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Li, Zhongqi

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EMPIRICAL MODELS & ANALYSIS OF THE JAPANESE EQUITY MARKET

LI ZHONGQI

NANYANG BUSINESS SCHOOL

A thesis submitted to the Nanyang Technological University
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^{*} College of Business and Economics, California State University-Northridge

[†] Business School, Auckland University of Technology

[‡] Lee Kong Chian School of Business, Singapore Management University

[§] *CtS Cognoscere tenus Solvere*

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Summary

This dissertation consists of two essays that empirically analyze the Japanese equity market. Factors (e.g., market trading mechanisms, corporate governance, keiretsu business structure) that may cause the Japanese market to behave substantially different from other (particularly Western) markets are analyzed in these two studies. These studies find not only unique Japanese market behaviors, but they also identify different behaviors under different market stages and conditions.

In Essay One, I investigate five key factors for the observed herd trading volume on the Tokyo Stock Exchange (TSE). There is significantly higher herd trading volume in the presence of information flow. Herd trading is predominantly generated by good news and not much by bad news. This study shows that market conditions, corporate governance, and trading motivations play an important role in investors' herd trading behaviors. Financial institutional investors herd trade more (less) on good (bad) news on a bull (bear) market. Individual investors herd trade more (less) on good news on a bull (bear) market. A significant keiretsu loyalty effect on clustered trading volume is observed during bear markets in the presence of bad news, as a result of loyalty indigenous to the keiretsu firms. More interestingly, the market sentiment manifested by overconfident herding appears to provide an alternative indicator for the future direction of an economy.

In Essay Two, I examine market valuation and sources of change in market valuation associated with JASDAQ firms' decision to switch their listing to the TSE. A statistically and economically significant increase in firm

market value is identified at the announcement of a switch. Significant liquidity improvement is identified for the switching firms, but not for matching firms on TSE or JASDAQ. Switching firms have a similar liquidity level to JASDAQ (TSE) matching firms before (after) a switch. Increased investor base and increased trading volume contribute to the increase in market value of the switching firms. The switching firms have a significantly better fundamental performance a few years before and after a switch comparing to the non-switching peers. The switching firms are able to maintain their better performance after their main board listing. There is evidence that the market perceives higher benefit associated to the low-performance switching firms and reacts more positively.

ESSAY ONE

**DAILY VOLUME AUTOCORRELATION, INFORMATION
FLOW, AND INVESTOR TRADING: EVIDENCE FROM
THE TOKYO STOCK EXCHANGE**

1. Introduction

Traders in financial markets pay attention to two metrics: (1) stock price movements and (2) volume. Of these two metrics, financial economists focus their attention on stock price movements. In particular, they are fascinated by predictable patterns in stock prices. Their fascination may be explained by the fact that predictability gives rise to profitable strategies. Eugene Fama, the noted financial economist from the University of Chicago, spent most of his career examining predictability in stock prices. He developed a concept of market efficiency that is inconsistent with stock return predictability.¹

Compared to stock prices, finance researchers devote less time examining trading volume and the predictable patterns associated with it. This may occur because the predictable patterns in trading volume do not directly translate into abnormal profits for investors.

Recently, an alternative school of thought, termed *behavioral finance*, has emerged. The adherents of this school challenge the efficient markets hypothesis, which posits that investors operate rationally when making financial decisions. According to behavioralists, investors are driven by greed and fear and, as a result, they engage in group behavior known as herding. *Herding* is defined as “a trading behavior in which investors do not engage in trading activity in isolation but trade on the same direction over a period of time.”

Trading volume is a natural metric that characterizes herding. Abnormally high buy or sell volume occurs when traders herd together, but

¹See Fama (1970).

high-trading volume can also occur as a result of the liquidity needs of investors. A better way to characterize herding is to examine volume autocorrelation. Volume data are aggregated on a daily basis and reported in the financial press, and as a result, volume autocorrelation using daily trading volume is a natural measure of herding.

In literature, there are two categories of theoretical models which explain herd trading volume; one is informational based and the other is behavioral based. The informational-based category models trading motivated by informational advantages, suggesting that informed investors would exhibit stealth trading pattern to prevent their information from being released too fast (Barclay and Warner, 1993; Chan and Lakonishok, 1995). The behavioral-based category models investors trading decisions being influenced by psychological motivation such as overconfidence (Bardar and Odean, 2001; Hirshleifer et al., 1994; Hirschleifer and Siew, 2003; to name a few) and disposition effect (Shefrin and Statman, 1985, Statman et al., 2003), positive feedback trading (Nofsinger and Sias, 1999; Hirshleifer et al., 1994), or simply for irrational reasons such as following a fad due to lack of information (such as, Bikhchandani et al., 1992; Nofsinger and Sias, 1999; Wermers, 1999). Both the informational-based model and behavioral-based model imply herd trading volume on individual stocks. Further more, the overconfidence and disposition theory imply higher herd trading volume on good news than on bad news. It is obvious that good (bad) news is preponderant on bull (bear) markets. Higher difference between herd trading volume on good news and bad news should prevail on bull markets than on bear markets.

Covrig and Ng (2004) investigate the impact of investors' trading behavior on the daily trading volume autocorrelation for individual stocks on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). Although serially correlated trading volume has been widely observed and studied on the U.S. market,² for the first time, Covrig and Ng (2004) find empirical evidence that supports the idea that institutional and individual investors' trading has an impact on observed volume autocorrelation. They find that information flow and the trading behavior of different types of investors contribute to clustering in trading. Individual investors contribute more to the clustering in trading when there is no information flow on the market (behavioral-based herding), but institutional investors are the driving force behind herd trading when there is an abundant flow of information (informational-based herding).

Although recent work that examines herd trading volume on the U.S. market provides interesting insights into the trading behavior of institutions and individuals, research on herd trading volume on other markets is rare. I remedy this lacuna by studying the Japanese market (i.e., Tokyo Stock Exchange). The reasons for selecting the Japanese market are as follows.

I choose to study the Tokyo Stock Exchange (TSE) because it is the second-largest stock exchange in the world in terms of market capitalization.³

Second, the Japanese economy is comparable to the U.S. economy because both

²Campbell, Grossman, and Wang (1993), Gallant, Rossi, and Tauchen (1992), and LeBaron (1992) study various stock indexes on the U.S. equity market and find that at the aggregate level daily trading volume displays strong serial correlation.

³See Appendix A for comparative data about market capitalization and Appendix B for a comparison of the value of share trading. Although the comparison of the value of share trading among different exchanges is not valid as a result of different trading mechanism, definition, and calculation method on each exchange, it can serve as a relevant reference.

countries have a full spectrum of industries that span the primary, secondary, and service sectors. Both Japan and the United States have mature economies and have adopted a democratic political system, and both countries use market forces to manage their respective economies. The above three points make the TSE comparable to NYSE, in terms of importance, nature and scale.

However, there are important differences between the two countries that make the present study worthwhile and interesting. Unlike NYSE, TSE is an order-driven market, and the structural differences of the two markets are the result of trading regulations and the use of intermediaries. These differences may arguably have a small impact on investor trading behavior and price formation in a frictionless environment, but in the real world, there are frictions that might magnify these differences. Market-trading mechanisms regulate the trading process, and the trading process generates price discovery and volume. Therefore, market-trading mechanisms can have a significant influence on the pattern of trading volume. Today, most exchanges are order-driven,⁴ and examining an order-driven market that is also the world's second-largest stock market can provide necessary, valuable information that may apply to other markets. Without market intermediaries, such as market specialists or market-makers, transactions are executed directly between the buyers and sellers. In order to prevent from their information being released too fast, it is rational for the informed traders engage more into stealth trading. Therefore, I expect more informational-based herd trading volume in the presence of information flow, on TSE than on NYSE. In fact, higher non-informational herd trading may exist as a result of TSE trading mechanism of special quotes and trading halts.

⁴See Comerton-Forde and Rydger (2004) and Jain (2003).

However, there is no prior literature on this concern yet. I will explore this possibility in detail after literature review.

There are also cultural differences between Japan and the United States. Japanese society is extremely conservative, and the Japanese have a strong sense of group loyalty, anti-individualistic. The United States is typified by an individualistic, adventurous style of decision making. Japanese culture represents the oriental, while the American culture represents the occidental. Therefore, studying the Japanese market may be useful to countries with cultures that are closer to Japan's culture than Western culture. The Japanese cultural impacts on herd trading can be analyzed from two aspects, i.e., Japanese corporate governance structure and *keiretsu* business structure as follows.

The Japanese corporate governance structure and *keiretsu* business structure is a direct manifestation and sublimation of her conservative, anti-individualistic culture. McLaughlin (2002) puts it clearly in his book reviews, "Indeed, the philosophical foundation of Japanese culture is entirely anti-individualistic". Seeking stable, long-term relationship, Japanese firms are characterized with relatively high cross-holdings and stable shareholdings.⁵ The objective and responsibility of such holdings imply that the cross-holding shareholders and stable shareholders are loyal to the firm, and do not exploit short-term profitability. Thus I expect less herd trading by financial institutional investors, the majority of whom are long-term stable investors or cross-holding investors (Bae et al., 2008; Kamesaka et al., 2003). On the other hand, due to

⁵See Appendix C.

their close monitoring to the firm, Japanese financial institutional investors have more access to firm information (Berglof and Petotti, 1994; Hoshi et al., 1991). Their informational advantage can induce stealth-trading, which in turn generates higher informational-based herd trading. The loyalty effect and stealth-trading effect move on opposite directions to herd trading. Under the two opposite market conditions, one of two effects: *loyalty effect* in the presence of bad news on a bear market, and *stealth-trading effect* in the presence of good news on a bull market, may be observed.

Another characteristic of Japanese business structure is the *keiretsu*, a distinct business structure that represents highly concentrated control and strong loyalty. Keiretsu is a long-term network composed of one or a few corporate main banks, major suppliers, subcontractors, and main distributors (Yoshimori, 1995). While Japan is not normally concerned about these business networks, the United States has antitrust laws and frowns on concentrated ownership holdings. Therefore, it is important to analyze the impact of keiretsu on trading volume, because this analysis could provide valuable insights about the impact of corporate governance on the trading behavior of market participants.

Having one or a few main banks in the top-tier of the business group, a keiretsu firm has higher intra-group lending capacity (Berglof and Perotti, 1994; Kester, 1986; Lai, 1999). Thus keiretsu firms have a higher capability to weather market downturns. Keiretsu firms also have higher stable holdings, and their trading volume is negatively related to the level of interlocking ownership (Chung and Lee, 1998). Hiraki and Ito (2009) also find biased support to weak keiretsu firms by the Japanese financial institutions, manifested by their over-investment in keiretsu firms with relatively lower fundamental performance.

These findings all imply higher loyalty to the keiretsu firms. Such keiretsu loyalty effect would generate higher herding in the presence of bad news on a bear market for the keiretsu firms, where the loyalty effect will be more prominent. In the meantime, due to such loyalty effect, keiretsu firms may have a thinner market (i.e., lower trading volume) during a bear market than independent firms. Thus liquidity traders may have to engage into more stealth trading in order to avoid hitting trading quotes. Higher non-informational herding may be induced as a consequence of such non-informational stealth trading.

The importance and uniqueness of the TSE make the present study important, worthwhile and interesting. The current study focuses on five major factors for herd trading: 1) informational-based motivation, 2) behavioral-based motivation, 3) the TSE trading mechanism, 4) Japanese corporate structure, and 5) keiretsu effect. Informational-herding is examined to investigate factor 1; non-informational herding is examined to investigate factor 3. Financial institutional investors herding behavior is analyzed to examine factors 1, 2, 3 and 4. Individual investors herding behavior is analyzed to examine factor 2. Keiretsu effect is examined in addition to financial institutional herding and individual investors' herding, in comparison to independent firms. The main findings of the present study are as follows.

The sample period in the present study covers a complete economic cycle (see Figure 1-1). The sample period starts with the fast, double-digit growth in the early 1980s, follows by a bubble economy and ends in a market crash at the beginning of 1990. This market crash was followed by a sharp decline over the next 2 years and finally ended in a long-term stagnant market

in the 1990s. The design and selection of the sample period enables me to observe different herd trading volume patterns and the impact of different investors' behavior during each economy stage. The use of a full economic cycle not only makes this study comprehensive, but it also preempts studies on any subset of the full cycle.

Substantially higher first-order daily volume autocorrelation for individual stocks on TSE is found, compared to the first-order daily volume autocorrelation for individual stocks found on the U.S. equity market.⁶ I find evidence of both informational-based and behavioral-based motivated herd trading volume. Herd trading volume is predominantly generated by good news and not much by bad news. Higher herd trading volume exists during bull markets than bear markets, consistent with overconfidence and disposition effects.

Japanese financial institutional investors' trading effect on herd trading volume is a joint effect of informational-based and behavioral-based motivation, corporate governance, and market trading mechanism. They herd trade more on bull markets in the presence of good news and when there is no information flow. They herd trade less during bear markets in absence of information flow and in the presence of bad news.

The individual investors appear to engage in behavioral-based herd trading. During a bull market, they are attention-grabbed by and thus herd trade more on previous day's good news. During a bear market, they pay more attention to the previous day's high trading volume (and herd trade more) in the

⁶Covrig and Ng (2004) document a first-order daily volume autocorrelation of 0.3156 during July 1, 1986 to June 30, 1998, for individual stocks on NYSE and AMEX, whereas the first-order daily volume autocorrelation found in the present study is 0.5676 on TSE.

absence of information flow than to previous day's good news (and herd trade less). This could be a reason of the lack of certainty about their future prospects; hence they herd on volume information rather than on price information.

A strong keiretsu loyalty effect is identified by the present study. Significantly lower herd trading is found for keiretsu firms in the presence of bad news during a bear markets, manifesting high loyalty associated with the keiretsu firms. The higher herd trading during a bear market in the absence of information flow is a joint manifestation of keiretsu loyalty effect and TSE trading mechanism.⁷

I document a significantly higher level of overconfident herding (i.e., cluster-trading volume with good news rather than bad news) on the market from July 1992 to June 1995 than during the rest of the sample period. This finding appears to conflict with the current literature that suggests a bull market produces more overconfident trading. However, when I analyze the root cause, I find that the GDP growth rate seems to be the driving force behind the observed overconfident cluster-trading volume. More important, it appears that overconfident herding can serve as a reinforcing indicator for GDP growth rate to predict the state of an economy. This initial attempt is meant to point out a potential new area of future research, which may have important implications for academic research and real practice, helping to predict market movement, determine investment strategy, and produce higher profit.

The remaining sections of this essay are organized as follows: Section 2 reviews the related literature; section 3 describes the market structure and trading mechanism of TSE and corporate governance in Japan, with an attempt

⁷ Explanations are provided in empirical result section.

to address their potential impacts on herd trading volume; section 4 describes the sample selection criteria and data sources; section 5 presents the research models and hypotheses; section 6 documents the empirical results; section 7 provides an alternative view of the observed overconfident-herd trading; and section 8 summarizes and concludes the paper.

2. Literature Review

Two existing theoretical models predict autocorrelated daily trading volume, informational-based and behavioral-based. Informational-based herding does not differentiate the nature of information flow. It predicts positive herding driven by information in addition to non-informational herding.⁸ Behavioral-based herding must be analyzed in different nature of information flows. Investors have different trading preferences in the presence of good news and bad news, thus it is necessary to investigate behavioral-based herding in the context of different natures of information, during a bull or a bear market.

2.1 Volume Autocorrelation by Informational-based Motivations

Information asymmetry, or differences in opinions among different investors, can generate trading volume (Admati and Pfleiderer, 1988; He and Wang, 1995). Admati and Pfleiderer (1988) find that because some investors are better informed than other traders, they may use several small orders to prevent private information from being revealed too fast. This trading strategy is likely to produce autocorrelated trading, and the magnitude of this trading strategy is likely to be a function of information asymmetry. Easley and O'Hara

⁸ Non-informational herding can be generated by the TSE trading mechanism. Detail explanation is developed in section 3.

(1987) indicate that large trades are transacted at less favorable prices. Barclay and Warner (1993) find that informed investors tend to hide their information by breaking their large trades into a number of medium-size trades. Chakravarty (2001) and Chan and Lakonishok (1995) find empirical evidence that supports the stealth-trading behavior of institutional investors on the U.S. equity market. Kim and Nofsinger (2005) find similar empirical evidence on the Japanese equity market. This stealth-trading behavior can induce correlated trading or herding, as documented by Covrig and Ng (2004).

He and Wang (1995) build a dynamic model, which allows multi-period trading when there is asymmetric information. Volume is related to the flow and nature of information. Investor's trading depends on the expected gains and amount of risk involved in the trading. As investors trade, more private information is revealed through prices, and there is a decrease in the speculation about expected gains. Trading volume triggered by new public or private information flow is typically accompanied by larger price changes; whereas volume based on existing information is not accompanied by large price changes. Thus it implies that informed trading can be characterized based on price changes. This framework can also be used to distinguish informational herding from non-informational herding.

Therefore, informational-based herding can be examined by observing volume autocorrelation in the presence of information flow represented by price change. The informational-based stealth-trading behavior theory implies higher informational-based herding associated with the more informed investors. Thus higher informational-based herd trading may be induced by the financial institutional investors than by the individual investors.

2.2 Volume Autocorrelation by Behavioral-based Motivation

Behavioral-based models predict herd trading volume due to psychological motivations such as overconfidence (Hirshleifer et al., 1994) and disposition effect (Shefrin and Statman, 1985; Statman et al., 2003), or simply for irrational reasons such as following a fad due to lack of information (such as, Bikhchandani et al., 1992; Nofsinger and Sias, 1999; Wermers, 1999).

Overconfidence can produce herd trading (Hirshleifer et al., 1994; Hirshleifer and Siew, 2003; Odean, 1998, 1999; Statman et al., 2003). Daniel et al. (1998) and Gervais and Odean (2001) suggest that a positive-trading pattern can be indicative of investor overconfidence. Odean (1998, 1999) shows that, in the presence of good news, investors are overconfident and tend to overreact. The converse is true in the presence of bad news. Statman et al. (2003) find that market-wide trading activity is positively related to good news. Ekholm (2006) studies Finland's equity market and finds that the majority of investors tend to sell on good news and buy on bad news. This overconfident trading can produce higher herding during a bull market when good news is abundant.

Shefrin and Statman (1985) propose a disposition effect in which investors tend to realize gains rather than realize losses. Statman et al. (2003) find empirical evidence that supports the disposition effect. Frazzini (2006) studies mutual fund holdings and finds that mutual fund managers tend to realize gains while they postpone losses. This trading behavior produces underreaction to bad news. Brown et al. (2006) find empirical evidence on the Australian Stock Exchange that supports the disposition effect. They find that

investors are reluctant to realize losses but relatively eager to realize gains, and this disposition effect is common in various investor classes. They also discover that shareholder loyalty partially offsets investors' relative preference for selling winning stocks. Normally on a bull market, there are more opportunities to realize gains than to realize losses, whereas on a bear market, there are fewer opportunities to realize gains than to realize losses. Therefore, higher herd trading on a bull market may be induced as a result of dispositional trading.

If overconfidence and disposition theories have significant impact on herd trading volume as the respective theories predict, they may induce higher herd trading volume on good news than on bad news. They also imply that the difference of herd trading on good news and bad news to be higher during a bull market than during a bear market.

Although behavioral-based herding can be observed in the presence of information flow, such herd trading is different in nature from the informational-based herding. The informational-based herding is motivated by preventing from informational advantage being lost; hence analyses on the informational-based herding only require the existence of information flow. It does not require differentiating good news from bad news. However, analyses on the behavioral-based herding require differentiating good news from bad news. Because behavioral-based herding is driven by psychological motivations, and different groups of investors have different psychological preferences under different situations. Research has found that both institutional and individual investors, for example, have different trading behaviors on bull and bear markets, in the presence of good news and bad news.

A group of literature predicts behavioral-based herding by the individual investors. Bikhchandani et al., 1992 and Hirshleifer and Siew, 2003 find that herding behavior can be induced due to the uninformed investors inferring private information from the informed investors and, therefore, trading in the same directions. The imitative behavior documented by Shleifer and Summers (1990) and positive-feedback trading behavior found by Lakonishok et al. (1994) suggest that individual investors' trading behavior can produce a correlation in trading volume. Barber and Odean (2005) report that individual investors are attention-based traders. They face more difficulty finding stocks to buy, and they tend to look at trading volume, daily return, and news to help them make purchase decisions. Their study finds that individual investors are more likely to buy stocks that experience abnormally high trading volume or extreme price movements on the previous day or stocks that are in the news. Unlike institutional investors, individual investors rarely short sell stocks, and they normally only sell stocks they own. This attention-based activity may produce a positive trading-volume autocorrelation, regardless of the type of information flow.

Kim and Nofsinger (2003) study the behavior and performance of Japanese individual investors on TSE from 1975 to 1997. Similar to Barber and Odean (2005), they find that individual Japanese investors are attention-based traders. They are more overconfident on a bull market than on a bear market. They own risky and high book-to-market stocks, trade frequently, and buy recent winners. Thus the attention-driven behavior of the Japanese individual investors may generate higher herding in the presence of good news on a bull market.

The literature also predicts behavioral-based herding by the financial institutional investors. Scharfstein and Stein (1990) find that investors also may trade with the crowd because it is often risky to trade differently from other investors. Nofsinger and Sias (1999) and Wermers (1999), among others, find strong evidence that institutional investors engage in herding and positive feedback-trading behavior. They find that herding is more prevalent when the flow of information has a large impact on a stock market. A recent study by Suto and Toshino (2005) also shows that herding is a common phenomenon in Japanese institutional trading. Kim and Nofsinger (2005) find that Japanese institutional investors are positive-feedback traders when buying, and they herd more during a bull market in the presence of good news. These findings imply that institutional trading can also generate positive herd trading, especially during a bull market in the presence of good news due to positive feedback-trading.

Therefore, both institutional and individual investors' behavioral-based motivation can produce volume autocorrelation, and their trading behavior should generate higher herding on a bull market than on a bear market, on good news than on bad news. There is, thus far, no theoretical model for predicting the type of investor trading that will have the largest impact on an individual stock's daily trading-volume autocorrelation.

As discussed in the previous section, the Japanese economy is similar to the U.S. economy, but Japan has a culture that is quite different from the culture in the United States. As a result of its cultural roots, Japanese firms have a business structure and corporate governance that is different from Anglo-American styles. In particular, Japan has a unique business structure (i.e.,

keiretsu) that involves a strong relationship between Japanese corporations and financial institutions. In addition, Japanese has a corporate structure with high percentage of stable holdings and crossholdings. The impact of these two business structures on cluster-trading volume is not yet well studied or widely known. Analyses of the potential impacts of corporation governance will be established in the next section.

The Tokyo Stock Exchange (TSE) is a pure order-driven market without any market intermediary. It has a warning or special quote-and-trading-halt system that shows the temporary demand and supply imbalance. However, the potential impact of such trading mechanism on the herd trading behavior has not been studied in any prior work. This paper attempts to address the plausible impact of this trading mechanism on serially correlated trading volume pattern, the details will be discussed in the next section.

3. Trading Mechanism and Corporate Governance in Japan

The TSE trading mechanism and Japan's corporate governance are distinct from trading mechanisms and corporate governance in the United States. This section contains a detailed discussion about the trading mechanism of TSE⁹, corporate governance and *keiretsu* business structure in Japan. I analyze their potential impact on volume autocorrelation to fill the lacuna of literature.

3.1 Trading Mechanism on TSE

Trading on TSE does not rely on designated dealers or market makers. Liquidity is supplied by the public limit-order book. The exchange-designated

⁹See Hamao and Hasbrouck (1995) and Lehmann and Modest (1994).

market intermediaries (i.e., *saitori*) only perform administrative duties, such as logging limit orders and matching them to incoming market orders. They do not provide market-making services.

TSE market mechanisms and regulations place limits on the magnitude of price changes within a day (see Appendix D) and between consecutive trades (see Appendix E). Liquidity is organized through temporary warning quotes, special quotes, and trading halts that show the need for additional liquidity and smooth quote adjustments between transactions. This trading process may delay the adjustment of quotes, effectively closing one or both sides of the market for short periods. It may also result in large price changes between successive transactions because there is no requirement for actual trades at the intermediate price to bridge the gap in quotes. Therefore, there is less price continuity and market liquidity on TSE than on markets with specialists or market makers, such as NYSE or NASDAQ. The price discovery process is slowed down so market participants can provide liquidity. A trader who places a large order that triggers a trading halt will risk losing control over order execution. Therefore, a rational trader will be reluctant to risk revealing his/her trading intention by placing large orders. In addition, he/she will not be willing to lose control over the full execution of an order. As a result, rational traders avoid placing large orders.

Lehmann and Modest (1994) find that the warning and special quote events occurred 1.25 times a day per stock during their sample period, 19.7% of which resulted in trading halts because the maximum price variation was reached. However, the event of hitting the special quote is rare and occurs less than once every 2 months per stock. Their finding implies that investors have

adopted a trading strategy of rarely hitting the trading halt, especially the special-quote trading halt.

In order to avoid hitting a special quote or trading halt, rational investors split their trades into smaller lots and gradually build up their position or unwind their position, and this behavior can generate herd trading. However, the TSE trading mechanism effect on herd trading volume is difficult to be isolated from other effects. The observed herd trading pattern is a joint manifestation of several forces discussed in this study. It may be possible to observe the TSE trading mechanism effect in the absence of information flow.

A rational trader will be reluctant to risk revealing his/her trading information by placing a large order because it can trigger a trading halt. Hence when trading is accompanied by information flow, the observed herd trading is informational-based herding. The TSE trading mechanism effect is not separable from the informational-based herding in such a scenario. But for a liquidity trader, it is also rational for him/her to avoid placing a large order at the risk of trigger a trading halt, especially in a thin market when trading volume is low. Thus, non-informational trading can induce herd trading volume as a result of the TSE trading mechanism.

3.2 Corporate Governance in Japan

Japan has a special style of business organization structure and corporate governance that is rooted in and nurtured by its culture. I highlight the main features that characterize the corporate governance system in Japan in the following two subsections.

i) **Corporate Governance: General**

The Japanese corporate structure differs substantially from the corporate structure of Anglo-Saxon countries. Ownership of Japanese firms is characterized by large, stable shareholdings and cross-shareholding among related corporations, and these setups account for more than 45% of stock ownership in Japan (see Hugh, 2004; JETRO, 2002; Nitta, 2001). Stable holdings refer to financial institutions and industrial corporations that hold shares on a long-term basis for business and managerial relationship reasons. Cross-shareholdings are shares that two listed companies hold in each other's firms, typically banks and their corporate clients. The average stable and cross-holding in 1990s exceed 30% and 10%, respectively.¹⁰ Appendix C contains a chart from the Japan Council of Stock Exchanges and Nissei Research Institute that highlights these ownership percentages.¹¹

As a result of this corporate ownership structure, Japanese institutional investors have to shoulder the responsibility to secure firms' success and long-term profitability. Therefore, the objective and responsibility of such institutional holdings imply that they do not exploit an informational advantage for short-term profitability. Thus, such Japanese corporate governance structure implies loyalty effect associated with the institutional investors. This loyalty effect induces less herd trading.

Herding can be induced, however, by informed investors' stealth-trading behavior (Barclay and Warner, 1993; Chan and Lakonishok, 1995). As a result of their important monitoring role in a company, Japanese financial institutional

¹⁰ Although there is a declining trend in stable and cross-holding shares in Japanese corporate governance, such holdings still consist of substantial amount with relatively low turnover (Bae et al., 2008). Hence the corporate governance impact analyzed here remains relevant.

¹¹ The chart from JETRO (2002) is available at <http://www.jetro.go.jp/thailand/e/data/CorpGov.pdf>

shareholders suffer less information asymmetry problems, comparing to Anglo-American institutional investors (Berglof and Perotti, 1994; Hoshi et al., 1991). As a result of their informational advantage, the financial institutional investors' stealth trading can induce higher herding.

As a result, Japanese financial institutional investor trading affects volume herding in two opposite directions: 1) positive herd trading due to informational stealth-trading, 2) negative herd trading due to loyalty effect. The loyalty effect may be more prominent on a bear market in the presence of bad news, where short-term investors are less obliged to hold their investments. The informational stealth-trading implies higher informational-based herding associated with financial institutional investors than individual investors, regardless of market conditions

According to Bae et al. (2008) and Kamesaka et al. (2003), there are five groups of domestic institutional investors in Japan. They are: (1) banks, (2) investment trust (mutual) funds, (3) insurance companies, (4) proprietary traders, or securities firms, (5) nonfinancial companies, i.e., corporate investors. The trades of nonfinancial corporations (and a relatively small portion of trades by commercial banks) are generated not only by corporate asset management but also from adjustment of cross-shareholdings in keiretsu business groups (Bae et al., 2008). However, the nonfinancial companies may not have the same level of information as the banks (Bae et al., 2008), as the degree of internal control, the direction of information flow, and the distribution of information vary among different types of keiretsu business groups (Lai, 1999). As a result, the first three groups of institutional investors, i.e., banks, mutual funds and insurance companies have more similar or positively correlated herding

behaviors as indentified by Bae et al. (2008) and Kamesaka et al. (2003). Their grouping method is different from Hiraki and Ito (2009), which group the cross-shareholdings by financial institutions with the non-financial companies as stable investors group, and groups trust banks, mutual funds and pension funds as institutional investors in the context of investment preference. However, Hiraki and Ito (2009) study investment preference by analyzing holding positions. The current study focus on pattern of herd trading, hence the classification on herding behavior by Bae et al. (2008) and Kamesaka et al. (2003) is more suitable to the current study. The other targeting group in the current study is domestic individual investors, whose investment decisions and behavior differ substantially from those of financial institutional investors (Bae et al., 2008; Hiraki and Ito, 2009; Kamesaka et al., 2003; Kim and Nofsinger, 2003, 2005).

ii) Corporate Governance: Keiretsu Firms

A distinct Japanese corporate structure is characterized by the keiretsu system. Corporate governance mechanisms, capital structure and liquidity, asymmetry, and agency costs have been found to be quite different between keiretsu and independent firms (e.g., Berglof and Perotti, 1994; Hoshi et al., 1991; Prowse, 1990). Each keiretsu group is centered around one or a few major banks, and may compose of manufacturers, services firms, trading company, suppliers, subcontractors, distributors, and customers depends on which type of keiretsu groups (Lai, 1999). As a result of its unique corporate structure and business relationship, keiretsu firms are characterized by their

substantial, high, stable cross-holding ownership and high intra-group lending and trading credits.

