on arbitraging generate mispricings that are not exploited by rational investors. At the same time, this evidence implies that the traditional notion of the EMH is violated when limits on arbitraging restrict the trading behaviors of rational investors.

1.2. Focuses on this dissertation

As documented in the previous section, issues that remain unsolved and ongoing in the literature are (a) why stock prices do not rapidly respond to earnings announcements, (b) whether security prices in stock markets incorporate all available information, including private information, and (c) whether stock prices are mispriced in the presence of limits on arbitraging. These questions are still ongoing and require further investigation. This dissertation explores these topics and explains how and under what circumstances the EMH is violated in the following three chapters.

In Chapter 2, entitled "The influence of academic interactions on stock selection and Performance: Evidence from Japan", I investigate the controversial issue of strong form informational market efficiency. Specifically, I explore whether public security prices incorporate all available information, including private information. To test this hypothesis, I examine mutual funds with academic interactions between fund managers and board managers to determine if performance correlation exists because, as previously mentioned, this relationship is purported to have the strongest positive effect on returns. I find that mutual fund managers are more likely to hold academically related stocks. Furthermore, performance tests provide empirical evidence that academic interactions increase fund profits. My research also suggests that mutual fund managers appear to miss profitable investment opportunities that take advantage of academic interactions because of their investment styles. Overall, the essay provides evidence that mutual fund managers appear to take advantage of academic interactions to earn greater profits.

Chapters 3 and 4 provide empirical evidence on whether stocks are mispriced when limits are placed on arbitraging. In Chapter 3, entitled "Short-sale inflow and stock returns: Evidence from Japan", I examine whether short-sale constraints keep stock prices overinflated and less informative. To test this hypothesis, I focus on the demand side of short sales. In the majority of finance studies, short sellers are assumed to be rational, sophisticated, and informed. If this assumption is appropriate, strong shorting demand should predict negative subsequent returns. Using a ten-year panel of flow-based information on stock borrowings and a flow-based measure for shorting demand in Japan, I examine the relationship between shorting demand and subsequent stock price movements. My research suggests that the least heavily shorted stocks tend to outperform the most heavily shorted stocks by 0.707 percent in the next month and that this outperformance persists for up to three months. In addition, I find that this outperformance is not confined to stocks with high information asymmetry. This provides evidence that short sellers act as skillful investors in order to detect stock price deviations rather than as informed investors. The combined evidence implies that stocks are overpriced and that some short sellers exploit these arbitrage opportunities.

In Chapter 4, entitled "Individual investor flows and cross-section of stock returns: Evidence from Japan," I conduct a more straightforward analysis. I examine whether trading patterns of individual investors generate cross-sectional differences in future stock returns. I find that stocks that are heavily sold by individual investors outperform stocks that are heavily purchased. Additionally, this relationship is more pronounced among firms with stronger limits on arbitraging. These findings are consistent with the predictions of noise trader models in which the systematic activities of noise traders affect stock returns when they trade in concert and there are limitations to the activities of rational arbitrageurs. The evidence provided in Chapter 4 also supports the notion that stocks are mispriced when there are limits on arbitraging.

Overall, this dissertation provides counter-evidence that challenges the traditional EMH by analyzing stock return anomalies in more detail. However, the findings in this dissertation are not necessarily consistent with the EMH. In the first essay, I demonstrate that the milder form of the EMH is more suitable to the real world. In the second and third essays, I argue that when limitations to rational investors are present, it is possible that stock prices cannot incorporate all available information and that the irrationality of noise traders can distort stock prices. These empirical findings illustrate how the traditional form of the EMH is violated in the actual markets, not that the hypothesis is inappropriate. At the same time, the evidence implies that there is a need to revise the notion of market efficiency in order to more accurately reflect what actually occurs in the markets. In other words, a more adaptive version of the EMH must be developed.

CHAPTER 2

The influence of academic interactions on stock selection and performance: Evidence from Japan

In this chapter, using mutual fund holdings data and fund manager demographic data, I examine whether academic interactions between fund managers and board members affect fund manager investment decisions and fund performance. I show that mutual fund managers are more likely to hold academically related stocks. Performance tests provide empirical evidence that academic interactions are beneficial to earn more profits. In addition, I show that mutual fund managers seem to lose profitable opportunities due to academic interactions because of their investment styles. Overall, it is shown that mutual fund managers seem to take advantage of academic interactions to earn greater profits.

2.1. Introduction

In this chapter, I examine whether an academic link between mutual fund managers and board members affects managers' investment styles and performance. Based on an analysis of mutual funds' equity holdings data, the results show that mutual fund managers favor academically related stocks. I also show that the academic link between mutual funds and board members is important with regard to yielding higher performance.

In the field of finance, how information has been incorporated into securities prices has been rarely discussed in the past few decades despite the common sense that information moves prices. To understand the mechanism through which information affects asset prices, academics have recently tried to relate the effect of information on prices to social interactions. In keeping with previous studies, this essay examines whether one type of social interaction, namely, the academic interactions of fund managers, impacts fund managers' preferences for stocks and the subsequent performance of stocks. The contribution in this chapter is its implications for stock market efficiency. Under the traditional efficient market hypothesis (hereafter EMH), no investor can beat the market if the stock market is efficient in terms of information. The finding of profitability due to academic interactions indicates a violation of the traditional EMH. Instead, as documented in Grossman and Stiglitz (1980), it implies that some investors can outperform the market because of an informational advantage.

This study considers one kind of social interaction, namely, academic interaction. I expect that fund managers who engage in academic interaction are more likely to hold academically related stocks that perform well due to informational advantages.[1] To test

[1]There is a possibility that such fund managers only hold these stocks because they are subject to some behavioral bias. In this case, we expect a performance lower than the market performance.

whether academic interactions have important effects on stock selection and performance, I use holdings data on 79 active mutual fund managers. As these data are produced semi-annually or annually, I can observe trading decisions by observing changes between the two reporting dates. Combining these data with demographic data regarding fund manager' academic backgrounds obtained from the Morningstar website, I examine whether academic backgrounds influence stock preferences and fund performance. I construct variables to measure the strength of the academic interactions of managers. If a fund manager graduated from the same university as one of board members in a listed firm, the firm is regarded as "academically related" to the fund manager.

By measuring academic interactions between managers and board members, I examine whether academic interactions impact the stock preferences of fund managers. In the analyses of stock picking by mutual fund managers, I find that they tend to hold academically related stocks even after controlling for the effects of investment style, manager-specific characteristics, and time-series fixed effects. However, in the analysis of portfolio weight decisions, fund managers do not always tilt their investment toward academically related stocks, which implies that mutual fund managers cannot take advantage of the full information obtained from academic interactions. To test whether holding academically related stocks is beneficial, I compare the performance of academically related stocks to that of academically unrelated stocks. I create calendar-time portfolios that mimic the aggregate portfolio allocation of mutual funds in related and non-related stocks. The results show that academic interactions yield economically and statistically significant profits for the mutual funds. Academically related stocks outperform academically unrelated stocks by 0.018 percent per day, that is, 4.5 percent per annum. The results hold in some robustness checks. In addition, I examine whether mutual fund managers can take full advantage of information induced from academic interactions by comparing the performance of academically related stocks held by them to that of these stocks not held by them. The results show that academically related stocks held by mutual fund managers do not always outperform academically related stocks not held by them, which implies that mutual fund managers seem to be unable to take advantage of full information included in academic interactions. The comparison of academically related stocks held by mutual fund managers to stocks not held by them also shows that stocks in the latter group are more likely to be concentrated among smaller and value stocks, which are less likely to be held by mutual funds. Because of the investment styles that fund managers employ, these managers might be unable to take advantage of full information from academic interactions. Overall, the empirical evidence shown in this chapter is consistent with the prediction that one type of social interaction, namely, academic interactions, drives informational advantages of mutual funds and yields higher performance.

The remainder of this chapter is organized as follows. In Section 2.2, I describe the background and related literature based on theoretical and empirical evidence. In Section 2.3, I describe the data. Section 2.4 provides empirical results on holding decisions. The empirical results on performance tests are reported in Section 2.5. In the last section, concluding remarks are documented.

2.2. Background and related literature

Many researchers have devoted their work to addressing whether security prices are set in an informationally efficient way. If securities prices are informationally efficient, then investors cannot outperform the market. Using mutual funds holdings data, many studies have examined the informational efficiency of security prices. Most studies (Jensen, 1968; Carhart, 1997; Davis, 2001) find that mutual funds consistently underperform relative to the market. Though these studies examine the returns of a particular type of investors, mutual fund demographic data have only rarely been used to discriminate investments for which there is evidence of stock selectivity. Recent works by Coval and Moskowitz (2001) and Cohen, Frazzini, and Malloy (2008) succeed in finding evidence that an informational advantage can be used to help mutual funds outperform the market. Coval and Moskowitz (2001) report that mutual fund managers who live near firm headquarters of held stocks tend to earn abnormally high returns. They point out that their findings imply that fund managers have a substantially enhanced ability to select local stocks due to a local informational advantage.[2] Cohen, Frazzini, and Malloy (2008) find that academic ties between mutual fund managers and board members lead to higher performance than the market. They also suggest that academic ties may be a source of informational advantage.

In this study, I consider one type of social interactions, namely, academic interactions, as likely to yield informational advantages for mutual fund managers. An academic interaction is a form of social interaction that tends to persist after an individual graduates college. Most people select their schools according to their interests and educational levels. Students in the same university are therefore expected to have similar backgrounds and characteristics even before matriculation. Opportunities to continue college-based interactions after graduation include such events as alumni parties. As people from the same university tend to have similar cultures and backgrounds as well as stronger relationships

[2] However, Grinblatt and Keloharju (2001) report that local bias of institutional investors may does harm their performance.

with one another after graduation than with others from different universities, academic ties are expected to provide an informational advantage for fund managers. There is also empirical evidence to support this hypothesis. Flap and Kalmijn (2001) show that academic ties are more effective bases for building relationships than other ties.

2.3. Data

2.3.1. Mutual fund data

This study obtains data from several sources. Mutual fund holdings data are obtained from the Electronic Disclosure for Investors' Network managed by the Financial Service Agency of the Japanese government. The data contain the annual or semi-annual holdings of individual mutual funds from 2003 to the present. In the analysis presented here, I focus on actively-managed Japanese equity funds; index funds, funds that invest mainly in foreign equities or bonds, real estate funds and closed-end funds are excluded. This restriction yields a sample of about 650 funds during the sample period.

The use of demographic data on mutual funds portfolio managers is also important in this study; these data are obtained from the Morningstar website. To enhance the sample used in this study, I use data from the websites of firms to which fund managers belong or from articles in Nihon Keizai Shinbun. The combined dataset provides the name of portfolio managers, brief cumulative vitae of some managers, the university from which they graduated, the degree earned, and the graduation year. After matching the data to the mutual fund holdings data, I obtain 79 actively-managed funds. This sample is employed in my tests. Stock return and financial data on firms are obtained from Nikkei

NEEDS. The analysis in this study is limited to common stocks. Table 2.1 shows summary statistics on fund holdings and demographics data in more detail.

2.3.2. Academic interaction

I assume that strong academic ties between fund managers and managing boards lead to informational advantages for fund managers. To construct the academic interaction variable, I rely on the cumulative vitae of management board members. I obtain these data from Nikkei Telecom, which is managed by Nikkei Media Marketing. The data provide detailed biographies on board members, their alma mater, degree, year of graduation, birth date, hobbies, and so on. I only use the biographies of chief executive officers, chief operating officers, and board directors. By matching the data to mutual fund demographic data, I construct the academic interaction variable. If a board member graduated from the same university as a fund manager, I define the company stock as "academically related". For example, take the case of a fund manager who graduated from Tokyo University. If she holds a Mitsui Co. and Ltd. stock (a company in which a Tokyo University graduate is the CEO), the company stock is defined as academically related. If she holds Denso stock, a company in which a Nagoya University graduate is the CEO, the company is regarded as "academically unrelated". In the regression and performance tests, I use a dummy variable that takes the value of one if a stock is academically related and zero, otherwise.

2.4. Academic interactions and holding decisions

In this section, I examine the effects of academic interactions between fund managers and board members on the investment styles of mutual funds. If mutual fund managers consider academic interactions as a source of informational advantage, it would be possible that fund managers tend to hold academically related stocks and concentrate portfolio allocations. To test this hypothesis, first, I conduct two analyses that consider the stock-picking decisions of listing stocks. Mutual fund management consists of fund managers, who are the final authority in investment decisions, as well as analysts, who collect information for fund managers. It is possible that mutual funds obtain all available information about firms listed on a stock exchange. Thus, this study considers the decision of fund managers to hold certain listed stocks in their portfolios. That is, each stock requires a decision, namely, to hold or not to hold. When I conduct an analysis of stock-picking decisions, I use a dependent variable that takes one if a mutual fund holds a stock of a listed firm and zero otherwise. Furthermore, I run a regression employing the dependent variable, which is defined as a log-transformed portfolio weight in each fund.[3] To gauge the effects of academic interactions on mutual fund investment styles, I include an academic interaction variable as the main explanatory variable. To control for the well-documented investor preferences regarding small firm size, value, and recent good performance, I include monthly quintile values for market capitalization, book-to-market ratios, and the past six-month cumulative returns five days prior to the reporting date. I run pooled cross-sectional regressions with fixed effect components to control for fund manager-specific characteristics and time-series effects.

[3]If the values for portfolio weight are below 0.0001 or above 0.9999, I replace the values with 0.0001 and 0.9999, respectively.

The results are described in Table 2.2. As can be seen in the first column of Table 2.2, the coefficient of the academically related variable is 0.042 with a t-statistic of 2.15 when I conduct a logit model. The second column of Table 2.2, which conducts a regression employing a log-transformed portfolio weight as the dependent variable, also shows that he coefficient of the academically related variable is 0.003 with a t-statistic of 2.35. These results indicate that fund managers are more likely to hold academically related stocks than academically unrelated stocks. Furthermore, Table 2.2 also indicates that mutual funds favor growth and large-market-capitalization stocks.

In addition to the analyses of stock-picking decisions by mutual fund managers, I conduct a analysis of portfolio weights as done in Cohen, Frazzini, and Malloy (2008) and Butler and Gurun (2009). If mutual funds regard academic interactions as informational advantage, fund managers are considered to overweigh academically related stocks. Employing log-transformed portfolio weights as the dependent variable, I conduct a pooled cross-sectional regression. Explanatory variables used in this analysis are the same in the analysis of stock-picking decisions. The results are presented in the last column of Table 2.2. As can be seen in the column, the coefficient of the academically related variable is 0.010 with a t-statistic of 0.56. The results imply that fund managers do not overweigh academically related stocks.

From the analyses of stock picking decisions and portfolio weights, I find that mutual fund managers tend to pick up academically related stocks but do not overweigh these stocks within their portfolios. These two combined results suggest that fund managers do not overweigh academically related stocks simply because these stocks are familiar or are more likely to generate informational advantage. In fact, as controlling exposures to systematic risks and their investment styles are more important than holding more academically related stocks for mutual fund managers, they simply choose more stocks suitable to their investment style among academically related stocks. The empirical evidence presented in this section indicates that mutual fund managers cannot take advantage of full information from academic interactions. To test this prediction, in addition to the comparison of academically related and academically unrelated stocks, I compare the performance of academically related stocks that mutual fund managers choose to hold with that of academically related stocks that mutual fund managers choose not to hold, which is also conducted in Cohen, Frazzini, and Malloy (2008).

