Stock splits, liquidity, and information asymmetry
– An empirical study on Tokyo Stock Exchange

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Abstract:

This paper comprehensively investigates the effects of stock splits on the market characteristics of the stocks and tries to give an explanation for the results referring to the existing hypotheses and previous empirical results. We investigate the trading activity, liquidity, information asymmetry and the investors' behavior changes around the stock splits. The result on the trading activity supports the trading range hypothesis and tick size hypothesis, which states that small traders will be attracted by the lower price following stock splits. The result about liquidity effects shows that the liquidity is enhanced after stock splits. So the liquidity enhancement assumption predicted by the trading range hypothesis is supported by the empirical evidence. The result about information asymmetry shows that the adverse-selection component decreases significantly after the stocks splits, which supports the signaling hypothesis that predicts the reduction of information asymmetries due to the revelation of private information to the public after split events. Though different from the existing findings of other researchers, the result can be explained by their arguments that the increase in noise trading will reduce the adverse-selection component, while the increase in informed trading will increase this component. The result on investors' behavior shows that the appearance of both uninformed traders and informed traders increase significantly after stock splits. This finding supports the trading range hypothesis. The fact that the probability of informed trades (PIN) decreases can accommodate the previous results on trading activity, liquidity, and information asymmetry.

Keywords: Stock splits; Liquidity; Information asymmetry

JEL classification: G14; G32

1. Introduction

The event of stock split is a very popular phenomenon in the equity market, yet it is also the least understood one. Many observations have found that the price and trading activity changed significantly after the stock splits, which can not be explained by the classic finance theory. The hypotheses provided by the researchers after having studied the effects of the stock split can only explain partly the trading characteristics change around the event. This is the important reason why this event draws a lot of interest of the researchers.

As the split only changes the number of shares outstanding of one company, in theory it will not bring any effect on the intrinsic value of the company as the past performance of the company has been certain. And also the stock split will not involve the cash flows of the firm and change the relative strengths of the various interested parties of the firm. So there should be no motivation for the company to split its shares and no effect on the price and trading characteristics of the shares after split. But the reality is different. Stock split is one of the most common phenomena in the stock markets (there are 235 happenings on the NYSE in 1997), and also the observation of the high cumulative abnormal return and increased trading volume after splits is quite different from the theoretical inference.

As a matter of fact, the split is such a common phenomenon in the financial markets that it makes people to have to think why one company bothers to take action to increase their outstanding shares that will incur cost without bringing any profit. Baker and Gallagher (1980) made a survey on financial executives and concluded that the stock split is a useful device to bring the stock into an optimal price range and to increase the liquidity of the stock. It is believed by the managers that the lower price will attract more small investors to trade their companies' stocks and this will increase the ownership base. The increase of ownership base is confirmed by the studies of Lamoureux and Poon (1987) and Maloney and Mulherin (1992).

It is the increase of ownership base rather than the number of shares outstanding that affects the market value of the firm's equity. This has been explained by Merton (1987) in his "Investor Recognition Hypothesis". He stated that "an increase in the relative size of the firm's investor base will reduce the firm's cost of capital and increase the market value of the firm". As many researchers have found the significant change in the market characteristics of the splitting stocks, how to explain this phenomenon is of great importance. What changes happen to the investors' behavior and what is the relation between the traders' behavior change and the market characteristics change of the stocks caused by stock splits are still unsolved questions.

Up to now, there are some hypotheses proposed to explain the effects of stock splits. Three of them are the most popular: signaling hypothesis, trading range hypothesis, and tick size hypothesis. The signaling hypothesis states that the management intends to transfer good information about the company's future performance to the public. The trading range hypothesis thinks the management would like to bring the stock price into a certain optimal range and the stability and liquidity of the stock will increase after split due to the increase of ownership base. The last one, tick size hypothesis, explains the stock split as a solution to keep the tick size relative to the stock price at an optimal level.

However, some of the empirical results are not consistent with these hypotheses. But this does not mean the explaining power of the hypotheses is weak. The motivation of this study is to conduct a detailed empirical study on the trading characteristics and traders' behavior change around the stock splits by investigating the cases happened in the Tokyo Stock Exchange. With the empirical results, we try to explain the effects with respect to the investors' behavior change and to link the results to the existing hypotheses to verify whether they are supported.

In this study we will focus on three aspects of effects induced by stock split: trading activity, liquidity, and information asymmetry. All investors are classified into uninformed or informed traders and their appearances will be studied. The trades and quotations will be investigated in the stocks' trading activity. A stock's market liquidity refers to the ability of the market to absorb the buying or selling order in measure of time and size. The study on information asymmetry is based on the decomposition of the bid-ask spread into order-processing component and adverse-selection component. The uninformed and informed traders' behaviors are studied by adopting a sequential structural model and one important parameter is the probability of informed trading (PIN).

Attributable to the accessibility to intra-daily datasets from the Tokyo Stock Exchange, we can investigate the market characteristics and traders' behavior in more details. The market characteristics are composed of the number of quotes, the number of trades, trade size, trading volume, quoted depth, bid-ask spread, and etc. The traders' behaviors are measured by the probability of informed trading. As an event study, every measure is calculated separately in two time periods that are pre- and post- splits. And then, we compare them to find whether there are changes and whether the changes are significant. There exist conflicting results on the liquidity change after stock split. Some studies find that the liquidity increases after split while others document that the post-split liquidity is lower relative to the pre-split one. Any way, the market liquidity is affected definitely if the stock split happens.

Liquidity measures the feasibility and immediacy of buying or selling stock at certain price and certain volume. The main measure of liquidity used in this study is the bid-ask spread. Following Glosten and Harris (1988), we decompose the bid-ask spread into two parts: adverse-selection component and order-processing component. These two parts are generally adopted to measure information asymmetry cost and processing cost.

Investors' behavior describes the trading activities on the stock. Generally, researchers measure the trading activities with the variables such as trade number, trade size and trading volume. The general measures are adopted in this study, and we also follow Easley, Kiefer and O'Hara (1996) and use an empirical technique to define the uninformed and informed traders' behavior. In previous studies, it has been observed that the stock split is followed by the increase of uninformed trades. But what happen to the informed trades is scarcely mentioned. In this study we will give a detailed study on the change of uninformed and informed trades around the event of stock split.

There are two objectives in this study. The first is to investigate the changes in trading activity, liquidity, information asymmetry and the investors' behavior around the stock split. In these aspects, existing research works mainly focus on the U.S. stock exchanges. We do not find the corresponding studies on the stock split effects on Tokyo Stock Exchange. We take this opportunity with the intention to give a more detailed study on market characteristics and investors' behavior with the availability of intra-daily trading records. The sequential trading model is adopted to study the investors' behavior change while the investors are classified into uninformed and informed traders. The key indicator is the probability of informed trading (PIN) that gives the percentage of the informed trades to the total trades conducted by both the uninformed and informed traders. The behavior of these two kinds of investors will certainly be affected by the stock split happening and their behavior changes are supposed to impact the market characteristics of the stocks. To our knowledge, there is no study in the literature on the traders' behavior on the event of stock split on Tokyo Stock Exchange. The second objective is to give a comprehensive explanation on the empirical results of the above-mentioned trading characteristics change around the stock splits. Many research results of other studies can hardly be explained by the existing hypotheses. One of the important findings of our study is that our empirical results are almost consistent and can be explained very well.

The rest of this paper is organized as follows. Section 2 is the literature review. Section 3 presents the data description and methods adopted in this study. Empirical results and the explanation are presented in section 4. Summary and conclusion are given in section 5.

2. Literature Review

Fama, Fisher, Jensen and Roll (1969) took advantage of the opportunity of stock split to study the market efficiency on the adjustment of stock price to new information. It is regarded as the first one to study the effects of stock splits on market. From then on, more and more researchers contributed their efforts to this event study and several hypotheses were tested in order to explain such event. They use different samples from different markets at different periods. There are two mainstreams on this topic. One is the motivation of the management to split the stocks. The other one concentrates on the effects of stock split on market. Meanwhile, some researchers use the stock split as a chance to test some theories, maybe combining the two aspects mentioned above.