According to Berglof and Perotti (1994), intra-group lending typically contributes 18% of the gross financing for nonfinancial groups. Intra-group lending provides a network of support as well as monitoring within a group. Chung and Lee (1998) find that keiretsu firms have higher stable holdings, and trading volume is negatively related to the level of interlocking ownership. Hiraki and Ito (2009) find that domestic financial institutional investors contributing to rescue zombie keiretsu firms by over-investment in these low performed keiretsu firms. Such finding also implies the keiretsu firms have higher financial capability to weather market downturn than independent firms.

Therefore, keiretsu firms have two characteristics: 1) they have higher intra-group support; 2) they have higher financial capability, thus should be less vulnerable when facing financial problems than independent firms. As a result, 'loyalty effect' associated with a keiretsu firm not only come from affiliated institutional investors, but also from other non-affiliated investors as a result of its higher financial capability when facing economic downtown. Such 'keiretsu loyalty effect' implies lower herd trading on a bear market in the presence of bad news is associated with a keiretsu firm than with an independent firm. Such keiretsu loyalty effect is different from the financial institutional loyalty effect due to corporate governance.

Due to the same keiretsu loyalty effect, keiretsu firms have thinner market (i.e., lower trading volume) than the independent firms on a bear market. Thus liquidity traders will find themselves to engage into more stealth-trading in order to avoid hitting trading halt or trading quote. Thus higher herd trading

may be observed as a result of joint forces of keiretsu loyalty effect and TSE trading mechanism.

However, Miwa and Ramseyer (2002a, 2002b) strongly challenges the idea of keiretsu's important role in the Japanese economy. Miwa and Ramseyer contend that the existence of keiretsu is largely a myth; therefore, in order to resolve this controversy, I investigate whether the keiretsu effect exists in herd trading volume on the TSE.¹²

4. Sample Selection and Data Sources

The sample period in the present study runs from June 30, 1983 to June 30, 1998. The sample period is designed to cover a complete economic cycle. I chose the sample period from the beginning of July to the end of June in order to avoid the turn-of-the-year effect documented by Keim (1983). I use the PACAP database as the source for data on daily trading volume, daily return with cash dividends reinvested, and number of shares outstanding for stocks on the first section of TSE. I exclude all financial firms because PACAP does not have investor ownership data for financial firms. PACAP provides investor ownership data for government shareholders, financial institutional shareholders, corporate shareholders, foreign shareholders, security firms shareholders and individual shareholders. The financial institutional investor group in this current study comprises the first three classes of institutional investors in Bae et al. (2008) and Kamesaka (2003). For each year over the

¹² McGuire and Dow (2009) provide a review of the major theoretical and empirical work on the changing role of the keiretsu structure in the Japanese economy. They find mixed empirical evidence on the continued strength and role of keiretsu. The finding of recent cross-keiretsu mergers may imply keiretsu firms engage into strategic evolution to adapt to the changing environment. Although the role of keiretsu structure changes, recent evidence still find significant high keiretsu loyalty impact on investors' investment decisions (see Bae et al., 2008, and Hiraki and Ito, 2009).

sample period, I include stocks that have at least 200 trading days in each year to avoid the nonsynchronous trading effect (see Scholes and Williams, 1977).

Chan and Chen (1991) document large changes in firm size and other firm characteristics over time. To ensure stability of the stock-specific characteristics throughout the testing period, I divide the entire sample period into five subperiods of 3 years each. This partition enables me to capture features of a Japanese economic cycle and examine volume autocorrelation during different market stages, which has not been done in previous studies.

The sample period falls into three different economic stages, from stock market boom to market crash, followed by a long-depressed market. The Japanese economy saw double-digit growth in the 1980s as a result of innovation in the consumer electronic industry. To facilitate the growth of Japan's economy, Japanese financial markets experienced deregulation at the start of the 1980s. The sample period starts in 1983 because this was the first year market deregulation had an effect on TSE.¹³

The high growth, however, was not sustainable, and it turned into a bubble, which burst at the beginning of 1990.¹⁴ Therefore, the first two subperiods of the sample (i.e., from 1983 to 1989) represent a bull market stage, followed by the market crash of 1990 to 1992, during which the whole market dropped by more than 50%. The remaining 6 years of the sample is a period when the market was stagnant or depressed.

The selected sample period covers a time window of a complete economic cycle. I chose to end the sample period in June 1998 because TSE

¹³See Kim and Limpaphayom (1997).

¹⁴TSE experienced a market crash at the beginning of 1990. Kang and Stulz (1996, 2000) use 1990 as the beginning year of a bear market.

launched Tokyo Stock Exchange Trading Network System (ToSTNeT) on June 29, 1998. This is an 'off-hour' trading system to take care of the diversified trading needs of investors. ToSTNeT has two sub-categories, ToSTNeT-1 and ToSTNeT-2, designed for different types of trading.¹⁵ The ToSTNeT system allows large block trades and basket trades with wider price change range (7% for block trades and 5% for basket trades). From its launch to 2003, ToSTNeT accounted for an average of 11.62% of total trading value.¹⁶ The ToSTNeT transactions are substantial in volume; however, it is not possible to measure its impact on the market, and the trading volume may not be consistent or representative of the information sought by the present study. Therefore, the sample period ends on June 30, 1998 to keep a complete 3-year subperiod and avoid an unreliable reported trading volume.

The daily market index performance of TOPIX for all stocks in the first section of TSE is illustrated by Figure 1-1. Partitioning the whole sample period according to the various stages of the economy enables me to investigate the volume autocorrelation pattern during different market conditions.

To gauge cross-sectional stock characteristics, I sort the data in two ways for different testing purposes. First, when I test for the impact of information flow, I sort the sample firms into five quintiles based on firm size, which is proxied by their market capitalization as of June before each subperiod. As large firms suffer less information asymmetry (Lo and MacKinlay, 1990), sorting stocks based on their market values can help reveal the impact of

¹⁵ ToSTNeT-1 provides two kinds of transactions, Single-Issue Transactions and Basket Transactions, which are mainly for institutional investors. ToSTNeT-2 provides Closing Price Transactions for the purpose of expanding trading opportunities for both individual and institutional investors. Refer to Guide to TSE Trading Methodology 3rd Edition, <http://www.tse.or.jp/english/rules/equities/dstocks/guide.pdf>.

¹⁶ Guide to TSE Trading Methodology 3rd Edition, <http://www.tse.or.jp/english/rules/equities/dstocks/guide.pdf>.

differences in the rate of information flow. Second, to test for the impact of investor trading behavior, I sort the stocks into five quintiles according to different categories of investor ownership ratios.¹⁷ Within each quintile, I sort the firms according to their ownership ratios and further divide each quintile into five ownership-ranking groups. Then I stratify the ownership-ranking groups among different quintiles. As a result, I construct five ownership-ranked quintiles while holding the firms' market capitalization relatively constant among different ownership quintiles. By doing this, I minimize the size effect, and I am able to study the impact of ownership separately.

Ajinkya and Jain (1989) document the non-normality of daily stock trading and excess trading volume. They demonstrate that the natural log of detrended trading volume is normally distributed. I follow the methods of Campbell et al. (1993) and Covrig and Ng (2004) and use the detrended log normal turnover as a proxy for trading volume. The turnover of a stock is measured by the number of shares traded on a given day relative to the number of common shares outstanding. Therefore, the daily volume series $v_{i,t}$ of each stock is

$$v_{i,t} = \log \text{turnover}_{i,t} - \frac{1}{200} \sum_{s=1}^{200} \log \text{turnover}_{i,t-s} \quad (1-1)$$

where $\log \text{turnover}_{i,t} = \log(100 * \text{turnover}_{i,t} + 0.000255)$.

In this study, daily trading volume refers to daily abnormal trading turnover with respect to its 200-day moving average. Positive trading volume

¹⁷ *Investor ownership* is defined as “the ratio of shares owned by the class of investors at the fiscal year-end divided by the total number of shares outstanding on the same day.” For each subperiod, I use the investor ownership ratio at the start of the first year in that subperiod. Two groups of investors have attracted my interest: (1) financial institutional investors, (2) individual investors.

means relatively high-trading turnover; negative trading volume means relatively low-trading turnover. He and Wang (1995) show that clustered trading is accompanied by large price changes, and it is a consequence of trades based on a flow of new information. Therefore, following He and Wang (1995) and Covrig and Ng (2004), I use the absolute value of daily return as a proxy for the flow of new information.

In order to test the keiretsu effect on the daily trading-volume autocorrelation, I use information about keiretsu affiliations compiled by Dodwell Marketing Consultants (1994/95). Across the five subperiods of the present study, 52% of the firms in the sample belong to a keiretsu group. The descriptive statistics for size portfolios are shown in Table 1-1. The largest quintile has a mean market capitalization of 662 billion Yen, and the market capitalization for the smallest quintile is only 13 billion Yen, on average. The mean returns for TSE stocks during the sample period monotonically decrease with firm size. The financial institutional ownership ratio increases with firm size, with 47% for the largest quintile and 23% for the smallest quintile. Individual ownership is negatively correlated to firm size, with 22% for the largest quintile and 35% for the smallest quintile.

Figure 1-2 illustrates the distribution of average daily detrended trading volume during each subperiod for each quintile. There are two major attributes of the detrended volume distribution. First, firms in the smallest quintile have significantly lower daily trading volume. This is the result of relatively lower trading activity for the smallest firms. Second, analysis across different market stages shows that, in general, daily trading volume is significantly higher during a bull market. It drops significantly during a market crash period and slowly

increases during the stagnant bear market. During the last subperiod, the detrended trading volume becomes positive. The negative average daily trading volume during the market crash period (i.e., the 3rd subperiod) indicates a significant drop in trading volume compared to the previous 10 months.

5. Methodology

I start with a simple parsimonious model to capture the dynamics of trading volume in individual securities. The model is further modified in a manner that enables me to test the following hypotheses.

5.1 Daily Trading Volume Autocorrelation

Hypothesis 1: Markets herd on trading volume.

First, I consider a simple first-order autoregressive process for daily trading volume. In order to control for the day-of-the-week effect (see Gallant et al., 1992; Lehmann and Modest, 1994), I introduce five weekday dummies to capture differences in mean trading volume in the following parsimonious model of volume autocorrelation:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \varepsilon_{i,t+1} \quad (1-2)$$

where $v_{i,t+1}$ represents the trading volume of stock i at time $t+1$, $D_{k,t+1}$ s are the five weekday dummies, and $\varepsilon_{i,t+1}$ is the disturbance term. The estimated coefficient $\alpha_{1,i}$ measures the magnitude of first-order autocorrelation in trading volume for each stock. Regression estimates are obtained for each of the five subperiods in each quintile. A significant positive $\hat{\alpha}_{1,i}$ implies that today's

trading volume is serially correlated to yesterday's trading volume, and they are moving in the same direction (i.e., if today's trading volume is high, it is highly likely that tomorrow's trading volume will also be high; or if today's trading volume is low, it is highly likely that tomorrow's trading volume will also be low). In both cases, it implies herd-trading activity. I expect a significantly positive $\hat{\alpha}_{1,i}$ on TSE.

5.2 Informational-based Herding and Behavioral-based Herding

Hypothesis 2: Markets herd trade on information flow (i.e., informational-based herding).

Hypothesis 3: Markets herd trade more on good news than on bad news (i.e., behavioral-based herding).

He and Wang (1995) build a theoretical model to capture volume autocorrelation in the presence of information flow. In order to test whether the arrival of new information contributes to clustered trading (i.e. informational-based herd trading volume), I follow their model and expand it as follows:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} f_{i,t} + \varepsilon_{i,t+1} \quad (1-3)$$

where $f_{i,t}$ is the proxy for the flow of new information. Following the method of He and Wang (1995) and Covrig and Ng (2004), I use $|r_{i,t}|$, the absolute value of the stock return at time t , as a proxy for $f_{i,t}$. Regression estimates are obtained, separately, for each quintile and across the five subperiods. I expect positive significant $\hat{\alpha}_{2,i}$, which suggests incremental herd trading generated by

informational-based motivation. As financial institutional investors are more informed than the individual investors, I expect positive (negative) correlation between the financial institutional (individual) investors ownership ratio and the observed informational-based herding.

In order to investigate behavioral-based herding, it is necessary to separate good news from bad news. Following He and Wang (1995) and Covrig and Ng (2004), I test whether good and bad news have different effects on the correlated trading-volume pattern by modifying equation 1-3 as follows:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1} \quad (1-4)$$

where $r_{i,t}^+$ denotes positive return on the stock, or the flow of good news at time t , and $|r_{i,t}^-|$ represents the absolute value of negative return, or the flow of bad news.

Evidence of positive significant $\hat{\alpha}_{1,i}$ in this model suggests herding on non-informational trading. Evidence of positive significant $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$ suggests incremental herd trading caused by a flow of good and bad information. Since the behavioral-based models predict higher herd trading on good news than on bad news, I expect significantly positive $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$, and $\hat{\alpha}_{3,i}$ on TSE, and $\hat{\alpha}_{2,i}$ should be significantly higher than $\hat{\alpha}_{3,i}$.

Hypothesis 4: Overconfidence trading and dispositional trading generate higher overconfident herding during bull markets than during bear markets.

As discussed in section 2.2, overconfidence and dispositional trading can generate herd trading volume. Overconfident trading (Odean, 1998, 1999; Statman et al., 2003) and disposition effect (Shefrin and Statman, 1985; Statman et al., 2003) imply higher herd trading on good news than on bad news. For convenience, I label $\hat{\alpha}_{2,i} - \hat{\alpha}_{3,i}$, which is the difference between herding generated by good news and bad news, as overconfident herding. There is more good news during bull markets than during bear market; therefore, I expect the overconfident herding to be higher during bull markets than during bear markets.

5.3 Investor Trading Effects – Manifestation of Joint Forces

Investors trading decision is a result of informational-based motivation, behavioral-based motivation, market trading mechanism, corporate governance and macroeconomic conditions. In this study, these forces' joint impact on herd trading volume via financial institutional investors and individual investors trading are analyzed under different market stages. Financial institutional investors and individual investors are two major investors groups on TSE, accounting for 58% - 68% of the ownerships on TSE from the smallest size quintile to the largest quintile during my sample period.

Hypothesis 5: Financial institutional investors' trading impact on herd trading volume:

- i) **They herd trade more on a bull market in the presence of good news (manifestation of stealth trading and positive-feedback trading);**

- ii) **They herd trade less on a bear market in the presence of bad news (manifestation of loyalty effect implied by corporate governance);**

The better informed financial institutional investors may engage into stealth trading behavior to prevent their information being released too fast (Barclay and Warner, 1993; Chan and Lakonishok, 1995). Such stealth trading induces herd trading volume. On the other hand, the financial institutions are characterized by high loyalty because of their obligation of stable shareholding and rescuing zombie firms (Hiraki and Ito, 2009). Such loyalty effect reduces herd trading. I expect the loyalty effect will be more prominent during bear market in the presence of bad news when the possibility of firms at stake is higher; I expect the stealth trading effect will be more prominent during bull market in the presence of good news, when good news is abundant.

Hypothesis 6: Behavioral-based motivation can induce herd trading volume by the individual investors.

Individual investors tend to be attention-attracted by previous day's high abnormal trading volume and extreme one-day return (Barber and Odean, 2005). Such behavioral-based motivation can induce herd trading by individual investors. However, the direction of herd trading volume during different market stages and in the presence of good news verse bad news is difficult to predict. I, therefore, let the data bear out the prediction.

I apply two methods to test Hypothesis 5 and 6. First, I compare the time-series and cross-sectional regression means of the estimated autocorrelation coefficients between a high individual ownership quintile and a low individual ownership quintile (and therefore, a high financial institutional

investor ownership).¹⁸ I construct the ownership-ranked quintile using a two-way sorting approach to eliminate the size effect, and therefore, the mean difference between the highest and lowest quintiles should reflect the difference of investor trading effects. Second, after controlling for firm size, I perform a cross-sectional regression of the estimated volume autocorrelation coefficients on the ratio of investor holdings during each period, after controlling for firm size using the following equation:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{marketcap}) + \beta \log(\text{ownership}) + \varepsilon_i \quad (1-5)$$

where $x = 1, 2, \text{ or } 3$, and $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$, and $\hat{\alpha}_{3,i}$ are estimated volume autocorrelation coefficients from equation 1-4. *Marketcap* is market capitalization, and it is defined as the number of outstanding shares times the market price as of June before each subperiod. *Ownership* is the percentage of shares held by financial institutional investors or individual investors at the fiscal year-end at the start of each subperiod. A significantly positive (negative) β indicates that ownership has a strong positive (negative) impact on the herd trading volume.

5.4 Keiretsu Effect on Herd Trading

Hypothesis 7: The keiretsu structure imposes loyalty effect on the observed herd trading volume.

As analyzed in section 3.2-ii, the keiretsu loyalty effect is established in comparison to the independent firms. Therefore, in order to differentiate

¹⁸ Comparisons based on financial institutional ownership sorting is also performed. There is no substantial difference on the empirical result. Test result is available upon request.

keiretsu loyalty effect from the plausible loyalty effect by corporate governance, keiretsu effect is examined in addition to investors' trading to avoid confusion.

To test the keiretsu effect, I include a *keiretsu* dummy variable in the following regression of estimated volume autocorrelation on firm size and ownership ratios:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \varepsilon_i \quad (1-6)$$

where $x = 1, 2, \text{ or } 3$, and $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$, and $\hat{\alpha}_{3,i}$ are estimated volume autocorrelation coefficients from equation 1-4. I expect lower clustered trading with bad news on a bear market for the keiretsu firms, when the possibility of firms at stake is higher. For all the time-series and cross-sectional regressions, I apply the Newey and West (1987) autocorrelation and heteroskedasticity-consistent test statistics.

6. Empirical Findings

6.1 Daily Trading Volume Autocorrelation

Table 1-2 shows the time-series and cross-sectional distribution of the estimated first-order autocorrelation of the five size quintiles for the entire sample period found using equation 1-2. There is strong statistical evidence for a positive first-order autocorrelation in daily trading volume in individual stocks: 99% of the stocks have a significant positive first-order volume autocorrelation at the 5% level. This finding is consistent with the findings on the U.S. equity market; however, the average magnitude of the first-order

autocorrelation is 0.5676, which is about 80% higher than the amount (i.e., 0.3156) found on the U.S. equity market by Covrig and Ng (2004) from July 1986 to June 1998. This finding is consistent with my expectation on the TSE trading mechanism effect. Though there might be other reasons for the observed higher herding on TSE, at least the evidence found here is not against the expectation based on TSE trading mechanism.

Herd trading volume under different market stages is observed according the volume autocorrelation coefficient distribution in different subperiods, the result is indicated in Table 1-3 and Figure 1-3. The distributions during the five subperiods are almost the same across the five size quintiles. Herd-trading activities are higher during bull markets than during bear markets.

6.2 Informational-based Herd Trading and Behavioral-based Herd Trading

I investigate the informational-based herd trading by using equation 1-3. The test results are presented in Table 1-4. Approximately 75% of the individual firms have significantly positive (at the 10% level) daily volume autocorrelation in the presence of information flow, with the exception of the smallest firm group. The magnitude of the informational impact increases monotonically with firm size, from 2.0028 for the smallest firm quintile to 3.4877 for the largest firm quintile (see Table 1-4, Panel B). The non-informational trading volume autocorrelation, $\hat{\alpha}_{1,i}$, is still highly significant for 98% of individual firms (see Table 1-4, Panel A). The magnitude of $\hat{\alpha}_{1,i}$ decreases with firm size, except for the smallest quintile.

Furthermore, I investigate informational-based herd trading volume during different market stages. Table 1-5 shows the distribution of the estimated volume autocorrelation coefficients in different subperiods found using equation 1-3. Figure 1-4 illustrates the distribution of $\hat{\alpha}_{1,i}$, while Figure 1-5 illustrates the distribution of $\hat{\alpha}_{2,i}$.

The results show that there is higher non-informational herd trading during the bull markets than during the bear markets (see Table 1-5, Panel A). The distribution of $\hat{\alpha}_{1,i}$ in different subperiods found using equation 1-3 is similar to the distribution found using equation 1-2 and illustrated by Figure 1-3. In general, in the presence of information flow, large firms have higher herd trading volume than small firms (see Table 1-5, Panel B). A significant difference among the five subperiods is reported for informational-based herd trading in Table 1-5, Panel B, with an F-statistic of 40.91. Informational-based motivation does not differentiate information of different nature; behavioral-based motivation shall induce different trading decisions with information of different nature. Table 1-5, Panel C shows correlation between the observed informational-based herd-trading by equation 1-3 and the investor ownership ratios for financial institutional investors and individual investors. Consistent with my expectation, I find positive (negative) correlation between informational-based herding and the financial institutional (individual) investor ownership ratio, significant at the 1% level.

In order to test the behavioral-based herd trading, I further use equation 1-4 to investigate herd trading volume on good news and on bad news. Test results are shown in Table 1-6, Panel A, B, and C for $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$, and $\hat{\alpha}_{3,i}$,

respectively and Figure 1-6 and Figure 1-7 display the distribution of $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$, respectively. In a second step, I perform a statistical mean comparison between $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$ for the entire sample period, during the bull and bear markets (see Table 1-6, Panel D).¹⁹

In general, the informational volume autocorrelation is predominantly driven by good news. A significantly higher herd trading volume in the presence of good news is observed (3.766, on average) during the whole sample period compared to the herd trading volume in the presence of bad news (0.110, on average). The difference in mean between herd trading on good news and on bad news amounts to 3.656 and is significant at the 1% level (see Table 1-6, Panel D, Group 1). This finding is consistent with behavioral-based herd trading expectation described in Hypothesis 3. The observed overconfident herding, $\hat{\alpha}_{2,i} - \hat{\alpha}_{3,i}$, during bull markets is significantly higher than during bear markets at the 1% level (see Table 1-6, Panel D, Group 2). Hence the empirical result is consistent with my expectation in Hypotheses 4 in general.

As the overconfidence trading and disposition effect theories predict that good (bad) news induces higher (lower) behavioral-based herd trading, it is expected that higher (lower) herd trading on a bull (bear) market where good news is more (less) prevalent. Due to the same reason, it is expected that higher (lower) overconfident herding during a bull (bear) market where good news is

¹⁹TSE experienced a market crash at the beginning of 1990. Kang and Stulz (1996, 2000) use 1990 as the start of a bear market. The third subsample period in the present study starts at July 1989, and it covers only half a year of a bull market, and the remainder is a bear market. In order to prevent contamination of the test results, I skip the third subperiod and use the next two subperiods (i.e., from July 1992 to June 1998) as the bear market period. For easier presentation and comparison, I present the results for two subperiods with a bull market (from July 1983 to June 1989) and two subperiods with a bear market (from July 1992 to June 1998).

more (less) prevalent. The empirical test results for the entire bull (bear) market in this study are consistent with these two predictions.

However, a relatively high behavioral-based herd trading in the fourth subperiod during July 1992 – June 1995 catches my attention. In subperiod 4, herding on good news and bad news is significantly higher than herding during the rest of the sample period on average (see Table 1-6, Panel D, Group 3 and Group 4). Herding on good news in subperiod 4 is 4.6121, 30% higher than the other four subperiods and is significant at the 1% level. Herding on bad news in subperiod 4 is 0.3909, while rest of the sample period averaged 0.0394. Taken together, overconfident herding in subperiod 4 is 4.2212, 20% higher than in the other subperiods on average (see Table 1-6, Panel D, Group 5; Figure 1-8), and it is significant at the 1% level. This finding seemingly contradicts the overconfident trading and disposition effect theories which predict higher behavioral-based herd trading and overconfident herding during a bull market than during a bear market. Such predictions have been proven in general during different market stages as shown above. Hence, investigating the cause behind such an unexpectedly high behavioral-based herding trading and high overconfident herding observed during part of a bear market is worthwhile and interesting.

If the contention of Odean (1998) and Statman et al. (2003) is true, then Japanese investors should be more overconfident on a bull market than on a bear market. Therefore, there are three plausible explanations for the present study's findings. The first possibility is that Odean's (1998) and Statman et al.'s (2003) contention that a winning market produces higher overconfidence may not apply to the Japanese market. The second possibility is that overconfidence

may not be the dominating factor for herd trading on favorable news all the time.

Another plausible explanation for my findings is that there are other factors that affect investors' overconfidence level. To keep the flow of mainstream of this study, I carry on the rest of the empirical results for tests on Hypotheses 5-7 in the remaining part of this section, and develop the plausible explanation to the unexpected finding of high overconfident herding during subperiod 4 in Section 7.

6.3 Investor Trading Behavior Effects and Keiretsu Effects

To analyze the effects of investor trading behavior, I perform a two-way sorting of the stocks into ownership quintiles. First, I sort by firm size. Then within each size quintile, I sort by ownership of interest. By stratifying ownership-ranking groups among the different size quintiles, I try to hold firm size relatively constant among different ownership quintiles.

Table 1-7 shows the descriptive statistics for quintiles sorted by the two ownership categories (i.e., financial institutions and individual investors). Panel A of the table shows statistics for ownership quintiles sorted by financial institutional investors, while Panel B shows statistics for ownership quintiles sorted by individual investors. Even though I form the ownership quintiles in two steps in an effort to make an even distribution of market capitalization among different ownership quintiles, there remains a statistically significant size difference between the highest and lowest financial institution quintiles

because financial institutional investors are more dominant in large firms. The difference, however, is not substantial.

Table 1-8 shows the statistical comparison for the estimated volume autocorrelation coefficients between the highest- and lowest-ranking individual ownership quintiles.²⁰ The highest-individual-ranking quintile has a statistically significant higher non-informational volume autocorrelation than the lowest-ranking quintile at the 1% significance level (see Panel A). This finding is consistent with Covrig and Ng's (2004) results. Barber and Odean (2005) suggest that individual investors are attention-based traders who trade on extreme trading volumes and, as a result, produce a high volume autocorrelation.

Table 1-8, Panel B, which contains the coefficient associated with informational-based herd trading, shows no significant difference between the highest-ranking and lowest-ranking individual ownership quintiles. This finding is different from Covrig and Ng (2004), who find higher (lower) informational-based herd trading by the financial institutional (individual) investors. They attribute their finding to positive feedback trading and stealth trading by institutional investors on the U.S. equity market.

Cross-sectional regressions are performed for the entire sample period and each subperiod based on equation 1-5. The empirical test results for bull markets and bear markets²¹ are shown in Table 1-9 for regressions by financial institutional ownership ratios and Table 1-10 for regressions by individual ownership ratios. In each table, Panels A, B, and C show the test results for

²⁰Sorting by financial institutional ownership shows the similar results. Statistical results are available upon request.

²¹Bull and bear markets are chosen for the same reason as noted in footnote 13.

$\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$, respectively. For convenience of table presentation, I include test results for the keiretsu effect (produced by equation 1-6) and a robustness test, which includes the control variable (i.e., return volatility) in the same table. The regression model for the robustness test is as follows:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \delta(\text{RetVol}) + \varepsilon_i \quad (1-7)$$

where *marketcap* is market capitalization, defined as the number of outstanding stocks times the market price as of June before each subperiod; *ownership* is the percentage of shares held by the institutional/individual investors at the fiscal year-end at the start of each subperiod;²² *keiretsu* is a dummy variable with a value of 1 if the firm belongs to a keiretsu group or 0 for an independent firm (data obtained from Dodwell Marketing Consultants, 1994/1995); and *RetVol* is the individual stock daily return volatility during the sample period (data obtained from the PACAP database).

i) Financial Institutional Investors' Trading Effect

As expected, I find evidence of financial institutional trading effects on the observed herd trading volume, motivated by factors of informational-based trading, behavioral-based trading, TSE trading mechanism, and corporate governance.

There is a significant positive herd trading on good news during bull markets (0.0602; see Table 1-9, Panel B) by the financial institutional investors.

²²I also perform a cross-sectional regression on the average ownership ratios during each subperiod. The test results are not substantially different from tests based on ownership at the start of each subperiod. Test results are available upon request.

This finding is consistent with the stealth trading hypothesis (Barclay and Warner, 1993; Chan and Lakonishok, 1995) and positive-feedback trading hypothesis (Nofsinger and Sias, 1999; Wermers, 1999). This finding is also consistent with Kim and Nofsinger (2005) that Japanese institutional investors are positive-feedback traders when buying, and they herd more during a bull market on good news.