2.5. Performance test

The evidence that fund managers are more likely to hold academically related stocks does not imply that their holding decisions are valuable. This section examines the difference in the performance of related and unrelated stocks in mutual fund holdings. I also provide some robustness checks for the main results.

To examine the benefit of the tendency of fund managers toward academically related stocks, I employ a standard calendar-time portfolio approach. At the beginning of each calendar period (whether annual or semi-annual), I assign all stocks held by mutual funds to academically related or academically unrelated portfolios. After this category is assigned, I compute the daily returns on related and unrelated stocks between two given reporting dates. In carrying out this calculation, I assume that mutual funds do not change their holding portfolios between the two reporting dates. Portfolios are rebalanced every calendar period, and stocks are weighted by the fund dollar holdings within a given fund portfolio. This strategy thus classifies academically related and academically unrelated stocks after investing equally in all funds.

To measure returns on testing portfolios, I employ two methods to adjust risks. First, for the factor-based risk adjustment, I estimate time-series regressions of the return on each stock net of the government bond (i.e., risk-free) rate on several factors, including the excess of value-weighted market returns listed in the Japanese stock markets over the risk-free rate, a size factor, a book-to-market ratio factor, a momentum factor (Carhart, 1997), and a liquidity factor as suggested by Pastor and Stambough (2003). In the constructions of these factors, I employ a similar method to Fama and French (1993). The size and book-to-market factors are calculated by taking the value-weighted average of the top three deciles in terms of market capitalization and book-to-market portfolio returns and subtracting the average of the bottom three-decile portfolio returns. To calculate size and book-to-market factors, I employ the top three and the bottom three deciles of firm market capitalization and book-to-market ratios as listed in the Tokyo Stock Exchange (TSE) as breakpoints to divide stocks into three portfolios. In these constructions, I use market capitalization at the end of the previous month as well as the book-to-market ratio based on the most recently announced book equity value. The momentum and liquidity factors are calculated by taking the value-weighted average of the upper quintile momentum and liquidity portfolio returns and subtracting the average of the lower quintile portfolio returns. In the construction of the momentum factor, the previous three months of cumulative returns are used. Following Pastor and Stambough (2003), I calculate the liquidity ratio and construct the liquidity factor based on these values.[4] I calculate the 5-factor model alpha by regressing excess returns on five factors as described above.

Second, for the characteristic-based risk adjustment, I follow a procedure similar to the approach used by Daniel et al. (1997, DGTW). Specifically, I place each stock into one of 75 portfolios based on its market capitalization at the end of the previous month, its book-to-market ratio using its most recently announced book equity value, and its previous three months of cumulative returns. Using the same breakpoints as in the factor adjustments, I divide all stocks into five portfolios for market capitalization and book-to-market classifications. In the case of momentum classification, all stocks are divided into the top quintile, the bottom quintile, and other. Therefore, I construct five size categories, five book-to-market categories, and three momentum categories, which results in seventy-five possible classifications for each stock. I calculate daily equal-weighted average returns for each of these 75 stock classifications, taking the characteristic-adjusted return of a particular stock as its realized return minus the average return of a stock with its classification.

2.5.1. Academic interactions and performance

Table 2.3 describes the main results of this study. This table reports daily returns for academically related, academically unrelated portfolios, and portfolios that long academically related stocks and short academically unrelated stocks. All t-statistics are computed using

[4]Pastor and Stambaugh (2003) suggest that a stock's liquidity can be measured by the interaction between returns and lagged-order flow. As prices of less liquid stocks are expected to overshoot in response to order flow, the greater value in predicted return reversal for a given dollar volume implies a lower level of stock liquidity. To calculate this measure, I regress a market-adjusted return for a given firm on the lagged stock return, the interaction term of the stock's daily yen volume and the sign of the lagged stock return. The coefficient of the interaction term is expected to be negative and larger in absolute magnitude if the firm's adverse selection problem is severe.

Newey-West adjusted standard errors with four lags. Comparison of returns on academically related stocks to returns on academically unrelated stocks shows whether academic interactions are beneficial to mutual fund performance. First, I focus on the first column in Table 2.3 labeled "All Holdings", which reports returns on mutual fund portfolios. For any return measure, it shows that returns on mutual fund portfolios are statistically insignificant. For example, in the case of the 5-factor model alpha, the return on the mutual fund portfolios equals 0.002 percent per day, that is, 0.5 percent per annum with a t-statistic of 0.23. This result implies that mutual funds cannot outperform the market on average, which is consistent with previous empirical evidence (Jensen, 1968; Carhart, 1997; Davis, 2001). The inability of mutual funds to outperform the market seems to indicate that mutual fund managers do not have an informational advantage relative to other investors. However, as Frazzini and Lamont (2008) document that mutual fund performance on the entire holdings depends on retail investor decisions, the performance of mutual funds is sensitive to retail investor sentiment. Therefore, the empirical evidence that mutual funds cannot outperform the market does not necessarily mean that finding an informational advantage in academic interactions is promising. That is, it is possible to detect an informational advantage of fund managers through the academic interactions between fund managers and board members.

The main objective in this study is to analyze whether academic interactions between fund managers and board members are beneficial to mutual fund performance. Thus, I next focus on the second column, which report daily returns on academically related stocks, As can be seen in the second column labeled "Related", all risk-adjusted returns (except the CAPM alpha) show positive values with a statistical significance at the 10 percent significance level. For instance, the 5-factor model alpha shows that the academically related portfolio outperforms the market by 0.021 percent per day, that is, 5.25 percent per annum with a t-statistic of 1.94. The result implies that academic interactions are beneficial to mutual fund portfolios.

Comparison of an academically related portfolio with an academically unrelated portfolio is more useful than comparing it with the market to emphasize the effect of academic interactions on mutual fund performance. This is because it is possible that effects other than academic interactions between fund managers and board members are included in means or intercepts of risk-adjusted models. Lastly, I present the results described in the third and fourth columns in Table 2.3. The third column in Table 2.3 reports returns on academically unrelated portfolios. Compared to returns on academically related portfolios, as can be seen in the column labeled "Unrelated", returns on the academically unrelated portfolio do not show any statistically significant value. In addition, as can be seen in the fourth column labeled "L/S' that reports returns on portfolios that long academically related stocks and short academically unrelated stocks, returns on such portfolios do show positive values with strong significance. For example, the 5-factor model alpha shows 0.018 percent per day (4.50 percent per annum) with a t-statistic of 3.24. A comparison of academically related portfolios with academically unrelated portfolios also indicates that academic interactions are beneficial for mutual fund portfolios.

2.5.2. Robustness

The previous section shows that academic interactions are beneficial for mutual fund portfolios. Table 2.4 provides some robustness checks for the results in Table 2.3. First, I examine whether the results in Table 2.3 are driven by information asymmetry, which is unique to stocks with smaller market capitalization. Panel A and B indicate that the difference in returns between a portfolio of related stocks and one of unrelated stocks is stronger for small cap stocks (6.00 percent per annum), although it is still large and reliable for large stocks (3.75 percent per annum). Thus, it does not seem that the information asymmetry unique to smaller firms is driving the results.

Panel C considers the effect of informational advantage due to locality. Coval and Moskowitz (2001) demonstrate that the extent to which a firm is held by nearby investors is positively related to its future expected return. As all mutual fund companies to which fund managers belong are located in Tokyo, I test whether the benefit of academic interactions is observed after controlling for the effect of locality. Panel C shows that the difference in returns between a portfolio of related stocks and one of unrelated stocks equals 5.50 percent per annum, which implies that the benefits gained from academic interactions are not due to informational advantage related to locality.

Panel D and E report results on the subsample analysis of performance tests, which divide mutual funds into two groups, specifically, top-three most related universities and other universities. As can be seen in the last column in Table 2.4, both groups show positive values with statistical significance at the 10 percent level, although the benefits gained from academic interactions are less weak and reliable for funds not in the top-three most related universities group. Overall, Panel D and E provide empirical evidence to support the main results in Table 2.3.

2.5.3. Held versus not-held

In previous sections, by comparing the performance of academically related stocks to that of academically unrelated stocks, I show that academic interactions show higher performance. In this section, by comparing the performance of academically related stocks within mutual funds' positions to that of academically related stocks that fund managers do not hold, I test whether mutual fund managers can allocate portfolios to take advantage of their full information due to academic interactions. As documented in Section 2.4, mutual fund managers do not seem to take advantage of full information obtained from academic interactions. Furthermore, trading behaviors of mutual funds are regulated in most countries, including Japan. For example, they are restricted from selling stocks short. Therefore, they might lose profitable opportunities due to academic interactions.

To examine this prediction, I construct the portfolio of academically related stocks that fund managers do not hold and compare the performance of the portfolio to that of academically related stocks within mutual funds. I construct the value-weighted portfolio of academically related stocks that fund managers do not hold. Table 2.5 reports 5-factor model alphas and factor loadings on calendar-year portfolios that mimic the aggregate portfolio allocation of the mutual funds in academically related stocks, academically related stocks which is held by mutual fund managers, and academically related stocks not held by them. As can be seen in the last column, academically related stocks held outperform academically related stocks not held by 0.017 percent per day with a t-statistic of 1.82. Compared to the performance of the portfolio that longs academically related stocks and shorts academically unrelated stocks, the long-short strategy of academically related stocks held and those not held yields a nearly equal but less reliable return. The results imply that mutual fund managers cannot allocate portfolios to take advantage of their full information due to academic interactions.

From factor loadings on the long-short strategy of academically related stocks held and not held, I can assess the reason why mutual fund managers cannot fully take advantage of academic interactions. As can be seen in the last column, the long-short strategy has negative loadings of SMB and HML with economic and statistical significance. The results indicate that academically related stocks not held by mutual fund managers are more likely to be smaller and value stocks. Even if mutual fund managers have some informational advantage with regard to academically related stocks not held, they do not choose to hold these stocks simply because owning these stocks is not compatible with their investment styles.

2.6. Concluding remarks

In this chapter, I examine whether academic links between mutual fund managers and board members affect fund managers' investment styles and performance. In the analyses of stock-picking decisions, I show that mutual fund managers are more likely to hold academically related stocks. However, they do not always seem to overweigh academically related stocks. These two combined results imply that mutual fund managers cannot take advantage of full information obtained from academic interactions. Performance tests provide empirical evidence that academically related stocks outperform academically unrelated stocks by about 4.5 percent per annum, which is measured by a 5-factor model. This empirical evidence holds when I consider some other ways in which fund managers might acquire informational advantages. In addition, I show that mutual fund managers lose profitable opportunities due to academic interactions by comparing the performance of academically related stocks within mutual funds' positions to that of academically related stocks that fund managers do not hold. Overall, these results imply that mutual fund managers seem to take advantage of academic interactions to earn greater profits. The results in this chapter are consistent with previous studies, such as Cohen, Frazzini, and Malloy (2008) and Massa and Simonov (2005). This study suggests one way to explain how informed investors acquire informational advantages and yield higher performance.

Table 2.1. Summary statistics on fund holdings and demographics

Total Number of Funds	79
Total Number of Managers	56
University	
Number of Funds from Keio Univ.	12
Number of Funds from Tokyo Univ.	10
Number of Funds from Waseda Univ.	6
Fund Size	
Mean	34,550
Median	6,977
Min	366
Max	974,270
Number of Firms followed	
Mean	85
Median	77
Min	24
Max	269

notes: This table demonstrates the total number of funds and managers employed in this study, the number of funds appearing in top-three academically related universities, simple statistics on the fund size (in millions of Yen) and the number of firms followed by funds.

Table 2.2. Academic interactions and portfolio decisions

	Holding decision		Portfolio weight
Method	Logit	$\log(\frac{frac}{1-frac})$	$\log(\frac{frac}{1-frac})$
Academy	0.042	0.003	0.010
	(2.15)	(2.35)	(0.56)
Size	1.498	0.128	0.538
	(153.03)	(190.85)	(47.37)
BtoM	-0.511	-0.025	-0.168
	(-49.59)	(-42.13)	(-15.78)
Momentum	-0.025	0.004	0.147
	(-2.31)	(4.97)	(14.50)

notes: This table reports the results of holding decisions and portfolio weights of fund managers. In the analysis of the holding decisions of mutual funds, each stock requires a decision, namely, to hold or not to hold. The first dependent variable takes the value one if a fund manager holds a stock of a listed firm and takes zero otherwise. The second dependent variable are logit-transformed percentages of holdings of a particular stock ($\log(\frac{frac}{1-frac})$). When a particular stock is not included in the portfolios of mutual fund managers, $\frac{frac}{1-frac}$ takes 0.0001. In the analysis of the portfolio weights of mutual funds, the logit-transformed percentages of holdings of a particular stock are used. The variable Academy takes one if a fund manager graduated from the same university from which board members graduated and takes zero otherwise. Quintilized market capitalization, book-to-market, momentum, and fixed-effect components to control fund managers' characteristics and time-series effects are also included. This table provides the coefficients with t-statistics. In the first column, the result employing a logit model is reported. The second and third columns present the results of OLS regressions.

Table 2.3. Returns on academically related and unrelated stocks

	All holdings	Related	Unrelated	L/S
Raw return	0.008	0.028	0.003	0.025
	(0.19)	(0.69)	(0.09)	(3.47)
CAPM alpha	-0.012	0.013	-0.011	0.024
	(-0.90)	(1.15)	(-0.82)	(3.42)
3-factor model alpha	0.002	0.021	0.003	0.019
	(0.20)	(1.94)	(0.27)	(3.21)
DGTW char-adjusted return	0.001	0.015	-0.002	0.017
	(0.23)	(2.48)	(-0.34)	(3.12)
4-factor model alpha	0.002	0.021	0.003	0.018
	(0.21)	(1.95)	(0.29)	(3.28)
5-factor model alpha	0.002	0.021	0.003	0.018
	(0.23)	(1.95)	(0.30)	(3.24)

notes: This table reports results for abnormal returns on the calendar-time portfolio that mimics the aggregate portfolio allocation of mutual funds in academically related and unrelated stocks. The variable Academy is defined as in Table 2.2. "All holdings" reports the performance of mutual funds holdings. "Related" reports portfolio returns on stocks that have academic interactions, while "Unrelated" reports returns on stocks with no academic interaction. "L/S" reports returns on portfolios that long academically related stocks and short academically unrelated stocks. This table provides the mean and factor model alphas with Newey-West adjusted t-statistics, as described below.