There are mainly three explanations on firm's motivation on stock split: signaling hypothesis, trading range hypothesis or so called liquidity hypothesis, and tick size hypothesis. The signaling hypothesis is formed after observing the abnormal announcement returns of stock split. It says that the management is sending a signal to the market that the firm is expecting an income increase or that the firm's value is underestimated. The trading range hypothesis is based on the assumption that the manager intends to set the stock price to an optimal trading range by splitting stocks and consequently to increase the stock's market liquidity. The tick size hypothesis states that the company tends to split their stocks so that the minimum tick size is optimal relative to the stock price.

The stock split's effects on market mainly focus on the abnormal return, liquidity, trading volume, and return volatility. Many studies have found that there are positive excess returns around announcement day and effective day and that the trading volume and stock liquidity increase significantly. These findings support the signaling hypothesis. But some studies have observed that the bid-ask spreads increase significantly, which contradicts the liquidity enhancement hypothesis. Meanwhile, many empirical studies found that the stock return volatility increase, which is against some modern finance theories which regards that the increase in number of outstanding shares will not affect the firm's market value or the risk faced by the investors.

While all these hypotheses seem plausible, it is difficult to reach a consensus on which one is correct. People begin to use different measures to measure the market characteristics of the stocks after splits. They use not only the absolute bid-ask spread but also relative bid-ask spread, including quoted spread as well as effective spread, to measure the liquidity of the stock instead of the trading volume. They also define the small trades as the uninformed trader's participation in order to observe the change in the uninformed and informed traders' behavior. Also, more and more researchers try to use the microstructure approaches to settle this problem. Besides the general measures of different kinds of bid-ask spreads and depths, they develop some models that may be used not only on the event of split but also to investigate the information contained in the bid-ask spreads and trading activity. Two of them are adopted in this study: bid-ask components and PIN value.

2.1 Signaling hypothesis

The happening of stock split will not affect the cash flows of the firm as the cash dividend and capital structure changes do, so the value of the company shall not be affected by the stock split according to the modern theory. But the empirical researches on splits by Fama, Fisher, Jensen and Roll (1969), Bar-Yosef and Brown (1977), and Charest (1978) found abnormal returns around the announcement day, which is explained as the support to the hypothesis of split announcement effect. According to the signaling model of Spence (1973), Ross (1977), Leland and Pyle (1977) and Bhattacharya (1979), the financial decisions of the management convey information about the firm value. This hypothesis assumes that the information between managers and investors are asymmetric and the managers intent to convey good information to investors. This hypothesis also states that the managers are confident to their company's future earnings and will push their price upward.

Grinblatt, Masulis and Titman (1984) studied the valuation effects of stock splits and stock dividends. They eliminated other significant simultaneous announcement, such as merger announcement, earnings report and cash dividend declaration, which will contaminate the stock split announcement. They concluded that some of the information content of stock split and stock dividend appears to be associated with firms' future cash flow or their future earnings or their equity value. Lamoureux and Poon (1987) studied the abnormal return and trading volume after the stock split. Their findings of the positive cumulative abnormal return and the increase in raw volume of shares traded after the announcement also provide the evidence to support the signaling hypothesis.

To find the support to the signaling hypothesis, McNichols and Dravid (1990) tested whether the stock dividends and splits convey information about company's future earnings and also tested whether the split factor acts as a signal. They used the analysts' earnings forecast error, measured as the percentage difference between the after-split annual earnings reported and the median analysts' before-split earnings forecast, as a proxy for management's private information. To control the two variables of pre-split share price and the market value of the firm's equity which will influence the management's split factor choice according to the trading range hypothesis, they added these variables into the model with analyst's earnings forecast error that is the management's information proxy to find whether the residual variation in split factors can be explained. The result shows that when stock price pre-split and market value of equity are controlled, the correlation between split factors and earnings forecast errors is significant. This suggests that the choice of split factor by the management is incorporated with their private information about future earnings. Their result also supports the signaling hypothesis.

Basing their theory on the assumption that trading is costly, Brennan and Copeland (1988) develop a two-period signaling model of stock splits to explain the abnormal return. They conclude that management can convey its private information about the firm's prospects to investors through the stock split announcement and the reason is that the cost of trading depends on the stock price. Brennan and Hughes (1991), Ikenberry, Rankine and Stice (1996), and Conroy and Harris (1999) also found the supports to the signaling hypothesis that managers of undervalued firms communicate good information by splitting their stocks.

The positive signaling conjecture is not always incredible by taking the stock split's abnormal return as an evidence, as the positive reaction to split may also be due to the improved liquidity after the stock price decreases. Kadiyala and Vetsuypens (2002) found an alternative way to make the signaling test. They proposed the change in short interest as a new measure of the signaling strength of a corporate event. They think that the level of short interest responds differently to the positive signal and enhanced liquidity. It declines if the first one happens and increases if the second one happens. Their findings give weak evidence that stock splits convey a positive signal. However this is not enough to reject the signaling hypothesis.

Though the signaling hypothesis can be supported by the empirical studies, it remains a puzzle why company splits its stock. There shall be no price limit on one stock and other devices (such as dividend) can also be adopted to issue the good signal. Furthermore, empirical researches have documented the negative effects after the split such as the increase of the price return volatility, larger relative bid-ask spread, and the worse information asymmetry. And also the signaling hypothesis can not explain why excess stock returns are also observed around the ex-split date as the ex-split date is predictable following the split announcement and there should be no information content on the ex-date. So researchers give other explanations for the stock split. Grinblatt, Masulis, and Titman (1984), Maloney and Mulherin (1992) explained the excess returns from the viewpoint of microstructure and suggested the liquidity-based explanation for stock splits, and this induces the second hypothesis.

2.2 Trading Range Hypothesis

Copeland (1979) argued that firms prefer to keep the price of their stocks within a certain range. He explained that keeping the certain price range can attract a certain kind of clientele or disperse the ownership of the company. This kind of clientele attracted by the lower price after stock split is usually thought as the uninformed or small investors. Baker and Gallagher (1980) made a survey on management's view to stock split. The survey revealed that the majority of firm's financial officers believed that the stock split was a good device to bring the stock price to an optimal trading range. A lower stock price will attract investors and then enhance the ownership base. Evidences have been found to support this hypothesis.

Lamoureux and Poon (1987) found the daily number of transactions along with the raw trading volume of shares increased following splits. Kryzanowski and Zhang (1996) made use of the trading value to measure the small and large traders and found that the small traders traded more frequently after stock split and the trade direction changed significantly from sell to buy. Angel, Brooks and Mathew (1997), Desai, Nimalendran and Venkataraman (1998), and Schultz (2000) also found the evidence to support the trading behavior change after stock split.

But why does a company want to attract the small or uninformed traders to invest on its stocks? One of the most popular explanations is that the enlarged investor base will increase the liquidity of the stock and thereby reduce the trading cost to the investors. The motivation of the managers to split stocks is to enhance the liquidity. From the viewpoint of liquidity, the trading range hypothesis is also called "liquidity hypothesis". Merton (1987) set up a model of capital market equilibrium with incomplete information. The model indicates that an increase in the relative size of the firm's investor base will reduce the firm's cost of capital and increase the market value of the firm. And he also stated that the managers have incentive to expand firm's investor base. This theory can explain the stock price reaction to stock split. Because the small investors take part in the buying or selling stock after split due to the attraction of lower price, the liquidity of the stock increases consequently. Small traders are also thought as noise traders in contrary to the informed traders. Black (1986) stated that noise trading is essential to the existence of liquid markets, and the more noise trades there are, the more liquid the markets will be. But Black (1986) thought the noise trades also put noise into the prices that reflects in the price return volatility increasing. For example, Lamoureux and Poon (1987) stated that the increased trading volume results in an increase in the noisiness of the security's return process.

There can be many kinds of measures on the liquidity, but the more general or traditional ones are trading volume, bid-ask spread, number of trades, number of shareholders, etc. The proxies can be classified into two categories as measures of friction and activity which are the two dimensions of liquidity. The friction measure is defined by Demsetz (1968), Grossman and Miller (1988), Stoll (2000) as the price concession for immediacy. The activity measures reflect the extent of trading. The bid-ask spread, price and return can be categorized into the friction measure. In contrast, the depths, volume, number of shares and transaction value can be classified into the activity measure. Using different proxies for liquidity, the empirical evidences on the impact of stock splits are mixed. Some support the liquidity enhancing hypothesis, while others contradict it.