There is a significant negative herd trading in the presence of bad news (-0.0536 ; see Table 1-9, Panel C) by the financial institutional investors. This is a manifestation of the loyalty effect due to the Japanese corporate governance. Japanese institutional investors are long-term oriented and align themselves with the management of firms (Kang and Stultz, 1996). They usually own significant amounts of equity stakes and are important creditors for the firms (Hoshi et al., 1991). They are long-term strategic shareholders who rescue the zombie firms (Hiraki and Ito, 2009). Therefore, they are more devoted and loyal to the firm in which they hold shares. Their loyalty is more prominent during the bear market when there is unfavorable information; therefore, less herd-trading activity is observed for firms with high financial institutional holdings.

When there is no information flow, the financial institutional investors engage in a high level of herd trading during bull markets (0.0861 ; see Table 1-9, Panel A), or lower level of herd trading during bear markets (-0.0614 ; see Table 1-9, Panel A). Such a non-informational herd trading volume may be induced by the TSE trading mechanism as discussed in section 3-1. Rational investors shall try to avoid triggering trading quotes and trading halts, both for informational trading and non-informational trading. One normal technique is to break a large trade into smaller trades. Such trading technique can induce

correlated trading volume, both with information flow and without information flow. When such technique is applied in the presence of information flow, the observed herd trading is inseparable from the informational-based herd trading. When such technique is applied in the absence of information flow, it is observable as the empirical finding here suggests.

ii) Individual Investors' Trading Effect

Table 1-10 shows the test results for the cross-sectional regression of the estimated volume autocorrelation coefficients on firm size, individual investor ownership ratios, keiretsu dummy, and return volatility using equations 1-5, 1-6, and 1-7. The structure of Table 1-10 is the same as the structure of Table 1-9.

During a bull market, the individual ownership ratio is significantly positively correlated to herd-trading volume in the presence of good news (0.0649) at the 1% significance level. During a bear market, the individual ownership ratio is significantly positively correlated to non-informational herd trading (0.1344; see Table 1-10, Panel A) and negatively related to herd-trading volume in the presence of good news (-0.0445; see Table 1-10, Panel B). This finding is consistent with Barber and Odean (2005) and Odean (1998), who find that individual investors are attention-based traders, and tend to be attention-grabbed previous day's price and volume changes.

A bull market is rife with good news and past winners, and individual investors are convinced by these messages and trade more often on these indicators. On a bear market, however, when there is lack of information flow, stocks with abnormally high trading volume tend to catch individual investors'

attention. As a result, during a bear market, I observe significant herding on a previous day's abnormal volume while significant lower herding is observed on a previous day's positive return.

iii) Keiretsu Effect

A strong keiretsu effect is found for trading during bear markets but not during bull markets for the keiretsu firms, in addition to both financial institutional trading and individual investors trading. During bear markets, keiretsu firms have higher non-informational herd trading (see Table 1-9, Panel A, and Table 1-10, Panel A) and significantly less herd trading on bad news (see Table 1-9, Panel C, and Table 1-10, Panel C). These phenomena can be attributed to the unique characteristics of the keiretsu structure: (1) its high level of interlocking holdings (Berglof and Perotti, 1994), and (2) the financial strength (Berglof and Perotti, 1994) and ability to survive (Kester, 1986) produced by substantial, stable cross-holdings among corporations. This cross-holding is long-term oriented, and it enhances keiretsu firms' financial strength or debt capacity. Therefore, keiretsu firms have less herding on bad news during bear markets.

The observed positive herding for keiretsu firms on the bear market without information flow is a joint impact of the keiretsu loyalty effect and market-trading mechanism effect. Trading volume is significantly lower for keiretsu firms (Chung and Lee, 1998), and it is expected to be more prominent on bear markets where trading volume in general is substantially lower than on bull markets (see Figure 1-2). As a result of less trading activity compared to independent firms during a bear market, liquidity traders for keiretsu firms need

to engage into more stealth-trading to avoid hitting a trading halt. Therefore, I observe that keiretsu firms engage in higher herd trading when conducting non-informational trading on a bear market.

I do not find any significant evidence of a keiretsu effect during bull markets or bear markets with informational trading with good news. This reinforces the argument that the keiretsu effect is more apparent under extreme market conditions than under normal conditions. The observed keiretsu effect remains significant even when return volatility is taken into consideration.

iv) Robustness

When return volatility is taken into consideration, the above findings for financial institutional trading effect and keiretsu effect persist, except that herding on good news during a bull market becomes insignificant. This finding implies that informational-based herd trading is subdued when return volatility is high.

A summary of the findings for investors' trading effect and keiretsu effect is presented in Table 1-11. As shown in Panel A, during a bull market, financial institutional investors herd trade more in the presence of good news and in the absence of information flow. In comparison, during a bear market, financial institutional investors herd trade less in the absence of information flow and in the presence of bad news. The higher herd trading can be attributed to the informational-based motivation in the presence of good news and TSE trading mechanism effect in the absence of no information. The observed lower

herd trading can be attributed to the loyalty effect of the financial institutional investors.

As shown in Table 1-11, Panel B, during a bull market, individual investors are found to herd trade more in the presence of good news. During a bear market, they herd trade more in the absence of information flow, and herd trade less in the presence of good news. This finding can be attributed to the attention-based trading behavior of the individual investors. During a bull market, when good news prevails, individual investors' attention is grabbed by good news, and they herd trade on good news. During a bear market, when bad news prevails, individual investors' attention is grabbed by a previous day's abnormal high trading volume, and they herd trade more on the volume information than on other news.

During a bear market, positive keiretsu effect is found in the absence of information flow and negative keiretsu effect is found in the presence of bad news (Table 1-11, Panel C). The former is a joint impact of the keiretsu effect and TSE trading mechanism; while the later is due to the keiretsu effect.

7. An Alternative View of Herd-Trading Volume

The observation of higher overconfident herding on a bear market (during July 1992 to June 1995) than on a bull market (see section 6.2) seems to be inconsistent with the overconfidence and dispositional trading theories. This implies that either those theories that work well in some markets do not explain the Japanese market's behavior, or there are some key factors in major relationships yet to be discovered. This section is only an attempt to address this

discrepancy using an analytical approach, and it is not a major focus of the present study. In this section, I hope to point out an important new direction for possible future research.

Aggregative investors' overconfident herd-trading behaviors can be manifestations of market sentiment and common consensus of market movements and trends. In the present study, I investigate the distribution of individual volume autocorrelation, which is the aggregate action of all investors on that market. Therefore, the driving force must also be aggregate in nature. There are two types of commonly used aggregate indicators: (1) stock exchange market index, which is used as a key indicator for an exchange; and (2) Gross Domestic Product (GDP), which is used as a key indicator for an economy.²³

A stock market index cannot determine the movement of stock. A market index is only an aggregation of stock price. Even in the case of an efficient market (Fama, 1970), a stock price reflects only the value of a stock. It cannot determine the movement of stock because it is the driven and not the driving force.

Clearly the predominant force that moves stock price is closely related to wealth generation. Therefore, the sum of a nation's wealth creation, its GDP, is an appropriate choice for determining the movement of a stock market.²⁴ In an attempt to illustrate an area for future research, I use an analytical approach to compare real GDP growth rate²⁵ and the TOPIX monthly index movement

²³ See Rogers (1998).

²⁴ According to the U.S. Federal Reserve Bank, GDP is the most comprehensive measure of overall economic performance, and it is probably the best measure of the overall condition of an economy. (see <http://www.frbsf.org/education/activities/drecon/1999/9911.html>; <http://www.newyorkfed.org/education/bythe.html>)

²⁵ Global Market Information Database (<http://www.euromonitor.com/gmid/>).

during the sample period (see Figure 1-9) to the observed overconfident herding.

The first subperiod (July 1983–June 1986) is the start of a significant, sustainable boom. Real GDP increased monotonically at an annual rate of about 4%. During this period, the high momentum of GDP growth supported the growth of the market index, and market sentiment was high. In this period, I observe high overconfident cluster trading (5.2628).

In the second subperiod (July 1986–June 1989), the market index grew by 125%. However, real GDP growth rate dropped from 6.8% to 5.3% from 1988 to 1989, which was a leading indicator of a slip in the economy's momentum. The market, however, did not take this signal seriously, and the market index further climbed by 20.7% in 1989. The observed overconfident herding in this period dropped significantly (3.1593), which was a leading indicator of a market downturn, even when the market index was still climbing. This affirms the above assertion that a market index is a driven and not the driving force.

In the third subperiod (July 1989–June 1992), the market crashed at the start of 1990, and the market index dropped approximately 50%. The real GDP growth rate dropped to 1% in 1992. Overconfident herding dropped further to a low (3.1096), indicating low market sentiment about the economy.

In the fourth subperiod (July 1992–June 1995), the market was bearish, and the market index hovered around the 1500 level. The real GDP growth rate became positive after dropping for 3 years. The observed overconfident herding rose significantly to 4.2212, indicating higher market sentiment about the economy.

In the fifth subperiod (July 1995–June 1998), the market was stagnant. The real GDP growth rate dropped eventually below 0 in 1998. The observed overconfident herd-trading activity dropped to the lowest point (2.6923) during the entire period examined in the present study.

This analysis implies that investors' overconfident herd trading seems to be an earlier indicator of macroeconomic movement than a market index. In this case, the market index lagged behind the economy. Therefore, the level of overconfident herd trading may help to reveal the major changes in the movement of economic growth.

This finding provides a new potential indicator for predicting the movement of a market and an economy (see Lim, 2006). This provides vast opportunities for future economic research, modeling, testing, forecasting.

8. Summary and Conclusions

In this study, I investigate daily volume autocorrelation in individual stocks on TSE, the second-largest stock exchange in the world. I investigate five key factors, they are: informational-based motivation, behavioral-based motivation, TSE trading mechanism effect, Japanese corporate governance effect and keiretsu effect. The implications of these five key factors are analyzed during different market stages and under different market conditions. The main part of this research is based on empirical study of the herd trading pattern for 1) the whole market, 2) two groups of investors tradings, i.e., financial institutional investors and individual investors, 3) two types of firms, i.e., keiretsu firms and independent firms. An attempt to address an apparent

discrepancy found in this study is examined using an analytical approach, in an attempt to explore the possibility of a new direction for further research.

In general, a significant daily volume autocorrelation is documented in individual stocks on TSE from July 1983 to June 1998. Consistent with the informational-based motivation theory, I find significant evidence of informational-based herding in the presence of informational flow. Herd trading is predominantly generated by good news and not much by bad news, both during the bull and bear markets, consistent with behavioral-based motivation theory.

Higher overconfident herding is found during bull markets than during bear markets in general. However, a relatively high overconfident herding is observed on one bear market during the period of July 1992 to June 1995. At the first glance, this finding appears to contradict the idea of overconfidence and disposition trading effects. In an initiative attempt to explore the possible underlying causes of this apparent discrepancy, I find that the real GDP growth rate appears to be an underlying influential factor for overconfident herding. It appears that overconfident herding may serve as a validating indicator of economic movement when supported by a GDP growth rate.

The observed herd trading by financial institutional investors and individual investors manifests different impacts by different leading factors under different market conditions. Financial institutional investors herd trade more on bull markets in the presence of good news (due to stealth-trading and positive-feedback trading) and when there is no information flow (as a result of TSE trading mechanism effect). They herd trade less during bear markets when there is no information flow and in the presence of bad news (as a result of the

loyalty effect). Individual investors tend to herd trade more on good news on bull markets or without information on bear markets, and they herd trade less on bear markets in the presence of good news. These findings are the result of the attention-based trading behavior of individual investors.

Keiretsu firms have higher herd trading on bear markets in the absence of information flow as a result of a joint effect of the keiretsu loyalty effect and TSE trading mechanism; and they engage in less herding on bear markets in the presence of bad news as a result of the keiretsu loyalty effect.

This study shows that market conditions, corporate governance, and trading motivations play an important role on investors' herd trading behaviors. As market conditions change, different groups of investors with different trading motivations can produce different herd trading volume patterns. More interestingly, the market sentiment manifested by the overconfident herding appears to provide an alternative indicator for the future direction of an economy. This may open a new area for future research.

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Figure 1-1. Daily Market Index – TOPIX

TOPIX daily market index on TSE during the sample period in the present study.

Figure 1-2. Mean Distribution of Detrended Trading Volume Turnover

Detrended Trading Volume Turnover is calculated as follows:

$$v_{i,t} = \log turnover_{i,t} - \frac{1}{200} \sum_{s=1}^{200} \log turnover_{i,t-s}$$

where $\log turnover_{i,t} = \log(100 * turnover_{i,t} + 0.000255)$

Mean distribution is presented for different size quintiles during every subperiod.

Figure 1-3. Mean Distribution of Estimated Daily Volume Autocorrelation Coefficients from Equation 1-2

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \varepsilon_{i,t+1}$$

Mean distribution of the estimation is presented by each quintile during every subperiod.

Figure 1-4. Mean Distribution of Estimated Daily Volume Autocorrelation Coefficients from Equation 1-3

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} |r_{i,t}| + \varepsilon_{i,t+1}$$

$|r_{i,t}|$ is the absolute value of the stock return at time t for stock i, representing information flow.

Mean distribution of the estimation for $\hat{\alpha}_{1,i}$ is presented by each quintile during every subperiod.

Figure 1-5. Mean Distribution of Estimated Daily Volume Autocorrelation Coefficients from Equation 1-3

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} |r_{i,t}| + \varepsilon_{i,t+1}$$

$|r_{i,t}|$ is the absolute value of the stock return at time t for stock i , representing information flow.

Mean distribution of the estimation for $\hat{\alpha}_{2,i}$ is presented by each quintile during every subperiod.

Figure 1-6. Mean Distribution of Estimated Daily Volume Autocorrelation Coefficients from Equation 1-4

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

$r_{i,t}^+$ is the positive return for stock i at day t , representing good news;

$|r_{i,t}^-|$ is the absolute value of negative return for stock i for day t , representing bad news.

Mean distribution of the estimation for $\hat{\alpha}_{2,i}$ is presented by each quintile during every subperiod.

Figure 1-7. Mean Distribution of Estimated Daily Volume Autocorrelation Coefficients from Equation 1-4

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

$r_{i,t}^+$ is the positive return for stock i at day t , representing good news;

$|r_{i,t}^-|$ is the absolute value of negative return for stock i for day t , representing bad news.

Mean distribution of the estimation for $\hat{\alpha}_{3,i}$ is presented by each quintile during every subperiod.

Figure 1-8. Mean Difference of Estimated Daily Volume Autocorrelation Coefficients with Good News vs. Bad News

Daily Volume Autocorrelation Coefficients of each individual stock during every subperiod are estimated by the following model:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

$r_{i,t}^+$ is the positive return for stock i at day t , representing good news;

$|r_{i,t}^-|$ is the absolute value of negative return for stock i for day t , representing bad news.

Mean distribution of the estimation for $\hat{\alpha}_{2,i} - \hat{\alpha}_{3,i}$ is presented by each quintile during every subperiod.

Figure 1-9 TOPIX Monthly Index & GDP Growth Rate Comparison

Table 1-1. Descriptive Statistics

Mean Return is stock daily return with cash dividend reinvested. Turnover Ratio is daily number of shares traded over number of shares outstanding, in decimals. Market Capitalization is total market value of common shares and preferred stocks at the end of June prior to each subperiod. Individual Ownership and Financial Institution Ownership are shareholdings by respective groups of owners over total number of share outstanding at fiscal year-end prior to each subperiod, in decimals.

Detrended Log Turnover is daily abnormal trading turnover in natural log with respect to its 200-day moving average, by the following model:

$$v_{i,t} = \log turnover_{i,t} - \frac{1}{200} \sum_{s=1}^{200} \log turnover_{i,t-s}, \text{ where } \log turnover_{i,t} = \log(100 * turnover_{i,t} + 0.000255)$$

Size-Ranked Quintiles	Mean Return	Detrended Log Turnover	Turnover Ratio	Market Capitalization (Million Yens)	Individual Ownership	Financial Institution Ownership	No. of Obs.
<i>Largest</i>							
Mean	0.0003	-0.0039	0.0018	66220	0.2177	0.4695	1139
Median	0.0003	0.0080	0.0014	393820	0.2031	0.4904	
Stdev	0.0008	0.1126	0.0015	1061555	0.1035	0.1310	
<i>Quintile 2</i>							
Mean	0.0003	-0.0044	0.0022	129670	0.2348	0.4049	1139
Median	0.0003	-0.0034	0.0016	111773	0.2134	0.4078	
Stdev	0.0008	0.1251	0.0018	69835	0.1109	0.1401	
<i>Quintile 3</i>							
Mean	0.0004	0.0102	0.0023	60153	0.2592	0.3604	1139
Median	0.0003	0.0036	0.0017	52475	0.2383	0.3713	
Stdev	0.0009	0.1387	0.0019	32218	0.1160	0.1335	
<i>Quintile 4</i>							
Mean	0.0006	0.0101	0.0021	31679	0.3056	0.3194	1139
Median	0.0004	-0.0012	0.0016	28407	0.2853	0.3226	
Stdev	0.0009	0.1551	0.0015	17710	0.1240	0.1298	
<i>Smallest</i>							
Mean	0.0009	0.0000	0.0021	13873	0.3519	0.2332	1149
Median	0.0008	0.0000	0.0017	12095	0.3305	0.2219	
Stdev	0.0011	0.0004	0.0015	9971	0.1404	0.1284	

Table 1-2. Serial Correlation Patterns in Daily Trading Volume of Individual Stocks

Distribution of estimated volume autocorrelation coefficients from regression equation 1-2:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{0,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \varepsilon_{i,t+1}$$

for the whole sample period.

All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

Distribution of $\hat{\alpha}_{i,t}$ (Equation 1-2)							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs. Mean for the adjusted R ²
Largest	0.5743	0.5816	0.1361	1139	0	0	1139 0.3589
Q2	0.5587	0.5678	0.1493	1139	0	0	1139 0.3417
Q3	0.5484	0.5527	0.1461	1139	0	0	1139 0.3260
Q4	0.5196	0.5150	0.1414	1139	0	0	1139 0.2921
Smallest	0.6363	0.6509	0.1152	1145	0	4	1149 0.4166
All	0.5676	0.5806	0.1434	5701	0	4	5705 0.3471

Table 1-3. Herd Trading Volume for Individual Stock in Different Subperiods

Distribution of estimated volume autocorrelation coefficients from regression equation 1-2:

$$V_{i,t+1} = \sum_{k=1}^5 \alpha_{0,ik} D_{k,t+1} + \alpha_{1,i} V_{i,t} + \varepsilon_{i,t+1}$$

for each subperiod.

All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

Panel A: Subperiod 1: 1983:07 ~ 1986:06							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs.
Largest	0.6531	0.6701	0.0966	214	0	0	214
Q2	0.6192	0.6531	0.1353	214	0	0	214
Q3	0.5827	0.5755	0.1230	214	0	0	214
Q4	0.4900	0.4751	0.1118	214	0	0	214
Smallest	0.6763	0.6824	0.0764	217	0	0	217
Mean for the adjusted R ²							
							0.4375
							0.4015
							0.3544
							0.2534
							0.4614
Panel B: Subperiod 2: 1986:07 ~ 1989:06							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs.
Largest	0.6652	0.6862	0.1178	227	0	0	227
Q2	0.6404	0.6698	0.1450	227	0	0	227
Q3	0.6149	0.6367	0.1395	227	0	0	227
Q4	0.5693	0.5782	0.1336	227	0	0	227
Smallest	0.6848	0.6987	0.0870	230	0	1	231
Mean for the adjusted R ²							
							0.4612
							0.4330
							0.3979
							0.3415
							0.4750

Panel C: Subperiod 3: 1989:07 ~ 1992:06							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs.
Largest	0.6091	0.6072	0.0986	217	0	0	217
Q2	0.5855	0.5926	0.1185	217	0	0	217
Q3	0.5529	0.5568	0.1290	217	0	0	217
Q4	0.4953	0.4945	0.1121	217	0	0	217
Smallest	0.6240	0.6318	0.1131	217	0	2	219
Panel D: Subperiod 4: 1992:07 ~ 1995:06							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs.
Largest	0.5261	0.5258	0.1030	228	0	0	228
Q2	0.5068	0.4843	0.1247	228	0	0	228
Q3	0.5016	0.4962	0.1370	228	0	0	228
Q4	0.5247	0.5336	0.1470	228	0	0	228
Smallest	0.5991	0.6197	0.1275	225	0	3	228
Panel E: Subperiod 5: 1995:07 ~ 1998:06							
	Mean	Median	Stdev	No. of Sgn @5% +ve	No. of Sgn @5% -ve	No. of Non- sgn@10%	No. Obs.
Largest	0.4395	0.4412	0.1063	253	0	0	253
Q2	0.4580	0.4436	0.1337	253	0	0	253
Q3	0.4979	0.4962	0.1594	253	0	0	253
Q4	0.5165	0.5261	0.1732	253	0	0	253
Smallest	0.6018	0.6046	0.1291	251	0	3	254

Table 1-4. Influence of Information Flow on Herd Trading Volume of Individual Stocks

Estimated volume autocorrelation coefficients from the regression equation 1-3 below, for the whole sample period:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{0,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} | r_{i,t} | + \varepsilon_{i,t+1}$$

$\hat{\alpha}_{1,i}$ is the estimated non-informational volume autocorrelation coefficient;

$\hat{\alpha}_{2,i}$ is the estimated volume autocorrelation coefficients when there is high information flow on the previous trading day;

$|r_{i,t}|$ is the absolute value of the stock return at time t for stock i .

All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

Panel A: Distribution of $\hat{\alpha}_{1,i}$ (Equation 1-3)							
	Mean	Median	Stdev	No. of Sgn @5% Sgn +ve	No. of Sgn @5% Sgn -ve	No. of Non- sgn@10%	No. Obs. Mean(Adj RSQR)
Largest	0.5233	0.5336	0.1344	1139	0	0	1139 0.3699
Q2	0.5282	0.5414	0.1472	1139	0	0	1139 0.3618
Q3	0.5565	0.5672	0.1412	1139	0	0	1139 0.3617
Q4	0.5842	0.5950	0.1255	1139	0	0	1139 0.3484
Smallest	0.5431	0.5521	0.2093	1052	0	97	1149 0.4420

Panel B: Distribution of $\hat{\alpha}_{2,i}$ (Equation 1-3)							
	Mean	Median	Stdev	No. of Sgn @5% Sgn +ve	No. of Sgn @5% Sgn -ve	No. of Non- sgn@10%	No. Obs. Mean(Adj RSQR)
Largest	3.4877	3.3666	2.2377	799	3	337	1139 0.3699
Q2	3.2440	3.1007	2.0285	820	0	319	1139 0.3618
Q3	3.1632	3.0155	1.7839	872	0	267	1139 0.3617
Q4	3.1319	3.0336	1.7635	930	0	209	1139 0.3484
Smallest	2.0028	1.8469	4.0197	446	0	703	1149 0.4420

Table 1-5. Distribution of the Estimated Volume Autocorrelation during Each Subperiod by Equation 1-3

Estimated volume autocorrelation coefficients from the regression equation 1-3:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{0,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} |r_{i,t}| + \varepsilon_{i,t+1}$$

for different subperiods.

$\hat{\alpha}_{1,i}$ is the estimated non-informational volume autocorrelation coefficient; $\hat{\alpha}_{2,i}$ is the estimated volume autocorrelation coefficients when there is high information flow on the previous trading day;

$|r_{i,t}|$ is the absolute value of the stock return at time t for stock i .

All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

Financial Institution and Individuals represent the share-holding ratios of the respective investor groups at the financial year-end prior to each subperiod.

Panel A: Distribution of $\hat{\alpha}_{1,i}$ (Equation 1-3)						
	Largest	Q2	Q3	Q4	Smallest	Average
Whole Sample Period	0.5233	0.5282	0.5565	0.5842	0.5431	0.5471
1983:07~1986:06	0.6086	0.6235	0.6616	0.6546	0.5944	0.6285
1986:07~1989:06	0.6248	0.622	0.6392	0.6585	0.5734	0.6236
1989:07~1992:06	0.5625	0.5669	0.5683	0.5762	0.5554	0.5659
1992:07~1995:06	0.453	0.4492	0.4761	0.5334	0.4961	0.4816
1995:07~1998:06	0.39	0.4014	0.4559	0.5107	0.5034	0.4523
Panel B: Distribution of $\hat{\alpha}_{2,i}$ (Equation 1-3)						
	Largest	Q2	Q3	Q4	Smallest	Average
Whole Sample Period	3.4877	3.244	3.1632	3.1319	2.0028	3.0059
1983:07~1986:06	4.0202	3.6817	3.0848	3.161	1.3394	3.0574
1986:07~1989:06	2.7594	2.9156	2.8902	2.8039	2.0601	2.6858
1989:07~1992:06	2.7359	2.4227	3.0155	3.2846	1.8449	2.6607
1992:07~1995:06	4.6461	4.144	3.886	3.7877	2.6271	3.8182
1995:07~1998:06	3.2918	3.0619	2.9496	2.6793	2.0934	2.8152
<i>F-Stat for difference among 5 subperiods</i>	40.91					
Panel C: Correlation between $\hat{\alpha}_{2,i}$ and Investor Ownerships						
		$\hat{\alpha}_{2,i}$	FIN	IND		
$\hat{\alpha}_{2,i}$	Pearson Correlation	1.0000				
	Sig. (2-tailed)					
FIN	Pearson Correlation	0.0885	1.0000			
	Sig. (2-tailed)	0.0000				
IND	Pearson Correlation	-0.0565	-0.3094	1.0000		
	Sig. (2-tailed)	0.0000	0.0000			

Table 1-6. Distribution of the Estimated Volume Autocorrelation during Each Subperiod by Equation 1-4

Estimated volume autocorrelation coefficients from the regression equation 1-4:

$$v_{i,t+1} = \sum_{k=1}^5 a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} r_{i,t}^+ + a_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

for different subperiods. All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

$\hat{\alpha}_{1,i}$ is the estimated non-informational volume autocorrelation coefficient;

$\hat{\alpha}_{2,i}$ is the estimated volume autocorrelation coefficients when there is high information flow of good news on the previous trading day;

$\hat{\alpha}_{3,i}$ is the estimated volume autocorrelation coefficients when there is high information flow of bad news on the previous trading day;

$r_{i,t}^+$ is the positive return for stock i at day t ; $|r_{i,t}^-|$ is the absolute value of negative return for stock i for day t .

Panel A: Distribution of $\hat{\alpha}_{1,i}$ (Equation 1-4)						
	Largest	Q2	Q3	Q4	Smallest	Average
Whole Sample Period	0.5426	0.5482	0.5773	0.6072	0.5739	0.56984
Period 1983:07~1986:06	0.6679	0.6831	0.7187	0.7214	0.6618	0.69058
Period 1986:07~1989:06	0.6368	0.6366	0.6529	0.6731	0.5961	0.6391
Period 1989:07~1992:06	0.5752	0.5767	0.5798	0.5887	0.5676	0.5776
Period 1992:07~1995:06	0.4656	0.4607	0.4911	0.5479	0.521	0.49726
Period 1995:07~1998:06	0.3935	0.4092	0.4653	0.5209	0.5317	0.46412

Panel B: Distribution of $\hat{\alpha}_{2,i}$ (Equation 1-4)						
	Largest	Q2	Q3	Q4	Smallest	Average
Whole Sample Period	4.5251	4.0856	3.937	3.655	2.6256	3.76566
Period 1983:07~1986:06	5.7529	4.852	4.2426	3.896	4.567	4.6621
Period 1986:07~1989:06	3.5085	3.2965	3.1345	3.0447	1.9833	2.9935
Period 1989:07~1992:06	3.5557	3.1939	3.7833	3.9169	1.8122	3.2524
Period 1992:07~1995:06	5.8644	5.1985	4.8977	4.4328	2.6668	4.61204
Period 1995:07~1998:06	4.0234	3.9071	3.6646	3.0731	2.2157	3.37678

Panel C: Distribution of $\hat{\alpha}_{3,i}$ (Equation 1-4)						
	Largest	Q2	Q3	Q4	Smallest	Average
Whole Sample Period	0.0524	0.1359	0.1784	0.3489	-0.1649	0.11014
Period 1983:07~1986:06	-0.5309	-0.2992	-0.1228	-0.0519	-1.9809	-0.5971
Period 1986:07~1989:06	-1.0721	-0.3076	0.1543	0.1196	0.2518	-0.1708
Period 1989:07~1992:06	-0.6491	-0.3273	0.1378	0.4448	1.086	0.13844
Period 1992:07~1995:06	0.6679	0.7647	0.0078	0.3952	0.1188	0.39088
Period 1995:07~1998:06	1.6018	0.7324	0.6432	0.7698	-0.3256	0.68432

Panel D: Comparisons of Estimated Herd Trading Volume in the Presence of Different Types of News Across Different Subperiods						
Group	Estimated Herd Trading	Period	No. of Obs	Mean	Stdev	Mean Dif Sig
1	$\hat{\alpha}_{2,i}$ (Herdling at Good News)	Whole Sample Period	5705	3.7657	2.8764	3.6556
	$\hat{\alpha}_{3,i}$ (Herdling at Bad News)	Whole Sample Period	5705	0.1101	4.2698	0.0000
2	$\hat{\alpha}_{2,i} - \hat{\alpha}_{3,i}$ (Overconfident Herding)	Bull Market (83:07-89:06) Bear Market (92:07-98:06)	2212 2406	4.1797 3.4167	3.6593 4.8020	0.7630 0.0000
3	$\hat{\alpha}_{2,i}$ (Herdling at Good News)	Subperiod 4 (92:07-95:06) Rest of the Sample Period	1140 4565	4.6121 3.5518	3.0419 2.7939	1.0603 0.0000
4	$\hat{\alpha}_{3,i}$ (Herdling at Bad News)	Subperiod 4 (92:07-95:06) Rest of the Sample Period	1140 4565	0.3909 0.0394	5.3432 3.9542	0.3514 0.0129
5	$\hat{\alpha}_{2,i} - \hat{\alpha}_{3,i}$ (Overconfident Herding)	Subperiod 4 (92:07-95:06) Rest of the Sample Period	1140 4565	4.2212 3.5124	5.3704 3.9841	0.7088 0.0000

Table 1-7. Distribution of Firm Size and Ownership Ratios- by Ownership-ranked Quintiles

Market Capitalization is market capitalization at the financial year-end prior to each subperiod.
Financial Institution and Individuals represent the share-holding ratios of the respective investor groups at the financial year-end prior to each subperiod. I perform a two-way sorting, first by firm size, then within each size quintile, I further sort by ownership of interest. Then I stratify ownership-ranking groups among the different size quintiles.