Table 2.4. Robustness checks

	All holdings	Related	Unrelated	L/S
A. Large cap stocks	0.014	0.022	0.006	0.017
	(1.31)	(1.92)	(0.50)	(2.86)
B. Small cap stocks	0.010	0.023	-0.002	0.024
	(0.85)	(1.35)	(-0.13)	(1.69)
C. Firms located in Tokyo	0.017	0.028	0.005	0.022
	(1.53)	(2.27)	(0.47)	(3.10)
D. Top-three university	0.012	0.023	0.001	0.022
	(1.23)	(2.12)	(0.09)	(2.97)
E. Non-top-three university	0.010	0.017	0.004	0.012
	(0.97)	(1.34)	(0.38)	(1.84)

notes: This table provides some robustness checks of the results in Table 2.3. Table 2.4 provides 5-factor model adjusted returns of all holdings of the mutual funds (All holdings), returns on stocks that have academic interactions (Related), returns on stocks with no academic interaction (Unrelated), returns on portfolios that long academically related stocks and short academically unrelated stocks (L/S). Panel A reports returns on large-market capitalization stocks (i.e., the top three deciles based on TSE market capitalization). Panel B reports returns on small-market capitalization stocks (i.e., the bottom three deciles based on TSE market capitalization). Panel C reports returns on stocks of firms located in Tokyo. Panel D reports returns on mutual funds with managers who graduated from the top-three most academically related universities in academic interactions, while Panel E reports returns on mutual funds with managers who graduated from universities other than the top-three most academically related universities.

Table 2.5. Abnormal return on held and not-held related stocks

	Related	Held	Not-held	L/S
Intercept	0.011	0.021	0.004	0.017
	(1.18)	(1.90)	(0.34)	(1.82)
Mkt	1.146	1.240	1.168	0.072
	(61.08)	(57.76)	(49.26)	(3.53)
SMB	-0.006	0.102	0.300	-0.198
	(-0.31)	(4.73)	(14.24)	(-11.32)
HML	-0.136	-0.232	-0.040	-0.192
	(-5.24)	(-7.38)	(-1.41)	(-6.94)
WML	0.024	-0.012	0.040	-0.052
	(2.05)	(-0.92)	(2.54)	(-4.82)
LIQ	-0.007	0.023	-0.093	0.116
	(-0.13)	(0.31)	(-1.45)	(2.38)
Adj. R^2	93.55	92.54	90.06	46.23

notes: This table reports the results of 5-factor model alphas and loadings on a calendar-year portfolio that mimics the aggregate portfolio allocation of the mutual funds in academically related stocks, academically related stocks held by mutual funds, and academically related stocks not held by mutual funds. Academically related and academically related stocks not held by mutual funds are value-weighted within each portfolio. Academy is defined in Table 2.2. The column "Related" reports portfolio returns on stocks that have academic interactions. The column "Held" reports portfolio returns on stocks that have academic interactions and are held by mutual funds, while the column "Not-held" reports returns on stocks with no academic interactions and that are not followed by mutual funds. Stocks with no academic interactions and not followed by mutual funds are value-weighted within the portfolio. This table provides the mean and intercepts, with t-statistics, described below.

CHAPTER 3

Short-sale inflow and stock returns: Evidence from Japan

In this chapter, using a ten-year panel of flow-based information on stock borrowings and using a flow-based measure for shorting demand, I examine the relation between shorting demand and subsequent stock price movements. I find that the least heavily shorted stocks tend to outperform the most heavily shorted stocks by 0.707 percent in the next month and that this outperformance persists up to three months. In addition, I find that this outperformance is not confined to stocks with high information asymmetry. This indicates that short sellers act as skillful investors in order to detect stock price deviations rather than as informed investors.

3.1. Introduction

Both from a practical and an academic perspective, it would appear that short sales have a large impact on stock prices. Practitioners criticize that short sellers destabilize stock markets by taking short positions in price depreciation conditions. In particular, security issuers, governments, and the media blame short sellers for confounding bad market conditions. Governments in many countries set limitations on short-selling activities to displace short sellers and prevent the depreciation of stock markets. In contrast, the finance literature suggests that short sales help in achieving market efficiency, since short sellers can be regarded as more rational, sophisticated, and informed. At the same time, based on this perspective, short-sale constraints are considered impediments to market efficiency. Therefore, short-sale constraints keep stock prices overpriced and less informative.

To provide empirical evidence in support of this view, there have been two standard approaches to examining the relation between short sales and stock prices. The first approach focuses on the relation between the supply side of short sales and stock prices. When market participants sell stocks short, they are first required to borrow the shares. If they face a low supply level of lendable shares in the face of expensive borrowing costs, this indicates that short-sale constraints are tightly binding. Theoretical models predict that stocks with tighter short-sale constraints are more likely to be overpriced and thus less likely to be affected by negative information, thereby generating negative subsequent returns.[1] By employing a variety of proxies for shorting supply, previous studies have found results consistent with this prediction, including Chen, Hong, and Stein (2002), who

[1]See Miller (1977), Harrison and Kreps (1978), Duffie, Garleanu, and Pedersen (2002) and Diamond and Verrecchia (1987).

use a change in the breadth of mutual fund ownership, Nagel (2005), who use institutional ownership, Lamont (2004), who employ a firm's actions toward limit short selling, and D'Avolio (2002), Cohen, Diether, and Malloy (2007), Jones and Lamont (2002), Reed (2007), who use actual costs in stock borrowing markets.

The second approach focuses on the relation between the demand side of short sales and stock prices. In the majority of finance studies, short sellers are assumed to be rational, sophisticated, and informed. If this assumption is appropriate, strong shorting demand should predict negative subsequent returns. The most commonly-used data in this analysis is short interest data. Using this type of data, some previous studies have examined the relation between short interest levels and stock prices. Brent, Morse, and Stice (1990) find that the monthly short interest does not predict either the cross-section or time-series behavior of stock returns. Asquith, Pathak, and Ritter (2005) find a negative relation between short interest and stock returns only among smaller firms. Lamont and Stein (2004) also do not find any predictive power for aggregate short interest with respect to future market returns. Cohen, Diether, and Malloy (2007) examine the relation between shorting demand and stock prices by employing a change in short interest level and find that the changes predict subsequently lower returns. However, their analysis is confined to smaller firms. As seen above, the empirical evidence on the relation between short interest levels or changes and stock prices is mixed; whether short sellers are rational, sophisticated, and informed remains controversial.

The difficulty in establishing an explicit link between shorting demand and stock prices is attributed to limited information included in short interest data. First, the monthly frequency of short interest data does not give researchers detailed information on short selling activities. As Diether (2008) points out, short sellers cover their positions very rapidly, usually within two weeks. To account for the short-term liquidations of short sales, short interest data would ignore much information included in short selling activities. In addition, it is possible that a lower level of short interest simply indicates the unavailability of shares for borrowing due to the higher costs of finding lenders or the higher rebate rates for borrowing. To avoid these effects and construct more suitable proxies for shorting demand, some studies employ alternative measures. Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Wermer (2009) succeed in detecting a negative relation between shorting demand and subsequent stock returns by constructing a flow-based measure for shorting demand. Boehmer, Jones, and Zhang (2008) show that stocks most heavily shorted by institutions on a given day underperform the market in the next one month after the formation period, while Diether, Lee, and Wermer (2009) also find that increased short selling activity predicts negative abnormal returns in the following five days.[2] Although these two studies show explicit links between shorting demand and stock prices, they have much shorter sample periods of at most four years as compared to examinations with short interest data that have panels of more than ten years. Therefore, to show that the negative relation between flow-based proxies for shorting demand and subsequent stock returns is robust, further examinations employing the flow-based measure over a longer sample period are required.

[2]Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Wermer (2009) construct flow-based measures, which are defined as the total number of shares sold short divided by trading volume executed on the stock exchange for a given stock on a given day. Boehmer, Jones, and Zhang (2008) construct a flow-based proxy for shorting demand from proprietary order system of the NYSE from January 2000 to April 2004, while Diether, Lee, and Wermer (2009) employ new SEC-mandated data for 2005.

In this chapter, in order to examine the relation between shorting demand and subsequent stock returns, I analyze the short sales of borrowed stocks in Japan from April 1998 to March 2008. In Japan, as in the U.S. before the SHO regulation became effective, investors who make naked short sales are forbidden to place orders at prices above the prices at which the immediately preceding sales were effected.[3] Furthermore, after October 1998, short selling by borrowing stocks from large shareholders through negotiations is also subject to the same regulation. Consequently, it is difficult for those who place large orders by borrowing stocks from large shareholders, such as institutional investors, to sell short in large numbers in the Japanese stock exchange. Meanwhile, investors who sell stocks short by borrowing stocks from market makers in stock lending markets are not subject to the price regulation.[4] Those who short stocks borrowed from market makers can short stocks as far as the market makers supply stocks. However, in reality, market makers in stock lending markets require short sellers who borrow stocks to pay higher lending fees than usual or raise their minimum margin requirement rate, when the shorting demand outstrips the shorting supply.[5] As market makers make efforts to maintain their inventory levels so as to minimize their losses, their inventory levels cannot meet

[3]In the U.S., the SEC employs the up-tick rule, which restricts short selling at a price below the price at which the immediately preceding sale was effected, or the last sale price if it is lower than the last different price. In Japan, regulators employ a price regulation that restricts short selling at a price below the price at which the immediately preceding sale was effected.

[4]After Mach 2002, all short sales, including short sales of stocks borrowed from market makers, are subject to the up-tick rule. However, short sales of less than 50 units borrowed from market makers are not regulated by the up-tick rule.

[5]Before May 2002, when investors borrowed stocks, they were charged fixed costs of 0.75 percent per annum. After May 2002, the fixed lending fee increased by about 0.4 percent per annum. When the shorting demand exceeds the shorting supply, investors are required to pay an additional lending fee. With some exceptions, the additional lending fee is approximately zero.

the shorting demand by institutional investors in many cases. Thus, most short sales of borrowed stocks from market makers are mainly driven by individual investors.

I construct a proxy for shorting demand from data on borrowed stocks from the largest market maker in the Japanese stock lending markets; namely, the Japan Securities Finance Company.[6] There are some advantages to using these data. First, the data provide the flow of shorting borrowed stocks rather than the stock of shorting. The advantage of using the flow-based measure is that it allows researchers to construct a finer proxy for shorting demand than the traditional short interest data, because the flow-based measure provides much additional information that is ignored in the stock-based measure. Second, the Japan Securities Finance Company reports the flow of their lending activities over ten years. As this period is much longer than previous studies that have focused on the flow-based measures, the data allows me to examine the relation between shorting demand and subsequent stock return more robustly. Third, as the Japanese stock exchange regulators introduced the short selling rules from the U.S. and employ similar and more restrictive rules, the empirical results in this study are useful not only for Japan, but also for the U.S.

On the other hand, the flow-based measure used in this study does not provide information on institutional shorting, and most of the short sales in this study are thought to be driven by individual investors. As individual traders are often regarded as uninformed or fools, it would seem that a shorting demand proxy constructed from short selling by

[6]In Japan, three companies act predominantly as market makers in the stock lending markets. The Japan Securities Finance Company is the largest market maker of the three.

individual investors is not so promising to predict future returns.[7] However, recent studies have found evidence that some individual investors are more informed or skilled than others.[8] As short selling is a more complicated form of trading that is generally practiced by more skillful investors, according to previous empirical findings on individual investors, it is not entirely unlikely for a shorting demand proxy constructed from short selling by individual investors to produce accurate predictions.

The flow-based measure for shorting demand is defined similarly to Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Wermer (2009). Specifically, based on the flow-based shorting data, I divide the monthly-aggregated shares of new borrowing by the amount of trading volume in a month to normalize across stocks for each stock. I define this measure as the relative short-sale inflow (RSSI). Employing this flow-based measure for the shorting demand, I examine whether stocks with low RSSI can outperform stocks with high RSSI. The stocks are divided into portfolios on the basis of RSSI. I measure the equal-weighted and value-weighted returns for those portfolios in which the returns are measured up to six months into the future.[9] The results show that stocks with low

[7]In theoretical models that assume the presence of noise trades, such as Black (1986) and De Long et al. (1990), individual investors only serve to generate demands that are generally driven by liquidity needs or psychological considerations unrelated to market information on fundamental security values. Odean (1998, 2000) reports that individual investors perform poorly on average relative to the market and to institutional traders because individual investors trade too much, maintain underdiversified portfolios, and hold losing stocks for too long.

[8]Coval, Hirshleifer, and Shumway (2005) document significant performance persistence among individuals, and show that some investors can outperform the market persistently.

[9]Whether long short sellers can enjoy overpricing/informational advantage is a contentious issue within the literature. In Diamond and Verrecchia (1987), prices are expected to incorporate negative private information fairly quickly. However, the empirical literature seems to assume that overpricing is a long-term phenomenon that is corrected slowly over a series of months and quarters rather than days or weeks. Chen, Hong, and Stein (2002) use changes in the breadth of mutual fund ownership to forecast returns up to four quarters into the future, while Lamont (2004) looks at returns one to three years after battles between firms and short sellers. As there is no clear theoretical suggestion for the appropriate time length for analyzing the phenomenon under study, I employ holding periods between one month and six months for the return prediction tests.

RSSI outperform stocks with high RSSI. For instance, in the case of a one-month holding strategy, the average monthly return difference between two equal weighted portfolios is 0.707 percent with a t-value of 4.03; this return difference persists for up to three months. This finding is consistent with those of Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009). In the case of value-weighted portfolios, the main results do not change. Furthermore, subsample period analysis, which divides the entire sample period into two halves, also supports the main results. In contrast to previous studies, I find that the return difference persists for more than one month. Stricter rules on short selling, which limit short selling by institutional investors after October 1998, might contribute to this finding.

Second, I examine whether the return difference between the highest RSSI portfolio and the lowest RSSI portfolio is due to the effect of shorting supply or not. To consider the possibility that higher RSSI simply indicates tighter short-sale constraints, I examine the return difference of two RSSI portfolios after dividing all available stocks into two groups according to the degree of shorting supply. Following Nagel (2005), I employ residual institutional ownership as the proxy for shorting supply. Stocks with higher (lower) residual institutional ownership are expected to be less (more) short-sale constrained. I find that stocks with low RSSI outperform stocks with high RSSI by 0.636 (0.746) percent with a t-statistic of 3.41 (4.10) in the next one month among high (low) residual institutional ownership stocks. These results imply that the return difference of two RSSI portfolios is not due to shorting supply, but rather, shorting demand has a great impact on stock returns. Furthermore, I find that the return difference of two RSSI portfolios among stocks with higher residual institutional ownership does not persist for longer periods than the return difference among stocks with lower residual institutional ownership. This result implies that, among stocks with higher residual institutional ownership that are less costly for institutional investors to borrow, the mispricing in the stock markets is more easily arbitraged away by institutional short sale trading.

Lastly, I also examine whether the return difference of two RSSI portfolios is confined to stocks with high information asymmetry in which informed investors can make more profits. It is useful to know the resource of short sellers' profits. Employing proxies for information asymmetry derived from the market microstructure literature, I show that stocks with low RSSI outperform stocks with high RSSI by 0.565 to 0.849 percent with strong statistical significance in the next month among stocks with lower information asymmetry. This implies that the outperformance of short sellers is due not only to informational advantages but also to their skillfulness in detecting market inefficiencies.

The rest of this chapter is organized as follows. Section 3.2 briefly describes background studies on short sales. Section 3.3 defines the main variable, that is, the flow-based proxy for shorting demand. I also provide data descriptions and information on variable construction. In Section 3.4, I report abnormal returns for the main test portfolios. Concluding remarks are presented in Section 3.5.