Copeland (1979) took both the trading volume and bid-ask spread as measures of the liquidity in studying the 162 OTC firms for the period 1968-1976. The results show that the trading volume is proportionately lower after split while the post-split bid-ask spread increases significantly as a percentage of the stock value. In the two dimensions, the liquidity of stock decreases after split. But Murray (1985) studied 100 OTC splitting firms for the period 1972-1976 and found no evidence of a change in percentage spread relative to a control group. Lakonishok and Lev (1987) took the monthly shares traded relative to the shares outstanding as the measure of stock's marketability and found that the result did not support a decrease in marketability though the stock split's effects on the trading volume was not permanent. Lamoureux and Poon (1987) studied the stock's factor-adjusted trading volume relative to the market's trading volume after stock split, and the result shows that 87 sample stocks' market-adjusted and factor-adjusted trading volume decreases significantly while that of 27 sample stocks shows a significant increase. They concluded that the value of shares traded falls subsequent to the ex-split day.

Conroy, Harris and Benet (1990) also took the absolute spreads and percentage spreads as the measures of liquidity but employed high-quality inside quotes, which captured the lowest ask and highest bid that would have been available to an investor. Their empirical result shows that the shareholder liquidity is worse after stock splits as measured by the percentage bid-ask spread. Although the absolute spread decreases after split, the drop in price is sufficient enough to offset the decrease in absolute spread and leads to an increase in the percentage spread. They also contributed the spread increase to the decrease in share price and showed that the observed increase in return variability after split was partly the result of increase in spreads. The confliction on the result of liquidity change after split mainly origins from the difference in measures adopted by the researchers.

One of the arguments why companies split their stocks, though it may not be regarded as one hypothesis, is the reduction of information asymmetry. Grimblatt, Masulis and Titman (1984) argued that managers use the stock split or stock dividend to convey good information to the market or just call attention to the firm to trigger reassessments of the firm's future cash flows by market analysts. The consequence of the information-leakage or attention-attraction will be the reduction of the information asymmetry existing between the managers and common investors. Brennan and Copeland (1988) presented a model to explain that stock splits are able to signal managerial information about the prospects of the firm precisely because of the influence of the stock price on the cost of trading. Brennan and Hughes (1991) argued that the brokerage commission rate on share price was an incentive for brokers to produce research reports on firms with low share prices. And the stock split is one of the events that will attract the attention of the investment analysts. Also, managers with favorable private information have an incentive to split their companies' shares. Their evidence supports the prediction that the number of analysts following a firm is inversely related to its share price.

But does more information-leakage will result in the information asymmetry' reduction? Desai, Nimalendran and Venkataraman (1998) argued that the change in trading activity would affect the adverse-selection component of the bid-ask spread which was decomposed into three components: order processing cost, adverse selection cost, and inventory holding cost (Stoll (1989)). The increase in noise trading will reduce the adverse-selection component, while an increase in informed trading will increase this component. If both types of traders increase, the effects on the adverse-selection component will be complex and unpredictable. They adopted the method in George, Kaul and Nimalendran (1991) to decompose the total spread into the order-processing and adverse-selection components, and found that the adverse-selection component increased by 0.17 or 22% relative to the pre-split value. The result obviously does not support the assumption that the information-leakage will improve the information environment.

2.3 Tick size hypothesis

This hypothesis suggests that the stock split will create an optimal tick size for stocks. And this optimal tick size will attract liquidity providers to take part in transactions. The liquidity providers are regarded as uninformed traders who can gain from supplying liquidity via limit orders.

Angel (1997) used the minimum price variation to explain the price change around the stock split. She stated that the management tended to keep the tick size relative to the stock price at an optimal level. If the relative tick size is larger than optimal, the company will allow the long-term upward trend of stock prices to reduce it to the desired level. When the relative tick size is too small, the stock split can be adopted to increase it back to an optimal level. As Harris (1991) noted that the tick size could not be zero for the reason that tick simplifies trader' s information sets and reduces time spent on bargaining and the potential for costly error. Also the nonzero tick enforces time and price priority in a limit order book, providing incentive for investors to provide liquidity with limit orders. Furthermore, the tick also provides incentives for dealers to make market. However, the increase of tick also increases the trading cost and offsets the liquidity gains from dealers' incentive. The optimal tick is the trade-off between the benefits of a nonzero tick and the cost that a tick imposes.

By combining the Merton's (1987) model of an incomplete information capital market with Amihud and Mendelson's (1986) finding that higher bid-ask spreads are associated with higher rates of return, Angel (1997) constructed a model. As the increase in number of investors who know about a stock tends to increase the stock price while a higher transaction cost due to the increase of tick size depresses the stock price. The solution to this model is the optimal relative tick size that can balance these effects. The result shows that the tick size can explain partially why the stock price levels differ across countries. Since the rule on tick size varies across countries, the optimal trading range varies accordingly. However, the relative tick size is comparable from country to country.

After Angel (1997), the results of some other researchers support directly or indirectly Angel's (1997) conclusion that the wider percentage bid-ask spread stimulates the brokers to promote the stock. Schultz (2000) provides evidence that in measure of percentage effective spreads the market making is more profitable following splits. Moreover, the increase in the number of small buy orders following splits proves the traditional explanation that the shareholder base of stock increases after splits. Some other studies such as Lamoureux and Poon (1987), Maloney and Mulherin (1992), Angel, Brooks and Mathew (1997), and etc., show the proof that the number of shareholders increases after splits, which support Angel's (1997) argument that a large relative tick size gives brokers more incentives to promote the stock.

2.4 Models

The three hypotheses can partly explain the effects caused by the stock splits and also be supported by the empirical research results. But on more occasions, the results are mixed and the consensus is not reached on which one is correct. Researchers try to find the evidence to support or against the hypotheses by using other techniques that can reveal more information on the trading activities or price change. Two most widely used methods are bid-ask spread decomposition and the probability of informed trading (PIN) calculation. These two techniques are generally used to reveal the traders' behavior change where the traders are commonly classified into noise traders (or uninformed traders) and informed traders. By finding the traders' behavior change and the price-change components, scholars try to find the information which is private and not public revelation that may happen at the trading activities. If more informed traders appear among the trading or the adverse-selection component of the bid-ask spread increases, it can be concluded that the information asymmetry is more serious.

2.4.1 Components of Bid-Ask Spread

Taken the idea that a bid-ask spread can be a purely informational phenomenon, Glosten, and Milgrom (1985) establish the sequential trade model in which the coming buyers and sellers are divided into informed traders and liquidity traders. It is believed that the loss suffered on specialist caused by trading with the informed traders should be compensated by the gains in trades with liquidity traders. Their conclusion is that the adverse selection can account for the existence of a spread. The exogenous arrival patterns of insiders and liquidity traders are one of the parameters that determine the average magnitude of the spread.

Glosten and Milgrom (1985) took the trade as "signals" of information in their sequential model of the market maker's pricing decision. Their model is based on the assumption that informed trader's trading behavior will reflect their information in a competitive market. The market maker will change the offering price of the stock upon receiving trades from the uninformed and informed traders which he can not distinguish. Then stock's price is linked with the concerning information. In their model the bid-ask spread is decomposed into two parts: one is called adverse-selection component which is attributed to the asymmetric information and the other one is called transitory component that arises due to inventory costs, specialist monopoly power, and clearing cost.

Does the technique developed using the bid-ask spread from NYSE, which is quote-driven, single (multiple) dealer market, can also be applied to the Tokyo Stock Exchange which is an order-driven market? Cohen, Maier, Schwartz and Whitcomb (1981) established the existence of the bid-ask spread in a limit-order market when investors face transaction costs of assessing information, monitoring market, and conveying orders to the market. Glosten (1994) showed that a positive bid-ask spread arising from the possibility of trading on private information exists in the limit-order market. Ahn, Cai, Hamao and Ho

(2002) examined the bid-ask components in a limit-order book of the Tokyo Stock Exchange (TSE). They decompose the spread into two components: adverse selection cost and order-processing cost. Their study provides a support on using this technique to investigate the components of the spread in an order driven market.

The bid-ask spread decomposition technique is adopted by researchers to analyze the event of stock split. It is thought that the stock splits would reduce the information asymmetry, but the evidence on the reduction in the extent of information asymmetry following splits is also mixed. Brennan and Copeland (1988) found that the firm's choice of the number of shares outstanding is related to the abnormal announcement return, in line with their signaling model. Brennan and Hughes (1991) thought that the stock splits attract analysts' attention based on the finding that there is a positive relation between the change in analyst following and the split factor. It seems that the findings support the hypothesis that the information asymmetry is reduced after splits. Desai et al. (1998) documented the adverse-selection component of the spread increases after the split. This finding suggests that the information asymmetry is not reduced. Because an increase in noise trading reduces the adverse-information component, while an increase in informed trading increases this component. An increase in both types of traders has a more complex effect on the adverse-information component. Their finding therefore suggests that informed trading increases as well. Thus, it is not clear whether the information environment of the firm following a split is characterized by higher or lower information asymmetry. But the technique of decomposing the spread is a method to test whether the information asymmetry does change.