Panel A: Financial Institution Ownership-ranked Quintiles			
	Log (Market Capitalization)	Financial Institution	Individuals
Highest Ownership	11.0405	0.5318	0.2359
Quintile2	11.0313	0.4305	0.2758
Quintile3	10.9916	0.3635	0.2992
Quintile4	10.9591	0.2921	0.2958
Lowest Ownership	10.9065	0.1777	0.2633
(Highest - Lowest)	0.134	0.3542	-0.0274
t-stat	2.2655	89.102	-5.1067

Panel B: Individual Ownership-ranked Quintiles			
	Log (Market Capitalization)	Financial Institution	Individuals
Highest Ownership	10.9544	0.3201	0.4462
Quintile2	11.0031	0.3832	0.3201
Quintile3	10.9671	0.3783	0.2565
Quintile4	10.9883	0.3707	0.2009
Lowest Ownership	11.0137	0.3367	0.1376
(Highest - Lowest)	-0.0594	-0.0166	0.3086
t-stat	-1.5536	-1.3254	68.2193

Table 1-8. Information Flow and Herd Trading Volume by Financial Institutions vs. Individuals

Mean difference comparison among estimated volume autocorrelation coefficients from the regression equation 1-3:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{0,ik} D_{k,t+1} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} \mid r_{i,t} \mid + \varepsilon_{i,t+1}$$

for quintiles of Individual Investors ownership. I first sort by firm size, then within each size quintile, I further sort by individual investor ownership ratios. Then I stratify ownership-ranking groups among the different size quintiles.

$\hat{\alpha}_{1,i}$ is the estimated non-informational volume autocorrelation coefficient;

$\hat{\alpha}_{2,i}$ is the estimated volume autocorrelation coefficients when there is high information flow on the previous trading day;

$|r_{i,t}|$ is the absolute value of the stock return at time t for stock i .

All test statistics are calculated based on Newey-West Heteroskedasticity-consistent standard errors.

	Mean	Stdev	No. of Sig	No. of +ve Sig	No. of non-sig	No. of Obs.	Mean(Adj RSQR)
Panel A: Distribution of $\hat{\alpha}_{1,i}$ (Equation 1-3)							
Sort by Individuals							
Highest	0.5525	0.1566	1143	1143	21	1164	0.3862
Quintile2	0.5620	0.1508	1090	1090	21	1111	0.3937
Quintile3	0.5517	0.1494	1100	1100	11	1111	0.3790
Quintile4	0.5401	0.1581	1088	1088	23	1111	0.3702
Lowest	0.5233	0.1603	1092	1092	19	1111	0.3478
Highest - Lowest	0.0291						
t-stat	(4.3857)						
Panel B: Distribution of $\hat{\alpha}_{2,i}$ (Equation 1-3)							
Highest	3.1843	2.5984	833	833	331	1164	0.3862
Quintile2	2.8658	2.5025	762	762	349	1111	0.3937
Quintile3	2.8669	2.4709	724	724	387	1111	0.3790
Quintile4	3.1002	2.6567	744	743	367	1111	0.3702
Lowest	3.0448	2.5916	739	737	372	1111	0.3478
Highest - Lowest	0.1394						
t-stat	(1.2810)						

Table 1-9. Financial Institutional Investors Trading Effects with Different Information

This table shows regression estimates of the model:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \varepsilon_i$$

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \varepsilon_i$$

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \delta(\text{RetVol}) + \varepsilon_i$$

where the dependent variables $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$ is the estimated volume autocorrelation coefficients from the regression equation 1-4:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

Marketcap is market capitalization, defined as the number of outstanding stocks times the market price as of June prior to each subperiod;
Ownership is the percentage of shares by financial institutional investors at the fiscal year-end prior to each subperiod;
Keiretsu is a dummy variable of 1 if the firm belongs to a keiretsu group or 0 for independent firm, obtained from Dodwell Marketing Consultants (1994/1995);
RetVol is individual stock daily return volatility during the sample period.

Ownership - Financial Institutions			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel A: Dependent Variable: $\hat{\alpha}_{1,i}$ (Equation 1-4)			
83:07-89:06	0.0861		
<i>t-stat</i>	3.3334		
83:07-89:06	0.0874	0.0330	
<i>t-stat</i>	3.3818	1.5207	
83:07-89:06	0.0982	0.0343	0.0769
<i>t-stat</i>	3.7750	1.5833	3.0692
92:07-98:06	-0.0614		
<i>t-stat</i>	-2.6817		
92:07-98:06	-0.0585	0.0547	
<i>t-stat</i>	-2.5571	2.7378	
92:07-98:06	-0.0440	0.0383	0.2012
<i>t-stat</i>	-1.9432	1.9343	8.2964

Ownership - Financial Institutions			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel B: Dependent Variable: $\hat{\alpha}_{2,i}$ (Equation 1-4)			
83:07-89:06	0.0602		
<i>t-stat</i>	2.3329		
83:07-89:06	0.0615	0.0354	
<i>t-stat</i>	2.3854	1.6341	
83:07-89:06	-0.0038	0.0276	-0.4619
<i>t-stat</i>	-0.1603	1.3888	-20.0814
92:07-98:06	0.0258		
<i>t-stat</i>	1.1328		
92:07-98:06	0.0248	-0.0194	
<i>t-stat</i>	1.0869	-0.9751	
92:07-98:06	0.0042	0.0038	-0.2843
<i>t-stat</i>	0.1899	0.1952	-11.9599
Ownership - Financial Institutions			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel C: Dependent Variable: $\hat{\alpha}_{3,i}$ (Equation 1-4)			
83:07-89:06	0.0009		
<i>t-stat</i>	0.0355		
83:07-89:06	-0.0003	-0.0320	
<i>t-stat</i>	-0.0119	-1.4675	
83:07-89:06	0.0048	-0.0314	0.0363
<i>t-stat</i>	0.1841	-1.4395	1.4380
92:07-98:06	-0.0536		
<i>t-stat</i>	-2.2826		
92:07-98:06	-0.0557	-0.0396	
<i>t-stat</i>	-2.3699	-1.9297	
92:07-98:06	-0.0521	-0.0436	0.0490
<i>t-stat</i>	-2.2139	-2.1150	1.9421

Table 1-10. Individual Investors Trading Effects with Different Information

This table shows regression estimates of the model:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \varepsilon_i$$

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \varepsilon_i$$

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \delta(\text{RetVol}) + \varepsilon_i$$

where the dependent variables $\hat{\alpha}_{1,i}$, $\hat{\alpha}_{2,i}$ and $\hat{\alpha}_{3,i}$ is the estimated volume autocorrelation coefficients from the regression equation 1-4:

$$v_{i,t+1} = \sum_{k=1}^5 \alpha_{o,ik} D_{k,t} + \alpha_{1,i} v_{i,t} + \alpha_{2,i} v_{i,t} r_{i,t}^+ + \alpha_{3,i} v_{i,t} |r_{i,t}^-| + \varepsilon_{i,t+1}$$

Marketcap is market capitalization, defined as the number of outstanding stocks times the market price as of June prior to each subperiod;

Ownership is the percentage of shares by individual investors at the fiscal year-end prior to each subperiod;

keiretsu is a dummy variable of 1 if the firm belongs to a keiretsu group or 0 for independent firm, obtained from Dodwell Marketing Consultants (1994/1995);

RetVol is individual stock daily return volatility during the sample period.

Ownership - Individual Investors			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel A: Dependent Variable: $\hat{\alpha}_{1,i}$ (Equation1-4)			
83:07-89:06	-0.0085		
<i>t-stat</i>	-0.3653		
83:07-89:06	-0.0002	0.0305	
<i>t-stat</i>	-0.0101	1.3603	
83:07-89:06	0.0059	0.0328	0.0646
<i>t-stat</i>	0.2430	1.4626	2.5819
92:07-98:06	0.1344		
<i>t-stat</i>	6.2381		
92:07-98:06	0.1556	0.0887	
<i>t-stat</i>	7.0709	4.3709	
92:07-98:06	0.1500	0.0707	0.1997
<i>t-stat</i>	6.9122	3.5131	8.3335

Ownership - Individual Investors			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel B: Dependent Variable: $\hat{\alpha}_{2,i}$ (Equation 1-4)			
83:07-89:06	0.0649		
<i>t-stat</i>	2.7919		
83:07-89:06	0.0791	0.0523	
<i>t-stat</i>	3.2953	2.3412	
83:07-89:06	0.0357	0.0361	-0.4577
<i>t-stat</i>	1.6114	1.7607	-20.0051
92:07-98:06	-0.0445		
<i>t-stat</i>	-2.0646		
92:07-98:06	-0.0519	-0.0309	
<i>t-stat</i>	-2.3492	-1.5193	
92:07-98:06	-0.0440	-0.0054	-0.2832
<i>t-stat</i>	-2.0500	-0.2720	-11.9525
Ownership - Individual Investors			
Sample Period	Ownership	Keiretsu	Return Volatility
Panel C: Dependent Variable: $\hat{\alpha}_{3,i}$ (Equation 1-4)			
83:07-89:06	0.0295		
<i>t-stat</i>	1.2634		
83:07-89:06	0.0223	-0.0267	
<i>t-stat</i>	0.9227	-1.1876	
83:07-89:06	0.0259	-0.0254	0.0382
<i>t-stat</i>	1.0680	-1.1271	1.5244
92:07-98:06	-0.0032		
<i>t-stat</i>	-0.1443		
92:07-98:06	-0.0128	-0.0400	
<i>t-stat</i>	-0.5594	-1.8995	
92:07-98:06	-0.0143	-0.0448	0.0538
<i>t-stat</i>	-0.6250	-2.1192	2.1360

Table 1-11. Summary of Discovery

This table is a summary of the effects of institutional and individual trading, and keiretsu effect reported in Table 1-9 and Table 1-10.

The regressions are based on the equations as follows:

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \varepsilon_i$$

$$\hat{\alpha}_{x,i} = c + \alpha \log(\text{market cap}) + \beta \log(\text{ownership}) + \gamma(\text{keiretsu}) + \varepsilon_i$$

where, ownership is the percentage of shares by financial institutional investors or individual investors at the fiscal year-end prior to each subperiod;
keiretsu is a dummy variable of 1 if the firm belongs to a keiretsu group or 0 for independent firm, obtained from Dodwell Marketing Consultants (1994/1995).

More herding indicates significant positive correlation between the subject of interest and observed herd trading volume; less herding indicates significant negative correlation between the subject of interest and observed herd trading volume; nil represents no significant correlation found.

Panel A. Financial Institutional Trading Effect on Herd Trading Volume		
Market Condition Information	Bull Market	Bear Market
Good News	More herding	Nil
No Information	More Herding	Less herding
Bad News	Nil	Less herding

Panel A. Individual Trading Effect on Trading Volume Autocorrelation		
Market Condition Information	Bull Market	Bear Market
Good News	More herding	Less herding
No Information	Nil	More herding
Bad News	Nil	Nil

Panel A. Keiretsu Trading Effect on Trading Volume Autocorrelation		
Market Condition Information	Bull Market	Bear Market
Good News	Nil	Nil
No Information	Nil	More herding
Bad News	Nil	Less herding

ESSAY TWO

INVESTOR RECOGNITION, LIQUIDITY EFFECTS, AND THE MARKET VALUATION OF SWITCH LISTING: THE CASE OF JASDAQ TO TSE

1. Introduction

The switching of firms from an over-the-counter (OTC)¹ market to an exchange listing is an important event that conveys new information to the market. Research that examines the switch of listing location was pioneered by Ule (1937) and continued by researchers such as Baruch and Saar (2006), Kadlec and McConnell (1994), Papaioannou et al. (2003), Sanger and McConnell (1986), and Ying et al. (1977), to name a few.

Many switch-listing studies focus on the U.S. equity market and examine the switch from dealer markets to specialist markets, especially from the National Securities Dealers Association Quotation (NASDAQ) to the New York Stock Exchange (NYSE) or American Stock Exchange (AMEX). Sanger and McConnell (1986) provide evidence that switch listing to a more liquid market improves stock liquidity. Christie and Huang (1994) attribute liquidity improvement to the change from a dealer market to a specialist-trading system. More recent studies, however, find that the liquidity improvement associated with switch listing reduced substantially in the wake of the market reforms that occurred in 1997 (Barclay et al., 1999; Bessembinder, 1999; Sapp and Yan, 2003) and the market decimalization that occurred in 2001 (Chung et al., 2004). Baruch and Saar (2006) find that a stock will be more liquid when it is listed on a market where similar securities are traded, and firms make listing decisions that enhance their firms' liquidity. These findings imply that a market-trading mechanism has an important impact on liquidity. Therefore, the observed

¹This refers to dealership markets such as NASDAQ and JASDAQ, which evolved from the over-the-counter market.

liquidity change is at least partially the result of differences in market-trading regulations and mechanisms in the respective markets under investigation. If there is no advantage in terms of trading mechanism, what are the factors that motivate a firm switching to a main board listing? The event of firms switching from the Japan Securities Dealers Association Quotation (JASDAQ) to the Tokyo Stock Exchange (TSE) provides a unique opportunity to answer these questions.

JASDAQ is an automated trading system for smaller firms. In December 1989, JASDAQ has introduced a market-making system and allowed firms to choose voluntarily between the order-driven (OD) and the market-making (MM) trading system and move between these two systems.² Firms trading on MM system have one or more market-makers for each firm. As of August 2006, 221 out of 970 stocks on JASDAQ were traded using the MM system with a total of 21 market-makers.³

Suzuki and Yasuda (2005) study switching effects when firms move between the two trading systems on JASDAQ. They find evidence that the MM system has a relative trading-cost advantage compared to the OD system. Firms initially trading on the OD system with high bid-ask spreads have improved liquidity and reduced spread after switching to the MM system. Even though JASDAQ firms have the flexibility to easily switch between MM and OD systems, why JASDAQ firms still opt for listing on TSE, even though TSE has more stringent listing requirement? There must be important reasons that

²The MM system was introduced on JADSAQ in December 1989. On JASDAQ, OD firms tend to be larger firms with higher stock prices and a larger number of shareholders than MM firms (Uno et al., 2002).

³See the JASDAQ website: <http://jasdaq.co.jp>

motivate JASDAQ firms to switch-list on TSE. Therefore, the event of JASDAQ firms switching to TSE provides a good opportunity to examine sources of switch-listing benefits beyond market-trading mechanism.

Uno et al. (2004) investigate the market reaction, investor recognition, and liquidity effect of firms switching from the JASDAQ to the TSE. However, their study does not provide evidence on whether the identified liquidity improvement is solely associated with the switching firms. Such liquidity improvement observed could be due to a market effect that also applies to non-switching firms. Therefore, it is not possible to attribute the liquidity improvement in their study to the switching effect per se. As a result, their conclusion of liquidity improvement due to switch-listing is found wanting.⁴

Okada and Yamasaki (2005) examine firms switching from JASDAQ to TSE and from TSE's second section to the first section, with the sole focus of managers' opportunistic hypotheses. They find that Japanese switching firms consistently performed well up to three years after switch. However, their study does not examine any external/exogenous factors associated with the switch-listing.

The present study fills the gaps in the extant literature. I examine switch-listing from JASDAQ to TSE, with the objective of identifying motivations for switch-listing that beyond market trading mechanism. Both internal/endogenous factors and external/exogenous factors that motivate such switch-listing

⁴ There is also ambiguity in their methodology. A detailed analysis of this methodology is illustrated in section 2.

decisions are investigated. These plausible factors are further verified to be solely applicable to the switching firms but not the non-switching firms.

In order to fulfill these objectives, I investigate the following: (1) I examine market reaction to the announcement of switch and the actual switch. This examines whether there is substantial benefit for firms to switch from JASDAQ to TSE. I expect that the market perceives switch-listing decision as good news and reacts positively. (2) I examine the plausible external/exogenous factors that motivate firms to switch to main board listing. I expect liquidity improvement for the switching firms only. I also expect that increase on investor base contributes to the increase on market value associate with the switch; bigger investor base means higher appreciation on firms' market value. (3) Firms' attributes are examined to determine the internal/endogenous factors that motivate the switch. I expect switching firms to be of a higher quality than non-switching firms, in terms of fundamental performance such as higher return on equity (ROE) and higher return on asset (ROA). I also anticipate that switching firms with relatively lower pre-switching performance will have a higher adjustment in their market value.

I analyze 171 JASDAQ firms that listed on TSE from 1997 to 2002. I apply the Campbell, Lo, and MacKinlay (1997) event study method, a proven and commonly used method for examining liquidity effect, investor recognition effect, and signaling effect. The use of a commonly used method enables cross-market comparisons by researchers and industrial professionals.

I find a significant positive market reaction to the announcement of a switch, but there is not as much evidence for a significant reaction to the actual

switch. This indicates that the Japanese market is semi-form efficient as per Fama (1970)'s definition. I find that significant improvement in liquidity and higher investor recognition are two external/exogenous factors that motive firm's switch-listing decision. The switching firms enjoy liquidity improvement on main board listing, manifested by a lower bid-ask spread, lower return volatility, and higher trading volume. No liquidity improvement is found for the matching firms on the TSE or JASDAQ. I also find that increases in investor base and trading volume on main board listing contribute significantly to the market value increase for the switching firms.

I find that the switching firms have a better fundamental performance than the matching firms, both before and after the switch. The market reacts more positively to the low-performance switching firms than the high-performance switching firms. If investors can identify JASDAQ firms that have a consistently strong fundamental performance, which make them potential candidates for switching to an exchange listing, then they have a better chance of making a profit by investing in these firms.

This essay is organized as follows: Section 2 contains a literature review; section 3 discusses the market structure and trading mechanism of the JASDAQ and the TSE; section 4 describes the sample selection criteria and data sources; section 5 describes the hypotheses and models; section 6 presents the empirical test results; and section 7 summarizes and concludes the study.

2. Literature Review

Market reaction to a switch of OTC stocks to an exchange listing has interested scholars for more than 50 years. Many researchers (such as Grammatikos and Papaioannou, 1986a, 1986b; Kadlec and McConnell (1994), Sanger and McConnell, 1986) have examined the effect of a switch-listing announcement or actual switch on stock price. In these studies, excess returns for the event window are measured against a market-pricing model. According a survey by McConnell et al. (1996), market reaction to an exchange listing on the U.S. market has been consistently and significantly positive at the announcement of the switch and at the actual switch.

Ying et al. (1977) focus on the announcement effect and analyze the abnormal returns in the application month and the month following. In an efficient market, the market should be able to adjust its valuation with the arrival of information rather than when the event occurs. More than 99% of the applications for an exchange listing are successful;⁵ therefore, focusing on the announcement day helps to pinpoint the listing effect. Ying et al. discover a significant abnormal return of 7.54% during the application month and another 5% in the following month, when 75% of the actual switches take place. The switching firms, however, are found to underperform the benchmark by almost 6% over the 12 months after a switch.

Other researchers (Barclay et al., 1998; Grammatikos and Papaioannou, 1986a, 1986b; Sanger and McConnell, 1986, to name a few) examine the

⁵See Sanger and McConnell (1986).

switching effect using monthly, weekly, or daily data to analyze switching effects on U.S. equity markets. In general, the market perceives an exchange-listing decision as good news, and stock prices increase significantly at the announcement of a listing application. Positive abnormal return is also identified during the interval from application to listing, but these studies report a negative abnormal return after the switch. This finding is common to a cross-listing and IPO listing, and it is considered a post-listing puzzle (Hwang and Jayaraman, 1993; McConnell and Sanger, 1987).

There are three benefits that motivate firms to switch to an exchange listing: (1) improved market liquidity; (2) improved investor recognition; and (3) signaling for firms' better quality. The first two benefits are external/exogenous factors that are determined by market characteristics. The third benefit is an internal/endogenous factor that is determined by firm's attributes.

The liquidity effect hypothesis is perhaps the most commonly analyzed topic associated with the exchange-listing phenomenon. There are two groups of studies that examine the liquidity effect. The first group of studies (Christie and Huang (1994), Kadlec and McConnell (1994), and Sanger and McConnell (1986), to name a few) examines whether an organized exchange is inherently more liquid than an OTC market. These studies use a statistical comparison of liquidity before and after a switch. The empirical findings from this group of studies consistently show improved market liquidity on organized exchange markets, reporting a significant drop in the bid-ask spread after firms switch to an exchange listing. Christie and Huang (1994) identify two sources for the

large decrease in trading costs associated with NASDAQ firms switching to NYSE or AMEX: (1) the change from dealer trading to a specialist system and (2) different trading locations. Sanger and McConnell (1986) investigate the switching effect before and after the NASDAQ system is adopted by the OTC market. They find that NYSE has superior liquidity compared to the OTC or NASDAQ system; while the OTC market's adoption of the NASDAQ system improves liquidity.

Another group of studies examines how market values are related to liquidity improvement. Grammatikos and Papaioannou (1986a) and Kadlec and McConell (1994) examine the correlation between the change in market value and the change in liquidity for switching firms. They find that the excess return at the event window is significantly positively related to a change in bid-ask spread. Their finding implies that an improvement in liquidity is one source of value improvement for switching firms.

However, main board listing does not necessarily have liquidity advantage over the OTC market. Affleck-Graves et al. (1994) show evidence that exchanges do not always have a liquidity advantage over NASDAQ. They find that trading structure and firm characteristics affect bid-ask spread. Moreover, changes in market regulations or investor behavior can erode NYSE's perceived liquidity advantage of NYSE. Barclay et al. (1999) and Bessembinder (1999) for example, report a significantly lower bid-ask spread on NASDAQ after market reforms in 1997. Weston (2000) also finds that the difference in bid-ask spread between NYSE and NASDAQ has reduced significantly after the reforms in 1997. Sapp and Yan (2003) find little evidence

that suggests liquidity improvement for the NASDAQ firms switch-listing to AMEX in the post-reform regime.

A study by Chung et al. (2004) compared the bid-ask spread between NYSE and NASDAQ in the post-decimalization period. Their empirical evidence shows that NYSE offers low-cost executions for small, low-volume stocks, and NASDAQ provides lower execution costs for large, high-volume stocks. So far, however, empirical discoveries on liquidity advantage are confined to specific markets and periods, hence it gives rise the necessity to study the Japanese equity market, the second largest equity market in the world.

Some recent research examines liquidity on the Japanese market. Uno et al. (2002) study the market microstructure of JASDAQ's MM and OD systems and the bid-ask spread pattern on these two systems. They find that effective bid-ask spreads are tighter for MM stocks. Their finding suggests that the MM system improves market liquidity on JASDAQ. However, as a result of their small sample size, their finding may not be representative and it is not as convincing as Suzuki and Yasuda's (2005) findings discussed below.

Suzuki and Yasuda (2005) study the switching effect on JASDAQ from 1999 to 2001 for a group of 258 JASDAQ firms that change from the OD to the MM trading system. They find significant positive market reaction to the announcement of a switch decision, and the switching firms' market price has a permanent increase of 3%, on average. In addition, relative bid-ask spreads and effective bid-ask spreads decrease approximately 50%, on average, after shifting to the MM system. The correlation between the increase in market value and the improvement in liquidity is highly significant. However,

approximately 23% of the switching firms change back to the OD system within 3 years after a switch. These are the firms that have a relatively lower bid-ask spread before the shift, and the stock-price increase for this subset of switching firms is insignificant. Suzuki and Yasuda's finding implies that the MM system has certain liquidity advantage over the OD system. It gives rise to the question that why JASDAQ firms still decide to switch-list on TSE while they can stay on JASDAQ with options to choose either system. It implies that there are benefits, significant benefits, that motivate the firm to switch to TSE-listing, even though much more stringent listing requirements shall be imposed.

Another group of research studies examine the investor recognition effect, and their findings suggest that an exchange listing produces a larger investor base for firms and, therefore, improves firm market value. Kadlec and Sanger (1994), based on Merton's (1987) model of asymmetric information, use an empirical model to test this effect and find that the investor recognition factor is a significant source of the switch-listing abnormal return. The impact of this increased investor base on market excess return is statistically significant, even after taking the liquidity effect into account. Foerster and Karolyi (1999) investigate the effects of market segmentation and investor recognition on asset pricing for non-U.S. stocks listed on AMEX or NYSE as American Depositary Receipts (ADRs). Their findings support the investor recognition hypothesis.

Tse and Devos (2004) study firms that switch from AMEX to NASDAQ. They find that even though the bid-ask spreads (quoted, effective, and realized spreads) increase when firms switch from AMEX to NASDAQ, the market

reacts positively to the switch announcement, especially for high-tech firms. They also find that the institutional ownership and number of institutional shareholders increase after the switch. Their findings imply that market value increases with investor recognition, even with higher transaction costs.

Uno et al. (2004) study the switching effect of firms that move from JASDAQ to TSE during the August 1999 to March 2002 period with the focus on investor recognition and liquidity effect. They find a significant relationship between the investor recognition effect and an increase in market value. They examine the liquidity effect and estimate the change in price impact of trades using the following regression equation:

$$|r_{i,t}| = \alpha_i + \lambda_i \ln Q_{i,t} + d_{i,t} \lambda'_i \ln Q_{i,t} + \eta_i \quad (2-1)$$

where $|r_{i,t}|$ is the absolute stock daily return, $Q_{i,t}$ is the log of the number of stocks traded at day t for firm i , λ_i measures trading volume impact on return before the switch, and η_i is the error term. The dummy variable, $d_{i,t}$, which indicates a post-switching window, and λ'_i measures the change in the price impact of trades after the switch.

There are concerns, however, about Uno et al.'s (2004) model. Firstly, they measure the change of the impact of each unit of trade on absolute return. This change could also be the result of a change in the number of outstanding shares: that is, a change in the percentage trade turnover, *ceteris paribus*. I find a significant increase in the number of outstanding shares for a switching firm

after an exchange listing,⁶ and each unit of trade is associated with a smaller percentage trade turnover. Therefore, the decreased change in price impact in Uno et al. (2004) could be the result of an increase in number of outstanding shares after the switch, and have no relation with liquidity change. As a result, their conclusion that switching from JASDAQ to TSE improves stock liquidity is questionable. Secondly, they do not show whether the observed liquidity improvement is only associated to the switching firms. Therefore, their conclusion liquidity improvement after a switch may not be the result of the switching effect per se. It could be the result of market factors that apply to all firms; or it could be simply a result of increase in the number of outstanding shares. As a result, their conclusion about an improvement in liquidity due to the switch-listing effect is not credibly established. Therefore, I use a more comprehensive approach to investigate the liquidity effect in the current study.

Other than the above two exogenous factors which are widely examined in switch-listing study, switching firms' quality is the endogenous factor that is often analyzed. Exchange-listing firms are subject to more stringent regulations and higher exposure,⁷ and therefore switching firms are deemed to have better quality than the non-switching firms. Management of the switching firm designs the switch-listing as a signal that their firm fits the quality of being promoted to the main board. Ying et al. (1977) find that switching firms have significant positive monthly returns for 24 months before they apply for a listing switch. Their finding suggests that management uses an exchange listing to express their confidence in their firm's good quality. Grammatikos and

⁶ See the empirical results in section 6.2.1.

⁷ See Grammatikos and Papaioannou (1986a), Kadlec and McConnell (1994), and Sanger and McConnell (1986).

Papaioannou (1986b) find that the market reaction is only significantly positive for poor-quality pre-listing firms. Therefore, they suggest that the increase in firm's market value is a signal of management's confidence in a firm's prospects. Hence, the signaling hypothesis predicts that the lower-quality firms should have higher appreciation on market value associated to the switch.

Switch-listing is a signal⁸ designed by the management of the switching firms to communicate to the market that their firm fits the quality to be promoted to list on the main board. All main board listing firms are under the supervision by the TSE, and need to satisfy its annual assessment. Firms fail to meet the assignment criteria will be either downgraded (from the First Section to the Second Section) or even delisted if it falls under the delisting criteria.⁹ As downgrading or delisting is damaging to the firm's image, switch-listing also signals that the management of the switching firms is confident to their firm's future prospects.

Some listing event studies, however, show that switching firms underperform the benchmarks after they switch to major exchanges.¹⁰ Hwang and Jayaraman (1993) study this post-listing puzzle and attribute it to a lack of trading interest after the listing. McConnell and Sanger (1987) explore several possibilities but are not able to explain the negative return and decline in price after a listing switch. Brav and Gompers (1997) find that a stock's post-IPO buy-and-hold return performance varies against different benchmarks. The

⁸ The Nobel laureate, Michael Spence, on the 100th anniversary of the founding of the Nobel Prize when he received the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel, stated, "Signals are things one does that are visible and that are in part designed to communicate. In a sense they are alterable attributes" (see Spence, 2002).

⁹ TSE Fact Book 2003.