3.2. Background

The majority of the finance literature analyzes whether short sellers help stock prices become more efficient and suggest that impediments to short sales disturb stock market efficiency. Miller (1977) theoretically documents that short-sale constraints lead to overpricing in stock markets through a combination of differences of opinions and short-sale constraints.[10] Under short-sale constraints, more optimistic opinions tend to be incorporated into stock prices because investors with more pessimistic opinions cannot sell stocks that they do not own. As optimistic investors adjust their prior beliefs by learning from stock prices and trades, stock prices converge to their fundamental values, thus generating negative subsequent returns. Diamond and Verrecchia (1987) develop a theoretical model that there is no overpricing because rational uninformed investors make consideration of short-sale impediments when they form prior beliefs about firm value. In this model, all market participants share the view that negative opinions are not incorporated into stock prices. That is, short-sale constraints disturb the release of negative private information in stock markets. In this model, the release of negative private information has greater impact on stocks with higher short-sale constraints, as these stocks generate lower subsequent returns.

The most direct and simple prediction based on the theoretical models on short selling is that stocks with higher short-sale constraints (that is, lower shorting supply) are more likely to generate lower subsequent returns. As described in the first section, a number of studies show consistent results with respect to this expectation. Another prediction is that stocks with strong shorting demand tend to yield lower subsequent returns. As Diamond and Verrecchia (1987) document, shorting demand is a sign of the release of private information. In addition, shorting demand indicates deviations of stock prices from their fundamental values because price deviations drive short sales of skillful investors. Compared to studies that focus on the relation between shorting supply and stock prices, there is no consensus on the relation between shorting demand and stock prices due to

[10]According to Harrison and Kreps (1978) and Duffie, Garleanu, and Pedersen (2002), stock prices can be higher than even the most optimistic investor's assessment of their value.

limitations in short interest data. The main objective in this study is to provide more robust empirical evidence to support theoretical expectations by constructing a flow-based measure for shorting demand over ten years. Furthermore, I try to identify the main driver of return predictability with shorting demand by controlling for the effect of information advantage of short-sellers.

3.3. Data

3.3.1. Primary data

In this study, to construct a proxy for shorting demand, I use the data on borrowing stocks from securities finance companies, which act as market makers in the stock lending markets. When investors borrow stocks from securities finance companies, there are restrictions on the stocks that can be sold short, the reimbursement terms, and the fees, all of which are determined by the stock exchange according to various standards, such as individual stock liquidity. Borrowing is processed after brokerage firms accept short-selling orders from investors. Lending stocks are borrowed from securities finance companies, while investors receive borrowed stocks from brokerage firms. In this study, I use a dataset on daily stock borrowing and construct a flow-based measure for shorting demand. The data is from the Japan Securities Finance Co., Ltd., which plays the most important role of market maker in Japanese stock lending markets. The data cover all information on borrowings through brokerage firms, but they do not contain information on negotiation-based borrowings which are mainly driven by institutional investors. The data provide the following information: date, identification code, number of shares in inventory, the number of shares that are newly lent and lent back, transaction price, and backwardation rate. The number of shares newly lent for the market maker refers to the number of shares short sellers borrow in order to sell short (i.e., short-sale inflow), while the number of shares lent back to the market maker refers to the number of shares short sellers cover to liquidate short positions (i.e., short-sale outflow). The data contain all available short-sale stocks in the Tokyo Stock Exchange from December 1997 to March 2008.

I match data on borrowing stocks with market and financial data obtained from the Nikkei NEEDS. As in many previous studies, I exclude financial firms and regulated utilities from the analysis. I also omit firms with stock prices lower than 50 yen. After matching the stock lending data with the market and financial data, approximately 1,360 firms are left in the sample across the entire period under study. Although firms with available short-sale shares comprise only 63 percent of the market, these firms are involved in about 94 percent of market capitalization.

3.3.2. Construction of variables

3.3.2.1. Short-sale inflow. In order to examine the relation between shorting demand and subsequent stock returns, I employ a flow-based measure for shorting demand rather than short interest (i.e., the number of shares on loan), which has been employed in most previous studies. There are at least two reasons why I prefer a flow-based measure to the stock-based measure. First, because the time length of short-sale positions is very short (on average, it lasts about two weeks), the stock-based measure cannot incorporate information included in short selling. Second, it is possible that higher short interest simply reflects strong shorting supply. In addition, I ignore short-sale covering, or outflow, information in the construction of the flow-based measure. Short-sale outflow is mainly motivated by liquidity needs, such as the restitution of stocks on loan or financing deficit. If information on short-sale outflow is included, it is difficult to discriminate information motivating trades involved in new short-sale positions from liquidation needs. Therefore, I focus on short-sale inflow (i.e., new borrowing), which is most appropriate for detecting the private information obtained by short sellers as well as their skillfulness in trading. To normalize across stocks, I define relative short-sale inflows (RSSI) as the aggregate daily number of shares newly borrowed by short-sellers of a given stock in a given month and divide the aggregate number by the total number of shares traded on the Tokyo Stock Exchange of a given stock in a given month.

Table 3.1 presents the summary statistics on RSSI. As can be seen in the first row, the time-series mean of equal-weighted cross-sectional averaged RSSI is 6.76 percent. Meanwhile, the Tokyo Stock Exchange has a short interest level of 0.28 percent from August 2002 to March 2008 according to the TSE statistical reports. This comparison indicates that short-sale trades are short-lived; moreover, there is substantial information that is not included in short interest, which has motivated researchers to construct more appropriate proxies for shorting demand from flow-based data. In the second and third rows, summary statistics in the subsample periods are described. There is a dramatic decrease in relative short-sale inflows in the latter sample period from April 2003 to March 2008. It drops from 8.971 percent to 4.551 percent. There are at least two reasons for the dramatic decrease in RSSI. First, in 2002, there were some changes in the short-sale regulations, which restrict short selling more significantly. After 2002, most short sellers are subject to the up-tick rule even when the shorted stocks are borrowed. In addition, the fixed fee to borrow stocks increased. These tighter regulations on trades by short sellers might contribute to the dramatic decrease in RSSI. Second, in the period from April 2003 to March 2008, the Japanese stock markets experienced appreciations. In fact, while the Japanese stock market faced depreciation in the first period, with the monthly average of value-weighted market portfolio declining 0.431 percent, the monthly average of the value-weighted market portfolio increased 0.756 percent in the latter period. It is expected that negative information is less prevalent in periods when stock prices experience appreciations, which leads to the dramatic decrease in RSSI. As it remains possible that the dramatic decrease in RSSI could affect the return predictability of the flow-based measure for shorting demand, I have conducted a subsample analysis to support my findings by dividing the entire sample period into two periods, namely, the period from April 1998 to March 2003 and the period from April 2003 to March 2008.

3.3.2.2. Short-sale constraints. As has been previously described, it is possible that higher RSSI simply indicates tighter short-sale constraints, that is, lower shorting supply. To show that results in this study are not simply the effect of shorting supply on stock prices, I also examine the return difference of RSSI portfolios by dividing all stocks into two groups according to the degree of short-sale constraints. Following Nagel (2005), I employ residual institutional ownership as the proxy for shorting supply. After performing a logit transformation of institutional ownership that is bounded by 0 and 1, I regress logit transformed institutional ownership on a logarithm of market capitalization as well as a squared logarithm of market capitalization.[11] Regressions are run each month using the latest value of institutional ownership; I refer to the residuals as residual institutional

[11]If the values for institutional ownership are below 0.0001 or above 0.9999, I replace the values with 0.0001 and 0.9999, respectively.

ownership. Stocks with higher (lower) residual institutional ownership are expected to be less (more) short-sale constrained.

3.3.2.3. Proxies for information asymmetry. This study also examines whether short sellers can better predict future stock price depreciations than other investors, even among stocks with low information asymmetry and for which profits due to information advantages are low. Note that in this context, I should measure information asymmetry between informed and uninformed investors. Market microstructure studies have attempted to extract the degree of information asymmetry among market participants from market trading data. The subsequent theories based on these analyses assume that market trading is not only driven by inventory or liquidity needs but also by informed trading, and market makers who offset market imbalances between the supply and demand sides set bid-ask spreads to avoid losses. Therefore, measures of illiquidity, such as Kyle's (1985) λ and bid-ask spreads, should reflect the degree of information asymmetry among market participants. As such, this study also employs four liquidity measures as proxies for information asymmetry.

The first measure I use is an information asymmetry measure developed by Llorente et al. (2002, LMSW). Their measure is based on the interaction between trading volume and stock returns. I regress the stock return of a given firm on the lagged return and the interaction term between the lagged return and the natural logarithm of the daily turnover detrended by its mean over the past 200 days. The coefficient of the interaction term can be interpreted as the degree of information asymmetry. The lower (higher) of the estimates (henceforth, LMSW ASY) indicate the lower (higher) information asymmetry of a firm. Llorente et al. (2002) show that their measure can capture the relative importance of informed trading in the fluctuation of stock prices. The second measure is intended to detect the adverse selection component of a stock's proportional spread. Following George, Kaul, and Nimalendran (1991), I estimate the adverse selection component of a stock's proportional spread.[12] The third measure is Amihud's (2002) illiquidity ratio, which is defined as the average daily ratio between the absolute value of a stock return and its yen volume. This measure indicates the stock price response to one dollar of trading volume. A previous study by Amihud (2002) shows that this measure is positively related to the high-frequency measures used in the market microstructure literature, such as price impacts and trading costs. The last measure I employ is Pastor and Stambaugh's (2003) liquidity ratio. They suggest that a stock's liquidity can be measured by the interaction between returns and lagged-order flow. As prices of less liquid stocks are expected to overshoot in response to order flow, the greater value in predicted return reversal for a given dollar volume implies a lower level of stock liquidity. To calculate this measure, I regress a market-adjusted return for a given firm on the lagged stock return and the interaction term of the stock's daily yen volume and the sign of the lagged stock return. The coefficient of the interaction term is expected to be negative and larger in absolute magnitude if the firm's adverse selection problem is severe. These four measures are estimated using market data and updated every quarter.

[12]Using the residuals of a regression of daily firm i's stock return on the daily value-weighted market return, I calculate the filtered effective spread of firm i, which is denoted as Y_i. In the calculation of the residuals, the intercept and the coefficient are estimated using a market model based on the previous year's data. I also estimate Roll's (1984) proportional effective spread as $RS_i = 200\sqrt{|cov(r_{i,t}, r_{i,t-1})|}$ over a 60-day rolling interval. Finally, I estimate the adverse selection component by regressing Y_i on RS_i. The coefficient of RS_i is expected to reflect the degree of information asymmetry. I estimate the coefficients for every quarter.

I also employ firm characteristics, including firm market capitalization and analyst coverage, as proxies for information asymmetry among market participants. Firms with higher values for these two measures are expected to have lower information asymmetry. Market capitalization is obtained from market data, while analyst coverage is obtained from the Institutional Brokers Estimates System (I/B/E/S).

3.3.3. Risk adjustment

This study employs two methods to calculate benchmark-adjusted returns. For the factor-based risk adjustment, I estimate time-series regressions of the return on each stock net of the government bond (i.e., risk-free) rate on several factors, including the excess of value-weighted market returns listed in the Japanese stock markets over the risk-free rate, a size factor, a book-to-market ratio factor, a momentum factor (Carhart, 1997), and a liquidity factor suggested by Pastor and Stambough (2003). In the constructions of these factors, I employ a similar method to Fama and French (1993). The size and book-to-market factors are calculated by taking the value-weighted average of the top three deciles in terms of market capitalization and book-to-market portfolio returns and subtracting the average of the bottom three decile portfolio returns. To calculate size and book-to-market factors, I employ the top three and the bottom three deciles based on firm market capitalization and book-to-market ratios as listed in the Tokyo Stock Exchange (TSE) as breakpoints to divide stocks into three portfolios. In these constructions, market capitalization at the end of the previous month as well as the book-to-market ratio based on the most recently announced book equity value are used. The momentum and liquidity factors are calculated by taking the value-weighted average of the upper quintile momentum and liquidity portfolio returns and subtracting the average of the lower quintile portfolio returns. In the construction of the momentum factor, the previous three months of cumulative returns are used. Following Pastor and Stambough (2003), I calculate the liquidity ratio and construct the liquidity factor based on these values.[13] I calculate the 5-factor model alpha by regressing excess returns on five factors as described above.

For the characteristic-based risk adjustment, I follow a procedure similar to the approach used by Daniel et al. (1997, DGTW). Specifically, I divide each stock into three portfolios based on its market capitalization at the end of the previous month, its book-to-market ratio based on its most recently announced book equity value, and its previous three months of cumulative returns. Using the same breakpoints as in the factor adjustments, I divide all stocks into the top three, middle four, and bottom three portfolios for market capitalization and book-to-market classifications. In the case of momentum classification, all stocks are divided into the top quintile, the bottom quintile, and all others. Therefore, I construct three size, three book-to-market, and three momentum categories, which results in twenty-seven possible classifications for each stock. When employing equal-weighted (value-weighted) returns in subsequent tests, I calculate monthly equal-weighted (value-weighted) average returns for each of these twenty-seven stock classifications, taking the characteristic-adjusted return of a particular stock as its realized return minus the average return of a stock with its classification.

[13] Details on the calculation of Pastor and Stambough's (2003) liquidity factor are described in the previous section.

3.3.4. Description of data

Table 3.2 presents firm characteristics of five portfolios and is divided according to relative short-sale inflows. As can be seen in the second and fifth rows, the lowest RSSI portfolios are more likely to have lower values of market capitalization and institutional ownership than the highest RSSI portfolios. This tendency tells us that it is necessary to control the supply side effect in shorting markets because stocks with lower market capitalization and institutional ownership tend to be stocks with tighter short-sale constraints (D'Avolio, 2002). To show the robustness of the results in this study, I conduct a subsample analysis according to the degree of shorting supply. Subsequently, I focus on the seventh and eleventh rows. The lower RSSI portfolios tend to show higher values of information asymmetry with respect to their effective spread, Amihud's illiquidity ratio and the absolute value of PS liquidity, while they tend to show lower values for the LMSW information asymmetry measure. If short sales are mainly motivated by private information, it is expected that short selling is more predominant among stocks with higher levels of information asymmetry. In contrast to this expectation, the results show that short selling is more predominant among stocks with lower levels of information asymmetry. That is, short sellers might act more as skillful investors who detect market inefficiencies. However, to draw such a conclusion, further validation is required. In the following sections, I examine the return predictability of RSSI and whether its predictability persists even among stock with lower levels of information asymmetry.

3.4. Empirical results

3.4.1. Returns on short-sale inflow portfolios

The main question addressed in this study is whether RSSI, that is, the flow-based measure for shorting demand, has explanatory power to predict future negative stock returns. This section shows that portfolios of stocks with the lowest RSSI outperform portfolios of stocks with the highest RSSI.

I begin by explaining the construction of the RSSI portfolios. Each month, stocks are sorted into five equal-weighted (value-weighted) portfolios according to RSSI as measured over the prior month. Future returns generated by these portfolios are computed over horizons of K months, where K equals 1, 2, 3, and 6 months. I report 5-factor model alphas and the DGTW characteristic-adjusted returns. Similar to Jegadeesh and Titman (1993), the holding period portfolio returns are calculated as the average of the current period's return on the previous K-month portfolios. When K equals 6, for instance, the portfolio return is the average of this month's return for the portfolios constructed in each of the prior six months. By averaging across prior strategies rather than prior returns, the overlapping problem should be avoided, and t-statistics can be computed using Newey-West adjusted standard errors with four lags.