2.4.2 PIN Value

The decomposition of the bid-ask spread can only give the information on the change of the transitory and adverse-selection components after the splits. As to the change of the composition of the trading population, it is not so easy to give a conclusion. With this intention, but not for the event of splits, of trying to discover the trading activity, researchers develop a microstructure model used to calculate the rates of informed and uninformed trading, the probability of information events. And this method is commonly called PIN value calculation.

Easley, Kiefer and O'Hara (1996) developed an approach using the trading flow information to infer the difference in information content between trading locales. This approach is used to test the cream-skimming versus competition issue. They studied the NYSE and the Cincinnati Stock Exchange. Their trade-based estimation can also provide intriguing insights into the information differences between markets and between individual stocks as well.

As to studying the effects of stock splits with the help of PIN value, one of the studies is Easley, O'Hara and Saar (2001). They used this method to test alternative hypotheses concerning the stock splits. Their model is an extension of the model of Easley, Kiefer and O'Hara (1996) and is used to estimate the underlying parameters that define trading activity. The main parameters are the rates of informed and uninformed trading, the probability of information events, and the propensity to execute trading strategies using limit orders. As they stated, analyzing stock splits using the trading data will sacrifice some of the non-trade related implications of the explaining hypotheses, because any signaling-related effects of splits may be immediately reflected in prices, and thus would not be reflected in trades. They found that both the uninformed and informed trading activities increase after the split and there is a small decrease on the percentage of informed trades or PIN.

The model proposed by the Easley, O'Hara and Saar (2001) is based on the quote-driven market in which more than one market-maker come to compete. But this model can also be adopted in the order-driven market in which the liquidity is provided by the traders who submit the limit-order and the trader plays the role of market-maker as that in the quote-driven market. What's more, the competition on price also exists between traders. And the empirical research has been conducted on the latter market. Ahn, Cai, Hamao and Melvin

(2005) adopt this method in studying the event of minimum trading unit (MTU) change on Tokyo Stock Exchange which is a quote-driven market.

3. Data and Methodology

In this part, we present the source and description of the sample and trading data at first. And then the measures definitions are given. Finally the methods adopted in this study are explained in details.

3.1 Sample

The basic sample is comprised of all Tokyo Stock Exchange (TSE) common stocks that have split with a factor greater than 1.5 from January 1996 to December 2005 and the stock price shall be less than JP Yen 30,000 before the announcement day. The split sample is provided by the TSE, accompanying with the company name, trading symbol, announcement date, effective date and the split factor. The work to confirm the announcement date, effective date and split factor is done by checking with the corresponding splits data from the Bloomberg News Service. Ten firms are eliminated due to the discrepancy between TSE and Bloomberg on these three aspects. In order to avoid the effects of the previous split on the consequent split of the same stock, if the interval between one stock's two split happenings is less than 8 calendar months when the same stock makes more than one time splits during the study period, the stock is deleted from the basic sample. According to this procedure, three more firms are deleted from the basic sample. After all these filtrations, there are 138 stock splits remained.

The real-time trading data or the tick data are obtained from the Nikkei Electronic Database System. The database is complete and comprehensive enough to meet the aim and requirement of this study. Especially, some types of contracts are clearly identified such as contract at the previous bid quote, contract at the previous ask quote, contract at the price which is somewhere between the bid quote and ask quote, and etc. This flag offers great convenience such that we do not need take trouble to identify which contract is buyer initiated and which one is seller initiated. The price and volume on the contract or quote are indicated clearly. The trading time or quotation time is nearest to minute.

3.2 Estimation Windows

This is a typical event study. There are two windows where the observations are made from: one is before split and the other is after split. The observations in these two periods are compared to find any change aroused from the stock split. As the split announcement makes the market know the split event, so the pre-split period shall precede the announcement date. To avoid other events such as stock dividends and mergers contaminating the effects of the stock splits, the pre-split period begins 10 days prior to the split announcement (See Conroy, Harris and Benet (1990)). Correspondingly, the post-split period starts at 10 days after the split effective day. The period is set to be 60 days except for that used to make the estimation of the structural trading models for which 120-day period is chosen.

3.3 Definition of Measures

Some proxies are taken to measure the liquidity and trading activity of the stock. The definitions of these variables are given at this part.

Three variables are used to measure the liquidity of the stock: trading volume, bid-ask spread, and quoted depth.

The most commonly accepted proxies in measuring the liquidity of the stock are trading volume and bid-ask spread. Trading volume as a measure of the stock's liquidity is obvious. Copeland (1979), Murray (1985), Lakonishok and Lev (1987), and Lamoureux and Poon (1987) all use trading volume to measure liquidity in their studies. The bid-ask spread is adopted by researchers more and more since the high-frequency data is available and it discovers more information on trading. Conroy, Harris and Benet (1990) use absolute and percentage bid-ask spread to measure the liquidity. Gray, Smith and Whaley (2002) calculate the effective spread which is thought to be able to reflect the real transaction costs to investors or the revenue to market makers. The information contained in the event will always be reflected in the trading characteristics change around the event. Of course these two variables are not the only used to observe the trading activity. The number of quotations and deals are also important variables that indicate the participation degree of the traders in the market.

The spread can be measured in several ways and we hereby adopt three types of bid-ask spreads: absolute spread, effective spread, and relative spread. Absolute spread is defined as the dollar difference between ask price and bid price at certain time. Effective spread is defined as the twice of the absolute difference between the trade price (P_t) and the quote midpoint (M_t). The relative spread is scaled by the trading price and is defined as (Absolute Spread)/Price. In more clear and concise way, these three types of bid-ask spreads are defined as follows:

$$\text{Absolute Spread} = \text{Ask} - \text{Bid} \tag{1}$$

$$\text{Effective Spread} = \mid \text{Price-(Bid + Ask) / 2} \mid *2 \tag{2}$$

$$\text{Relative Spread} = \text{(Absolute Spread) / Price} \tag{3}$$

All these spread measures are calculated in the time window of a minute unit. That means each variable's value is the result of calculation based on the trading data of one certain minute in a trading day.

The depth of the quotation is also adopted in this study as a measure of the liquidity. The depth is measured by the number of shares of the bid/ask orders submitted at the best bid and offer prices at a certain time. The spread and depth together are two dimensions of the liquidity. The spread measures the price dimension of liquidity, while the depth measures the quantity dimension of liquidity. There is the possibility that the two dimensions will not move in the same direction. So it is ideal to find one way to combine these two measures into one. Gray, Smith and Whaley (2002) introduce a concept of "market quality", which integrates the two dimensions of liquidity into one measure. The quality index is defined as follows:

$$QI_t = \frac{\left(depth-at-bid_t + depth-at-ask_t\right)/2}{percentage-quoted-spread_t \times split-adjustment} \tag{4}$$

In this research, the depths at bid and ask have been adjusted by the split factors, so the split-adjustment can be ignored in the computation of the QI. The higher the depths, the higher the liquidity is. The lower the bid-ask spread, the higher liquidity is. So, if the value of the quality index is larger no matter which of the two measures cause it, the market quality is higher, meaning that the liquidity is higher.

The trading activity is investigated on two aspects: quotations and trades. In further details, the quotations are measured with three variables: daily number of quotes, bid quotations, and ask quotations. The trades are studied in three aspects: the number of trades, trade sizes, and daily trading volume. The quotations and trades calculation are both based on the daily data. But we first find the quotation and trade records at each trading-time during the trading day, then get the sum of the corresponding variables studied. The sum of one variable in one trading-day is then used to find the average value during the study periods. Equally weighted daily averages of the six variables are calculated by averaging the daily values of each variable.

3.4 Methodology

3.4.1 Mean and Median Test

As this is an event study, the major task is to find whether the difference between the values of variables during pre-event period and post-event period is significant. The null hypothesis is the mean or median of a certain variable before splits equals the mean or median of that variable after splits. The alternative hypothesis is the means or medians during the two periods are not equal. The paired t-test and Wilcoxon paired signed-rank test are used to test the hypothesis. If the result is significant, we will reject the hypothesis that the event of stock split does not make effects on the stock characteristics of interest. If it is insignificant, we can not reject our null hypothesis.