¹⁰ See, for example, Dharan and Ikenberry (1995), McConnell and Sanger (1987), and Ying et al. (1977), among others.

level and pattern of stock's post-IPO market performance is sensitive to the method of calculating returns. Therefore, no clear-cut conclusion can be drawn based on market performance examination. The finding by Brav and Gompers (1997) implies that investigation of the fundamental performance is more applicable in the context of current study. This sets up a frame work of signaling effect analysis in the present study.

Therefore, it is necessary to investigate both firm attribute and market attributes that motivate the switch listing. First, however, it is necessary to understand the differences between TSE and JASDAQ.

3. TSE and JASDAQ: Understanding the Differences

The Tokyo Stock Exchange Co., Ltd. was founded in 1878. It was forced to suspend trading at the end of World War II, and was reconstituted in its present form in 1949. Its second section was opened in 1961. TSE is now the largest stock exchange in Japan and the world's second-largest exchange in the world in terms of market capitalization (see Appendix A and Appendix B).

JASDAQ is the largest stock market for venture businesses and small and medium enterprises (SMEs) in Japan. JASDAQ was established in 1963 and reorganized in 1983 as a stock-trading market for medium and small venture companies. In 1991, it upgraded its trading system such that it automatically executes orders and disseminates information about quotations. It was recognized as a securities exchange market after it acquired a securities

exchange license, and its name was changed to JADSAQ Securities Exchange, Inc. in December 2004.

There are four main differences between TSE and JASDAQ: (1) listing criteria, (2) listing firm characteristics, (3) type of investor, and (4) trading mechanism and regulation. The following brief discussion about these differences indicates possible motivations for firms that decide to switch from JASDAQ to TSE.

3.1 Listing Criteria

TSE has more stringent listing criteria than JASDAQ. TSE requires a higher market value, larger number of shareholders, higher net assets, higher pretax profit before listing, lower free float weight percentage, and larger number of operating years for firms than JASDAQ. TSE's first section has much more stringent requirements than its second section. In November 1999, a new section, called Mothers, was opened for high-growth emerging companies. This section has much lower requirements than TSE's first and second sections. As a result of these different listing criteria, each market (i.e., JASDAQ and TSE's first, second and Mothers sections) attract different groups of firms for initial listings. A comparison of the listing criteria for TSE first section, TSE second section, and JASDAQ is summarized in Appendix F. In principle, newly listed domestic stocks are assigned to the second section of TSE, except for a

Mothers issue. However, the exchange may assign stocks that are expected to have particularly high liquidity to the first section at the time of listing.¹¹

TSE implemented a major deregulation of the listing criteria for TSE's first and second section in August 1999. It reduced the required number of outstanding shares for firms outside the Tokyo metropolitan area, and it changed its regulations to allow firms to have a higher percentage of large shareholders. In addition, it relaxed the requirements for net profit, net assets, minimum shareholder's equity per share, and dividends. This deregulation enabled many JASDAQ firms to switch their listing to the TSE.

3.2 Listing Firms Characteristics and Market Activities

TSE has approximately twice as many listed firms as JASDAQ (see Table 2-1). JASDAQ targets venture businesses and small and median enterprises; therefore, JASDAQ firms have significantly lower market capitalization than TSE firms. On average, JASDAQ firms are only 4% to 10% of the size of TSE's first section firms, and on average, JASDAQ firms are only 6% to 13% the size of TSE firms during the sample period of the present study. Market-trading activities on JASDAQ are also substantially lower than market-trading activities on TSE. The total value of trades on JASDAQ is approximately 2% to 7% of the value of trades on TSE, while the total volume of trades on JASDAQ is approximately 1% to 3% of the volume of trades on

¹¹See the TSE website: <http://www.tse.or.jp/english/rules/listing/>.

TSE (see Table 2-2). The same percentage applies to average daily market-trading activities.

3.3 Type of Investor

TSE and JASDAQ attract different types of investors. Figure 2-1 shows the percentage of trading value by individual investors, foreign investors, and others on TSE and JASDAQ. The others group on TSE consists of domestic organizational investors, including financial institutional investors, securities firms, corporations, and government organizations. Financial institutions are the largest group in the others group. On TSE, individual investors only account for 10% to 20% of the trading activity, foreigner investors account for 30% to 36% of trading activity, and the remaining 50% to 60% of trading is conducted by domestic organizational investors that are mainly financial institutions.

On JASDAQ, the others group includes financial institutions, brokers, dealers, and corporations. Individual investors appear to be more active on JASDAQ than on TSE, and they account for a significantly larger proportion of trading: During the whole sample period, individual investor trading ranged from a low of 36% in 1998 to a high of 55% in 1999. Foreign investors account for 10% to 28% of trading activity, and local organizational investors account for 32% to 45% of trading on JASDAQ.

3.4 Trading Mechanism and Regulation

The TSE is a pure order-driven, auction market without market makers. Stocks are traded through *itayose* (i.e., a single-price batch auction session at the beginning and closing of morning and afternoon sessions) or *zaraba* (i.e., continuous trading). Approximately 65% to 70% of the trading volume occurs during the *zaraba* session (see Lehmann and Modest, 1994).

All orders, whether limit or market orders, are matched according to price-priority and time-priority rules. Under the price-priority rule, a sell (buy) order with the lowest (highest) price takes precedence. Under the time-priority rule, an earlier order takes precedence over other orders at the same price. Therefore, when the lowest sell and highest buy orders match in price, the transaction is executed at that price. The *saitoris* (i.e., the exchange-designated intermediaries) only serve as book-keepers to log and maintain the limit-order book and match orders on the book with the incoming market orders.

Other than a mandatory tick size (see Appendix G, Panel A), the TSE adopts two unique measures to prevent wild short-term fluctuations in prices: (1) special warning quotes and (2) daily price limit. The special warning quotes and daily price limit not only help ensure price continuity, but they also work as circuit breakers in an emergency.

When there is a major order imbalance, the *saitoris* issue special warning quotes to the market through the market information system. If counter-orders coming to the market have a matching price, the special quote is withdrawn. If the imbalance continues, the special quote is revised up or down within a

certain range (Appendix E) at intervals of at least 5 minutes until the imbalance is resolved.

The TSE sets daily price limits for each individual stock to prevent day-to-day wild price swings, provide a time-out in the event of a sharp increase or decrease in price, and control the investing public's reaction. Daily price limits are set in terms of absolute yen values according to the price range of each stock (Appendix D). If a stock opening price or price change exceeds the exchange-prescribed limit, the *saitoris* issue a trading halt to cool down the market.¹² Daily price limits also apply to special quotes, and special quotes cannot be outside the daily price limit.

Transactions on TSE are matched directly by investors from the buy side and sell side, and as a result, the speed of trade execution is constrained by the absence of specialists or market-makers. Therefore, market liquidity may not be as smooth as market liquidity in the presence of specialists or market-makers. On the other hand, because buy and sell traders are direct investors, the bid-ask spread should reflect the discrepancy between the market value of the buyers and sellers, the demand versus the supply forces on the market, and how desperate investors are to buy/sell the stock. The magnitude of the bid-ask spread reflects market liquidity to a certain extent, and the narrower the bid-ask spread is, the easier it is to execute a trade.

JASDAQ is the only market in Japan that has two transaction methods: (1) the auction method and (2) the market-maker method. Before 1998, the trading system was based on auction; however, the equity market has slowed

¹²See the 2003 TSE fact book.

down as a whole since 1997, and as a result, trading activity became thin on JASDAQ (see Table 2-2). In December 1998, the Japan Securities Dealers Association (JSDA) introduced a full-fledged MM system in an attempt to help trading activities. Since the end of 1998, firms can choose to trade on either OD or MM.¹³

Under the MM system, a market-maker, which is a securities company, constantly quotes a stock's selling price, a buying price, and the number of shares. The market-maker is obliged to buy or sell a volume of the stock offered by an investor at the quoted price. There are two ways of trading MM issues. First, orders can be directly placed with a market-maker over the telephone or through its computer system. These orders are reported to the JASDAQ system after they are executed. Only small orders up to five trading units can be routed through the JASDAQ Small Trade Execution System, which automatically matches the order with the best bid or ask price. Time-priority rules apply when several market-makers quote the same price.

In 2002, the JSDA required a minimum of four market-makers for a MM issue to ensure there was competition among market-makers. JSDA also required market-makers to place small limit orders of two units or less on the JASDAQ MM system to ensure that small limit orders were executed at the best possible quote on the market.¹⁴

¹³My study focuses on a sample starting in 1997, and the total number of firms in 1997 and 1998 is 28, out of total 171 switching firms. In spite of this small number of firms, I perform a statistic test for the subgroup of firms that switch after 1998, and the test results are not different from the results for the whole sample.

¹⁴ JSDA Annual Report 2003.

For OD issues, limit orders are executed when matching orders exist on the order book in the automated system. If there is no matching order, it is recorded on the order book and matched with incoming orders. Market opening is a collective auction process, while the subsequent matching is a continuous auction process. Price-priority and time-priority rules are the same as the rules on TSE.

At the end of the 2002 fiscal year, 331 out of 939 firms on JASDAQ were listed on the MM system. By the end of December 2006, 971 listed firms had an aggregate market capitalization of 13.3692 trillion yen, 221 firms were traded using the MM system, and there were 21 market-makers.¹⁵

4. Sample Selection and Data Sources

My sample period is from 1997 to 2002. Before 1997, there were only a couple of JASDAQ firms switching to TSE every year, but since 1997, there has been an increasing number of JASDAQ firms switching to TSE. In the present study, firm performance data are needed for 2 years after a switch; therefore, the sample period ends in 2002. In 2003, JASDAQ introduced the Application Program Interface (API) system, which is designed to improve the transmission of market information. By ending the sample period in 2002, it is possible to avoid the potential confounding effect of the new system.

¹⁵See the JASDAQ website: <http://jasdaq.co.jp>

The sample includes 171 out of 225 switching firms with data available. Data for these firms were obtained from the Bloomberg Corporate Action Calendar. Two groups of carefully matched firms are selected from TSE and JASDAQ. Data for the matching firms were obtained from Bloomberg and Research Insights. These firms serve as a control group, and their performance is compared to the performance of the switching firms. Therefore, I am able to analyze whether the effects (if any) of the observed event are the result of the switch (which only apply to the switching firms) or market forces (which also apply to the matching firms).

Matching firms have to meet three criteria: (1) They should have the same two-digit SIC code; (2) they should have a similar market value in the event year; and (3) if more than one matching firm meets the first two criteria, then the firm with the closest price level is chosen. Following such criteria can avoid biases due to marketwise impact, industrial impact and size effect. I do not expect that the switching firms and non-switching firms are of the same quality level; therefore I do not choose matching firms based on their performance. A total of 88 firms from TSE and 51 firms from JASDAQ are selected.

It is not possible to match some of the switching firms to firms on the TSE or the JASDAQ. In order to compare the switching firms and matching firms on a fair basis, the switching firms (SF) are divided into three groups: (1) The SF-ALL group includes all 171 switching firms; (2) the SF-MFTSE group consists of 88 switching firms with matching TSE firms; and (3) the SF-MFJQ group consists of 51 switching firms with matching JASDAQ firms. Data for

the matching firms are also collected from Bloomberg and Research Insights. Table 2-3 shows the descriptive statistics for the three switching-firm groups and two matching-firm groups. Table 2-3, Panel A presents the mean distribution for SF-ALL and the TSE matching firms (i.e., MF-TSE) group and JASDAQ matching firms (i.e., MF-JQ). Table 2-3, Panel B presents the statistical difference between the SF-MFTSE group and MF-TSE group, and Panel C shows the statistical difference between the SF-MFJQ group and matching MF-JQ group.

The SF-All group has a higher market capitalization than the matching TSE and JASDAQ groups (see Table 2-3, Panel A). However, when switching firms are compared to matching firms, both the SF-MFTSE group and the SF-MFJQ group have the same level of market capitalization as their matching firms group (see Table 2-3, Panels B and C). In particular, the SF-MFJQ group matches well with the MF-JQ group in size, price level, number of shareholders, and number of outstanding shares.

Among the 171 switching firms, 18 firms switched to the TSE the day after an announcement, and 94 firms switched within 4 to 7 days after an announcement. Therefore, approximately two-thirds of the firms switched within one week after an announcement, and approximately 25% switched within 4 to 6 weeks after an announcement (see Figure 2-2).

Data on the daily closing bid and ask quotes, 260-days price volatility, opening price, closing price, daily high and low prices, and trading volume are collected for switching firms and matching firms. These microstructure variables allow me to examine the liquidity effect of the switch. The daily

market indices for TOPIX and JASDAQ are collected from Bloomberg and used to estimate the abnormal and cumulative abnormal returns for the switching firms.

Financial accounting data are collected to measure the switching and matching firms' fundamental performance 2 years before and 2 years after a switch. These data are used to test the signaling and timing hypotheses. The number of common shareholders and the number of common shares outstanding are used to investigate the investor recognition effect. All these data are based on the fiscal year-end, and they are obtained from Bloomberg and Research Insights.

5. Methodology

I apply a standard event study method to examine market reaction to a switch of listing. Factor analysis method and statistical comparisons are used to investigate the change in liquidity proxies due to the switch listing. Cross-sectional regression method is use to investigate the investor recognition effect. Signaling effect is examined by statistical comparisons among firms' fundamental performance, and by comparing market value increase among switching firms with different pre-switching quality. Hypotheses of the present study are stated as follows.

5.1 Market Reaction to Switching Event

Hypothesis 1: The market views the switch of a stock listing from JASDAQ to TSE as good news and reacts positively to its announcement.

The first step of this empirical study is to establish whether there is a significant benefit associated to switch-listing as what I have expected. I apply the standard event study method, following Campbell et al., 1997; Linn and McConnell, 1983; Sanger and McConnell, 1986. In the present study, abnormal returns (AR) and cumulative abnormal returns (CAR) for the -20 to +20 day window around an event date are estimated based on the market model. The estimation of the market model is based on -140 to -21 days and +21 to +140 days around an event date, with TOPIX as the market index. I assume that the market model is a valid representation of the stochastic process of the stock return:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \tilde{\varepsilon}_{it} \quad (2-2)$$

where $\tilde{R}_{it}$ = stochastic daily return on security i on day t , $\tilde{R}_{mt}$ = stochastic daily TOPIX index on day t , $\tilde{\varepsilon}_{it}$ = disturbance term for security i at day t , and $E(\tilde{\varepsilon}_{it}) = E(\tilde{\varepsilon}_{it} \cdot \tilde{\varepsilon}_{i,t-1}) = 0$ and $E(\tilde{\varepsilon}_{it} \cdot \tilde{\varepsilon}_{it}) = 0$.

The ex-post abnormal return for each security during the event window is

$$AR_{it} = R_{it} - E(R_{it}) = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \quad (2-3)$$

I examine average abnormal return and the cumulative abnormal return for the announcement and switching dates. The average abnormal return and the cumulative abnormal return for day t are determined using the following equations:

$$\overline{AR}_t = \sum_{i=1}^N \frac{AR_{it}}{N} \quad (2-4)$$

$$CAR_t = \sum_{k=-20}^t \overline{AR}_k \quad (2-5)$$

Statistics for the distribution of everyday abnormal return in the event window are computed following Linn and McConnell (1993) and Campbell et al. (1997). Significant positive abnormal return and cumulative abnormal return are expected, especially around the announcement day event window in an efficient market. This significant positive market reaction is likely the result of an expected improvement in trading liquidity on the exchange, increased investor recognition, or the signaling effect. The following hypotheses tests will examine whether such expectations are valid.

5.2 Liquidity Effect of Switch Listing

In order to test whether TSE provides better liquidity than JASDAQ, I perform paired comparisons of selected liquidity proxies before and after a switch and a cross-sectional comparison of the liquidity proxy with the liquidity of the matching firms on TSE and JASDAQ. The details are discussed in section 5.2.1. In section 5.2.2, I use a factor analysis technique to decompose

these liquidity factors into orthogonal principal components and comparison of the change in the factor loadings before and after a switch.

5.2.1 Investigation of the Liquidity Effect

Hypothesis 2: Switching to a TSE listing provides better liquidity, with reduced bid-ask spread, reduced return volatility, and higher trading volume than on JASDAQ.

I use statistical comparisons to investigate the liquidity effect. Relative bid-ask spread, trading turnover, shares outstanding, return volatility, and Garman and Klass' (1980) intraday volatility estimator (GK) are used as liquidity proxies for comparisons. To investigate the impact of a switch, I perform a paired comparison of the averaged liquidity proxies during the pre-switch and the post-switch years. In order to identify whether the expected change in the liquidity proxies is a result of the switching effect or other market forces, I perform a paired comparison in the same time window for the matching firms on TSE and JASDAQ. If changes are discovered only for the switching firms, then these changes should be the result of switching effects. The test statistics are based on one-sample mean comparisons.

The cross-sectional mean-difference between the switching firms and matching firms in the pre-switching and post-switching windows are compared in order to determine the liquidity properties of the switching firms and matching firms on the two markets. Test statistics are based on two-sample

mean comparisons. The construction of these liquidity proxies is discussed below.

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid-point of bid-ask price (Mid). The daily relative bid-ask spread is calculated using the following equation:

$$BAS_{it} = 100\% \times (Bid_{it} - Ask_{it}) / Mid_{it} \quad (2-6)$$

$$Mid_{it} = (Bid_{it} + Ask_{it}) / 2 \quad (2-7)$$

The pre-switching and posts-switching years' daily *BAS* is calculated for individual switching firms and matching firms on TSE and JASDAQ. *BAP* is an alternative measure for the average daily relative bid-ask spread, deflated by daily closing price. A decrease in *BAS* or *BAP* from pre-switching to post-switching window implies a liquidity improvement associated to the switch.

DAV is the average daily number of shares traded. *SHOUT* is the number of common outstanding shares. An increase in *DAV* or *SHOUT* from pre-switching to post-switching window implies a liquidity improvement associated to the switch.

TDV is the average daily trading turnover. Daily trading turnover for stock *i* on day *t* is calculated using the following equation:

$$TDV_{it} = 100\% \times Trading\ Volume_{it} / Share\ Outstanding_{it} \quad (2-8)$$

TDV is influenced by number of shares traded and number of outstanding shares, and while I expect an increase in the daily number of shares traded after

firms switch to TSE, I also expect an increase in the number of outstanding shares. Therefore, the ratio of trading turnover may not necessarily increase after the switch, even if there is an increase in daily trading volume.

Return volatility (*RetVol*) is measured by the standard deviation of the difference in the log closing price during the calendar year of interest. Both the pre-switching and post-switching years' daily return volatilities are calculated for the switching firms and matching firms. A decrease in volatility implies an improvement in market liquidity.

Other than the commonly measured return volatility, I also estimate extreme-value estimator volatility (Garman and Klass, 1980; see also Bessembinder and Rath, 2002; Tse and Devos, 2004). This GK estimator is used to calculate the intraday volatility using not only the close-to-close daily return, but also the high versus low and close versus open price spread, and it is used as an alternative measure of the daily return volatility. The GK intraday return volatility estimator is calculated using the following equation:

$$GK_{it} = 0.5(P_{it}^h - P_{it}^l)^2 - 0.386(P_{it}^c - P_{it}^o)^2 \quad (2-9)$$

where the high (P_{it}^h), low (P_{it}^l), close (P_{it}^c), and open (P_{it}^o) prices are natural logarithms of security i 's high, low, close, and open price on day t . The average daily GK estimator (*GKV*) is estimated for the switching and matching firms in the pre-switching year and post-switching year.

In the robustness tests, market model return residual volatility is used as one proxy for liquidity measure. A lower residual volatility indicates higher liquidity. The following equation is used to estimate the residual volatility:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \tilde{\epsilon}_{it} \quad (2-10)$$

where $\tilde{R}_{it}$ = stochastic daily return on security i on day t , $\tilde{R}_{mt}$ = stochastic daily TOPIX index on day t , and $\tilde{\epsilon}_{it}$ = disturbance term for security i on day t . The residual volatility is estimated by the standard deviation of the regression residuals for the switching firms and matching firms on the two markets during the pre-switching year and post-switching year.

The JASDAQ daily index is used to estimate the residual volatility for the switching firms during the pre-switching year, and the TOPIX daily index is used to estimate the residual volatility for switching firms during the post-switching year. In addition, the JASDAQ daily index and TOPIX daily index are used to estimate the residual volatility for the JASDAQ matching firms and TSE matching firms, respectively, for the pre-switching and post-switching year.

In addition, I estimate the residual variance from the GK estimator market model regression using the following equation:

$$GK_{it} = \alpha_i + \beta_i GK_{mt} + \epsilon_{it} \quad (2-11)$$

where GK_{it} and GK_{mt} are the GK estimators for individual firms and market index, respectively. Volatility of GK estimator ($GKVol$) is estimated by the standard deviation of the daily market model GK estimator.

The JASDAQ daily index is used to estimate the residual variance for switching firms during the pre-switching year, and the TOPIX daily index is used to estimate the residual variance for switching firms during the post-switching year estimation. The JASDAQ daily index and TOPIX daily index are also used to estimate the residual variance for the JASDAQ matching firms and TSE matching firms, respectively, during the pre-switching and post-switching year.

5.2.2 Analysis of the Liquidity Effect

In a stock exchange with market-makers or specialists (e.g. the U.S. equity market), the bid-ask spread can be decomposed into three components: (1) order processing cost, (2) inventory cost, and (3) adverse selection cost.¹⁶ The TSE market is a pure auction market; therefore, the bid-ask composition is different from markets with intermediaries who provide liquidity. In order to further investigate how improved liquidity functions with a switch event, I perform a factor analysis to extract two orthogonal principal components of the liquidity proxies in order to determine what happens to market liquidity as a result of a switch. This method can be traced back to the asset pricing theory (APT) developed by Ross (1976), among others. A change in the factor

¹⁶See Glosten and Harris (1988) and Stoll (1989), to name a few. For a comprehensive survey of this issue and the policy implications, see Biais, Glosten, and Spatt (2005).

loadings of the liquidity proxies reveals a variation in different types of trading that is distinct in nature.

5.3 Investor Recognition Effect of the Listing Switch

Hypothesis 3: Higher investor recognition on TSE contributes to an increase in stock value when a stock switches its listing from JASDAQ to TSE.

Merton's (1987) λ represents a risk factor caused by incomplete market information. It is affected by firm-specific risk, firm size and investor base. Following Kadlec and McConnell (1994), I measure the change in Merton's λ as a result of a switch using the following equation:

$$\Delta\lambda_i = \frac{Resvar_i \times Mktval'_i}{TSE\ holder_i} - \frac{Resvar_i \times Mktval_i}{JASDAQ\ holder_i} \quad (2-12)$$

where $Resvar_i$ is the residual variance from equation 2-2 during the estimation window of ± 20 to ± 140 days around an effective switching day; $Mktval_i$ is the relative market value before a switch, which equals the market value of security i 's common stock during the fiscal year-end month before an effective switch divided by the JASDAQ index in the same month; $Mktval'_i$ is the relative market value after a switch, which equals the market value of security i 's common stock during the fiscal year-end month after an effective switch divided by the JASDAQ index in the same month. $TSE\ holder_i$ and $JASDAQ\ holder_i$ are the number of TSE and JASDAQ common stock shareholders.

$JASDAQ\ holder_i$ is calculated using the number of shareholders reported on the balance sheet at the fiscal year-end just before a switch. $TSEholder_i$ is calculated using the number of shareholders reported on the balance sheet at the fiscal year-end after a switch. Therefore, $\Delta\lambda_i$ represents the change in the level of firm-specific risk and relative market value of a security scaled by the number of shareholders in the pre- and post-switching periods. A change in investor base before and after an exchange listing will cause a shift in the risk associated with incomplete information. I expect a larger investor base on TSE, and I anticipate a decrease in this risk factor after a switch. In order to analyze the impact of this change to the market valuation of a stock, I conduct the following regression:

$$CAR_{it} = \alpha_l + \beta_l f_i + \varepsilon_{it} \quad \text{for } l = 0 \text{ to } \pm 20 \quad (2-13)$$

where CAR_{it} is event window cumulative abnormal return of $\pm l$ day around an announcement day for firm i ; therefore, when $l = 0$, the dependent variable is the abnormal return on the announcement day.¹⁷ $f_i = \Delta\lambda_i, \Delta BAS_i, \Delta TDV_i$ respectively. $\Delta\lambda_i$ is the change in Merton's λ estimated by equation 2-12; ΔBAS_i is the difference between the post- and pre-switching average daily relative bid-ask spread as in the liquidity effect analyses; ΔTDV_i is the difference in the average daily trading turnover during the same period. Although $\Delta\lambda_i, \Delta BAS_i, \Delta TDV_i$ is information that is not available to a market at the time

¹⁷ I also perform an empirical test based on the effective switching day. As on an efficient market, market reaction to an event should occur when an event is announced rather than during the actual occurrence of the event, and I expect a more significant result in the announcement window under investigation.

of a switch, I use them as proxies for the ex ante market expectation of a change in the information risk factor and liquidity factors as a result of a switch.

As a result of Merton's (1987) model, an increase in post-switch investor base generates negative $\Delta\lambda_s$. Therefore, I expect a negative correlation between $\Delta\lambda_i$ and CAR, which implies that increased investor recognition creates a positive market reaction to the decrease in the risk associated with incomplete information. The market reaction proxy CAR is also regressed against the change in liquidity proxies, ΔBAS_i and ΔTDV_i respectively, in order to investigate whether the market react to the improvement in liquidity on main board listing. As increased post-switch liquidity generates negative ΔBAS s and positive ΔTDV s, I expect negative correlation between ΔBAS_i and CAR, and positive correlation between ΔTDV_i and CAR.

In a robustness test, equation 2-13 is modified in the following way:

$$CAR_{it} = \beta_{0t} + \beta_{1t}\Delta\lambda_i + \beta_{2t}\Delta BAS_i + \varepsilon_{it} \quad (2-14)$$

$$CAR_{it} = \beta_{0t} + \beta_{1t}\Delta\lambda_i + \beta_{2t}\Delta TDV_i + \varepsilon_{it} \quad (2-15)$$

$$CAR_{it} = \beta_{0t} + \beta_{1t}\Delta\lambda_i + \beta_{2t}\Delta BAS_i + \beta_{3t}\Delta TDV_i + \varepsilon_{it} \quad (2-16)$$

Holding the liquidity effect constant, a significant investor recognition effect during a switching event is expected.

5.4 Firm Attributes and Signaling Effect

A comprehensive investigation of motivating factors for switch listing should ideally include both internal and external factors analyses. In the previous two subsections, I explored the external factors, i.e., market liquidity and investor base. In this subsection, the internal factors, i.e., firms' attributes, are investigated.

Main board listing has much stringent criteria than JASDAQ (Appendix F); therefore, switching firms must have good quality in order to meet the standard of listing on TSE. To avoid the limitations in market performance analysis (see Brav and Gompers, 1997), the current study analyze firm's fundamental performance. Pre-switching fundamental performance between the switching and non-switching firms is compared to identify the specific attributes that differentiate the switching firms from their peers. To test signaling effect, the post-switching fundamental performance between the switching and non-switching firms is compared to examine whether the switching firms still can out-perform their non-switching peers after the switch. Pre- and post-switching fundamental performance of the switching firms is also compared to identify if there is significant deterioration after the main board listing. Moreover, if good quality is a firm attribute that motivates the switch, then switch-listing by a low-performance firm is a bigger surprise to the market. Thus, market reaction to the low-quality switching firms should be higher than to the high-quality firm. Hence, the following hypotheses are examined.

Hypothesis 4: Switching firms have better fundamental performance than the non-switching peers before switch listing.

Hypothesis 5: Switching firms have better fundamental performance than the non-switching peers after switch listing.

Hypothesis 6: Switching firms keep their good performance for a period after the switch.

Hypothesis 7: Market reacts to low-performance switching firms more positively than the high-performance switching firms.

I use the following group of proxies to capture firms' performance: market value, number of common outstanding shares, number of shareholders, trading volume, total assets, total liability, total debt to total assets, total debt to total equity, gross profit margin, gross profit margin growth rate, net profit margin, earning per share before extraordinary items, return on asset (ROA), return on equity (ROE), and dividend yield.

To identify the firm attributes that motivate the switch, independent sample mean comparisons of pre-switching performance proxies between the switching firms and the matching firms on both TSE and JASDAQ are performed. In order to identify the growth trend, I analyze 1 year (-1 period), 2 years (-2 period), and 3 years (-3 period) before a switch and the switching year (0 period), 1 year (1 period), and 2 years (2 period) after a switch. I expect switching firms out-perform the non-switching firms before the switch.

In order to examine whether the switching firms continuously perform well, two types of statistics comparison are performed. Firstly, independent sample mean comparisons of post-switching performance between the switching firms and the matching firms on both TSE and JASDAQ are

performed. This examines whether the switching firms can out-perform their market peers after their main board listing, as what I expected. Secondly, paired comparisons on the switching firm's fundamental performance before and after a switch are conducted. This is to investigate whether switching firms have significant deterioration after listing on the main board. I don't expect a significant drop on their performance after the switch.

In order to test market reaction to switching firm of different quality, I group the switching firms into terciles based on their pre-switching leading performance indicators according to the previous result of independent mean comparison test. Market reactions to the high-quality and low-quality firms are compared. Since switch-listing decision from a low-quality firm is a bigger surprise to the market, comparing to such decision from a high-quality firm, a higher market reaction to low-quality firm's switch-listing news is expected.

The empirical findings are presented in the following section.