3.4.1.1. Equal-weighted portfolios. Table 3.3 shows the monthly 5-factor model alphas and the DGTW characteristic-adjusted returns for the equal-weighted portfolios in RSSI quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. First, the results in Panel A show that RSSI portfolios display negative returns in many cases, and this return is monotonically decreasing as one moves from the bottom to the top quintile. In addition, the results show that the lowest RSSI portfolio tends to outperform the highest RSSI portfolio by 0.707 percent with a t-statistics of 3.99 over the next month. This outperformance persists up to three months after the formation period. Using a three-month rolling period, the lower RSSI portfolio outperforms the higher RSSI portfolio by 0.327 percent with a t-statistic of 2.10 over the next three months after the formation of the portfolio. Panel B shows the robustness of results presented in Panel A. When the performance measure is changed from the 5-factor model alphas to the DGTW characteristic-adjusted returns, the results do not change. The lowest RSSI portfolio tends to outperform the highest RSSI portfolio by 0.905 (0.360) percent with a t-statistics of 4.05 (2.90) over the next month (next three months).

The results support the expectation that strong shorting demand predicts negative subsequent returns. This result is comparable to the findings of Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Wermer (2009). I obtain these results by conducting a longer panel analysis of the flow-based measure for shorting demand. The results in this study provide empirical support that the flow-based measure for shorting demand can be used to robustly predict returns in stock markets. Furthermore, in contrast to previous studies, I show that the outperformance of the lowest RSSI portfolio as compared to the highest RSSI portfolio would persist up to three months after portfolio formation. Since October 1998, the Japanese exchange regulators apply stricter rules on short selling than the U.S., as they prohibit short sellers from selling stocks at a price below the price at which the immediately preceding sale was effected, except short sellers who borrow stocks from market makers in stock lending markets. As most institutional investors borrow stocks from large shareholders, consequently, the regulation changes restrict the short selling of institutional investors. The regulatory difficulty for institutional investors, who are more likely to be informed and sophisticated, to sell short might contribute to the finding of the longer-term persistence of the return difference between the lowest RSSI portfolio and the highest RSSI portfolio.

3.4.1.2. Value-weighted portfolios. Table 3.4 shows the average monthly abnormal returns for the value-weighted portfolios in RSSI quintiles and the value-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. Panel A reports monthly 5-factor model alphas for these portfolios. As can be seen in the last column of Panel A, the lowest RSSI portfolio outperforms the highest RSSI portfolio by 1.118 percent with a t-statistic of 2.89 over the next month after the formation of the portfolio. The return difference persists up to three months and decreases as the holding period becomes longer. This tendency is also shown in Panel B, which uses DGTW characteristic-adjusted returns as the performance measure; according to Panel B, the lowest RSSI portfolio outperforms the highest RSSI portfolio by 0.762 percent with a t-statistic of 1.84 (p-value equals 6.84 percent) over the next month after portfolio formation. However, the return difference between the two RSSI portfolios is statistically insignificant when the portfolio is held for more than two months. Overall, the results observed for value-weighted portfolios provide empirical support for the results found for equal-weighted portfolios.

3.4.2. Robustness

3.4.2.1. Subsample period analysis. The monotonically negative relation between RSSI ranks and subsequent abnormal returns as well as the outperformance of the lowest

RSSI portfolio over the highest RSSI portfolio show that shorting demand has negative impacts on stock prices. Furthermore, the analysis based on a longer panel of the flow-based measure implies that the relation is not a mere chance but a robust phenomenon in stock markets. However, as documented in the introductory section, the decrease in RSSI over the second half of the sample period might affect the return predictability using the flow-based measure for shorting demand. To check the robustness of return predictability, I conduct a subsample analysis by dividing the entire sample period into two periods, namely, the period from April 1998 to March 2003 and the period from April 2003 to March 2008.

Table 3.5 presents the monthly 5-factor model alphas for the equal-weighted portfolios according to RSSI quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. Panel A reports the results for the first period. As can be seen in the last column, the lowest RSSI portfolio outperforms the highest RSSI portfolio by 0.871 percent with a t-statistic of 3.39 over the first month following portfolio formation; the return difference persists up to three months. The results are similar to the results shown in Table 3.3. Panel B reports the results for the second period. As can be seen in the last column, the lowest RSSI portfolio outperforms the highest RSSI portfolio by 0.524 percent with a t-statistic of 1.92 (p-value is 5.74 percent) over the first month following portfolio formation. However, this return difference does not persist for more than two months. In comparing the results in Panel A to the results in Panel B, the return difference between the lowest RSSI portfolio and the highest RSSI portfolio over the first month following portfolio formation decreases from 0.871 percent to 0.524 percent with a decrease in statistical significance. This comparison indicates that the return predictability of the flow-based measure for shorting demand weakens during the second period. However, overall, the results show that the flow-based measure for shorting demand could predict subsequent negative returns, which supports the prediction that stocks with strong shorting demand are more likely to generate negative subsequent returns.

3.4.2.2. Supply-side effect. There is a possibility that relatively higher short-sale inflows simply indicate tighter short-sale constraints, that is, lower levels of shorting supply. To show that results in Table 3.3 do not merely capture the effect of shorting supply on stock prices, I also examine the return difference of RSSI portfolios by dividing all stocks into two groups according to the degree of short-sale constraints, those above and below the median value of residual institutional ownership. Stocks with higher residual institutional ownership are more likely to have tighter short-sale constraints.

Table 3.6 describes the monthly 5-factor model alphas for the equal-weighted portfolios of the lowest RSSI portfolio, the highest RSSI portfolio, and the long-short portfolio within each residual institutional ownership group. The first three columns report portfolio returns for stocks with low residual institutional ownership stocks. As can be seen in the third column, the lowest RSSI portfolio outperforms the highest RSSI portfolio over the next month by 0.746 percent with a t-statistic of 4.10. The last three columns report the portfolio returns for stocks with high residual institutional ownership stocks. As can be seen in the third column, the lowest RSSI portfolio outperforms the highest RSSI portfolio over the next month by 0.636 percent with a t-statistic of 3.41. As the return difference between the lowest RSSI portfolio and the highest RSSI portfolio is observed in both low and high residual institutional ownership stocks, these results indicate that the return difference is not due to a lower level of shorting supply. In addition, as compared to the returns on the long-short portfolio for low institutional ownership stocks, the returns on the long-short portfolio for high institutional ownership stocks show lower values. Although this indicates that shorting supply affects stock returns, the effect is considered limited in comparison with the effect of shorting demand.[14]

In addition, I find that the return difference between the lowest RSSI portfolio and the highest RSSI portfolio within stocks with higher residual institutional ownership stocks does not persist for longer periods than the return difference within stock with lower residual institutional ownership stocks. As can be seen in the column labeled as "L/S" in Table 3.6, while the return difference between the lowest RSSI portfolio and the highest RSSI portfolio within the higher residual institutional ownership group is 0.394 percent with strong statistical significance (the t-statistic is 2.69), the return difference within the lower residual institutional ownership group is 0.297 percent with an insignificant statistical value (the t-statistic is 1.55). This result implies that, among stocks with higher residual institutional ownership, which are less costly for institutional investors to borrow, the mispricing due to some market frictions is more easily arbitraged away by institutional short sale trading than in the case of stocks with lower residual institutional ownership. This means that the mispricing or informational inefficiency of stock prices persists due to strong restrictions on institutional short selling.

[14] Cohen, Diether, and Malloy (2007) also find similar results.

3.4.3. Short-sale inflow and information asymmetry

Although the previous empirical sections show that RSSI is useful in predicting future stock price drops, the reason for the return predictability is not clear. That is, it is not clear whether short sellers can predict negative subsequent returns because they have access to private information and/or the skills to detect mispricing. In this section, to test the skillfulness of short sellers in detecting stock price deviation, I examine whether the return difference between the lowest RSSI portfolio and the highest RSSI portfolio is confined to stocks with high information asymmetry, as these are the stocks in which informed investors can stand to make substantial profits. I employ proxies for information asymmetry derived from the market microstructure literature. Specifically, I divide all stocks into two groups according to each proxy for information asymmetry, those above and below its median. If short sellers simply hold private information not prevailed in stock markets, it follows that the outperformance of the lowest RSSI portfolio over the highest RSSI portfolio is confined to stocks with high information asymmetry. If short sellers are investors skillful in detecting the deviations of stock prices from their fundamental values, then the outperformance of the lowest RSSI portfolio as compared to the highest RSSI portfolio is also observed in stocks with low information asymmetry.

Table 3.7 reports the monthly 5-factor model alphas for the equal-weighted portfolios of the lowest RSSI portfolio, the highest RSSI portfolio, and the long-short portfolio for stocks with low information asymmetry. I report the returns over the next month and next three months after portfolio formation. The first three columns report portfolio returns over the next month. As can be seen in the third column, the returns on the strategy that longs the lowest RSSI portfolio and shorts the highest RSSI portfolio shows positive values with strong statistical significance for the proxies of information asymmetry. The long-short strategy yield the average return of at least 0.565 percent (t-statistic is 2.91). The results show that the outperformance of the lowest RSSI portfolio over the highest RSSI portfolio is not confined to stocks with high information asymmetry. That is, the results indicate that short sellers not only are investors who have access to private information but also are investors skillful in detecting stock price deviations.

3.5. Conclusion

The finance literature assumes that short sellers are more rational, sophisticated, and informed, and as such, they help stock prices to become more informative and efficient. Based on this perspective, short-sale constraints are considered impediments to achieving market efficiency. To provide empirical support for this view of short selling, two standard approaches are generally employed, namely, an examination of the relation between shorting supply and stock prices or an examination of the relation between shorting demand and stock prices. While the former approach succeeds in establishing negative relation supply-side short-sale constraints and subsequent returns, the latter approach fails in demonstrating an explicit link between shorting demand and stock prices, as there is limited information available on short-selling activities.

To provide more robust empirical evidence for the link between shorting demand and stock prices, this study examines this relation using a ten-year panel of a flow-based measure for shorting demand, which indicates a longer sample period than previous studies, including Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Wermer (2009). The main result of this study is that the least heavily shorted stocks outperform the most heavily shorted stocks by 0.707 percent over the next month; this outperformance may persist for up to three months. These results imply that short seller demand for stocks are useful in predicting future stock return depreciations. The results hold for both equal-weighted portfolios and value-weighted portfolios. Subsample analysis, which involves dividing the entire sample period into two periods, provides empirical support for the main results in this study. I also show that the negative relation between shorting demand and subsequent returns is not due to supply-side, short-sale constraints. In addition, using proxies for information asymmetry from the market microstructure literature, I examine whether the outperformance of the least heavily shorted stocks as compared to the most heavily shorted stocks is restricted to stocks with high levels of information asymmetry, that is, to those stocks for which informed investors stand to make substantial profits. Consequently, I find that outperformance is not confined to stocks with high levels of information asymmetry. This indicates that short sellers not only are investors who have access to private information but also are investors skillful in detecting stock price deviations.

Overall, this study provides empirical evidence to support the theoretical expectation that short sellers are more rational, informed, and sophisticated investors and that they thus help stock prices become more efficient and informative. Although some practitioners argue that short sellers are like a black hat with respect to the formation of stock prices, empirical evidence in this study shows that short sellers have important roles in the formation of efficient and informative stock prices.

Table 3.1. Summary statistics of the relative short-sale inflow

	Mean	Median	StDev	P20	P80	P(stocks)	P(MV)	N(firms)
Entire period	6.761	5.627	5.441	2.989	9.619	62.57	93.93	2156
Apr1998-Mar2003	8.971	7.628	7.215	4.008	12.737	61.45	94.50	1989
Apr2003-Mar2008	4.551	3.627	3.667	1.970	6.501	63.68	93.35	2322

notes: This table reports summary statistics for the relative short-sale inflow. The relative short-sale inflow is defined as the aggregate daily number of shares sold short of a given stock in a given month divided by the total number of shares traded on the Tokyo Stock Exchange of a given stock in a given month. The table reports the time-series average of the cross-sectional mean, median, standard deviation, and the 20th and 80th percentiles of the relative short-sale inflow for the entire period, the period from April 1998 to March 2003, and the period from April 2003 to March 2008. P(Stocks) is the percentage of stocks in the Tokyo Stock Exchange (TSE) with valid relative short-sale inflows. P(MV) is the total market value of stocks in the TSE with valid relative short-sale inflows. N(firms) is the time-series averaged number of listed firms in the TSE.

Table 3.2. Firm characteristics within RSSI portfolios

RSSI	1(L)	2	3	4	5(H)	1-5	t(1-5)
relative short-sale inflow (percent)	1.824	3.773	5.519	7.805	14.206	-12.382	-31.94
decilized market capitalization	5.841	6.682	6.896	6.843	6.398	-0.557	-3.88
decilized book-to-market	5.576	5.306	5.195	5.265	5.497	0.079	0.57
decilized momentum rank (six months)	5.076	5.400	5.585	5.753	5.815	-0.739	-9.99
institutional ownership	0.544	0.562	0.575	0.586	0.596	-0.052	-26.60
analyst coverage (number)	0.897	0.989	0.972	0.929	0.839	0.058	2.98
LMSW (2002)'s IA measure	-0.043	-0.046	-0.046	-0.042	-0.038	-0.005	-1.91
IA effective spread	0.365	0.377	0.372	0.375	0.307	0.058	3.05
Amihud (2003)'s illiquidity measure in million yen	0.246	0.134	0.110	0.108	0.136	0.109	9.24
Abs(PS liquidity measure) in million yen	0.018	0.011	0.009	0.009	0.012	0.006	6.30
price (thousand yen)	17.072	16.521	16.195	15.458	11.530	5.542	3.84

notes: This table reports the time-series average of firm characteristics within each relative short-sale inflow (RSSI) quintile. Quintiles are formed monthly from April 1998 to March 2008 based on the prior one-month RSSI. Decilized market capitalization, decilized book-to-market ratios, and decilized momentum ranks are sorted into ten groups within the TSE stocks, and the average decile of the stocks in each portfolio is reported. Institutional ownership as a percentage of shares outstanding is calculated every reporting month. Analyst coverage refers to the number of analysts covering a stock. Llorente et al.'s (2002) information asymmetry (IA) measure and IA effective spread, Amihud's (2003) illiquidity measure, and the absolute value of Pastor and Stambough's (2003) liquidity measure are used as proxies for information asymmetry from the market microstructure literature. Stocks with higher values for these variables are regarded as stocks with higher information asymmetry. The table reports the difference between the lowest and highest portfolios for each characteristic along with the Newey-West adjusted t-statistics.