3.4.2 GMM and MLE estimation

There are two methods of estimation used in this study. One is the Generalized Method of Moments (GMM) used to estimate the components of the bid-ask spread. The other one is Maximum Likelihood Estimation (MLE) on Probability of Informed Trades (PIN) value. The GMM estimation does not require knowing the distribution of the data which is unlike the method of MLE. The GMM is based on the very simple principle that one should estimate a moment of the population distribution by the corresponding moment of the sample. The MLE is based on the idea that different probability distribution of the population generates different sample. Both of them can be used to estimate the parameters of the linear or nonlinear models.

3.4.3 Decomposition of the Bid-Ask Spread

Desai, Nimalendran and Venkataraman (1998) found that the adverse-selection component of the bid-ask spread increased after stock split. They linked the adverse-selection component with the trading activity change of the uninformed traders and informed traders. They thought the increase in noise trading would reduce the adverse-information component, while the increase in informed trading would increase this component. The combined effect of the increase of both types of traders is complex. Admati and Pfleiderer (1988) argued that the effect depended on the degree of competition among informed traders. Competition among informed traders who receive the identical signals will reduce the adverse-selection component even if the number of informed traders increases. Conversely, if the signals are diverse, the information asymmetry could increase even if the number of informed traders decreases.

Admati and Pfleiderer (1988) used the method of decomposing the price return volatility into a transient component and a permanent component to distinguish the noisy traders and informed traders. The increase in noise trading will primarily affect the transient component, while the increase in informed trading will increase the permanent component of the volatility. In this study, we do not adopt this method to find the trading activity change, but use the sequential trading model that gives a clear trading activity change of the uninformed traders and informed traders in the form of the probability of their appearance. That is the PIN value model which will be explained in details in the following section.

Tokyo Stock Exchange (TSE) is a limit-order market unlike NYSE which is a quote-driven dealer market. But the study on the components of the bid-ask spread will also give the same information. Cohen, Maier, Schwartz and Whitcomb (1981) established the existence of the bid-ask spread in a limit-order market when investors face transaction costs of assessing information, monitoring market, and conveying orders to the market. Glosten (1994) showed that the limit-order market would have a positive bid-ask spread arising from the possibility of trading on private information. In fact each limit-order trader in an order-driven market plays a role of market maker as in a quote-driven market.

There are lots of theoretical and empirical works on the components of bid-ask spread. As Ahn, Cai, Hamao and Ho (2002) stated that there are two classes of statistical models. The first one relies on the serial covariance properties of the observed transaction prices. This can be found in the works of Roll (1984), Lin, Sanger and Booth (1995), and Huang and Stoll (1997). And the second class of models is based on the trade initiation indicator variables. The works by Glosten, and Harris (1988) and Madhavan, and Smidt (1991) can be classified into this one. As the trade direction is clearly indicated in the dataset from the NEEDs, the trade indicator models are appropriate in this study on decomposing the bid-ask spread.

Glosten and Harris (1988) set up a model which breaks the spread into two components.

The first one is transitory component which is to cover the inventory costs, clearing fees, and/or monopoly profits that are required by the market-makers. The second one is called adverse-selection component which is thought as an additional widening of the spread to compensate the loss aroused from the trade by the market-makers with informed traders. Though the model is based on the market-makers, the limit-order traders can be interpreted as market-makers. The two-component asymmetric information spread model is adopted in this study. Different to their econometric method used that is the Maximum Likelihood Estimation method, we estimate the parameters of the equation using Generalized Method of Moments (GMM), which imposes very weak distribution assumptions. As Ahn, Cai, Hamao and Ho (2001) stated that this is especially important because the error term includes rounding errors due to discreteness of stock prices.

Here we briefly describe the two-component asymmetric information spread model for estimating the components of bid-ask spread of the stocks making splits on the TSE. The change in transaction price at time t is denoted as $D_t=P_t-P_{t-1}$, where P_t indicates the transaction price at time t, and P_{t-1} indicates the previous transaction's price. And Q_t is defined to be the buy-sell indicator variable for the transaction. We let Q_t =+1 if the transaction is buyer initiated or transaction at ask quotation and -1 if the trade is seller initiated or transaction at bid quotation. The trading data from NEEDs have been marked which transaction is at the quotation of ask or bid. The trading volume is denoted as V_t. α is the transitory spread component, β is the adverse-selection component, and μ_t is the error term. With the trading data mentioned above, the following equation is used to estimate the transitory component or order-processing component and adverse-selection component.

$$D_t = \alpha(Q_t - Q_{t-1}) + \beta Q_t V_t + \mu_t \tag{5}$$

Since the transaction is classified as a buyer- or seller-initiated trade by the price location flags available from the dataset. Almost all the trades of the stock splits are made either at the bid or ask except that quite a small number of trades are made either within or outside the spread. As Ahn, Cai, Hamao and Ho (2001) argued that since the Tokyo Stock Exchange is a pure order-driven market without responsible market makers, a trade should always hit either the bid or the ask. So we follow them and exclude all trades made within or outside the spread. We also exclude the transactions made during the off-hours trading session. The reason is as Ahn, Cai, Hamao and Ho (2001) stated that the off-hours transactions often deal with negotiated large block trades through a system called ToSTNet (Tokyo Stock Exchange Trading Network System). Besides, we also exclude the opening and closing transactions in each trading day.

To facilitate the estimation of the two components of the bid-ask spread, we adopt the stocks that have the trading data with at least 20 valid trading days. A valid trading day is defined as a trading day with at least five valid transactions. When counting the valid transactions, we exclude the opening and closing trades for the morning and afternoon sessions, and the transactions against special quotes as well.

3.4.4 Probability of Informed Trade

Easley, Kiefer and O'Hara (1996) developed a method for estimating the probability of informed trading to explain the observed differences in spreads for active and infrequently traded stocks. They used this technique to find how frequently new information occurs, and how large a fraction of the order flows is from informed traders. Following this original paper, several others use this technique in different markets and events and also develop it. The sequential trade model developed by Easley, Kiefer and O'Hara (1996) gives us a method to estimate the probability of an informed trade which can also be used in a limit-order market.

In this model, the informed and uninformed individuals trade a single risky asset with the market maker who is thought to be risk neutral, and the price of the asset is set equal to his expected value of the asset. The information is defined as private if it affects trading and public if it does not. The uninformed traders are generally thought doing business on the public information. The informed traders are thought to trade on their private information.

The information events happen prior to the beginning of any trading day and they are thought to be independently distributed and to occur with probability α. The good information events occur with the probability of 1-δ and the bad information events occur with the probability of δ. The full information value of the asset is only realized after the end of trading on any day.

Market makers will deal with both informed traders and uninformed traders. Arrivals of uninformed buyers and uninformed sellers are determined by independent Poisson processes. Their trades arrive at the rate of ε per minute of the trading day. The uninformed traders arrive every day because their submissions of orders are unrelated to the existence of any private information signal. In contrast, the informed traders arrive only on days when there has been an information event. Because the informed traders are assumed to be risk neutral and competitive, they will buy when observing good news and sell when observing bad news. The arrival of the informed traders also follows a Poisson process. The arrival rate for this process is μ. All of these arrival processes are assumed to be independent. If there is a good information event this day, which has the probability of α(1-δ), the buying orders which are the sum of buying orders of both uninformed traders and informed traders will arrive at the rate of ε + μ, while the selling orders arrive at the rate of ε. If there is a bad information event this day, with the probability of αδ, the selling orders, which are the sum of selling orders of both uninformed traders and informed traders ,will arrive at the rate of ε + μ, while the buying orders arrive at the rate of ε. It can be found that the rate of arrival of uninformed traders will not be affected by the information events. If there is no information event on one day, with the probability of 1-α, there will be only uninformed traders to buy or sell the stock in the market. The buy and sell orders will arrive at the rate of ε and the number of buy or sell orders is expected to be equal. So, one of three situations happens every day: no event, good news, and bad news.

According to the results of Easley, Kiefer and O'Hara (1996), the probability of informed trading or PIN is defined as:

$$PIN(t) = \frac{\mu(1-P_n(t))}{\mu(1-P_n(t)) + 2\varepsilon} \tag{6}$$

Where Pn(t) represents the probability of no information event happening at time t. If the parameters of $\theta = (\alpha, \delta, \varepsilon, \mu)$ are known, the PIN can be easily calculated.