6. Empirical Findings

6.1 Market Reaction to a Switching Event

Market reaction is measured using an event study around the announcement day and effective switching day. Abnormal return and cumulative abnormal return (cumulate from the beginning of the event window) are estimated using the market model. The test statistics are estimated using the method described in section 5.1, and the results are reported in Table 2.4.

Significant ARs and CARs during ± 20 days around an event day are found, and a positive market reaction is more significant on the announcement day. I report a significant 1.81% abnormal return on the announcement day, followed by a peak of 2.51% on the following day (see also Figure 2-3). There are also significant positive abnormal returns on day -9, -8, -6 and -1, which could be the result of the market's anticipation of a switching announcement or a leak of information. Two days after the announcement, AR starts to become insignificant or even significantly negative (on day 6 and 7). This finding implies an efficient market reaction to the news on JASDAQ. CAR also becomes significantly positive from day -9 onwards, peaks at 9.21% on day 2 after the announcement, and continues to be significantly positive for the rest of the event window. The magnitude of an abnormal return appears to be economically significant, even after accounting for transaction costs.

There are only sporadically significant positive ARs before the actual switching day (on day -11, -4 and -3; see Table 2-5 and Figure 2-4). On the actual switching day, the abnormal return is negative, on average, and significantly negative on the 3 following days. The daily ARs for the event window after an actual switch are almost all negative, which could be caused by a lack of market support on TSE. This phenomenon is also common on the U.S. equity market. The CARs are significantly positive for day -11 to day 2, and they peak on day -4 at 6.58%. The cumulative abnormal returns from the third day after an actual switch onwards become insignificant. Plausible reason for positive (negative) CARs before (after) an actual switch could be that interested investors build up their position before a firm shifts to an exchange listing, and investors who are after a quick profit may sell the stock soon after the switch.

In summary, there is a significantly positive market reaction to the announcement of a switch, but the market reaction becomes negative after the actual switch. This evidence is a strong indication of market efficiency. The cumulative abnormal return to a switch announcement is not only statistically significant, but also economically significant, even after taking transaction costs into account. Therefore, if investors can predict a switch decision, it appears that they can make a good profit of almost 10%.

6.2 Liquidity Effect of the Switch

6.2.1 Evidence of the Switching Liquidity Effect

Mean difference tests for the paired sample comparisons before and after a switch are performed to investigate the time series evidence of liquidity effect on switch listing. Test results of the pre- and post-switching year mean difference tests for five sample groups are presented in Table 2-6, including three switching-firm groups (i.e., SF-ALL, SF-MFTSE, and SF-MFJQ) and two matching-firm groups (i.e., MF-TSE and MF-JQ). An independent *t*-test is performed to investigate the differences in mean among the five sample groups, both before and after a switch. The test results are shown in Table 2-7.

A paired comparison of the pre- and post-switching year liquidity variables shows significant improvement after a switch for the three switching-firm groups (see Table 2-6, Panels A, B, and C). Pre- and post-switching liquidity changes for the two matching groups (i.e., MF-TSE and MF-JQ) are not significant, except for the average daily number of shares traded for the

MF-TSE group, and the daily trading turnover and the number of common outstanding shares for the MF-JQ group (see Table 2-6, Panel D and Panel E). Figure 2-5 illustrates a straight-forward comparison of the pre- and post-switching distribution of the average *BAS*, *RetVol*, *DAV*, and *TDV* for the five sample groups.

For all three SF groups, *BAS* decreases significantly from the pre-switch to the post-switch period, whereas MF-TSE and MF-JQ firms maintain their pre-switching level (see Figure 2-5 A). For JASDAQ firms, *BAS* is significantly higher than the *BAS* for TSE firms. Pre-switching *BAS* for all three SF groups are very close to the pre-switching *BAS* for MF-JQ firms, whereas the post-switching *BAS* drops to almost the same level as the *BAS* for MF-TSE firms, especially the *BAS* for the SF-ALL and SF-MFTSE groups.

Figure 2-5 B illustrates the mean distribution of daily return volatility (*RetVol*) of the five sample groups. Before the switch, all three SF groups have significantly higher return volatilities than TSE firms, on average, while the SF-MFTSE group has a slightly lower daily return volatility than the SF-ALL and SF-MFJQ groups. After the switch, average daily return volatilities drop to the same level as MF-TSE firms and to a much lower level than the level of MF-JQ firms.

Figure 2-5 C illustrates the mean distribution of average daily trading volume measured by numbers of shares traded. For all three SF groups, average trading volumes increase after a switch, while MF-JQ firms' trading volume drops during the post-switching window. MF-TSE firms have much higher average trading volumes than the other four groups. This result indicates that

trading volume measured by number of shares traded is higher on TSE than on JASDAQ. This may be one of the motivations for firms to switch.

Figure 2-5 D shows the mean distribution of average daily trading volume turnover. Volume turnover is measured by dividing the trading volume by the total number of outstanding shares; therefore, the decrease in average daily trading volume for SF-MFJQ firms implies that the increase in the number of outstanding shares exceeds the increase in daily number of SF-MFJQ shares traded. The sharp drop for MF-JQ firms is the result of an increase in number of outstanding shares and decrease in absolute number of shares traded.

Other than the liquidity measurements presented in Figure 2-5, paired comparisons are performed for number of outstanding shares (*SHOUT*), two intraday return volatility proxies, *GKV*, and *GKVol* (see Table 2-6). Number of outstanding shares increase significantly for all three SF groups and the MF-JQ group. Intraday return volatility drops significantly after a switch for SF-MFJQ firms.

There may be two reasons for the decrease in bid-ask spread: (1) improved liquidity produced by different investors and higher trading volume and (2) different tick size structures on TSE and JASDAQ (see Appendix G).

On TSE, the tick size for stock prices up to 2000 Yen is 1 Yen; on JASDAQ, tick size for stock price up to 1000 Yen is 1 Yen. Therefore, the

distribution of SF in relation to tick size can be summarized using the following three price ranges:¹⁸

1. Retain the tick size for those firms less than 1000 pre-switch and less than 2000 post-switch or more than 1000 pre-switch and less than 3000 post-switch.
2. Reduce the tick size for those firms more than 1000 pre-switch and more than 3000 post-switch.
3. Increase the tick size for those firms less than 1000 pre-switch and more than 2000 post-switch.

Figure 2-6 shows that approximately 50% of SF groups have reduced tick size after switching as a result of different tick size structures. Approximately 40% to 45% of the SF groups retain their tick size after switch. Only 2% of the SF-ALL group and 3% of the SF-MFTSE group experience an increase in tick size, and this increase is the result of an increase in stock price. Therefore, a change in tick size is one reason for the decrease in bid-ask spread after switch listing.

Different markets have different trading rules and regulations. Trading rules should apply to the conditions on the market it serves. Trading rules change as market condition changes, for the purpose of improving market efficiency or stability. To a certain extent, trading rules reflect market conditions. Therefore, a tick size structure applies to the conditions on a particular market and reflects, to a certain extent, market conditions. Liquidity

¹⁸The rest falls outside the scope of the present study.

is an important market condition. Therefore, a decrease in tick size after a switch may imply, as well as reflect, higher liquidity on TSE than on JASDAQ.

The improvement in liquidity associated with switch listing can be shown by comparing the differences in mean distribution among the five sample groups. Table 2-7 shows the results of an independent *t*-test, which support the conclusions drawn from the difference in the mean tests.

Before a switch, there are significant differences between the SF-ALL group and matching MF-TSE group (see Table 2-7, Panel A), and the SF-MFTSE group (the matched switching firms) and MF-TSE group (see Table 2-7, Panel B). SF groups have a higher bid-ask spread, lower trading volume, and higher volatility than the TSE matching firms. However, the differences become insignificant after a switch, except for number of outstanding shares (which takes time to change) and less intraday return volatility for the SF-MFTSE group (see Table 2-7, Panel B, *GKVVol_Post*).

In contrast, before a switch, no significant differences are found between the SF-All group and MF-JQ group (see Table 2-7, Panel C), and the SF-MFJQ group (the matched switching firms) and MF-JQ group (see Table 2-7, Panel D), except for number of outstanding shares for the SF-All group and MF-JQ group. Post-switch comparisons show significant differences for the two pairs, except for trading volume variables for the SF-MFJQ group and MF-JQ group. The SF groups have a lower bid-ask spread and lower return volatility than the JASDAQ matching firms in the post-switching window. Table 2-7, Panel E shows the comparison statistics for the two matching groups on different

markets. There are significant differences in the pre-switching and post-switching windows.

Overall, there is a significant liquidity improvement for all three SF groups. The improvement in liquidity is demonstrated by a reduced bid-ask spread, increased trading volume, and reduced return volatility after a switch. This improvement in liquidity is statistically and economically significant and it is not the result of a homogeneous change in the whole market because no significant change is found for the matching firms on TSE and JASDAQ. In general, SF groups have the similar level of liquidity as their JASDAQ matching firms before the switch; they have the similar level of liquidity as their TSE matching firms after the switch.

6.2.2 Analysis of the Liquidity Effect

A factor analysis of the switching firms is conducted using the principal component analysis method (see Table 2-8). Three main liquidity factors (i.e., bid-ask spread, trading turnover, and return volatility) are used for the principal component analysis. Table 2-9 and 2-10 show the results for the TSE matching firms and the JASDAQ matching firms, respectively.

Communalities indicate the amount of variance in each variable that is accounted for by the factors. Communalities extractions are estimates of the variance in each variable accounted for by the factors. As shown in Table 2-8 Panel A, the communalities extractions for pre-switching and post-switching

are above 0.8, which indicate that the extracted factors are a good representation of the variables.

Two key factors are extracted from the three liquidity proxy inputs before and after an exchange listing, and these factors explain 87% (before switch) and 89% (after switch) of the total variance (see Table 2-8, Panel B). By construction, these two extracted factors are orthogonal to each other.

The component matrix in Table 2-8, Panel B shows the factor loadings that represent the correlation coefficients between the extracted factors and input variables. From the correlation of the factors and input variables, I assume that Factor 1 is associated with non-informational trading, and Factor 2 is associated with informational trading. The logic is discussed below.

Factor 1 is negatively correlated to bid-ask spread, and Factor 2 is strongly and positively correlated to bid-ask spread, which means an increase in a Factor 1 component will reduce bid-ask spread, but an increase in Factor 2 component will increase bid-ask spread. Factor 1 is significantly and positively correlated to daily trading turnover, with a coefficient around 0.9. The correlation coefficient between Factor 2 and daily trading volume is negative yet trivial. This result shows that most of the trading turnover is contained in Factor 1 trading rather than Factor 2 trading. While the correlation coefficient between Factor 2 and the trading turnover is almost negligible, the correlation coefficients between Factor 2 trading, bid-ask spread, and return volatility are quite high. Therefore, I infer that Factor 1 is associated with non-informational trading, and Factor 2 is associated with informational trading. The same

argument applies to the factor analysis for the matching firms on TSE and JASDAQ.

Table 2-8, Panel B shows factor loadings between Factor 1 and Factor 2 with the three input variables before and after a switch. While the non-informational trading component remains relatively stable (in terms of percentage of daily trading volume) before and after a switch, it has a stronger negative correlation to BAS after the switch (i.e., a change from -0.387 before a switch to -0.522 after a switch), and its impact on the return volatility decreases significantly after the switch (i.e., from 0.81 before a switch to 0.675 after a switch). The informational trading component, on the other hand, has a much stronger impact on daily return volatility (i.e., from 0.432 before a switch to 0.668 after a switch).

The factor analyses for the matching firms on TSE and JASDAQ also indicate two categories of trading (i.e., informational and non-informational trading), which can explain approximately 90% of the total variation in the liquidity proxies. Table 2-9 shows the results for TSE matching firms. Communalities extractions for pre-switching and post-switching are all high, which again indicates that the extracted factors are a good representation of the variables. Factor 1 can be attributed to non-informational trading for the TSE matching firms, and Factor 2 can be attributed to informational trading. Non-informational trading has a lower negative impact on bid-ask spread in the post-switching window, and informational trading has a slightly larger positive impact on bid-ask spread in the post-switching window. Both types of trading

have roughly the same level of correlation to trading volume and return volatility in the pre-switching and post-switching window.

Table 2-10 shows that pre-switching and post-switching communalities extractions are also high for JASDAQ matching firms. For JASDAQ matching firms, Factor 1 can be attributed to non-informational trading, and Factor 2 can be attributed to informational trading. Non-informational trading has a smaller negative impact on bid-ask spread in the post-switching window, whereas informational trading has a larger positive impact on bid-ask spread in the post-switching window. Both types of trading have roughly the same level of correlation to trading volume in the pre-switching and post-switching window. While the correlation between non-informational trading and return volatility decreases in the post-switching window, the correlation between informational trading and return volatility increases from 0.581 to 0.689.

Therefore, the factor analysis implies that non-informational trading for switching firms has a stronger negative impact on bid-ask spread and weaker positive impact on return volatility after a switch, which contributes to a decrease in bid-ask spread and return volatility after a switch. Informational trading also contributes to a decrease in bid-ask spread. The matching firms, on the other hand, experience a small change in informational and non-informational trading, which causes a slightly higher bid-ask spread in the post-event window.

The factor analysis only shows the direction of changes in liquidity caused by informational and non-informational trading. It does not indicate

what causes the changes in informational and non-informational trading. The next section examines the impact of a switching change on investors.

6.3 Investor Recognition Effect of the Switch

The investor recognition factor of a switch on firms' increased valuation is estimated by equation 2-12. The average change in Merton's λ for a switching firm is -0.000392, with $t = -5.145$, which implies that a larger investor base after a switch significantly reduces the risk factor caused by incomplete information. Based on equation 2-12, CARs up to ± 20 days around the event day are regressed on $\Delta\lambda_i$, ΔBAS_i , and ΔTDV_i respectively.

As expected, significant negative impacts of $\Delta\lambda_i$ on CARs are found for lags from ± 5 to ± 20 days at the 5% significance level (see Table 2-11, Panel A). The estimated coefficients range from -17.15 to -31.74. The reason for not discovering a significant investor recognition effect for $l = 0$ to ± 4 but finding a significant effect in the longer intervals is because λ is estimated with annual data, while abnormal return is estimated on a daily basis. Therefore, the investor recognition effect is more pronounced during longer periods. This evidence implies that an anticipated larger increase in the investor base after an exchange listing, which translates into a large reduction in the risk factor caused by incomplete information, is associated with a higher abnormal return, or larger increase in market value.

Panel B shows empirical results for regression of CARs on $\Delta BASs$ based on equation 2-13. Contrary to my expectation, the correlation between $\Delta BASs$ and CARs are almost all positive, but mainly insignificant. This test result implies that the market does not value the reduction on BAS associated with switch listing. In section 6.2, one of the findings is that about 50% of the switching firms experience a reduction in the tick size after main board listing. Whether it is related to my finding here is open to future research.

Panel C indicates test results for regression of CARs on $\Delta TDVs$ based on equation 2-13. Consistent to my expectation, the correlation between $\Delta TDVs$ and CARs are all positive, and significant for $l = \pm 12$ to ± 20 . This finding implies that the market values improvement on liquidity due to higher trading volume as a result of switch listing.

Robustness tests of the investor recognition effect, after controlling for the liquidity effect, produce consistent results. Table 2-11, Panel D to Panel F present the regression results from equation 2-14, 2-15, and 2-16, respectively. The investor recognition effect on firm valuation for $l \geq \pm 5$ to ± 20 from the three robustness tests all become stronger compared to results from equation 2-13.

In conclusion, the findings in the current study show strong evidence that the market appreciates larger investor base and high trading volume associated to switch-listing, and reacts positively. Therefore, liquidity improvement and investor recognition are two external/exogenous factors that motive switch listing.

6.4 Firm Attributes and Signaling Effect

In order to identify the firm attributes that motivate the switch-listing decision and the signaling effect of a switch, I perform the examination in four steps. In the first step, the switching firm's pre-switching fundamental performance is compared to the matching firms on the TSE and the JASDAQ. This is to investigate the internal/endogenous factor for the switch, i.e., what attributes make the switching firms outstanding from the flock. In the second step, the switching firm's post-switching fundamental performance is compared to the matching firms. In the third step, pre- and post-switching performance is compared for the switching firms. The second and third steps are designed to examine whether the switching firms can maintain their good performance after the switch. In the last step, market reaction to low- and high-performance switching firms is compared.

For easier presentation, test results for the first and second steps are shown in the same table. Both tests are based on matched groups comparisons (i.e., SF-MFJQ and MF-JQ, and SF-MFTSE and MF-TSE). Test results for SF-MFJQ and MF-JQ are shown in Table 2-12, and Table 2-13 shows the test results for SF-MFTSE and MF-TSE. In both tables, Panel A shows the difference in mean test results for the pre-switching window, and Panel B provides test results for the post-switching window. An independent *t*-test is used in this comparison test.

SF-MFJQ firms have a significantly lower debt-to-asset ratio, higher profit margin, higher return on assets (ROA), and higher dividend yield than the JASDAQ matching firms before a switch (see Table 2-12, Panel A). Similar results are found in the post-switching window. In particular, SF firms have ROAs 2% to 3% higher than MF-JQ firms, which is both highly significant and substantial. This finding shows that switching firms out-perform non-switching firms on JASDAQ in liability and profitability before the switch; the switching firms maintain to out-perform their non-switching peers on JASDAQ after the main board listing.

Table 2-13 presents the results of a comparison test that examines the performance of SF-MFTSE firms and matching TSE firms in the pre-switch and post-switch period. Table 2-13, Panel A documents the results for pre-switch periods, while Panel B shows the results for post-switch periods. Before and after a switch, SF-MFTSE firms have a significantly lower number of common outstanding shares, lower number of shareholders, lower trading volume, and lower total assets and liabilities than MF-TSE firms. At the fundamental performance level, SF firms have significantly lower leverage ratios, higher profit margin ratios, higher ROA, and higher return on equity (ROE) before and after a switch. In particular, SF profit margin ratios are 7% to 12% higher during the three testing periods before a switch and remain 6% to 7% higher than the TSE matching firms in post-switching windows. The ROA of the SF group is about 4% to 5% higher than the MF-TSE group before a switch, and it remains close to 4% higher after the switch. The ROE of the SF group is 13% to 14% higher than the TSE matching group, and it remains 7% higher after a switch. This finding implies that switching firms have a relatively smaller

investor base and smaller number of common outstanding shares, but they outperform their TSE peers, both before and after the switch.

In the third step, I examine the change in switching firm's performance before and after an exchange listing using paired comparisons. This step is to examine whether the switching firms can keep their good performance after main board listing from another perspective. Table 2-14 shows the results of these comparisons. There is a significant increase in the number of shareholders after a switch, and the longer the comparison window, the larger the increase. There is a significant drop of 0.5% in the pretax profit margin growth rate, and the ROE also drops significantly: that is, 2.6% to 3.7% from 1 year to 3 years after a switch. Dividend yield, however, increases significantly (i.e., 0.2% – 0.5%). The other changes (i.e., total assets, total liabilities, debt ratios, profit margins, EPS, and ROA) are not statistically significant. Therefore, the result is mixed; it shows the switching firms can maintain their performance in general.¹⁹

Some preliminary conclusions can be drawn based on the findings of the previous three steps: 1) the switching firms have better quality than their non-switching peers; 2) they maintain their good performance after the switch, and outperform the non-switching peers after their main board listing. Hence, switching listing is a signal for the firm's better quality and the management's confidence in their firm's future prospects.

¹⁹ A robustness test is conducted to examine the change in JASDAQ matching firms' performance from pre- to post-event window. Paired comparison tests are performed for the whole control group and a subgroup of JASDAQ non-switching firms that have a higher pre-event ROA. There is no significant mean difference in the performance of these two control groups. Test results are available upon request.

From the first step, it has been identified that ROA and ROE are two leading indicators for the switching firms' good performance. Therefore, in the final step, the switching firms are grouped to terciles based on ROA and ROE before the switch. CARs for the high-ROA and high-ROE firms are compared with CARs for the low-ROA and low-ROE firms. Table 2-15 and Figure 2-7 shows the test results for comparison based on year -1 pre-switching ROE for CARs $l = 0$ to ± 20 . The low-ROE firms have much higher CARs, and the difference is statistically significant at the 5% level for day 2 and day 3 after the announcement. This finding implies that the market perceives higher benefit associated with the switch-listing of a low-quality firm.²⁰

In conclusion, switching firms out-perform the matching firms on TSE and JASDAQ both before and after a switch. The switching firms maintain their performance in general after main board listing. These two evidences support the argument that the management of the switching firms use switch-listing to signal their confidence in the firms' future prospects. There is also evidence that the market perceives higher benefit associated with the switch-listing of a low-quality firm.

7. Summary and Conclusions

JASDAQ has a dual trading system, and firms can choose to operate using the MM or OD system. Therefore, the event of JASDAQ firms switching

²⁰ Empirical test based on pre-switching period ROA groupings also render the similar results. Test results are available upon request.

to TSE provides a unique opportunity to investigate switch listing when the change in trading system is not a concern.

Significant firm market value increase at the switch-listing announcement is identified. This evidence indicates there is significant benefit associated to the switch. External factors and internal factors that motivate the switch-listing decision are examined. Improved liquidity and increased investor base on main board listing are two external factors that motivate the shift. Firm's better quality is the internal factor that motivates the management of a switching firm to signal the market of their confidence in their firm's future performance.

Significant liquidity improvement has been found for the switching firms. In order to avoid marketwide and industrial impact, two groups of matching firms with similar market size and from the same industry are selected, one group from TSE and one from JASDAQ. There is significant evidence of liquidity improvement for the switching firms, but not the matching groups. The switching firms are found to have same (higher) pre-switching (post-switching) liquidity as (than) the JASDAQ matching firms. Meanwhile, the switching firms are found to have lower (same) pre-switching (post-switching) liquidity than (as) the TSE matching firms. It appears that non-informational trading helps to reduce bid-ask spread and return volatility, and that informational trading helps to reduce bid-ask spread as well.

Both the increase on investor base and the increase on trading volume associated to the switch contribute to the switching firms' market value

increase. However, reduction on bid-ask spread is not appreciated by the market in terms of direct reflection on stock price improvement.

The switching firms are found to out-perform their non-switching peers on TSE and JASDAQ both before and after the switch. The switching firms maintain their good performance after their main board listing, in general. Hence the management of a switching firm uses switch-listing to the main board as a signal of their confidence in the firm's future prospects. There is evidence that the market perceives that low-performance firms receive a higher benefit from switch-listing. If investors can identify good quality JASDAQ firms which can serve as candidates for switch listing, substantial investment profit can be achieved.

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Figure 2-1. Investor Types: TSE vs. JASDAQ

Trading Value is the total number of shares traded multiplied by their respective matching prices.

The others group on TSE consists of domestic organizational investors, including financial institutional investors, securities firms, corporations, and government organizations.

The others group On JASDAQ includes financial institutions, brokers, dealers, and corporations.

**Panel A. Proportion of Trading Value by Investor Types
TSE 1st Section**

**Panel B. Proportion of Trading Value by Investor Types
JASDAQ**

Source of data: JSDA Fact Book 2003, Japan Securities Dealers Association.

Figure 2-2. Day Elapse between Announcement Day & Effective Switching Day

Day elapse is the number of days between an announcement of a switch decision and an actual switch.

Figure 2-3. Distribution of Estimated AR & CAR around an Announcement of a Switch

Abnormal return (AR) is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an announcement of a switch. Daily TOPIX index is used for market model estimation.

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an announcement of a switch. Z-statistic is estimated following Linn and McConnell (1983) and Sanger and McConnell (1986).

Figure 2-4. Distribution of Estimated AR & CAR around an Effective Switching Day

Abnormal return (AR) is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an effective switching day. Daily TOPIX index is used for market model estimation.

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an effective switching day. Z-statistic is estimated following Linn and McConnell (1983) and Sanger and McConnell (1986).

Figure 2-5. Mean Distribution of Liquidity Proxies before & after a Switch

Figure 2-5 shows mean distribution of selected liquidity proxies before and after a switch for five sample groups. SF-ALL consists of all switching firms in the present study; SF-MFTSE is a group of switching firms with TSE matching firms (MF-TSE); SF-MFJQ is a group of switching firms with JASDAQ matching firms (MF-JQ).

Figure 2-5 A presents the mean distribution of relative bid-ask spread, i.e., BAS, the daily closing bid-ask difference deflated by the mid of Bid-Ask price during the calendar year of interest. Figure 2-5 B presents the mean distribution of daily return volatility, i.e., RetVol, measured by standard deviation of the difference in natural logarithm closing price.

Figure 2-5 C presents mean distribution of average daily trading volume in number of shares, i.e., DAV, measured by number of trades.

Figure 2-5 D presents mean distribution of average daily trading volume turnover, i.e., TDV, the number of shares traded over total number of common outstanding shares.

Figure 2-6. Tick Size Status for Switching Firms

This figure reports percentage of switching firms which (1) retain the tick size after a switch; (2) increase in the tick size after a switch; (3) reduce in tick size after a switch. SF-ALL consists of all switching firms in the present study; SF-MFTSE is a group of switching firms with TSE matching firms (MF-TSE); SF-MFJQ is a group of switching firms with JASDAQ matching firms (MF-JQ).

Figure 2-7. Cumulative Abnormal Returns for Switching Firms around Announcement Day
High-ROE vs. Low-ROE Firms

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an effective switching day. Abnormal return is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an announcement of a switch. Daily TOPIX index is used for market model estimation. High-ROE group consists of switching firms with top tercile pre-switching ROE in year -1 before the switch. Low-ROE group consists of switching firms with bottom tercile pre-switching ROE in year -1 before the switch.

Table 2-1. Market Capitalization – Comparison on TSE & JASDAQ

Market capitalization refers to the total market value at the end of a year in billions of Yen.
JASDAQ does not include securities issued by the Bank of Japan.

	Number of Listings			Total Market Capitalization			Average Market Capitalization		
	TSE 1st & 2nd	TSE	JASDAQ	TSE 1st & 2nd	TSE	JASDAQ	TSE 1st & 2nd	TSE	JASDAQ
	Sections	1st Section		Sections	1st Section		Sections	1st Section	
1997	1,805	1,327	847	280,930	273,907	9,246	156	206	11
1998	1,838	1,340	868	275,181	267,783	7,754	150	200	9
1999	1,890	1,364	871	456,027	442,443	27,414	241	324	31
2000	2,026	1,447	887	359,919	352,784	10,283	178	244	12
2001	2,067	1,491	927	296,092	290,668	8,927	143	195	10
2002	2,075	1,495	939	247,366	242,939	6,983	119	163	7

Source of data: JSDA Fact Book 2003, Japan Securities Dealers Association.

Table 2-2. TST & JASDAQ Market Activity 1997-2002

Trading volume is the total number of shares traded during a year, in millions of shares.

Trading value is the total value traded during a year, in billions of Yen.

Trading volume and trading value include listed issues and supervised issues.

Panel A. Tokyo Stock Exchange Activity (1st & 2nd Sections)				
(Millions of Shares, Billions of Yen)				
	Trading Volume	Trading Value	Average Daily Volume	Average Daily Value
1997	107,566	108,500	439	442.8
1998	123,198	97,391	498.7	394.2
1999	155,163	185,486	633.3	757
2000	174,147	248,292	702.2	1,001.10
2001	204,026	201,909	829.3	820.7
2002	213,093	192,849	866.2	783.9

Panel B. JASDAQ Market Activity				
(Millions of Shares, Billions of Yen)				
	Trading Volume	Trading Value	Average Daily Volume	Average Daily Value
1997	1,460	2,661	5.9	10.8
1998	1,303	1,554	5.2	6.2
1999	4,287	12,197	17.5	49.7
2000	3,507	11,424	14.1	46
2001	3,307	5,012	13.4	20.3
2002	4,256	3,668	17.3	14.9

Source of data: JSDA Fact Book 2003, Japan Securities Dealers Association.

Table 2-3. Descriptive Statistics of Sample Firms

MV is market capitalization in millions of US dollars. VWAP is volume weighted average price in Yen. HOLDER is the number of shareholders in thousands. SHOUT is the number of outstanding shares in millions.

PRE is measurement in fiscal year-end before a switch; POSE is measurement in fiscal year-end after a switch.

SF-ALL consists of all switching firms in the present study; SF-MFTSE is a subgroup of switching firms with TSE matching firms (MF-TSE); SF-MFJQ is a subgroup of switching firms with JASDAQ matching firms (MF-JQ).

Panel A. Mean Distribution for SF-All and Matching Firms Groups			
	SF-ALL	MF-TSE	MF-JQ
	Mean	Mean	Mean
MV_PRE	724.39	497.35	194.77
MV_POST	812.95	448.04	124.01
VWAP_PRE	1701.69	866.84	1504.14
VWAP_POST	1714.66	968.48	1570.58
HOLDER_PRE	3.03	6.39	1.89
HOLDER_POST	4.87	7.20	2.12
SHOUT_PRE	21.05	56.26	13.26
SHOUT_POST	21.65	58.69	14.75

Panel B. Statistic Distribution for SF-MFTSE and MF-TSE			
	SF-MFTSE	MF-TSE	Difference in Mean
	Mean	Mean	t-Stat
MV_PRE	452.64	497.35	-0.28
MV_POST	452.14	448.04	0.21
VWAP_PRE	1504.14	866.84	4.18
VWAP_POST	1570.58	968.48	2.60
HOLDER_PRE	2.29	6.39	-5.52
HOLDER_POST	3.73	7.20	-4.07
SHOUT_PRE	19.89	56.26	-4.68
SHOUT_POST	20.18	58.69	-4.75

Panel C. Statistic Distribution for SF-MFJQ and MF-JQ			
	SF-MFJQ	MF-JQ	Difference in Mean
	Mean	Mean	t-Stat
MV_PRE	208.41	194.77	0.13
MV_POST	134.18	124.01	0.26
VWAP_PRE	1532.84	1504.14	-0.98
VWAP_POST	1164.95	1570.58	-0.73
HOLDER_PRE	1.68	1.89	-0.63
HOLDER_POST	2.69	2.12	1.41
SHOUT_PRE	13.73	13.26	0.27
SHOUT_POST	14.10	14.75	-0.31

Table 2-4. Distribution of AR & CAR around an Announcement of a Switch

Abnormal return (AR) is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an announcement of a switch. Daily TOPIX index is used for market model estimation.