Table 3.3. Risk-adjusted returns based on equal-weighted RSSI portfolios

RSSI	1(L)	2	3	4	5(H)	L/S
Panel A: 5-factor model alphas						
k=1	0.002	-0.215	-0.220	-0.453	-0.705	0.707
	(0.01)	(-1.53)	(-1.56)	(-3.23)	(-4.26)	(3.99)
k=2	-0.143	-0.254	-0.267	-0.350	-0.600	0.457
	(-0.94)	(-2.00)	(-1.88)	(-2.55)	(-3.87)	(2.94)
k=3	-0.221	-0.273	-0.237	-0.335	-0.548	0.327
	(-1.49)	(-2.07)	(-1.73)	(-2.39)	(-3.68)	(2.10)
k=6	-0.280	-0.333	-0.292	-0.315	-0.436	0.156
	(-1.97)	(-2.52)	(-2.13)	(-2.25)	(-2.84)	(1.08)
Panel B: DGTW adjusted return						
k=1	0.134	-0.136	-0.270	-0.461	-0.771	0.905
	(0.80)	(-0.71)	(-1.32)	(-2.23)	(-3.28)	(4.05)
k=2	-0.020	-0.168	-0.296	-0.359	-0.688	0.668
	(-0.12)	(-0.88)	(-1.51)	(-1.73)	(-3.00)	(3.35)
k=3	-0.086	-0.180	-0.263	-0.366	-0.635	0.549
	(-0.53)	(-0.95)	(-1.37)	(-1.76)	(-2.82)	(2.90)
k=6	-0.160	-0.227	-0.288	-0.352	-0.520	0.360
	(-0.98)	(-1.19)	(-1.47)	(-1.69)	(-2.32)	(2.09)

notes: This table presents the monthly 5-factor model alphas and DGTW characteristic-adjusted returns for the equal-weighted portfolios for relative short-sale inflow (RSSI) quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. Quintiles are formed monthly from April 1998 to March 2008 based on the prior month's RSSI. Panel A reports the monthly 5-factor model alphas, while Panel B reports DGTW characteristic-adjusted returns. $K = 1, 2, 3, 6$ represents average returns over the next K months after portfolio formation, which is computed by averaging the current month's return on the previous K-month portfolios. Alphas are in monthly percentages, while Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 3.4. Risk-adjusted returns based on value-weighted RSSI portfolios

RSSI	1(L)	2	3	4	5(H)	L/S
Panel A: 5-factor model alphas						
k=1	0.326	0.457	-0.094	-0.115	-0.792	1.118
	(1.37)	(1.86)	(-0.69)	(-0.61)	(-3.40)	(2.89)
k=2	0.307	0.200	-0.047	-0.082	-0.469	0.776
	(1.61)	(1.04)	(-0.36)	(-0.55)	(-2.57)	(2.39)
k=3	0.220	0.044	0.002	-0.026	-0.374	0.594
	(1.20)	(0.28)	(0.02)	(-0.18)	(-2.29)	(1.89)
k=6	0.210	0.042	-0.055	0.006	-0.199	0.409
	(1.21)	(0.32)	(-0.78)	(0.05)	(-1.25)	(1.43)
Panel B: DGTW adjusted return						
k=1	0.189	0.435	-0.141	-0.022	-0.573	0.762
	(0.81)	(1.81)	(-0.91)	(-0.14)	(-2.16)	(1.84)
k=2	0.172	0.248	-0.106	-0.022	-0.333	0.505
	(0.94)	(1.19)	(-0.81)	(-0.15)	(-1.53)	(1.54)
k=3	0.120	0.115	-0.045	-0.006	-0.277	0.397
	(0.72)	(0.61)	(-0.39)	(-0.04)	(-1.45)	(1.32)
k=6	0.086	0.109	-0.113	0.043	-0.125	0.211
	(0.53)	(0.67)	(-1.41)	(0.32)	(-0.70)	(0.76)

notes: This table presents the monthly 5-factor model alphas and DGTW characteristic-adjusted returns for the value-weighted portfolios in relative short-sale inflow (RSSI) quintiles and the value-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. Quintiles are formed monthly from April 1998 to March 2008 based on the prior month's RSSI. Panel A reports the monthly 5-factor model alphas, while Panel B reports DGTW characteristic-adjusted returns. $K = 1, 2, 3, 6$ represents average returns in the next K months after portfolio formation as computed by averaging the current month's return on the previous K-month portfolios. Alphas are in monthly percentages, while Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 3.5. Subsample period analysis

RSSI	1(L)	2	3	4	5(H)	L/S
Panel A: Apr1998-Mar2003						
k=1	0.034	-0.335	-0.352	-0.653	-0.837	0.871
	(0.17)	(-2.27)	(-1.73)	(-3.87)	(-3.61)	(3.39)
k=2	-0.166	-0.332	-0.408	-0.506	-0.775	0.609
	(-0.86)	(-2.25)	(-2.09)	(-2.81)	(-4.01)	(2.69)
k=3	-0.282	-0.385	-0.369	-0.440	-0.701	0.419
	(-1.53)	(-2.56)	(-2.05)	(-2.30)	(-3.81)	(1.80)
k=6	-0.404	-0.450	-0.399	-0.444	-0.572	0.168
	(-2.68)	(-2.98)	(-2.20)	(-2.30)	(-3.08)	(0.90)
Panel B: Apr2003-Mar2008						
k=1	0.030	0.161	0.029	-0.199	-0.494	0.524
	(0.15)	(1.089	(0.23)	(-1.14)	(-2.31)	(1.92)
k=2	-0.015	0.018	0.004	-0.135	-0.347	0.332
	(-0.07)	(0.14)	(0.03)	(-0.81)	(-1.64)	(1.28)
k=3	-0.056	0.046	0.036	-0.175	-0.334	0.278
	(-0.26)	(0.35)	(0.28)	(-1.08)	(-1.61)	(1.09)
k=6	-0.015	-0.020	-0.054	-0.147	-0.230	0.216
	(-0.07)	(-0.15)	(-0.40)	(-0.98)	(-1.08)	(0.86)

notes: Dividing the entire sample period into two periods, namely, the period from April 1998 to March 2003 and the period from April 2003 to March 2008, this table presents the monthly 5-factor model alphas for the equal-weighted portfolios in relative short-sale inflow (RSSI) quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio. $K = 1, 2, 3, 6$ represents average returns in the next K months after portfolio formation as computed by averaging the current month's return on the previous K-month portfolios. Alphas are in monthly percentages, while Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 3.6. Returns on RSSI portfolios with high or low residual institutional ownership

		Low RIO			High RIO	
	Low RSSI	High RSSI	L/S	Low RSSI	High RSSI	L/S
k=1	0.088	-0.658	0.746	-0.087	-0.722	0.636
	(0.57)	(-4.13)	(4.10)	(-0.54)	(-3.89)	(3.41)
k=2	-0.029	-0.547	0.518	-0.241	-0.647	0.406
	(-0.19)	(-4.09)	(3.49)	(-1.42)	(-3.43)	(2.09)
k=3	-0.120	-0.514	0.394	-0.303	-0.600	0.297
	(-0.78)	(-3.92)	(2.69)	(-1.81)	(-3.37)	(1.55)
k=6	-0.213	-0.433	0.220	-0.347	-0.441	0.094
	(-1.54)	(-3.06)	(1.65)	(-2.09)	(-2.50)	(0.55)

notes: Dividing all stocks into two groups according to the residual institutional ownership as a proxy for the level of short-sale constraints, this table presents the monthly 5-factor model alphas for the equal-weighted portfolios in the top and bottom relative short-sale inflow (RSSI) quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio within each residual institutional ownership group as well as above and below its median. $K = 1, 2, 3, 6$ represents average returns in the next K months after portfolio formation as computed by averaging the current month's return on the previous K-month portfolios. Alphas are in monthly percentages, while Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 3.7. Returns on RSSI portfolios within low information asymmetry stocks

	k=1			k=3		
	Low RSSI	High RSSI	L/S	Low RSSI	High RSSI	L/S
A. Low LMSW (2002)'s illiquidity	-0.091	-0.705	0.615	-0.159	-0.636	0.477
	(-0.56)	(-4.03)	(3.00)	(-0.95)	(-4.38)	(2.56)
B. Low IA effective spread	0.083	-0.711	0.794	-0.126	-0.523	0.398
	(0.50)	(-3.63)	(4.38)	(-0.74)	(-3.08)	(2.21)
C. Low Amihud (2002)'s ILLIQ	0.069	-0.678	0.747	-0.059	-0.397	0.338
	(0.48)	(-3.55)	(3.36)	(-0.51)	(-2.23)	(1.97)
D. Low Abs(PS liquidity)	-0.103	-0.667	0.565	-0.202	-0.393	0.192
	(-0.70)	(-3.37)	(2.91)	(-1.37)	(-2.20)	(1.16)
E. Large market capitalization	0.164	-0.685	0.849	0.015	-0.468	0.483
	(1.35)	(-3.06)	(3.73)	(0.14)	(-2.34)	(2.77)
F. High analyst coverage	0.139	-0.694	0.832	-0.130	-0.468	0.338
	(0.71)	(-3.09)	(3.70)	(-0.76)	(-2.34)	(1.75)

notes: Dividing all stocks into two groups according to the proxies for information asymmetry, this table presents the monthly 5-factor model alphas for the equal-weighted portfolios in the top and bottom relative short-sale inflow (RSSI) quintiles and the equal-weighted portfolios that long the lowest RSSI portfolio and short the highest RSSI portfolio within each information asymmetry group as well as above and below those medians. As proxies for information asymmetry, Llorente et al.'s (2002) information asymmetry (IA) measure and IA effective spread, Amihud's (2003) illiquidity measure, and the absolute value of Pastor and Stambough's (2003) liquidity measure are all employed in addition to the number of covering analysts and market capitalization. $K = 1, 3$ represents average returns in the next K months after portfolio formation as computed by averaging the current month's return on the previous K-month portfolios. Alphas are in monthly percentages, while Newey-West adjusted t-statistics are shown below the coefficient estimates.

CHAPTER 4

Individual investor flows and cross-section of stock returns: Evidence from Japan

In this chapter, I examine whether noise trading has significant impacts on the cross-section of stock returns by analyzing the relationship between the trading activity of individual investors and future stock returns. I find that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, which is more pronounced among firms with stronger limits to arbitrage. These findings are in accord with the predictions of noise trader models in which the systematic activities of noise traders affect stock returns when they trade in concert and there is limitation to the activities of rational arbitrageurs.

4.1. Introduction

The question of whether noise traders significantly distort asset prices has been a much-debated topic for decades. Under the traditional finance paradigm, the current price of a stock closely reflects the rationally discounted value of expected cash flows, in which the cross-section of expected returns depends only on the cross-section of systematic risks. Even if there are irrational investors in the market, rational arbitrageurs cancel out the demand of irrational investors, which results in no significant impacts of irrationality on security prices. In contrast, there is an alternative view that noise traders have important roles in the formation of securities prices.[1] Correlated behaviors of noise traders and limits to arbitrage prevent rational investors from fully absorbing correlated shocks of noise trading, which induce commonality in stock returns other than systematic risks and thereby generate the cross-sectional difference in stock returns.

This study examines whether noise trading has significant impacts on the cross-section of stock returns. More specifically, this study analyzes the future returns to portfolios with buying or selling pressures of individual investors, who are likely to be regarded as noise traders in most theoretical models.[2] The main finding in this study is that stocks with a strong selling pressure of individual investors outperform stocks with a strong buying

[1]Shleifer and Summers (1990), De Long et al. (1990), De Long et al. (1991), and Shleifer and Vishny (1997) document that rational and informed traders face risks that are likely to limit their actions if noise trading influences securities prices, even in the markets where some investors are rational and informed. Without limits to their actions, the effect of noise trading would soon diminish because rational and informed investors arbitrage against the mispricing due to the presence of irrational noise traders.

[2]Recent empirical studies on individual investors also lend empirical support for the relevance for their irrationality. For example, individuals have the tendency to trade too much (Odean, 1999; Barber and Odean, 2000, 2001), realize capital gains quickly but hold onto capital losses (Odean, 1998), and hold underdiversified portfolios (Goetzmann and Kumar, 2008). In addition, their trading behaviors are correlated and persistent, which generates a systematic component in stock returns (Kumar and Lee, 2006; Barber, Odean, and Zhu, 2009).

pressure of individual investors. In other words, stocks that individual investors choose to include in their portfolios are more likely to underperform in the subsequent period.

To construct the measure of noise trading pressure of a particular stock, I use annual share-ownership data of listed firms in the Japanese stock markets, which provide the number of shares held by some investor groups: individual investors (including members of managerial boards), governments, brokerage firms, financial institutions, corporations, and foreign individuals and institutions. As all Japanese listed firms are mandated to disclose their share ownership profiles at the end of the fiscal year, this study can conduct a more robust empirical examination of the noise trading effect on stock prices with broader observations. Furthermore, although the data provide information on trading behaviors less frequently (only annually), the advantage of this data is to identify trading behaviors of noise traders, namely, individual investors more accurately than previous studies. For each stock, I calculate the change in individual investors' holdings, excluding managerial boards' holdings from the end of the last fiscal year to the end of the current fiscal year, which is divided by shares outstanding to normalize across stocks. The variable is defined as the net individual investor trading flow (NIF). Firms with strong individual buying pressure (high NIF) are more likely to have small market capitalizations, low one-year cumulative returns during the change, and high book-to-market ratios than firms with strong individual selling pressure (low NIF).

Using the net individual investor trading flow (NIF), I construct five value-weighted NIF portfolios each month. In each month, stocks are sorted into five value-weighted portfolios according to NIF as measured over a year prior to the latest end of fiscal year from the portfolio formation date. When performance is measured by Jensen's alpha, stocks heavily sold by individual investors do not outperform or underperform stocks heavily purchased. In contrast, when performance is measured by a five-factor model's alpha, results show that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, that is, about 8.8 percent per annum. This finding indicates that systematic behaviors of noise traders also have important roles in the formation of securities prices. In addition, I find that the NIF long-short portfolio has a positive factor loading on a value factor. This finding indicates that investment tilts of individual investors toward value stocks contribute to the improvement of the market-adjusted return on the NIF long-short portfolio. The results in this study remain unchanged in subsample analyses and other robustness checks. Using the annual ownership change of individual investors in Japan, this study first confirms the existence of a strong relation between the trading behaviors of individual investors and future stock returns.[3]

This study also tests whether the difference of difficulty to arbitrage affects the relationship between noise trading and subsequent stock returns. Theoretically, Shleifer and Vishny (1997) document that some limits to arbitrage must exist for mispricing to persist in the presence of sophisticated professional investors. The effect of noise trading on stock prices varies according to the degree to which it is difficult for rational investors to arbitrage. In recent empirical studies, financial anomalies are found to be more pronounced

[3] Although Kim and Nofsinger (2007) conduct a similar analysis for this study, they fail to find that stocks heavily sold by individual investors outperform stocks that are heavily purchased. Instead, they find the opposite result. While I exclude managerial ownership included in individual ownership in this study, they do not. When managers sell stocks they own to individual investors, the raw value of individual ownership does not change. However, as managers are corporate insiders rather than noise traders, the exclusion of managerial ownership is more preferable to calculate a more accurate proxy for the trading behaviors of noise traders. The failure to exclude managerial ownership from individual ownership might generate the difference between their paper and this study.

among firms with higher idiosyncratic risks (Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2005) and stricter short-sale constraints (Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Jones and Lamont, 2002; Lamont, 2004; Ofek, Richardson, and Whitelaw, 2004; Reed, 2003; Nagel, 2005). Therefore, I employ two measures of limits to arbitrage, idiosyncratic risk and residual institutional ownership (a proxy for short-sale constraints).[4] I find that the difference in returns between the lowest NIF portfolio and the highest NIF portfolio is stronger among firms with stronger limits to arbitrage. In particular, when I use a proxy for short-sale constraints as the measure of limits to arbitrage, the return difference between the lowest NIF portfolio and the highest NIF portfolio among firms with lower short-sale constraints (higher residual institutional ownership) is no longer significant, while the return difference is still significant among higher short-sale constraints. The findings indicate that stocks with strong purchase pressures tend to be overpriced and experience underperformance in the subsequent year. The underperformance is found to persist over a year when rational investors cannot fully arbitrage away mispricing.