The parameters can be estimated using MLE method from the structural model which extracts information on the parameters from the observable number of buys and sells. Though the Poisson process followed by the buys and sells are not known, the trading data reflects the information structure: more buy orders on good news days; more sell orders on bad news days; and fewer orders on days with no news. Thus, the buys and sells (*B*, *S*) data will be enough to estimate the order arrival rates. Weighting the likelihood of the observed orders by the probabilities of each type of day occurring ($1-\alpha, \alpha\delta, \alpha(1-\delta)$), the likelihood function is:

$$\begin{aligned} L((B,S)|\theta) = {} & (1-\alpha)^* e^{-\varepsilon T} \frac{(\varepsilon T)^B}{B!} e^{-\varepsilon T} \frac{(\varepsilon T)^S}{S!} \\ & + \alpha\delta^* e^{-\varepsilon T} \frac{(\varepsilon T)^B}{B!} e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^S}{S!} \\ & + \alpha(1+\delta)^* e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^B}{B!} e^{-\varepsilon T} \frac{(\varepsilon T)^S}{S!} \end{aligned} \tag{7}$$

Where *T* is the number of time intervals in each day. With the data of buys and sells (*B*, *S*), the estimations of the rate of informed and uninformed trading can be found.

Trade data are taken from the NEEDs Daily Summary data. From that database, the 'Number of Contract at Price of Asked Quotation' which equals to the Sells number at the structural model and the 'Number of Contract at Price of Bid Quotation' which equals to the Buys number are given in the morning or afternoon session. With regard to the trading period, Easley, Kiefer and O'Hara (1996) took the sixty day window to observe the trading activity and they thought it was sufficient to allow reasonably precise estimation of the parameters. Considering the relatively high stock price and the low frequency of trading at TSE, we follow Ahn, Cai, Hamao and Melvin (2005) and take 120 trading days as the observing window to estimate the parameters. We take the 120 trading days before the announcement date as the pre-period and the 120 trading days after the effective date as the post-period. Some stocks do not trade at certain trading days during these two periods. If one stock's number of valid trading days which requires at least 5 valid transactions is less than 20, this stock will be deleted from this parameters' estimation. Consequently, the final sample used in the PIN value estimation consists of 136 split events.

4. Empirical Results and Explanations

In this section, the sample characteristics are described at first. Then the empirical results on the trading characteristics change around the stock splits are presented in details. The trading characteristics include trading activity, liquidity, information asymmetry, and PIN value. The explanations are given following the results.

4.1 Sample Description

The distribution of these 138 samples at different years from January 1996 to December 2005 with different factors ranging from 1.5 to ≧10 is listed in the **Table 1**. The split happens only one time in 1996, and the number increases to be 16 at 1999. In the following 6 years it fluctuates from 13 times to 23 times. It reaches its highest value of 41 times in 2004.

The factors adopted by the companies range from 1.5 to ≧10. **Table 1** also gives the distribution of events grouped by the factors across different years. We can find the most frequently adopted factor by the companies is 2 and the number of samples reaches 85. Factors of 1.5 and 3 are also what companies prefer to choose and the total number of events is 47. These three factors account for 95.7% of the total splits. There are 4 samples that split their stocks by the factor equal to or bigger than 10.

Figure 1 plots the time interval between the announcement day and effective day for the 138 samples. The time intervals are classified into 7 periods: less than or equal to 10 days, bigger than 10 days but less than or equal to 20 days, and so on, the last period is bigger than 60 days. Most of the samples take splits in effect in less than 40 days after announcing them. The mean of the time interval is 32 days, and the median value is 26 days. The minimum days is 7 days and the maximum one is 117 days, which means the company takes almost half a year to take effect of the split.

The Tokyo Stock Exchange classifies the listed companies into 9 industries, according to PACAP, that cover from Fishery, Agriculture & Forestry, and Mining to Real Estate, Financial and Insurance, and Service. The frequency distribution of stock splits by industry is presented **Table 2**. It can be seen that splits concentrate on three industries (Manufacturing, Wholesale and Retail, and Service).

We also classify the stocks by the sections which are 1st section, 2nd section at **Figure 2**. The explanation given by the Tokyo Stock Exchange is that the first section is for the largest, most successful companies - often referred to as 'blue chips'. The second section is for smaller companies with lower trading volume levels. From the figure, we can find more than half of the splits belong to the 1st section.

4.2 Trading Activity Effects

To examine the trading activity effects of the stock split, we use three measures on trades: the number of trades, trade sizes, and daily trading volume, as well as three measures on quotations: the number of quotations, the numbers of quotations at ask and at bid.

It is thought that the lower price of the stock after split will attract small traders to come into the market to trade and small traders are thought to buy or sell at a small amount in measure of shares or in values. So there shall be an increase on the trading numbers and also on the number of quotations while the trading size may not increase proportionally. As

Admati and Pfleiderer (1998) posit, the number of both small and informed traders would increase after the announcement of stick splits.

Some previous studies try to distinguish the trader types by classifying the trading volume or trading value into small or large trades. It is not difficult to understand their reasoning that the noise or uninformed traders are attracted by the lower price and would buy or sell in small amounts with the wealth-constraint and without information on the stocks, while the informed traders prefer to buy or sell in large amount if they achieve private information on the stocks. The informed traders may be institutional buyers or sellers who are thought to trade in large amounts. Some researchers use the method of classifying trades into small and large trades according to either the number of shares in the trade or the trade value. For example, Kamara and Koski (2001) defined "small trade" as that less than or equal to 400 shares and "other trade" as that greater than 400 shares. But there is another possibility that the informed traders will hide them behind the noisy traders and may not trade the stock in such a large amount as people think. No matter what the reality is or which situation it is, it is hard to distinguish the types of traders only from the trading activities of the stock after split. Some other researchers adopt other methods. Desai, Nimalendran and Venkataraman (1998) made use of the volatility decomposition to distinguish the noise and informed traders. Their classification is based on the assumption that the an increase in noise trading would primarily affect the transient component, while an increase in informed trading would increase the permanent component of volatility. But this method is less powerful because the relations between the change on traders' activity and the return volatility' change need to be attested. So we do not divide the trades into small or large trades by the trading volume or value or by decomposing the return volatility into transient and permanent components.

The results can be found from the **Table 3** and **Table 4**. To each measure adopted to measure the trading activities effects, the mean and median values of pre-split period and post-split period are presented in the second and third column. The results of paired t-test for mean test (t value) and Wilcoxon matched-paired signed-ranks test for median (sign rank) are reported. The p-value of the log difference between the post-split and pre-split values is reported at the final column to show whether the result is statistically significant or not. As to the Trade Size and Daily Volume measures, the post-split results are based on the factor-adjustment. In detail, the post-split numbers are adjusted or divided by the split factor while the pre-split numbers are not. All these three measures are calculated on the equally weighted average, which means that the results are based on the equal weight of each stock not considering the difference on the price and trading value of each stock.

From the **Table 3** we can find the quotations change. The daily number of quotes increases significantly from the mean value of 654 during pre-split period to 925 during post-split period. There is a 38.8% increase in the daily quotation after stock splits on average. This increase is statistically significantly with the p-value is smaller than 0.01. The median value changes from 430 to 685 and there is an increase of 38.4%. The median test shows this increase is significant with the p-value being less than 0.01. The quotation changes on both ask and bid sides are also reported in **Table 3**. The results show that there are significant increases on both ask quotations and bid quotations after the stock splits. It is very interested to find that the quotation numbers on ask side (327.43) and bid side (327.44) are almost equal during pre-split period, while this situation does not change after the stock split with the quotation numbers increasing to be 462.43 on ask side and 462.52 on bid side. The median numbers are also in agreement with the mean result. The median value changes from 215.22 to 342.87 on ask and bid. It seems that the stock split does not affect the balance between the ask quotation and bid quotation.

The changes in trading number, trade size and trading volume are reported at **Table 4**. The daily number of trades increases significantly from the mean value of 132 during pre-split period to 182 during post-split period. In percentage, the increase is 41%. The increase is statistically significant with the p-value smaller than 0.01. The median value changes from 69 during pre-split period to 121 during post-split period with an increase by 42% and the p-value is smaller than 0.01, which shows that the change is statistically significant. The result on the number of trades also shows that there is a significant increase.