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an announcement of a switch. Z-statistic is estimated following Linn and McConnell (1983) and Sanger and McConnell (1986).

Day	Sample size	AR	Z-stat(AR)	CAR	Z-stat(CAR)
-20	138	0.0007	0.1444	0.0007	0.1444
-19	128	-0.0011	-0.4665	-0.0004	-0.0212
-18	134	0.0026	0.9489	0.0022	0.5826
-17	133	0.0046	1.4854	0.0068	1.0260
-16	130	-0.0026	-1.0643	0.0042	0.5554
-15	131	0.0016	0.8019	0.0058	0.8657
-14	137	0.0034	1.3708	0.0092	1.2557
-13	144	0.0039	1.0256	0.0131	1.4233
-12	140	-0.0023	-0.5889	0.0108	1.1346
-11	138	0.0006	0.8228	0.0114	1.3282
-10	130	0.0028	1.2727	0.0143	1.5841
-9	131	0.0059 ***	2.2782	0.0201 ***	2.0693
-8	133	0.0066 ***	2.4749	0.0267 ***	2.5427
-7	134	-0.0013	-0.5495	0.0254 ***	2.2917
-6	138	0.0057 ***	2.2350	0.0311 ***	2.7686
-5	139	0.0050	1.3143	0.0360 ***	3.0981
-4	140	0.0016	0.7825	0.0377 ***	3.1298
-3	132	0.0002	0.3113	0.0378 ***	3.0377
-2	137	0.0031	0.7975	0.0409 ***	3.2027
-1	143	0.0074 ***	2.5862	0.0483 ***	3.7074
0	149	0.0181 ***	6.3365	0.0664 ***	4.9636
1	155	0.0251 ***	9.8821	0.0915 ***	7.1280
2	151	0.0006	0.3248	0.0921 ***	6.9249
3	143	-0.0032	-1.5857	0.0890 ***	6.2820
4	144	-0.0027	-0.7967	0.0863 ***	6.0014
5	147	-0.0050	-1.3520	0.0813 ***	5.6851
6	143	-0.0048 ***	-2.0650	0.0765 ***	5.1600
7	146	-0.0067 ***	-2.6551	0.0698 ***	4.6919
8	148	-0.0052 **	-1.8488	0.0646 ***	4.2440
9	149	-0.0012	-0.5249	0.0635 ***	4.0502
10	146	0.0001	0.3792	0.0636 ***	3.9810
11	142	0.0013	0.5412	0.0649 ***	3.9478
12	147	-0.0012	-0.7634	0.0636 ***	3.8180
13	140	-0.0017	-0.4563	0.0620 ***	3.5744
14	137	-0.0006	-0.4065	0.0614 ***	3.4304
15	143	-0.0069 ***	-2.6050	0.0544 ***	3.0284
16	144	-0.0003	-0.0981	0.0541 ***	2.9594
17	149	0.0036	1.3445	0.0577 ***	3.1618
18	145	-0.0033	-0.8442	0.0544 ***	2.9166
19	137	0.0006	0.1430	0.0550 ***	2.8408
20	135	-0.0016	-0.5876	0.0534 ***	2.6736

*** indicates significant at the 1% level for a two-tail test; ** indicates significant at the 5% level for a two-tail test.

Table 2-5. Distribution of Estimated AR & CAR around an Effective Switching Day

Abnormal return (AR) is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an effective switching day. Daily TOPIX index is used for market model estimation.

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an effective switching day. Z-statistic is estimated following Linn and McConnell (1983) and Sanger and McConnell (1986).

Day	Sample size	AR(t)	Z-stat(ARt)	CAR(t)	Z-stat(CARt)
-20	140	-0.0026	-1.0621	-0.0026	-1.0621
-19	139	0.0031	1.5571	0.0005	0.4221
-18	140	-0.0005	-0.2154	-0.0001	0.0751
-17	141	0.0004	-0.2291	0.0003	-0.0753
-16	149	0.0052	1.8940	0.0055	0.7462
-15	138	0.0022	1.0789	0.0077	1.0319
-14	141	0.0023	0.6138	0.0100	1.2174
-13	146	-0.0005	0.0678	0.0096	1.2261
-12	143	0.0022	1.1171	0.0118	1.5959
-11	141	0.0046 ***	2.3663	0.0164 ***	2.2181
-10	141	0.0035	1.0035	0.0198 ***	2.4424
-9	140	0.0017	0.7052	0.0215 ***	2.5056
-8	142	0.0008	0.3410	0.0223 ***	2.4978
-7	137	-0.0013	-0.2176	0.0210 ***	2.3403
-6	137	0.0009	0.1930	0.0219 ***	2.2868
-5	145	0.0043	1.6466	0.0261 ***	2.6482
-4	155	0.0338 ***	13.1042	0.0599 ***	5.8458
-3	148	0.0059 **	1.8004	0.0658 ***	5.8983
-2	146	-0.0025	-1.6137	0.0632 ***	5.3273
-1	147	-0.0021	-1.1734	0.0611 ***	4.9460
0	157	-0.0036	-1.2964	0.0575 ***	4.5580
1	159	-0.0168 ***	-6.1698	0.0407 ***	3.1728
2	146	-0.0092 ***	-3.2897	0.0315 ***	2.3583
3	144	-0.0081 ***	-2.9379	0.0234 **	1.7366
4	143	-0.0008	-0.2786	0.0226	1.6156
5	140	-0.0041	-1.4836	0.0186	1.3202
6	140	-0.0021	-0.5828	0.0164	1.1724
7	135	-0.0025	-0.8251	0.0140	0.9709
8	138	-0.0007	-0.1403	0.0133	0.9664
9	139	-0.0034	-0.9710	0.0099	0.7652
10	139	-0.0066 ***	-2.6034	0.0033	0.2953
11	148	-0.0011	-0.2056	0.0022	0.2547
12	150	0.0006	0.2340	0.0028	0.2975
13	143	-0.0006	-0.1992	0.0022	0.2476
14	132	-0.0001	0.1072	0.0020	0.2403
15	132	0.0004	0.5098	0.0024	0.2958
16	143	-0.0001	-0.1795	0.0024	0.2659
17	146	-0.0027	-1.0963	-0.0003	0.1101
18	143	-0.0003	-0.2581	-0.0005	0.0005
19	139	0.0005	0.0763	0.0000	0.0023
20	138	0.0042	1.6573	0.0042	0.2345

*** indicates significant at the 1% level for a two-tail test; ** indicates significant at the 5% level for a two-tail test.

Table 2-6. Liquidity Effect - Comparisons of Differences within Groups

This table presents comparison statistics for mean differences of pre- and post-switching year liquidity proxies for five sample groups. Panel A is for all switching firms group; Panel B is for the group of switching firms with TSE matching firms; Panel C is for the group of switching firms with JASDAQ matching firms; Panel D is for TSE matching firms group; Panel E is for JASDAQ matching firms group.

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid of bid-ask price; BAP is the average daily relative bid-ask spread deflated by daily closing price. DAV is the average daily number of shares traded. TDV is the average daily trading turnover, where daily trading turnover is the number of shares traded over total number of common outstanding shares. SHOUT is the number of common outstanding shares in thousands. RetVol is the return volatility, which is measured by standard deviation of the difference in natural logarithm closing price. SHOUT is the average daily Garman and Klass intraday return volatility estimated by equation 2-9. GKVol is the market model residual volatility of Garman and Klass intraday return volatility estimated by equation 2-11. PRE is measurement at fiscal year-end before a switch; POST is measurement at fiscal year-end after a switch.

	Panel A. SF-ALL		Panel B. SF-MFTSE		Panel C. SF-MFJQ		Panel D. MF-TSE		Panel E. MF-JQ	
	Mean	t-Stat	Mean	t-Stat	Mean	t-Stat	Mean	t-Stat	Mean	t-Stat
BAS_PRE : BAS_POST	1.1422	11.5732	1.0833	7.3495	0.9929	4.8618	-0.0843	-0.5496	0.1417	0.5298
BAP_PRE : BAP_POST	1.0710	11.4303	1.0045	7.3551	0.8874	4.6365	-0.0757	-0.4947	0.1208	0.4694
DAV_PRE : DAV_POST	-22398.49	-1.4523	-13521.85	-2.1513	-5999.26	-0.58	-31057.1	-2.4084	6853.47	1.69
TDV_PRE : TDV_POST	-0.0084	-0.5314	-0.0272	-1.2975	0.0207	0.6198	-0.0350	-1.6990	0.0577	2.2679
SHOUT_PRE : SHOUT_POST	-0.6012	-3.8927	-0.2880	-3.0583	-0.3715	-2.7159	-2.4377	-1.3728	-1.4841	-2.0899
RetVol_PRE : RetVol_POST	0.0042	4.2092	0.0028	2.1131	0.0044	2.1616	-0.0002	-0.1357	0.0011	0.5284
GKV_PRE : GKV_POST	0.0000	1.1449	0.0000	0.0204	0.0001	1.9458	0.0000	-1.4078	0.0000	-0.0087
GKVol_PRE : GKVol_POST	0.0002	2.6010	0.0002	1.5778	0.0002	1.9981	-0.0001	-1.2129	-0.0002	-1.0678

Table 2-7. Liquidity Effect - Comparisons of Differences among Groups

This table presents statistical comparisons of differences in average liquidity proxies among different groups, during pre- and post-switching year. Panel A is for differences in mean between SF-ALL group and MF-TSE group; Panel B is between SF-MFTSE group and MF-TSE group; Panel C is between SF-ALL group and MF-JQ group; Panel D is between SF-MFJQ group and MF-JQ group; Panel E is between MF-TSE and MF-JQ groups. SF-ALL group includes all switching firms in the present study; SF-MFTSE group consists of switching firms with matching TSE firms; SF-MFJQ group consists of switching firms with matching JASDAQ firms; MF-TSE group consists of matching TSE firms; MF-JQ group consists of matching JASDAQ firms.

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid of bid-ask price; BAP is the average daily relative bid-ask spread deflated by daily closing price. DAV is the average daily number of shares traded. TDV is the average daily trading turnover, where daily trading turnover is the number of shares traded over total number of common outstanding shares. SHOUT is the number of common outstanding shares in thousands. RetVol is the return volatility, which is measured by standard deviation of the difference in natural logarithm closing price. GKV is the average daily Garman and Klass intraday return volatility estimated by equation 2-9. GKVVol is the market model residual volatility of Garman and Klass intraday return volatility estimated by equation 2-11.

PRE is measurement at fiscal year-end before a switch; POST is measurement at fiscal year-end after a switch.

	Panel A.			Panel B.			Panel C.			Panel D.			Panel E.		
	SF-ALL:MF-TSE			SF-MFTSE:MF-TSE			SF-ALL:MF-JQ			SF-MFJQ:MF-JQ			MF-TSE:MF-FQ		
	Mean	t-Stat		Mean	t-Stat		Mean	t-Stat		Mean	t-Stat		Mean	t-Stat	
BAS_PRE	1.2629	6.9699		1.3462	6.3943		-0.1618	-0.6852		0.2861	0.8811		-1.4247	-4.9310	
BAP_PRE	1.1690	6.6941		1.2358	6.0861		-0.2209	-0.8303		0.1861	0.5914		-1.3899	-4.8242	
DAV_PRE	-47498.63	-3.12		-58256.83	-3.28		12509.50	1.04		-544.46	-0.08		60008.14	3.31	
TDV_PRE	0.0221	1.2664		-0.0066	-0.3643		-0.0120	-0.4326		-0.0010	-0.0284		-0.0341	-1.2098	
SHOUT_PRE	-35.2037	-4.5148		-36.3657	-4.6777		7.7892	3.0581		0.4637	0.2677		42.9929	5.6852	
RetVol_PRE	0.0050	3.5746		0.0029	1.9685		-0.0017	-0.9220		-0.0016	-0.6320		-0.0067	-3.1566	
GKV_PRE	0.0001	0.9653		0.0000	-0.7339		0.0000	-0.2862		-0.0001	-0.6705		-0.0001	-0.8900	
GKVVol_PRE	0.0002	1.4256		0.0001	0.5471		0.0000	-0.3191		-0.0001	-1.0632		-0.0002	-1.5309	

	Panel A. SF-ALL:MF-TSE			Panel B. SF-MFTSE:MF-TSE			Panel C. SF-ALL:MF-JQ			Panel D. SF-MFJQ:MF-JQ			Panel E. MF-TSE:MF-FQ		
	Mean	t-Stat		Mean	t-Stat		Mean	t-Stat		Mean	t-Stat		Mean	t-Stat	
<i>BAS_POST</i>	0.0365	0.1993		0.1787	0.8027		-1.1623	-4.1626		-0.5651	-1.6088		-1.1987	-4.0335	
<i>BAP_POST</i>	0.0222	0.1233		0.1556	0.7182		-1.1712	-4.2909		-0.5805	-1.6910		-1.1935	-4.0801	
<i>DAV_POST</i>	-56157.24	-1.74		-75792.08	-2.73		41761.47	2.20		12308.26	0.98		97918.70	3.69	
<i>TDV_POST</i>	-0.0045	-0.1855		-0.0145	-0.5150		0.0542	2.9261		0.0361	1.0846		0.0587	2.4349	
<i>SHOUT_POST</i>	-37.0402	-4.5424		-38.5153	-4.7482		6.9063	2.4500		-0.6489	-0.3138		43.9464	5.5096	
<i>RetVol_POST</i>	0.0006	0.4302		-0.0001	-0.0491		-0.0047	-2.5340		-0.0048	-2.2871		-0.0053	-2.4773	
<i>GKV_POST</i>	0.0000	-0.8003		-0.0001	-1.7287		-0.0001	-1.0137		-0.0002	-2.2868		0.0000	-0.4165	
<i>GKVVol_POST</i>	-0.0001	-1.4235		-0.0002	-1.9757		-0.0004	-2.7324		-0.0005	-3.2837		-0.0003	-1.5613	

Table 2-8. Factor Analysis – Switching Firms

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid of bid-ask price; daily trading turnover is the average number of shares traded over total number of common outstanding shares; return volatility is measured by standard deviation of the difference in natural logarithm closing price. Factor 1 and Factor 2 are principal factors extracted by factor analysis. Communalities indicate the amount of variance in each variable that is accounted for by the factors. Communalities extractions are estimates of the variance in each variable accounted for by the factors.

Panel A. Communalities Extraction				
Inputs	Communalities Extraction			
	Pre-switching		Post-switching	
BAS	0.964		0.925	
Daily Trading Turnover	0.807		0.853	
Return Volatility	0.843		0.902	

Panel B. Component Extracted by Principal Component Analysis				
Inputs	Pre-switching		Post-switching	
	Factor 1	Factor 2	Factor 1	Factor 2
BAS	-0.387	0.902	-0.522	0.808
Daily Trading Turnover	0.899	-0.00036	0.923	-0.032
Return Volatility	0.81	0.432	0.675	0.668

Panel C. Variance Explained by Principal Component Analysis		
Component	Total Variance Explained	
	Pre-switching	Post-switching
Factor 1	53.81%	52.68%
Factor 2	33.34%	36.65%
Total	87.15%	89.33%

Table 2-9. Factor Analysis – TSE Matching Firms

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid of bid-ask price; daily trading turnover is the average number of shares traded over total number of common outstanding shares; return volatility is measured by standard deviation of the difference in natural logarithm closing price. Factor 1 and Factor 2 are principal factors extracted by factor analysis. Communalities indicate the amount of variance in each variable that is accounted for by the factors. Communalities extractions are estimates of the variance in each variable accounted for by the factors.

Panel A. Communalities Extraction			
Inputs	Communalities Extraction		
	Pre-switching	Post-switching	
BAS	0.918	0.904	
Daily Trading Turnover	0.932	0.942	
Return Volatility	0.916	0.908	

Panel B. Component Extracted by Principal Component Analysis				
Inputs	Pre-switching		Post-switching	
	Factor 1	Factor 2	Factor 1	Factor 2
BAS	-0.473	0.833	-0.324	0.894
Daily Trading Turnover	0.964	0.0481	0.967	-0.083
Return Volatility	0.4	0.87	0.438	0.846

Panel C. Variance Explained by Principal Component Analysis		
Component	Total Variance Explained	
	Pre-switching	Post-switching
Factor 1	43.79%	41.04%
Factor 2	48.41%	50.71%
Total	92.20%	91.75%

Table 2-10. Factor Analysis – JASDAQ Matching Firms

BAS is the average daily relative bid-ask spread, which is the daily closing bid-ask difference deflated by the mid of bid-ask price; daily trading turnover is the average number of shares traded over total number of common outstanding shares; return volatility is measured by standard deviation of the difference in natural logarithm closing price. Factor 1 and Factor 2 are principal factors extracted by factor analysis. Communalities indicate the amount of variance in each variable that is accounted for by the factors. Communalities extractions are estimates of the variance in each variable accounted for by the factors.

A. Communalities Extraction				
Inputs	Communalities Extraction			
	Pre-switching		Post-switching	
BAS	0.950		0.935	
Daily Trading Turnover	0.832		0.882	
Return Volatility	0.906		0.920	

B. Component Extracted by Principal Component Analysis				
Inputs	Pre-switching		Post-switching	
	Factor 1	Factor 2	Factor 1	Factor 2
BAS	-0.641	0.734	-0.527	0.811
Daily Trading Turnover	0.911	0.0361	0.938	-0.035
Return Volatility	0.754	0.581	0.668	0.689

C. Variance Explained by Principal Component Analysis		
Component	Total Variance Explained	
	Pre-switching	Post-switching
Factor 1	60.33%	53.47%
Factor 2	29.28%	37.77%
Total	89.60%	91.25%

**Table 2-11. Investor Recognition Effect –
Regression of Announcement Abnormal Return on Merton (1987)
Investor Recognition Factor**

Estimated cumulative abnormal return around the announcement day of a switch is regressed on the investor recognition factor, which reflects the change on risk factor of incomplete information before and after an effective switch. The investor recognition factor is estimated by:

$$\Delta\lambda_i = \frac{Resvar_i \times Mktval'_i}{TSE\ holder_i} - \frac{Resvar_i \times Mktval_i}{JASDAQ\ holder_i}$$

where $Resvar_i$ is the residual variance from the market model during the estimation window of ± 20 to ± 140 days around an effective switching day. $TSE\ holder_i$ and $JASDAQ\ holder_i$ are number of TSE common stock shareholders and JASDAQ common stock shareholders. For the JASDAQ shareholders, it is the number of shareholders on the balance sheet at the fiscal year-end just before a switch. The number of TSE shareholders is the balance sheet fiscal year-end data right after a switch. $Mktval_i$ is the relative market value before a switch, which equals the market value of security i 's common stock during the fiscal year-end month before an effective switch divided by the JASDAQ index in the same month; $Mktval'_i$ is the relative market value after a switch, which equals the market value of security i 's common stock during the fiscal year-end month after an effective switch divided by the JASDAQ index in the same month. P-value is for a one tail probability.

Panel A shows the test statistics for regression by equation: $CAR_{it} = \alpha_i + \beta_i \Delta\lambda_i + \varepsilon_{it}$

Panel A				
Lag Num	Coef $\Delta\lambda$	T-Stat	P-value	Adjusted R ²
0	2.633	0.719	0.236	-0.003
1	10.983	1.670	0.047	0.010
2	12.872	1.713	0.043	0.011
3	8.258	1.021	0.154	0.000
4	4.137	0.479	0.316	-0.005
5	-4.289	-0.478	0.316	-0.005
6	-3.597	-0.373	0.354	-0.005
7	-9.102	-0.967	0.167	0.000
8	-17.154	-1.806	0.035	0.013
9	-22.119	-2.220	0.013	0.023
10	-22.127	-2.094	0.018	0.020
11	-18.664	-1.684	0.046	0.011
12	-22.354	-1.860	0.031	0.014
13	-29.599	-2.279	0.011	0.024
14	-31.740	-2.284	0.011	0.024
15	-26.856	-1.824	0.034	0.014
16	-28.635	-1.909	0.028	0.015
17	-25.226	-1.644	0.050	0.010
18	-27.322	-1.741	0.041	0.012
19	-31.615	-1.958	0.025	0.016
20	-28.335	-1.711	0.044	0.011

Panel B shows the test statistics for regression by equation: $CAR_{it} = \alpha_l + \beta_l \Delta BAS_i + \varepsilon_{il}$,
where $CAR_{it} = \sum_{l=-l}^l AR_{it}$, $l=0$ to ± 20 , $\Delta BAS_i = BAS_i(post) - BAS_i(pre)$

Panel B				
Lag Num	Coef ΔBAS	T-Stat	P-value	Adjusted R ²
0	0.001	0.728	0.233	-0.003
1	-0.002	-0.426	0.335	-0.005
2	0.002	0.300	0.382	-0.005
3	0.005	0.775	0.219	-0.002
4	0.007	1.009	0.157	0.000
5	0.010	1.479	0.070	0.007
6	0.011	1.528	0.063	0.008
7	0.011	1.490	0.068	0.007
8	0.013	1.766	0.039	0.012
9	0.017	2.269	0.012	0.024
10	0.017	2.078	0.019	0.019
11	0.019	2.290	0.011	0.024
12	0.014	1.535	0.062	0.008
13	0.015	1.505	0.066	0.007
14	0.015	1.381	0.084	0.005
15	0.014	1.229	0.110	0.003
16	0.012	1.060	0.145	0.001
17	0.014	1.216	0.112	0.003
18	0.013	1.095	0.137	0.001
19	0.012	0.916	0.180	-0.001
20	0.009	0.709	0.239	-0.003

Panel C shows the test statistics for regression by equation:

$$CAR_{it} = \alpha_l + \beta_l \Delta TDV_i + \varepsilon_{il}, \text{ where } CAR_{it} = \sum_{t=-l}^l AR_{it}, l=0 \text{ to } \pm 20,$$

$$\Delta TDV_i = TDV_i(post) - TDV_i(pre)$$

Panel C				
Lag Num	Coef ΔTDV	T-Stat	P-value	Adjusted R ²
0	0.015	1.374	0.085	0.005
1	0.026	0.817	0.207	-0.002
2	0.052	1.421	0.078	0.006
3	0.044	1.120	0.131	0.001
4	0.060	1.455	0.073	0.007
5	0.038	0.889	0.187	-0.001
6	0.047	1.012	0.156	0.000
7	0.061	1.337	0.091	0.005
8	0.056	1.217	0.112	0.003
9	0.049	1.001	0.158	0.000
10	0.072	1.411	0.079	0.006
11	0.080	1.488	0.068	0.007
12	0.122	2.104	0.018	0.020
13	0.140	2.234	0.013	0.023
14	0.158	2.361	0.009	0.026
15	0.211	3.020	0.001	0.046
16	0.227	3.199	0.001	0.052
17	0.243	3.361	0.000	0.057
18	0.249	3.372	0.000	0.057
19	0.238	3.105	0.001	0.048
20	0.264	3.382	0.000	0.058

Panel D is the test statistics for regression by equation:

$$CAR_{it} = \beta_{0i} + \beta_{1i} \Delta \lambda_i + \beta_{2i} \Delta BAS_i + \varepsilon_{it},$$

where $CAR_{it} = \sum_{t=-l}^l AR_{it}$, $l=0$ to ± 20 , $\Delta BAS_i = BAS_i(post) - BAS_i(pre)$

Panel D								
Lag Num	Coef $\Delta \lambda$	T-Stat	P-value	Coef ΔBAS	T-Stat	P-value	Adjusted R^2	
0	3.159	0.845	0.199	-0.002	-0.726	0.234	-0.006	
1	11.984	1.785	0.037	-0.004	-0.767	0.221	0.008	
2	12.917	1.682	0.046	0.000	-0.031	0.488	0.005	
3	7.313	0.885	0.188	0.004	0.588	0.278	-0.004	
4	2.543	0.288	0.387	0.006	0.931	0.176	-0.005	
5	-7.120	-0.782	0.217	0.011	1.601	0.055	0.005	
6	-6.691	-0.685	0.247	0.012	1.629	0.052	0.005	
7	-12.281	-1.287	0.099	0.013	1.715	0.043	0.011	
8	-21.216	-2.215	0.013	0.016	2.183	0.015	0.035	
9	-27.551	-2.767	0.003	0.022	2.807	0.002	0.061	
10	-27.430	-2.589	0.005	0.021	2.576	0.005	0.051	
11	-24.487	-2.207	0.014	0.023	2.701	0.003	0.046	
12	-26.969	-2.219	0.013	0.018	1.954	0.025	0.030	
13	-34.740	-2.647	0.004	0.020	2.016	0.022	0.041	
14	-36.897	-2.624	0.004	0.020	1.887	0.030	0.039	
15	-31.583	-2.115	0.017	0.019	1.629	0.052	0.023	
16	-32.993	-2.165	0.015	0.017	1.472	0.071	0.022	
17	-29.996	-1.926	0.027	0.019	1.577	0.057	0.019	
18	-31.883	-2.000	0.023	0.018	1.473	0.070	0.019	
19	-35.868	-2.185	0.014	0.017	1.333	0.091	0.021	
20	-31.833	-1.886	0.030	0.014	1.067	0.143	0.012	

Panel E is the test statistics for regression by equation: $CAR_{it} = \beta_{0i} + \beta_{1i}\Delta\lambda_i + \beta_{2i}\Delta TDV_i + \varepsilon_{it}$,
where $CAR_{it} = \sum_{l=-l}^l AR_{it}$, $l=0$ to ± 20 , $\Delta TDV_i = TDV_i(post) - TDV_i(pre)$

Panel E						
Lag Num	Coef $\Delta\lambda$	T-Stat	P-value	Coef ΔTDV	T-Stat	Adjusted R ²
0	2.515	0.688	0.246	0.022	1.249	0.000
1	10.851	1.647	0.050	0.025	0.778	0.008
2	12.605	1.682	0.046	0.050	1.385	0.017
3	8.030	0.993	0.160	0.043	1.094	0.001
4	3.818	0.443	0.329	0.060	1.440	0.002
5	-4.497	-0.501	0.308	0.039	0.900	-0.006
6	-3.850	-0.400	0.345	0.047	1.020	-0.005
7	-9.431	-1.004	0.158	0.062	1.362	0.005
8	-17.464	-1.841	0.033	0.058	1.273	0.017
9	-22.394	-2.247	0.012	0.051	1.071	0.023
10	-22.528	-2.139	0.016	0.075	1.480	0.026
11	-19.102	-1.730	0.042	0.082	1.541	0.019
12	-23.018	-1.935	0.026	0.125	2.171	0.035
13	-30.366	-2.367	0.009	0.144	2.325	0.049
14	-32.604	-2.380	0.009	0.162	2.454	0.052
15	-27.999	-1.949	0.026	0.214	3.094	0.061
16	-29.866	-2.047	0.020	0.231	3.280	0.069
17	-26.538	-1.784	0.037	0.246	3.428	0.069
18	-28.670	-1.884	0.030	0.253	3.445	0.072
19	-32.905	-2.092	0.018	0.242	3.189	0.067
20	-29.761	-1.854	0.032	0.267	3.453	0.071

Panel F is the test statistics for regression by equation: $CAR_{it} = \beta_{0i} + \beta_{1i}\Delta\lambda_i + \beta_{2i}\Delta BAS_i + \beta_{3i}\Delta TDV_i + \varepsilon_{it}$
where $CAR_{it} = \sum_{l=-l}^l AR_{it}$, $l=0$ to ± 20 , $\Delta BAS_i = BAS_i(post) - BAS_i(pre)$, $\Delta TDV_i = TDV_i(post) - TDV_i(pre)$

Panel F										
Lag Num	Coef $\Delta\lambda$	T-Stat	P-value	Coef ΔBAS	T-Stat	P-value	Coef ΔTDV	T-Stat	P-value	Adjusted R ²
0	2.897	0.774	0.219	-0.001	-0.505	0.307	0.020	1.132	0.129	-0.004
1	11.714	1.738	0.041	-0.003	-0.634	0.263	0.021	0.647	0.259	0.005
2	12.252	1.596	0.055	0.001	0.227	0.410	0.052	1.399	0.081	0.011
3	6.688	0.809	0.209	0.005	0.804	0.211	0.049	1.222	0.111	-0.001
4	1.649	0.188	0.426	0.008	1.222	0.111	0.069	1.642	0.050	0.005
5	-7.809	-0.858	0.196	0.013	1.801	0.036	0.053	1.221	0.111	0.008
6	-7.508	-0.769	0.221	0.014	1.854	0.032	0.063	1.351	0.088	0.010
7	-13.294	-1.399	0.081	0.015	2.012	0.022	0.079	1.721	0.043	0.022
8	-22.236	-2.331	0.010	0.019	2.476	0.007	0.079	1.725	0.042	0.046
9	-28.562	-2.877	0.002	0.024	3.076	0.001	0.078	1.645	0.050	0.070
10	-28.751	-2.733	0.003	0.024	2.928	0.002	0.102	2.026	0.021	0.068
11	-25.931	-2.357	0.009	0.026	3.072	0.001	0.112	2.118	0.017	0.066
12	-28.907	-2.415	0.008	0.023	2.435	0.007	0.150	2.613	0.004	0.063
13	-36.967	-2.868	0.002	0.026	2.535	0.006	0.173	2.788	0.003	0.079
14	-39.368	-2.855	0.002	0.026	2.428	0.008	0.192	2.894	0.002	0.079
15	-34.726	-2.397	0.008	0.026	2.299	0.011	0.244	3.503	0.000	0.084
16	-36.333	-2.466	0.007	0.025	2.173	0.015	0.259	3.660	0.000	0.089
17	-33.563	-2.238	0.013	0.027	2.318	0.010	0.277	3.839	0.000	0.093
18	-35.529	-2.313	0.010	0.027	2.210	0.014	0.283	3.832	0.000	0.092
19	-39.350	-2.472	0.007	0.025	2.005	0.022	0.270	3.532	0.000	0.084
20	-35.609	-2.186	0.014	0.023	1.777	0.038	0.293	3.743	0.000	0.083

Table 2-12. Difference in Mean Distribution of Firm Fundamental Performance Individual Sample Comparison among Switching Firms & JASDAQ Matching Firms

Panel A reports difference in mean distribution of firm fundamental performance proxies between SF-MFJQ group and MF-JQ group during pre-switching periods. In Panel A, 1 Period Dif represents differences in year -1 before a switch, and 2 Period Dif represents differences in year -2 before a switch, and 3 Period Dif represents differences in year -3 before a switch.