This study is related to a growing literature in behavioral finance that examines the impact of individual investor behaviors on future stock returns. In similar veins, Hvidkjaer (2008) and Barber, Odean, and Zhu (2006) find that stocks with strong retail investor

[4]Ali, Hwang, and Trombley (2003) and Nagel (2005) use (residual) institutional ownership as a measure for short-sale constraints. The rationale for these studies' using institutional ownership is that the degree of institutional ownership explains much of the variation in the loan supply across stocks and that stocks with low institutional ownership are more expensive to borrow. D'Avolio (2002) shows that the main suppliers of stock loans are institutional investors.

buying over the prior year underperform those with strong retail investor selling by analyzing small trades in transactions data.[5] Frazzini and Lamont (2008) find that stocks favored by retail investors tend to underperform stocks out of favor in subsequent years by studying the effect of individual investors via mutual fund flows on stock returns. Because there is little evidence on the relation between behaviors of noise traders and future stock returns, further examinations of the issue are needed. In this respect, this study contributes to the existing literature.

The rest of this chapter is organized as follows. Section 4.2 defines a proxy for noise trading, that is, the net individual investor trading. This section also provides data descriptions used in this study. In Section 4.3, I report characteristics and abnormal returns for the main test portfolios. Concluding remarks are presented in Section 4.4.

4.2. Data

4.2.1. Primary data

I obtain annual share-ownership data to measure the trading behaviors of noise traders from Nikkei NEEDS. In Japan, according to the Commercial Code, firms are mandated to report their shareholder profile in their formal annual reports to the stock exchanges. The shareholder profile contains the number of shares held by individual investors (including members of managerial boards), governments, brokerage firms, financial institutions, corporations, and foreign individuals and institutions. Using the data, I construct a variable that captures the trading behaviors of noise traders. In this study, noise trading is

[5]Although Hvidkjaer (2008) and Barber, Odean, and Zhu (2006) use the same transaction data, the former uses signed small-trade share volume and constructs the measure as the shares bought less shares sold divided by shares outstanding, while the latter construct the measure of order imbalances as the proportion of signed small trades that are purchases.

computed as the change in individual investors' holdings, excluding managerial boards' holdings, from the end of the last fiscal year to the end of the current fiscal year. As managerial board members are considered to be corporate insiders among individual investors rather than noise traders, I deduct managerial holdings from shares held by individual investors. To normalize across stocks, I divide the change in individual investors' holdings, excluding managerial boards' holdings, by share outstanding. I define the variable as net individual investor trading flow (NIF).

Table 4.1 reports summary statistics of NIF. The table describes the time-series average of means, medians, standard deviations, skewness, 20th-percentile values, and 80th-percentile values of NIF. The first five rows in Table 4.1 show summary statistics in some selective years. As can be seen in these rows, the trading behaviors of individual investors are quite different across time. While individual investors decrease their holdings in 1985 and 1990, they increase their holdings in 1995 and 2000. While the odd moments of NIF are different across time, the standard deviation of NIF is stable across time.

4.2.2. Market and financial data

Market and financial data are also obtained from Nikkei NEEDS. Using the data, I calculate excess returns over the government bond (i.e., risk-free) rate and returns on factor-mimicking portfolios used in time-series regressions. When I calculate returns on factor-mimicking portfolios used in time-series regressions, I include the excess of value-weighted market returns listed in the Japanese stock markets over the risk-free rate, a size factor, a book-to-market ratio factor, a momentum factor (Carhart, 1997), and a liquidity factor suggested by Pastor and Stambough (2003). In the construction of these factors, I employ a similar method to Fama and French (1993). The size and book-to-market factors are calculated by taking the value-weighted average of the top three deciles in terms of market capitalization and book-to-market portfolio returns and subtracting the average portfolio returns of the bottom three deciles. To calculate size and book-to-market factors, I employ the top three and the bottom three deciles in terms of firm market capitalization and book-to-market ratios as listed in the Tokyo Stock Exchange (TSE) as breakpoints to divide stocks into three portfolios. In these constructions, the market capitalization at the end of the previous month as well as the book-to-market ratio based on the most recently announced book equity value are used. The momentum and liquidity factors are calculated by taking the value-weighted average of the upper quintile in terms of momentum and liquidity portfolio returns and subtracting the average of the lower quintile portfolio returns. In the construction of the momentum factor, the previous three months of cumulative returns are used. Following Pastor and Stambough (2003), I calculate the liquidity ratio and construct the liquidity factor based on these values.[6]

4.2.3. Sample selection

The sample used in this study covers all ordinary common stock listed in the Japanese stock markets. The sample period ranges from April 1980 to March 2008, in which annual-ownership data, market and financial data are sufficiently available. As in many previous studies, I exclude financial firms and regulated utilities from the analysis. I

[6]Following Pastor and Stambaugh's (2003) liquidity ratio, I calculate a stock's liquidity, which is measured by the interaction between returns and lagged-order flow. As prices of less liquid stocks are expected to overshoot in response to the order flow, the greater value in predicted return reversal for a given dollar volume implies a lower level of stock liquidity. To calculate this measure, I regress a market-adjusted return for a given firm on the lagged stock return and the interaction term of the stock's daily yen volume and the sign of the lagged stock return. The coefficient of the interaction term is expected to be negative and larger in absolute magnitude if the firm's adverse selection problem is severe.

also omit firms with stock prices lower than 50 yen, and insufficient observations on data used in this study are excluded. Furthermore, I exclude firms that experience large-scale increases or decreases of their outstanding stock during the period from the end of the last fiscal year to that of the current fiscal year. NIF does not always increase or decrease because of trading behaviors of individual investors. For example, private equity placements to a small number of institutions increase their ownership and decrease the ownership of individual investors. If the scale of private equity placements is large, the trading behaviors of individual investors are less likely to contribute to changes in NIF. Stock repurchases, stock splits, and reverse splits also increase/decrease NIF regardless of individual investor trading. To avoid these effects, I exclude from this analysis firms showing more than 10 percent increases/decreases of their outstanding. This exclusion process also contributes to separating the effect of noise trading on the cross-section of stock returns from the effect of change in outstanding (Pontiff and Woodgate, 2008). The sample of firms used in this study ranges from a minimum of 998 in 1980 to a maximum of 2,897 in 2008.

4.3. Empirical results

4.3.1. Characteristics of NIF-sorted portfolios

I begin by explaining the construction of the NIF portfolios. I construct five NIF portfolios each month. In each month, stocks are sorted into five value-weighted portfolios according to NIF as measured over a year prior to the latest fiscal year end from the portfolio formation date. Table 4.2 reports the characteristics of the NIF-sorted portfolios. As can be seen in the table, high NIF firms are more likely to have low individual ownerships, small market capitalizations, low cumulative stock returns, and high book-to-market ratios. The results indicate that individual investors have tendencies to purchase (sell) smaller (larger), value (growth), recently low (high) performing stocks. The investment style tilts of individual investors might complement those of institutions, in particular, foreign investors. Kang and Stulz (1997) document that foreign investors, which are predominantly institutions, in Japanese equity markets prefer large growth stocks.

4.3.2. Returns on NIF sorted portfolios

The main question addressed in this study is whether NIF, that is, buying or selling pressures of individual investors, has explanatory power to predict future stock returns. This section examines this predication by analyzing the return difference between stocks within the lowest NIF quintile and stocks within the highest NIF quintile.

Panel A of Table 4.3 report Jensen's alphas of five value-weighted NIF portfolios. T-statistics described below coefficients are computed using Newey-West adjusted standard errors with four lags. As can be seen in the first row of Panel B, the lowest NIF portfolio shows a value of 0.475 percent with a t-statistic of 2.60. On the other hand, the highest NIF portfolio shows a value of 0.559 percent with a t-statistic of 2.06. The return difference between the lowest- and highest NIF portfolios is -0.083 percent with a t-statistic of -0.55, which is presented in the last column. The results indicate that individual investor behaviors are not useful for predicting future stock returns. However, as documented in Section 4.3.1, individuals have the tendency to tilt their investments toward small, value stocks, and recent losing stocks. To control the effect of their investment tilts, I employ a five-factor model and characteristics-adjusted returns (Daniel et al., 1997) in empirical analyses.

Subsequently, I report five-factor model alphas on NIF portfolios. Panel B of Table 4.3 reports five-factor model alphas and factor loadings of five value-weighted NIF portfolios. The table also presents five-factor model alphas and factor loadings of the portfolio, longing stocks within the lowest NIF quintile and shorting stocks within the highest NIF quintile. As can be seen in the first row of Panel B, the lowest NIF portfolio shows a value of 0.230 percent with a t-statistic of 2.07. On the other hand, the highest NIF portfolio shows a value of -0.514 percent with a t-statistic of -3.81. The return difference between the lowest and highest NIF portfolios is 0.744 percent with a t-statistic of 3.77, which is presented in the last column. That is, stocks heavily sold by individual investors significantly outperform the market, while stocks heavily purchased by individual investors significantly underperform the market.

Furthermore, I find that the portfolio long the lowest NIF stocks and short the highest NIF stocks have statistically significant loadings on a value factor (HML) and a momentum factor (WML). The loading on a value factor is negative, while the loading on a momentum factor is positive. As shown in Section 4.3.1, individuals have tendencies to tilt their investments toward value stocks and recent losers. Although I find an insignificant negative Jensen's alpha of the long-short NIF portfolio, the tilt toward value stocks simply help the portfolio perform well. During the sample period in this study, the value factor shows a monthly average return of 1.015 percent.[7] At the first glance, it seems

[7]Asness, Moskowittz, and Pedersen (2008) document that the value effect in Japan is pronounced compared to U.S., U.K., and Europe. The value premium in Japan is 11.6 percent per annum during the period from January 1985 to February 2008.

that stocks heavily sold by individual investors do not outperform or underperform stocks heavily purchased by individual investors. However, after controlling for the effect of investment tilts, I can find that stocks heavily sold by individual investors outperform stocks heavily purchased by individual investors.

4.3.3. Robustness

4.3.3.1. Equal-weighted NIF portfolios. Panel A of Table 4.4 reports five-factor model alphas on equally weighted NIF portfolios. As the construction of value-weighted portfolios, I construct five equally weighted NIF portfolios. As can be seen in the last column, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.303 with a t-statistic of 2.43. Although the return difference is smaller and less reliable than the return on the value-weighted portfolio, the results are consistent with the main results.

4.3.3.2. NIF portfolios sorted by individual ownership. The absolute change in individual investors' ownership is considered to depend on their initial ownership level. For example, a five-percent change of NIF is more likely in firms with a larger initial ownership. Actually, as shown in the second row of Table 4.2, the lowest NIF portfolio, which experiences the largest change in ownership, has the largest initial ownership among other four NIF portfolios. To control the effect of the initial ownership level, for each month, I divide the entire sample into the bottom 50 percent and the top 50 percent based on individual ownership at the previous fiscal year end and then construct five NIF portfolios. Panels B and C of Table 4.4 present five-factor model alphas on value-weighted NIF portfolios. As can be seen in the last column, among both firms with high individual ownership and firms with low individual ownership, the lowest NIF portfolios outperform the highest NIF portfolios. In the case of firms with high individual ownership, the difference in returns is 0.532 (0.435) with a t-statistic of 2.58 (2.02), which is consistent with the main results.

4.3.3.3. Subsample period analysis. I also examine whether the return difference between two NIF portfolios persists in two subsample periods that are simply divided into two halves. Panels D and E of Table 4.4 present five-factor model alphas on value-weighted NIF portfolios in the period from April 1980 to March 1994 and from April 1994 to March 2008. As can be seen in the last column, the lowest NIF portfolios outperform the highest NIF portfolios in both periods. The return difference shows a value of 0.900 percent with a t-statistic of 3.17 in the former period, while the difference in the latter period shows a value of 0.609 percent with a t-statistic of 2.59. Although the return difference is small and less reliable in the latter period than in the former period, the main results in this study remain unchanged.

4.3.3.4. Characteristics-adjusted returns on NIF portfolios. Panel F of Table 4.4 shows characteristic-adjusted returns on value-weighted NIF portfolios. In the calculation of the characteristic-adjusted return, I follow a procedure similar to the approach used by Daniel et al. (1997, DGTW). Specifically, I divide each stock into three portfolios based on its market capitalization at the end of the previous month, its book-to-market ratio based on its most recently announced book equity value, and its previous three months of cumulative returns. Using the same breakpoints used in the factor adjustments, I divide all stocks into the top three, middle four, and bottom three portfolios for market capitalization and book-to-market classifications. In the case of momentum classification, all stocks are divided into the top quintile, the bottom quintile, and all others. Therefore, I construct three size, three book-to-market, and three momentum categories, which result in 27 possible classifications for each stock. I calculate monthly value-weighted average returns for each of these 27 stock classifications, taking the characteristic-adjusted return of a particular stock as its realized return minus the average return of a stock with its classification. As can be seen in the last column of Panel F of Table 4.4, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.362 with a t-statistic of 1.86. Although the return difference is more statistical reliable when I use five-factor model alphas, the main results remain substantially unchanged when I employ other risk adjustment models.

4.3.3.5. NIF normalized by trading volume. Up to this section, I use the change in individual investor holdings normalized by shares outstanding as the proxy for noise trading. In this section, instead of the measure, I use the change of individual investor holdings normalized by trading volume during the change. Panel G of Table 4.4 presents five-factor model alphas on value-weighted portfolios. As can be seen in the last column, the return difference between the lowest NIF portfolio and the highest NIF portfolio is 0.404 percent per month with a t-statistic of 1.92. Compared to NIF normalized by shares outstanding, although the difference in returns and its statistical significance weaken, these values provide empirical support for the main results in this study.

4.3.4. Limits to arbitrage

For mispricing to persist in the presence of sophisticated professional investors, some limits to arbitrage must exist (Shleifer and Vishny, 1997). In this section, I investigate whether two proxies for limits to arbitrage, namely, idiosyncratic risk and institutional ownership, affect the return predictability of NIF. If the return predictability of NIF is in accordance with the investor sentiment story, mispricing is more prominent among firms with higher limits to arbitrage.