Will the increase of trading number be accompanied by the increase of trading volume proportionally? The results of trading size and trading volume are reported at part B and part C. The trade size decreases from the mean value of 575 shares during pre-split period to 360 shares during post-split period which is factor adjusted. The t-value is -21.28 and p-value of the log-difference between pre-split and post-split values is less than 0.01 which is statistically significant. The result is confirmed by the median test, according to which the pre-split median is 343 and the post-split median is 204. The p-value of log-difference of the medians is less than 0.01 which is still statistically significant.

The results show that the trade size decreases significantly while the number of trades increases significantly. Then we may consider how about the result of trading volume, which is the result of the number of trades multiplied by the trade size. The part C of **Table 4** reports that there is no significant change on the daily trading volume after stock splits. The trading volume is measured in number of shares. The mean value decreases from 85,513 shares to 84,508 shares after stock splits and the median increases from 23,733 to be 22,665. The p-value of the log-difference is 0.45 which is insignificant. The median values test does support the null hypothesis that there is no significant change between the trading volumes of pre-split and post-split periods. The p-value of log-difference is 0.70.

There are two findings: one is that both the trading numbers at bid and at ask increase after the stock splits and this is consistent with the previous result on the trading number increase which does not differentiate whether the trades is at bid or at ask; the second is that the trades at bid almost equals to the trades at ask during both pre-split and post-split, and there is not an obvious and significant shift from sell to buy.

As signaling hypothesis states that management use splits to convey good information to the public. If this assumption is right, we can expect more buying orders or transactions shall appear because investors are motivated by good news. Different from other researchers' adopting the positive abnormal return (AR) or cumulative abnormal return (CAR) as proof to support the signaling hypothesis, we use the change on ratio between transactions at bid and transactions at ask to test this hypothesis. The result is presented at **Table 5**. The estimation period is 60 trading days before the AD and the observation period is 10 trading days after AD. The ratio decreases significantly after AD in the following 10 trading days and this decrease is significant. This shows a significant increase on number of transactions reached at ask compared to that of transactions reached at bid. Investors are more likely to buy stocks instead of selling them. We do not count the change after ED because the news of splits becomes known to the public at AD but not ED. Our empirical result gives support to the signaling hypothesis.

Some researchers examine the trade direction change. Kryzanowski and Zhang (1996) found that the trade direction changes significantly from sell to buy after split ex-dates for all but the large trades, where the change is in the opposite direction. We also investigate the trade direction change after the stock splits. The daily mean and median numbers of trades at ask, at bid, and within the bid-ask spread for the pre-split period and post-split period are presented in **Table 6**. Because the trading flag indicates clearly whether the transaction is reached at bid or at ask or between the bid and ask, it is not necessary to adopt the method of Lee and Ready (1991) to differentiate whether they are buyer-initiated or seller-initiated. We do not classify the trades into small or large ones. Because the number of trades increases and trades size decreases to a statistically and economically significant extent, we can think that there is a significant shift from large trades to small trades. So the results can reveal some information on the traders behavior change. The results show that there is a significant increase both on the number of trades at ask and number of trades at bid. The mean of the numbers of trades at ask increases from 69 to 91, while the median value changes from 35 to 58. The p-values of the mean and median tests are both less than 0.01. The mean of trades at bid increases from 64 to 90, while the median changes from 33 to 61. It seems that the stock splits do not only encourage the small traders to buy the stocks but also to sell the stocks, and it is possible that the sellers reduce the trade size. The balance between the seller-initiated trades and buyer-initiated ones does not change after the happening of the splits in long term.

According to the results of the trading activities, we discover the following findings:

after the stock split, the transaction frequency during post-split period increases significantly compared to that of the pre-announcement period. The trade size decreases significantly. The total trading volume in shares does not appear any change. The empirical results indicate that there is a large increase in the number of small trades which are thought to buy or sell comparatively small number of shares each time. Small trades are not necessarily caused by the small traders, but the results give us some evidence that the small traders' behavior changes responding to the event of split. From the results of the number of trades and trade size, we can infer that there are more small investors participating in trading following stock splits and small investors become more active in trading. At least investors decrease their trade size after the stock splits. The stock split is an attraction to noisy traders or small investors due to the lower price of the stock.

4.3 Liquidity Effects

We take three types of bid-ask spreads and the quoted depths at bid and ask to examine the liquidity effects of the stock split. To calculate the spreads, we first find the average value of the bid, ask, and transaction price at each moment. If there is no bid or ask at one moment though this situation scarcely happens, the transaction will be matched to the nearest previous bid and ask price. If there is no transactions at one moment, no action will be taken on the bid and ask price at that moment. First, we calculate the two average values of the three kinds of bid-ask spreads in a day during pre-split period and post-split period for each stock. Then, the average of each stock's daily average spreads is calculated. After the average daily spreads for each stock are calculated, the mean and median values of three measures across stocks in the sample are then computed. The values of quoted depths at bid and ask are also achieved following the above mentioned procedure. All the measures are equally weighted.

The results of the quoted depths are reported in the **Table 7**. Part A describes the results of depth at bid measured in shares and the results at ask are reported at part B. The cross-sectional means and medians of the daily average depths in shares tell us that there is a significant decrease on the depths after splits. The mean value of the depths at bid decreases from 1,599 shares before splits to 1,154 shares after splits and the p-value of the log-difference is less than 0.01 which is statistically significant. This decrease in percentage is 28.7%. The median values also decrease significantly with the p-value of the log-difference being less than 0.01 from 857 shares during the pre-announcement period to 574 shares during the post-split period. The depths at ask also show the same tendency. The mean value decreases from 1,865 shares to 1,139 shares and the median value decreases from 947 shares to 648 shares, which are also statistically significant. The decrease of the depths shows that one aspect of the stock liquidity becomes worsen after split.

The results of the spreads change are represented in **Table 8**. The mean and median values of each type of spread are given during two periods which are pre-announcement period (pre) and post-split period (post). The p-values of the log-difference are given in the last column to test whether the difference is significant or not. These three types of bid-ask spreads all show that there is a decrease on the spread after the stock splits compared with those of the pre-announcement period. In Part A, the mean value of the effective spread which is the difference between the trading price and the midpoint of the bid and ask at the same moment decreases from 44.55 to 23.46 with the p-value being less than 0.01. The median value of the effective spread decreases from 15.30 to be 7.35 with the p-value being less than 0.01. The decrease in percentage is 83.3% and 69.8% respectively. The absolute spread change shown in Part B indicates that the mean value of the absolute spread decreases from 63.73 JP Yen to 35.39 JP Yen with the p-value being less than 0.01. The median value of the absolute spread also decreases from 23.78 JP Yen to 10.96 JP Yen with the p-value being less than 0.01. In percentage the decrease is 83.2% and 69.3% respectively. As the effective spread and absolute spread are both measured in the absolute value, the median values of these two measures are more meaningful in study due to the outliers or extreme values. Because the price change will happen certainly after the stock splits, the absolute values change shown by the effective and absolute spread can not take the price change into consideration and also can not indicate the change on the real trading cost which is usually measured by the relative spread that is the ratio between the absolute spread and trading price. So we give the empirical result on the relative spread in Part C. It shows that the mean value of the relative spread decreases from 1% to 0.8% with p-value of the log-difference being less than 0.01 and the median value is found to decrease from 0.68% to be 0.48% with the p-value of the log-difference being less than 0.01. The results are statistically significant. The results of the three types of bid-ask spreads change are all statistically significant.

Spreads are important measures to examine the liquidity of the stock because these measures indicate the trading cost faced by the investors. The empirical result of decrease on the bid-ask spread in this study shows that liquidity increase after the stock split.

What is the mixed effects on liquidity change when the bid-ask spreads decrease enhances liquidity while the quoted depths decrease worsen liquidity. So we adopt the quality index to combine the effects from these two dimensions and use it to indicate the liquidity change after the stock splits. The result in Panel A of **Table 9** shows that the mean value of quality index increases from 41,560 to 160,784 with the p-value being less than 0.01. The median value also increases from 3,118 to 4,982 with the p-value being less than 0.01. We can conclude that the liquidity increases actually after the stock splits.

Taking the previous empirical results on the trading activities into consideration, we find liquidity change findings is consistent with what Demsetz (1968) stated that higher volume results in lower bid-ask spreads. There is no significant change on the trading volume after stock splits, while the bid-ask spread decreases significantly. So the trading volume itself can not explain the change on the bid-ask spreads.