Variable	Panel A. SF-MFJQ and MF-JQ during Pre-switching Period								
	1 Period Dif			2 Period Dif			3 Period Dif		
	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value
Market Value (USD millions)	13.6380	0.13	0.8946	-8.7620	-0.12	0.9051	-28.6973	-0.42	0.6716
Common Shares Outstanding (Millions)	0.4637	0.27	0.6033	-0.8649	-0.53	0.5967	-0.7485	-0.47	0.6399
Number of Shareholders (Thousands)	-0.2109	-0.63	0.5326	-0.3168	-1.16	0.2496	-0.3503	-1.40	0.1620
Trading Volume (Thousands shares)	-1.2511	-0.01	0.9882	16.3401	0.22	0.8265	30.8397	0.48	0.6329
Total Assets (USD millions)	-56.8124	-1.10	0.2737	-64.2745	-1.19	0.2369	-68.9790	-1.27	0.2053
Total Liabilities (USD millions)	-47.0290	-1.15	0.2518	-50.7858	-1.13	0.2603	-52.9685	-1.17	0.2437
Leverage (Total Debt to Total Asset)	-5.9748	-2.16 **	0.0326	-5.2638	-1.92*	0.0570	-4.5540	-1.63	0.1042
Total Debt to Total Equity (%)	-14.0894	-0.76	0.4473	-26.8540	-1.40	0.1629	-15.8845	-0.87	0.3839
Pretax Profit Margin (%)	7.7658	1.91 *	0.0575	4.4067	1.87*	0.0632	3.6752	1.84*	0.0669
Pretax Profit Margin Growth (%)	0.0499	0.09	0.9314	-0.3578	-1.02	0.3085	0.0791	0.27	0.7886
Net Profit Margin (%)	6.8963	1.75 *	0.0820	3.9692	1.85*	0.0666	3.2897	1.87*	0.0638
EPS excluding extraord items (USD)	8.6371	1.17	0.2419	0.9797	1.24	0.2174	-1.0868	-0.57	0.5670
ROA (%)	3.4623	4.32 ***	0.0000	2.5430	3.31***	0.0012	2.3782	3.56***	0.0005
ROE (%)	2.1823	0.43	0.6680	3.5179	1.24	0.2171	4.5422	2.16*	0.0325
Dividend Yield (%)	0.4417	3.14 ***	0.0020	0.2250	1.71*	0.0884	0.1689	1.37	0.1721

Panel B reports difference in mean distribution of firm fundamental performance proxies between SF-MFJQ group and MF-JQ group during post-switching periods. In Panel A, 1 Period Dif represents differences in a switching year, and 2 Period Dif represents differences in year 1 after a switch, and 3 Period Dif represents differences in year 2 after a switch.

Panel B. SF-MFJQ and MF-JQ during Post-switching Period										
Variable	1 Period Dif			2 Period Dif			3 Period Dif			P-value
	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	
Market Value (USD millions)	8.7563	0.20	0.8441	10.1712	0.26	0.7924	11.4154	0.35	0.7286	
Common Shares Outstanding (Thousands)	-1.3507	-0.62	0.5347	-0.6489	-0.31	0.5197	-1.3975	-0.65	0.5194	
Number of Shareholders (Millions)	0.4945	1.27	0.2049	0.5611	1.41	0.1618	0.6628	1.65	0.1012	
Trading Volume (Thousands shares)	-35.5035	-0.37	0.7092	-4.5831	-0.06	0.9536	17.3740	0.24	0.8087	
Total Assets (USD millions)	-22.0662	-0.49	0.6272	-18.4041	-0.42	0.6748	-14.6968	-0.34	0.7369	
Total Liabilities (USD millions)	-22.5211	-0.65	0.5186	-19.8177	-0.59	0.5559	-16.4417	-0.49	0.6241	
Leverage (Total Debt to Total Asset)	-5.6312	-1.92 *	0.0563	-5.6188	-1.90*	0.0599	-5.5992	-1.89*	0.0604	
Total Debt to Total Equity (%)	3.9648	0.20	0.8445	-9.8622	-0.40	0.6869	-16.4316	-0.69	0.4920	
Pretax Profit Margin (%)	2.2875	1.88 *	0.0621	3.8406	1.79*	0.0756	4.1333	1.71*	0.0900	
Pretax Profit Margin Growth (%)	0.4461	1.50	0.1350	-7.6083	-0.94	0.3464	-7.3288	-0.91	0.3651	
Net Profit Margin (%)	1.5006	1.89 *	0.0608	3.1781	1.60	0.1111	3.4882	1.53	0.1281	
EPS excluding extraord items (USD)	-2.5037	-0.66	0.5096	-2.3227	-0.63	0.5303	-2.4821	-0.68	0.5000	
ROA (%)	2.4673	2.58 **	0.0108	2.3769	2.91***	0.0042	2.2917	2.92***	0.0040	
ROE (%)	22.2991	1.20	0.2338	12.7764	1.43	0.1547	9.4104	1.60	0.1125	
Dividend Yield (%)	0.4996	3.02 ***	0.0029	0.5277	3.26***	0.0013	0.5196	3.26***	0.0014	

*** indicates significant at the 1% level for a two-tail test; ** indicates significant at the 5% level for a two-tail test; * indicates significant at the 10% level for a two tail test.

Table 2-13. Difference in Mean Distribution of Firm Operational Performance Individual Sample Comparison among Switching Firms & TSE Matching Firms

Panel A reports difference in mean distribution of firm fundamental performance proxies between SF-MFTSE group and MF-TSE group during pre-switching periods. In Panel A, 1 Period Dif represents differences in year -1 before a switch, and 2 Period Dif represents differences in year -2 before a switch, and 3 Period Dif represents differences in year -3 before a switch.

Variable	Panel A. SF-MFTSE and MF-TSE during Pre-switching Period								
	1 Period Dif			2 Period Dif			3 Period Dif		
	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value
Market Value (USD millions)	-44.7117	-0.28	0.7763	-45.5546	-0.35	0.72556	-48.5080	-0.41	0.6845
Common Shares Outstanding (Millions)	-36.3657	-4.68 ***	0.0000	-44.7018	-5.31 ***	2.3E-07	-44.5421	-5.32 ***	0.0000
Number of Shareholders (Thousands)	-4.0965	-5.52 ***	0.0000	-4.2642	-5.77 ***	2.3E-08	-4.3093	-5.79 ***	0.0000
Trading Volume (Thousands shares)	-1718.7818	-4.41 ***	0.0000	-1597.7141	-4.44 ***	1.4E-05	-1522.1184	-4.59 ***	0.0000
Total Assets (USD millions)	-839.8429	-2.22	0.0271	-863.5915	-2.34	0.02028	-870.6279	-2.32	0.0214
Total Liabilities (USD millions)	-718.0618	-2.09	0.0381	-730.3349	-2.15	0.03217	-736.0231	-2.13	0.0342
Leverage (Total Debt to Total Asset)	-7.5295	-2.97 ***	0.0032	-6.4452	-2.54 *	0.01177	-5.5635	-2.20 **	0.0290
Total Debt to Total Equity (%)	-4.2698	-1.45 **	0.1480	-1.4632	-1.66 *	0.09857	-7.2691	-1.73 *	0.0854
Pretax Profit Margin (%)	7.5030	5.86 ***	0.0000	12.2522	2.21 *	0.0279	9.7801	2.76 **	0.0063
Pretax Profit Margin Growth (%)	0.9969	2.23	0.0266	0.1055	0.15	0.878	0.3886	0.69	0.4902
Net Profit Margin (%)	5.2194	5.40 ***	0.0000	9.6969	1.77	0.0778	7.3559	2.13 *	0.0341
EPS excluding extraord items	7.7596	1.62 *	0.1073	8.1222	1.68 *	0.09362	7.9590	1.66 *	0.0991
ROA (%)	4.7481	8.02 ***	0.0000	4.6894	9.99 ***	6.2E-20	4.2899	10.22 ***	0.0000
ROE (%)	13.0218	3.82 ***	0.0002	14.5833	2.66 ***	0.00843	14.0406	4.70 ***	0.0000
Dividend Yield (%)	0.1006	0.74	0.4588	-0.0258	-0.22	0.82253	-0.0194	-0.18	0.8566

Panel B reports difference in mean distribution of firm fundamental performance proxies between SF-MFTSE group and MF-TSE group during post-switching periods. In Panel A, 1 Period Dif represents differences in a switching year, and 2 Period Dif represents differences in year 1 after a switch, and 3 Period Dif represents differences in year 2 after a switch.

Panel B. SF-MFTSE and MF-TSE during Post-switching Period									
Variable	1 Period Dif			2 Period Dif			3 Period Dif		
	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value
Market Value (USD millions)	41.5381	0.21	0.8323	4.0978	0.02	0.98184	-8.2925	-0.05	0.9585
Common Shares Outstanding (Millions)	-47.5352	-4.74 ***	0.0000	-38.5153	-4.75 ***	2.9E-06	-48.4913	-4.80 ***	0.0000
Number of Shareholders (Thousands)	-3.4755	-4.12 ***	0.0001	-3.4698	-4.07 ***	6.3E-05	-3.3855	-3.96 ***	0.0001
Trading Volume (Thousands shares)	-1867.0231	-4.49 ***	0.0000	-1874.5265	-4.36 ***	1.9E-05	-1886.5684	-4.18 ***	0.0000
Total Assets (USD millions)	-865.1917	-1.86 *	0.0646	-858.2762	-1.78 *	0.07692	-823.2514	-1.75 *	0.0811
Total Liabilities (USD millions)	-766.7446	-1.85 *	0.0660	-757.9460	-1.76 *	0.07902	-728.3128	-1.75 *	0.0807
Leverage (Total Debt to Total Asset)	-7.3562	-2.76 ***	0.0061	-7.2654	-2.74 ***	0.00661	-7.3037	-2.76 ***	0.0062
Total Debt to Total Equity (%)	-13.3981	-1.30	0.1939	-12.1005	-1.28	0.20057	-11.4595	-1.28	0.2021
Pretax Profit Margin (%)	6.7809	4.88 ***	0.0000	6.6464	4.88 ***	1.9E-06	6.3307	4.93 ***	0.0000
Pretax Profit Margin Growth (%)	-10.4782	-0.95	0.3415	-10.0309	-0.92	0.36072	-10.1099	-0.92	0.3569
Net Profit Margin (%)	4.2458	4.36 ***	0.0000	4.2211	4.36 ***	1.9E-05	4.0788	4.35 ***	0.0000
EPS excluding extraord items (USD)	6.3822	1.03	0.3024	6.6358	1.07	0.28375	6.5465	1.06	0.2902
ROA (%)	3.9250	6.01 ***	0.0000	3.8790	6.13 ***	3.6E-09	3.8101	6.09 ***	0.0000
ROE (%)	7.0725	3.37 ***	0.0009	7.4884	3.98 ***	9.3E-05	7.0542	3.83 ***	0.0002
Dividend Yield (%)	0.1889	1.42	0.1569	0.2450	1.83 *	0.06808	0.3011	2.30 **	0.0225

*** indicates significant at the 1% level for a two-tail test; ** indicates significant at the 5% level for a two-tail test; * indicates significant at the 10% level for a two tail test.

Table 2-14. Mean Difference Distribution of Firm Operational Performance
Paired-Sample Tests for Pre-switching and Post-switching Periods for Switching Firms

1 Period Dif represents mean differences between variables in year -1 before a switch and variables in a switching year. 2 Period Dif represents mean differences between variables in year -2 before a switch and variables in year 1 after a switch. 3 Period Dif represents mean differences between variables in year -3 before a switch and variables in year 2 after a switch.

Variable	1 Period Dif			2 Period Dif			3 Period Dif		
	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value	Mean Difference	T-stat	P-value
Market Value (USD millions)	111.9683	0.82	0.4131	-229.1464	-0.73	0.4646	-138.2831	-0.64	0.5244
Common Shares Outstanding (Thousands)	-0.6012	-0.46	0.6489	-2.0877	-0.60	0.5490	-2.4188	-0.70	0.4840
Number of Shareholders (Millions)	-1.6264	-2.29 **	0.0224	-2.5646	-4.03***	0.0001	-3.3605	-3.93***	0.0001
Trading Volume (Thousands shares)	-183.3716	-0.95	0.3413	-246.8903	-1.09	0.2746	-316.3128	-1.23	0.2189
Total Assets (USD millions)	-100.0962	-0.55	0.5794	-141.1286	-0.80	0.4270	-159.9062	-0.91	0.3617
Total Liabilities (USD millions)	-59.1818	-0.45	0.6506	-81.8664	-0.63	0.5275	-86.6552	-0.68	0.4947
Leverage (Total Debt to Total Asset)	0.3489	0.17	0.8634	1.5662	0.78	0.4378	2.5350	1.26	0.2092
Total Debt to Total Equity (%)	-1.2158	-0.11	0.9134	5.0533	0.44	0.6583	11.5337	0.97	0.3348
Pretax Profit Margin (%)	0.4837	0.44	0.6606	1.2827	1.29	0.1975	1.5766	1.69*	0.0917
Pretax Profit Margin Growth (%)	0.4840	3.07 ***	0.0023	0.5288	4.40***	0.0000	0.5433	5.13***	0.0000
Net Profit Margin (%)	0.2796	0.45	0.6499	0.6647	1.21	0.2287	0.7601	1.47	0.1439
EPS excluding extraord items (USD)	2.8287	1.09	0.2758	3.0016	1.14	0.2538	2.8987	1.12	0.2649
ROA (%)	0.7787	1.53	0.1264	1.0115	2.17**	0.0304	1.0137	2.23**	0.0266
ROE (%)	2.5659	2.40 **	0.0168	3.3990	3.24***	0.0013	3.6508	3.60***	0.0004
Dividend Yield (%)	-0.2042	-1.82 *	0.0690	-0.4531	-4.57***	0.0000	-0.5423	-5.65***	0.0000

*** indicates significant at the 1% level for a two-tail test; ** indicates significant at the 5% level for a two-tail test; * indicates significant at the 10% level for a two tail test.

**Table 2-15 Difference in Mean Distribution of Cumulative
Abnormal Returns around the Announce Day for Switching Firms,
Low-ROE vs High-ROE Groups**

Cumulative abnormal return (CAR) is cumulated abnormal return for -20 to +20 days around an effective switching day. Abnormal return is market model adjusted excess returns, where market model parameters are estimated over ± 21 to ± 140 days around an announcement of a switch. Daily TOPIX index is used for market model estimation. High-ROE group consists of switching firms with top tercile pre-switching ROE in year -1 before the switch. Low-ROE group consists of switching firms with bottom tercile pre-switching ROE in year -1 before the switch.

Day	Low-ROE	High-ROE	Difference Low - High	t-test
20	0.0092	-0.0005	0.0097	1.5054
-19	0.0026	-0.0060	0.0085	1.0759
-18	0.0058	-0.0077	0.0135	1.2915
-17	0.0112	-0.0015	0.0126	0.9635
-16	0.0088	-0.0050	0.0137	0.9911
-15	0.0113	-0.0022	0.0135	0.8719
-14	0.0096	-0.0005	0.0101	0.6060
-13	0.0069	0.0049	0.0021	0.1132
-12	0.0104	-0.0042	0.0145	0.7506
-11	0.0148	-0.0124	0.0272	1.3804
-10	0.0185	-0.0033	0.0218	1.1057
-9	0.0263	-0.0032	0.0294	1.3862
-8	0.0422	0.0002	0.0420	1.8405
-7	0.0432	0.0027	0.0405	1.7138
-6	0.0381	0.0045	0.0336	1.4676
-5	0.0451	0.0050	0.0401	1.7127
-4	0.0463	0.0090	0.0373	1.4745
-3	0.0434	0.0055	0.0379	1.4906
-2	0.0456	0.0065	0.0391	1.4532
-1	0.0519	0.0056	0.0463	1.7075
0	0.0543	0.0235	0.0308	1.1135
1	0.0902	0.0394	0.0507	1.6371
2	0.0979	0.0360	0.0619	1.9917
3	0.0985	0.0358	0.0627	1.9139
4	0.0930	0.0368	0.0562	1.6772
5	0.0867	0.0439	0.0429	1.2570
6	0.0919	0.0342	0.0576	1.5853
7	0.0834	0.0362	0.0472	1.2569
8	0.0790	0.0326	0.0464	1.2160
9	0.0789	0.0292	0.0497	1.2835
10	0.0776	0.0266	0.0511	1.2915
11	0.0824	0.0297	0.0527	1.2980
12	0.0811	0.0262	0.0548	1.3017
13	0.0801	0.0275	0.0525	1.1862
14	0.0771	0.0297	0.0474	1.0347
15	0.0745	0.0191	0.0554	1.1505
16	0.0746	0.0137	0.0609	1.2353
17	0.0772	0.0237	0.0535	1.0878
18	0.0744	0.0161	0.0582	1.1635
19	0.0775	0.0134	0.0641	1.2459
20	0.0841	0.0082	0.0759	1.4393

APPENDICES

Appendix A. Top Ten Equity Exchanges in Domestic Market Capitalization

Domestic market capitalization is in billions of US dollars at the end of a year. It includes common and preferred shares, and excludes investment funds, rights, warrants, convertibles, foreign companies. Ranking is based on 2006 market capitalization value.

Exchange	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
NYSE	2,692	3,484	3,798	4,213	4,148	5,655	6,842	8,880	10,278	11,438	11,535	11,027	9,015	11,329	12,708	13,311	15,421
Tokyo SE	2,929	3,117	2,319	2,906	3,592	3,545	3,011	2,161	2,440	4,463	3,157	2,265	2,069	2,953	3,558	4,573	4,614
Nasdaq	311	491	619	792	794	1,160	1,512	1,726	2,244	5,205	3,597	2,740	1,994	2,844	3,533	3,604	3,865
London SE	850	986	928	1,151	1,145	1,347	1,643	1,996	2,373	2,855	2,612	2,165	1,856	2,460	2,865	3,058	3,794
Euronext	NA	NA	NA	NA	761	907	1,106	1,323	1,903	2,444	2,272	1,889	1,539	2,076	2,441	2,707	3,708
Hong Kong Exchanges	83	122	172	385	270	304	449	413	344	609	623	506	463	715	861	1,055	1,715
TSX Group	242	266	242	327	315	366	487	568	543	789	766	611	570	889	1,178	1,482	1,701
Deutsche Börse	355	392	347	461	499	577	665	825	1,087	1,432	1,270	1,072	686	1,079	1,195	1,221	1,638
BME Spanish Exchanges	111	127	99	119	124	151	241	290	400	432	504	468	462	726	941	960	1,323
Swiss Exchange	158	174	189	271	285	398	400	575	702	693	792	626	547	727	826	935	1,212

Data source: World Federation of Exchanges, <http://www.world-exchanges.org>

Appendix B. Top Ten Equity Exchanges in Total Value of Share Trading

The share trading value is the total number of shares traded multiplied by their respective matching prices. Total value of share trading includes trading value for domestic shares, foreign shares and investment funds in billions of US dollars. Ranking is based on 2006 value.

Stock exchanges use different definitions and calculation methods to compile turnover statistics, and as a result, strict comparisons between stock exchanges are not valid.

Exchange	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
NYSE	1,325	1,520	1,745	2,283	2,454	3,083	4,064	5,778	7,318	8,945	11,060	10,489	10,310	9,691	11,618	14,125	21,791
Nasdaq	452	694	891	1,350	1,449	2,398	3,302	4,482	5,519	10,467	19,799	10,935	7,255	7,068	8,767	10,087	11,807
London SE	543	554	663	866	1,029	1,153	1,413	1,989	2,888	3,399	4,559	4,520	4,001	3,610	5,169	5,678	7,572
Tokyo SE	1,288	823	477	793	860	884	939	896	751	1,676	2,316	1,660	1,564	2,109	3,218	4,482	5,823
Euronext	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	2,093	1,974	1,937	2,472	2,906	3,853
Deutsche Börse	509	405	454	564	592	594	812	1,068	1,492	1,551	2,120	1,423	1,212	1,299	1,541	1,915	2,737
BME	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	450	500	653	933	1,203	1,566	1,934
Borsa Italiana	42	23	28	66	119	87	103	203	487	539	1,020	634	634	821	969	1,294	1,591
Swiss Exchange ¹	NA	83	118	210	262	340	443	569	689	562	639	591	600	610	792	974	1,397
Korea Exchange ²	76	85	116	212	287	185	178	171	145	733	556	380	597	459	625	1,211	1,342

Data source: World Federation of Exchanges. <http://www.world-exchanges.org>

¹ Swiss Exchange turnover includes shares traded on Virt-x, an electronic cross-border stock trading platform.

² From 2004, trading value includes Korean Securities Dealers Automated Quotations (KOSDAQ) following the integration of Korea Exchange.

Appendix C. Stable-holding and Cross-holding Ratio in Japan
Listing firms

Stable-holdings are firms which have at least one financial institution shareholder.

Cross-holdings are stocks which two listed companies (except trust banks) hold shares in each other's firm.

Ratios are observed holdings' market value out of the total market capitalization, according to a survey by the Nissei Research Institute.

Source of information: cited from JETRO, Japan External Trading Organization.³

³ Chart cited from JETRO, 2002. Statistics source: Japan Council of Stock Exchange (http://www.tse.or.jp/data/examination/distribute_h12.pdf); Nissei Research Institute (<http://www.nli-research.co.jp>).

Appendix D. TSE Daily Price Limits

Daily price limit is daily price variation range, according to previous day's stock closing price or special quote in terms of absolute yen value.

	Previous Day's Closing Price /Special Quote		Daily Price Limits
	(yen)	(yen)	
Less than	100	±30	
Less than	200	50	
Less than	500	80	
Less than	1,000	100	
Less than	1,500	200	
Less than	2,000	300	
Less than	3,000	400	
Less than	5,000	500	
Less than	10,000	1,000	
Less than	20,000	2,000	
Less than	30,000	3,000	
Less than	50,000	4,000	
Less than	70,000	5,000	
Less than	100,000	10,000	
Less than	150,000	20,000	
Less than	200,000	30,000	
Less than	300,000	40,000	
Less than	500,000	50,000	
Less than	1 million	100,000	
Less than	1.5 million	200,000	
Less than	2 million	300,000	
Less than	3 million	400,000	
Less than	5 million	500,000	
Less than	10 million	1 million	
Less than	15 million	2 million	
Less than	20 million	3 million	
Less than	30 million	4 million	
Less than	50 million	5 million	
50 million or more		10 million	

Source of information: TSE Fact Book 2003.

Appendix E. Renewal of Special Quotes Parameters on TSE

Renewal of special quotes is price variation range, according to the price rang of each stock in terms of absolute yen value.

Last Special Quote	Price Level (Yen)	Price Variation (Yen)
Less than	500	±5
Less than	1,000	10
Less than	1,500	20
Less than	2,000	30
Less than	3,000	40
Less than	5,000	50
Less than	10,000	100
Less than	20,000	200
Less than	30,000	300
Less than	50,000	400
Less than	70,000	500
Less than	100,000	1,000
Less than	150,000	2,000
Less than	200,000	3,000
Less than	300,000	4,000
Less than	500,000	5,000
Less than	1 million	10,000
Less than	1.5 million	20,000
Less than	2 million	30,000
Less than	3 million	40,000
Less than	5 million	50,000
Less than	10 million	100,000
Less than	15 million	200,000
Less than	20 million	300,000
Less than	30 million	400,000
Less than	50 million	500,000
50 million or more		1 million

Source of information: TSE Fact Book 2003

Appendix F. Listing Criteria by 2002

Application	TSE 1st Section		TSE 2nd Section		JASDAQ
	A company must meet criteria (1)~(6), (9), and also criteria (7) or (8)		A company must meet criteria (1)~(6), (9), and also criteria (7) or (8)		
(1)No. of Shares to be Listed	20,000 units or more		4,000 units or more		-
(2)No. of Shares Held by "Special Few" ¹⁴	70% or less of the number of shares to be listed.		75% or less of the number of shares to be listed by the time of listing		-
(3)No. of Shareholders Holding 1 unit or More (excluding "special few")	If the number of shares listed is:		If the number of shares to be listed is:		If the number of shares to be listed is: (1) Less than 10,000 units: 300 or more (2) 10,000 units or more but less than 20,000 units: 400 or more (3) 20,000 units or more: 500 or more
	(1) Less than 30,000 units: 2,200 or more		(1) Less than 10,000 units; 800 or more		
	(2) 30,000 units or more but less than 200,000 units: 2,300 plus 100 for each 10,000 units, or more		(2) 10,000 units or more but less than 20,000 units: 1,000 or more		
	(3) 200,000 units or more: 4,000 or more plus 100 for each 20,000 units, or more		(3) 20,000 units or more: 1,200 plus 100 per each 10,000 units in excess of 20,000 units, up to 2,200		
	Provided that the recent share price per 1 unit is:		However, if the recent share price per unit is:		
	(1) ¥100,000 or more but less than ¥500,000: half the number of shareholders required by the criteria above, 2,200 or more		(1) ¥100,000 or more but less than ¥500,000: half the number of shareholders required by the criteria above, 800 or more		
	(2) less than ¥100,000: 2,200 or more		(2) less than ¥100,000: 800 or more		
(4)Market Capitalization of Shares Listed	¥ 4 billion or more		¥2 billion or more		-
(5)Years of Business Operation	3 years or more of continued business operation		Same as 1st Section		-

⁴ "Special Few" refers to ten largest shareholders having special interest in the issuer & the issuer if the issuer also holds shares.

(6)Shareholders' Equity	¥ 1 billion or more	¥1 billion or more	At least ¥200 million on both consolidated and non consolidated basis
(7)Pre-tax Profit	Either (a or b) a. Annual total for each of the last two years: First year: ¥100 million or more, and Second (last) year: ¥400 million or more b. Annual total for each of the last three years: First year: ¥100 million or more, Third (last) year: ¥400 million yen or more, total for the three years: ¥600 million or more	Same as 1st Section	Value of net income in the fiscal year immediately before application was positive on both consolidated and non consolidated basis
(8)Total Market Capitalization	¥ 100 billion or more, provided that the previous year's sales surpass ¥10 billion.	Same as 1st Section	¥1 billion or more at time of listing, maintain at least ¥500 million for 9 consecutive months after listing
(9)Audit	a. There should be no false statements in the applicant's financial statements for the 5 most recent fiscal years. b. The opinion given by a certified public accountant, in the audit reports, should be 'fair' for the 5 most recent fiscal years.	a. There should be no false statements in the applicant's financial statements for the 2 most recent fiscal years (or for the 3 most recent fiscal years, in cases where neither the criteria (7)a nor the criteria (8) are met). b. The opinion given by a certified public accountant, in the audit reports, should be 'fair' for the 2 most recent fiscal years(or for the 3 most recent fiscal years, in cases where neither the criteria (7)a nor the criteria (8) are met). c. The auditor's opinions needed be non-qualified fair in principle.	Audited for 2 fiscal years before listing, the opinion of the auditor for the last year must be "satisfactory" without conditions.

Source of information: TSE Fact Book 2003 and JSDA Fact Book 2003.

Appendix G. Minimum Tick Size

Minimum tick size is the minimum price increment at which trades may be made, based on a stock's price.

Panel A. Tick Size on TSE

	Stock Price per Share	Tick Size
up to	2,000	1
up to	3,000	5
up to	30,000	10
up to	50,000	50
up to	100,000	100
up to	1,000,000	1,000
up to	20,000,000	10,000
up to	30,000,000	50,000
more than	30,000,000	100,000

Panel B. Tick Size on JASDAQ

	Stock Price per Share	Tick Size
up to	1,000	1
up to	10,000	10
up to	100,000	100
up to	1,000,000	1,000
more than	1,000,000	5,000

Source of information: TSE Fact Book 2003 for the tick size on TSE;

Source of information: JASDAQ tick size sources from Uno et al (2002).⁵

⁵ Refer to reference list for Essay Two, Investor Recognition, Liquidity Effects, and the Market Valuation of Switch Listing: the Case of JASDAQ to TSE.