4.3.4.1. Idiosyncratic risk. When investors are limited to arbitrage mispricing opportunities, NIF predicts stronger price reversals. To measure the extent of the limits to arbitrage, I employ the simplest measure, namely, idiosyncratic risk. According to several papers such as Wurgler and Zhuravskaya (2002), Ali, Hwang, and Trombley (2003), Mendenhall (2004), Mushruwala, Rajgopal, and Shevlin (2006), and Pontiff (2006), stocks with high levels of idiosyncratic risk are more difficult to arbitrage. In fact, some previous studies in this area show that idiosyncratic risk is highly correlated with more sophisticated measures. Specifically, I use the standard deviation of the monthly residual from a time-series regression of the firms' excess returns on the Fama-French three factors over the 36 months preceding the end of our ranking period as our measure of idiosyncratic risk. I then separately analyze return patterns by confining stocks to the bottom 50 percent and top 50 percent based on this measure of idiosyncratic risk.

Panels A and B of Table 4.5 report five-factor model alphas on value-weighted NIF portfolios, which are first sorted by idiosyncratic risk. As can be seen in the last column of the table, when the sample is confined to firms with higher idiosyncratic risks, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.619 percent with a t-statistic of 2.95. On the other hand, when the sample is confined to firms with the lower idiosyncratic risks, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.444 percent with a t-statistic of 2.43, which is smaller and less reliable than firms with the higher idiosyncratic risks. That is, firms with stricter limits to arbitrage are more likely to generate the higher difference in returns, which is consistent with the investor sentiment story. However, even when the sample is confined to firms with lower idiosyncratic risk, the return difference between the two NIF portfolios is still statistically significant. Idiosyncratic risk is used in empirical analyses not only to represent a limit to arbitrage but also as a sign of informed trading.[8] In the latter case, the level of mispricing declines in idiosyncratic risk. The noisiness of the idiosyncratic risk measure might contribute to the results.

4.3.4.2. Short-sale constraints. Short-sale constraints are a kind of limit to arbitrage. As Miller (1977) documents, short-sale constraints can prevent pessimistic opinions from being expressed in prices. When there is a divergence of opinions in the market regarding the value of an asset , optimistic investors will end up holding overpriced assets. In empirical studies, institutional ownership is the most frequently used proxy for short-sale constraints.[9] Following Nagel (2005), I employ residual institutional ownership as the proxy for short-sale constraints. After performing a logit transformation of institutional ownership that is bounded by 0 and 1, I regress logit-transformed institutional ownership on a logarithm of market capitalization as well as on a squared logarithm of market capitalization.[10] Regressions are run each month by using the latest value of institutional ownership. I refer to the residuals as residual institutional ownership. I then separately

[8]Pantzalis and Park (2006) find that that the level of mispricing declines with idiosyncratic volatility, which supports the notion that greater levels of firm-specific risk reflect greater participation of informed traders in the market for the stock. However, they also find that the relationship is U-shaped, with mispricing increasing with idiosyncratic risk for stocks with high levels of idiosyncratic volatility.

[9]D'Avolio (2002) finds that the degree of institutional ownership explains 55 percent of cross-sectional variation in loan supply and is its most important determinant.

[10]If the values for institutional ownership are below 0.0001 or above 0.9999, I replace the values with 0.0001 and 0.9999, respectively.

analyze return patterns by confining stocks to the bottom 50 percent and the top 50 percent based on the residual institutional ownership.

Panels C and D of Table 4.5 report five-factor model alphas on value-weighted NIF portfolios, which are first sorted by residual institutional ownership. As can be seen in the last column of the table, when the sample is confined to firms with the higher level of residual institutional ownership, the lowest NIF portfolio only outperforms the highest NIF portfolio by 0.222 percent, with a t-statistic of 1.02. On the other hand, when the sample is confined to firms with the lower residual institutional ownership, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.907 percent with a t-statistic of 4.01. In other words, the level of mispricing strengthens in the level of short-sale constraints.

4.4. Conclusion

This study examines the effect of noise trading on the cross-section of stock returns. Using the annual ownership change of individual investors as a proxy for noise trading, I provide two important results. First, I find that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, that is, about 8.8 percent per annum. This finding indicates that systematic behaviors of noise traders also have important roles in the formation of securities prices. Second, I find that the outperformance of stocks heavily sold by individual investors over stocks heavily purchased by them is stronger among firms with stronger limits to arbitrage. In particular, the tendencies are more pronounced when I use a proxy for short-sale constraints as the measure of limits to arbitrage. The findings indicate that stocks with strong purchase pressures tend to be overpriced and experience underperformance in the subsequent year.

Collectively, these findings are broadly consistent with the predictions of noise trader models in which the systematic activities of individual investors affect the returns of those stocks in which they are concentrated and the limits to arbitrage are stricter.

Table 4.1. Data descriptions on individual investor trading flow

Year	Mean	Median	StDev	Skew	P20	P80
1985	-0.011	-0.004	0.044	-1.166	-0.034	0.012
1990	-0.014	-0.008	0.040	-0.676	-0.039	0.011
1995	0.004	0.001	0.034	4.455	-0.011	0.016
2000	0.017	0.012	0.045	1.376	-0.003	0.041
2005	-0.006	-0.006	0.048	1.594	-0.032	0.015
1980-2008	0.001	0.001	0.040	0.197	-0.019	0.020

notes: This table reports summary statistics for the net individual investor trading flow (NIF). The NIF is defined as the change of individual investors' holdings, excluding managerial boards' holdings, from the end of the last fiscal year to the end of the current fiscal year. The table reports the time-series average of the cross-sectional mean, standard deviation, skewness, and the first and fifth quintiles for selected years and for the entire period.

Table 4.2. Firm characteristics within each NIF quintile

NIF	1(L)	2	3	4	5(H)	1-5	t(1-5)
change in ind. hold	-0.047	-0.011	0.001	0.012	0.050	-0.097	-48.57
individual holding	0.329	0.287	0.285	0.292	0.292	0.036	8.84
market capitalization (million yen)	123,506	126,213	94,144	81,392	80,251	43,255	7.35
book-tomarket	0.669	0.774	0.844	0.860	0.860	-0.191	-7.36
CR during the change	0.391	0.138	0.051	-0.006	-0.062	0.453	21.46
Turnover	0.051	0.034	0.027	0.032	0.047	0.004	2.51
Price (yen)	6,567	3,466	4,454	3,167	5,061	1,507	2.40

notes: This table reports firm characteristics within each NIF quintile. Quintiles are formed monthly based on the NIF at the latest end of the fiscal year. All characteristics are equally weighted within each quintile, and the table presents averages across formation periods. The table reports the time-series average of the NIF, individual holdings (defined as individual investors' holdings excluding managerial boards' holdings), market capitalization, book-to-market ratio, cumulative returns (CR) measured over a year during the change, turnover ratio, and stock prices. The last two columns in the table report the difference between the high and low NIF portfolios for each characteristic, along with the Newey-West adjusted t-statistics.

Table 4.3. Factor model adjusted alphas on NIF portfolios

NIF	1(L)	2	3	4	5(H)	1-5
Panel A: CAPM						
Intercept	0.475	0.678	0.857	0.810	0.559	-0.083
	(2.60)	(3.25)	(3.58)	(3.04)	(2.06)	(-0.55)
Panel B: 5-factor						
Intercept	0.230	-0.067	-0.189	-0.137	-0.514	0.744
	(2.07)	(-0.70)	(-1.98)	(-1.12)	(-3.81)	(3.77)
Mkt	1.001	0.962	0.958	0.958	1.014	-0.013
	(43.93)	(49.80)	(34.51)	(33.03)	(35.53)	(-0.34)
SMB	0.028	-0.025	0.006	0.146	0.154	-0.125
	(0.70)	(-0.72)	(0.13)	(2.97)	(2.64)	(-1.43)
HML	-0.121	0.105	0.201	0.242	0.329	-0.449
	(-2.66)	(2.65)	(3.94)	(4.80)	(5.52)	(-4.87)
WML	0.024	0.022	-0.048	-0.041	-0.109	0.133
	(1.08)	(0.97)	(-1.62)	(-1.39)	(-2.88)	(2.66)
LIQ	0.241	-0.154	-0.253	-0.082	0.034	0.207
	(3.04)	(-1.58)	(-2.58)	(-0.85)	(0.33)	(1.42)
Adj. R^2	89.75	87.58	86.52	87.05	84.92	47.23

notes: This table presents the monthly factor model adjusted alphas on the value-weighted portfolios in each NIF quintile and the value-weighted portfolios that are long the lowest NIF portfolio and short the highest NIF portfolio. Quintiles are formed monthly from April 1980 to March 2008 based on the NIF at the end of the latest fiscal year. Panel A reports the monthly Jensen's alphas, while Panel B reports five-factor model alphas, factor loadings, and adjusted R^2 values (reported in percent). Alphas are in monthly percentages, and Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 4.4. Robustness checks

NIF	1(L)	2	3	4	5(H)	1-5
A. Equal-weighted portfolio	0.226	0.298	0.366	0.251	-0.077	0.303
	(2.87)	(4.19)	(5.05)	(3.28)	(-0.91)	(2.43)
B. High ind. own.	0.176	-0.089	-0.135	-0.198	-0.356	0.532
	(1.06)	(-0.48)	(-0.89)	(-1.39)	(-2.30)	(2.58)
C. Low ind. own.	0.168	0.031	-0.057	-0.070	-0.268	0.435
	(1.44)	(0.31)	(-0.57)	(-0.52)	(-1.86)	(2.02)
D. 1980-1994	0.361	-0.175	-0.361	-0.202	-0.539	0.900
	(2.00)	(-1.20)	(-2.74)	(-1.12)	(-2.94)	(3.17)
E. 1994-2008	0.123	-0.167	-0.082	-0.175	-0.486	0.609
	(1.09)	(-1.29)	(-0.52)	(-1.01)	(-2.92)	(2.59)
F. DGTW char-adj.	0.146	0.009	-0.074	0.102	-0.216	0.362
	(1.50)	(0.09)	(-0.67)	(0.92)	(-1.47)	(1.86)
G. Normalize by trading volume	0.221	-0.041	-0.212	-0.259	-0.183	0.404
	(1.76)	(-0.46)	(-1.84)	(-2.06)	(-1.14)	(1.92)

notes: This table reports the five-factor model's alphas for the NIF portfolios. Panel A reports results when I use equally weighted portfolios instead of value-weighted ones. Panels B and C report results for subsamples based on individual investors' ownership levels. The breakpoint is the median ownership at the latest fiscal year-end. Panels D and E report results for subsamples in which I simply divide the entire sample period into two halves. Panel F reports the results when I employ characteristics-adjusted returns (Daniel et al., 1997). Panel G reports the results for NIF normalized by trading volume. Alphas are in monthly percentages, while the Newey-West adjusted t-statistics are shown below the coefficient estimates.

Table 4.5. NIF and the degree of limits to arbitrage

NIF	1(L)	2	3	4	5(H)	1-5
A. High idio. risk	0.203	-0.252	-0.303	-0.480	-0.416	0.619
	(1.56)	(-1.32)	(-1.75)	(-3.07)	(-2.33)	(2.95)
B. Low idio. risk	0.233	-0.028	-0.035	0.015	-0.211	0.444
	(1.73)	(-0.26)	(-0.31)	(0.13)	(-1.70)	(2.43)
C. High residual inst. own.	0.030	0.049	-0.327	-0.229	-0.192	0.222
	(0.29)	(0.36)	(-2.85)	(-1.81)	(-1.16)	(1.02)
D. Low residual inst. own.	0.419	0.043	0.052	-0.028	-0.488	0.907
	(3.39)	(0.38)	(0.48)	(-0.22)	(-3.19)	(4.01)

notes: This table presents the monthly five-factor model alphas for the NIF value-weighted portfolios after dividing all stocks into two groups, according to the degree of the limits to arbitrage. Panels A and B report the results for subsamples based on idiosyncratic risk, which is defined as the monthly residual from a time-series regression of the firms' excess returns on the Fama-French three factors over the 36 months preceding the end of our ranking period. The breakpoint is the median idiosyncratic risk at the formation date. Panels A and B report results for subsamples based on residual institutional ownership. Residual ownership is calculated as the residual by regressing logit-transformed institutional ownership on the logarithm of market capitalization as well as the squared logarithm of market capitalization each month. The breakpoint is the median residual ownership at the formation date. Alphas are in monthly percentages, and Newey-West adjusted t-statistics are shown below the coefficient estimates.

CHAPTER 5

Conclusions

As documented in the introductory section, issues that remain unsolved and ongoing in the literature are (a) why stock prices do not rapidly respond to earnings announcements, (b) whether security prices in stock markets incorporate all available information including private information, and (c) whether stock prices are mispriced in the presence of limits on arbitraging. This dissertation explores these topics and explains how and the circumstances under which the EMH is violated.

The first essay asks whether security prices in stock markets incorporate all available information, including private information, by analyzing mutual funds' performance. By exploring whether academic interactions are beneficial to a mutual funds' performance, I find that mutual fund managers appear to take advantage of academic ties established in school to earn greater profits. This empirical evidence lends support for the milder form of market efficiency suggested by Grossman and Stiglitz (1980) rather than the traditional version of the EMH. That is, in the real world, stock prices do not always incorporate all available information, thereby yielding opportunities to generate abnormal profits by acquiring an informational advantage.

The second and third essays focus on whether stocks are mispriced in the presence of limits on arbitraging. To test this prediction, I focus on the demand side of short sales, examining whether strong shorting demand predict negative subsequent returns. In the field of finance, short sellers are considered to be informed. Thereby, strong shorting demand should predict negative subsequent returns. In my investigation, I find that the least heavily shorted stocks tend to outperform the most heavily shorted stocks. This evidence implies that stocks with unmet shorting demand are overpriced. As a result, skillful short sellers who are able to detect the deviation of a stock price from its fundamental value should be able to exploit arbitrage opportunities.

The third essay examines the effect of systematic trading behavior of a particular investor group on stock returns. As previous empirical studies have reported, trading behaviors of a particular investor group are systematic and correlated, thereby generating cross-sectional differences in future stock returns. In the essay, I examine whether trading behaviors of individual investors, who are regarded as noise traders in the literature, affect stock returns. In my empirical analysis, I find that stocks that are heavily sold by individual investors outperform stocks that are heavily purchased. In addition, this effect is stronger among firms with stricter limits on arbitraging. This evidence is consistent with the predictions of noise trader models and implies that the effect of investor irrationality persists when arbitraging pressures are weaker.

In this dissertation, I provide empirical evidence that the traditional form of market efficiency is not, in some cases, consistent with the real world. The first essay suggests that a milder form of the EMH, such as the one proposed by Grossman and Stiglitz (1980), is more suitable to explain actual security markets. The second and third essays provide evidence that stock prices deviate from fundamental values in the presence of limits on arbitraging and, as a result, create security mispricings. However, these empirical findings do not necessarily imply that the notion of market efficiency is inappropriate to describe the real world. The hypothesis still provides a powerful analytical framework for understanding asset prices and has been responsible for an incredible volume of valuable research into market behavior. In actuality, the weak form and semi-strong form of informational market efficiency are confirmed by empirical studies. From an academic perspective, the empirical evidence found in this dissertation suggests that we should define a milder or more adaptive version of the EMH. The debate on whether to employ a more realistic form of the EMH is likely to continue into the future because empirical evidence for the traditional EMH is still controversial. For future research, the literature requires a number of empirical studies related to the issues that remain unsolved.

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