In summary, the results on the trading volumes, quoted depths and the bid-ask spreads are mixed. When liquidity is measured by the trading volume and quoted depth, the stock liquidity is worsen after split. Meanwhile, when the liquidity is measured with the bid-ask spread, the stock's liquidity increases after stock split. To unit the two dimensions in quantity and price of the stock, the market quality index is computed to give a comparatively comprehensive test. The increase of the quality index indicates that the extent of the decrease of the bid-ask spread is much larger compared to the decrease in quoted depth. From the result of the quality index, we can conclude that the stock's liquidity is enhanced in whole after stock splits.

Our finding is different to those of the previous researches most of which find that the relative bid-ask spread increases after the stock split and supports the hypothesis that stock split will enhance the liquidity of the stock.

4.4 Information Asymmetry Effects

Kyle (1985) argued that the presence of traders who possess superior knowledge of the value of a stock can impose adverse selection costs on liquidity traders and market makers. Market makers are compensated for bearing this cost by widening the bid-ask spread, and thus ultimately recoup the cost from liquidity traders. So the adverse-selection component of bid-ask spread is taken as a method to measure the information asymmetry.

We adopt the model of Glosten and Harris (1988) to estimate the adverse-selection component of the bid-ask spread and the results are presented at **Table 10**. The results indicate that the decrease happens on the adverse selection component but not on the order processing cost. We examine the components in the percentage of stock price. The mean value of the adverse selection component is 0.109% during pre-split period and 0.087% during the post-split period. The mean difference is significant with the p-value being less than 0.01. The significant mean decrease result is supported by the median test of which the median changes from 0.087% during pre-split to 0.072% during post-split with the p-value being less than 0.01. From Part B of **Table 10**, we can find that the order processing cost component shows no change after the stock splits. We also give the result on the proportion of adverse selection component among the spread. It can be seen that the proportion fall after the stock splits and the change is significant.

It can be deducted from the information asymmetry theory that the adverse-selection component of the bid-ask spread will increase due to the exposure of the market makers to the better informed traders. As we previously state that Desai et al. (1998) related the adverse-selection component change to the trading activity change of the traders who are formed by the uninformed traders and informed traders. The empirical results show that the adverse-selection component decreases after the stock split, can it be explained in this way that this decrease is because of the less informed traders participation, or more uninformed traders' joining, or the fact that both the informed and uninformed traders come to the market while the proportion of the informed traders to the total traders decreases after the stock splits. This question can not be answered before we go to next part that presents the study result on the uninformed and informed traders behavior change. The next section reports evidence on the probability of an informed trade before and after the stock splits. If it is right that the spread will arise to protect the market maker from losses due to trading with informed traders, the decrease on the adverse-selection component after stock splits is consistent with the decrease on the bid-ask spreads as previously observed.

If we take the adverse-selection component as the measure to measure the information asymmetry environment around the stock splits, the empirical results show that the information asymmetry has been reduced after the stock splits. At this point, our finding support the signaling hypothesis that states the information asymmetry will be reduced because the stock splits will bring the good information that previously was private to public.

4.5 Probability of Informed Trades Before and After Stock Splits

We expect that the participation of the uninformed traders and informed traders will increase after the stock splits as we think the uninformed traders will be attracted by the lower price after split. This is based on the assumption that more stockholders most of whom are uninformed traders will increase the liquidity of the stock. So the probability of the uninformed traders' appearance ε is expected to increase. More uninformed traders would, all else equal, lower the probability of the informed trades (PIN). The signaling hypothesis also foresees a decrease on the information asymmetry due to the information discovery speeding up. As the probability of information events happening (α) is taken to measure the private information happening but not the public information event, it is connected with the appearance of the informed traders (μ). It is also predicted to decrease after the split according to the signaling hypothesis which predicts that the private information revealed by trading will be turned into public information if the stock splits attract more analysts to follow the firm. But the information revelation by the analysts will in some degree stop the informed traders' participation in the transactions, because some of the previous private information they own now becomes public. So finally the information events appearance will determined by the appearance of the informed traders.

The informed traders' behavior change can hardly be predicted by the existing hypotheses. Admati and Pfleiderer (1988) stated that the informed traders would take advantage of the uninformed traders' trading activity. They thought the informed traders will trade more actively in the periods when liquidity trading is concentrated. So we expect that the informed traders will take part in the trades more aggressively if more uninformed traders are attracted to come in the market to buy or sell stocks by the lower price after stock splits and the latter situation is predicted by the trading range hypothesis. So the probability of the informed traders' appearance μ is expected to increase.

The estimation results on the pre-split and pot-split parameters are presented in **Table 11**. From the result we can find that the information event happening which is indicated by α increases significantly from the mean value of 0.337 during pre-split period to 0.419 during post-split period, and the post-pre difference is significant at the significance level of 1%. The median test is supportive to the post-pre change and it is significant at the significance level of 1%. The increase of the information events is consistent with the following result that the informed traders increase significantly after stock splits. Easley, O'Hara and Saar (2001) use the information events happening to test the information asymmetry and their finding of the statistically insignificant increase on the probability of an information event casts doubt on the information asymmetry explanation for splits. As stated before, we think the information events appearance is determined by the appearance of the informed traders. And the information environment shall be measured by the adverse-selection component of the bid-ask spread that shall not be caused only by the probability of the informed traders' appearance but also shall take the uninformed traders' appearance into consideration. This will be discussed after the PIN value is estimated.

The uninformed traders' appearance of ε shows a significant increase after splits. The mean value of the ε increases from 41.44 to 63.04 and the change is significant at the significance level of 1%. The same result can be found in the median test which is also significant at the significance level of 1%. As to the informed traders' appearance that is indicated by the symbol of μ, its mean value increases from 58.86 to 65.52 and median value increases from 39.52 to 44.60. The mean and median tests are both significant at the significance level of 10%. The increase in uninformed trade and informed trade is consistent with predication of the trading range hypothesis and tick size hypothesis.

The proportion of the informed trading which is indicated by the probability of informed trading or PIN value gives the estimation that how many trade are dealt by the informed traders among the total trades. The estimation result shows that the mean PIN value decreases from 0.23 to 0.21 and this decrease is significant at the significance level of 5%. And this result is also supported by the median test. Desai et al. (1998) argued that the increase in noise trading would reduce the adverse-information component, while the increase in informed trading will increase this component. So it is understandable that Easley, O'Hara and Saar (2001) used the PIN value to represent the extent of the adverse selection problem. The PIN value can show the combined effect when both types of traders increase. The trading range hypothesis and the signaling hypothesis both predict the decrease of the information asymmetry and the fall in PIN. The empirical results in this study support the trading range hypothesis that predicts the increase of the uninformed traders and the signaling hypothesis that predicts the decrease of information asymmetry which is caused by the decrease on the proportion of the informed trades to the total trades.

From the estimation results obtained, it can be concluded that after the split there is more information leaked concerning the companies that split their stocks and the information asymmetry condition' improvement is not because of the information events happening increase but it is reduced because of the decrease on the PIN value. After the split, the uninformed traders are attracted by the lower price compared to that of the pre-split period even though they are not updated by the new information brought by the informed traders. With the rush of the uninformed traders into the stock market, the informed traders are encouraged to trade more aggressively based on their judgment on the stock price. They will sell the stock if they think it is overpriced and buy it if they think it is undervalued. The uninformed traders are thought to achieve the increased liquidity of the stock due to the lower price after split but not because of the stock value adjusted by the information happened. Though both the uninformed and informed traders execute the transactions more frequently after stock splits, but the degrees of them are different.

The decrease in the PIN value shows that, among the total trades, the proportion of informed trades decreases significantly. As a result of the decreased PIN, the information asymmetry decreases, which would lower the risk faced by the traders and also narrow down the quoted spread. Because the PIN value change gives a good explanation for the previous results: changes in the adverse-selection component and bid-ask spread, the relation between the traders' behavior and the market characteristics of the stock proves existing.

5. Summary and Conclusion

Stock split is one of the topics that have been always attracting researchers' interest in the finance field. Yet the existing hypotheses concerning the effects of the stock split can not explain the phenomena happening subsequent to the stock split. In this study, we investigate the effects of the stocks splits on the market characteristics of the stocks and try to give an explanation for the results by the existing hypotheses and previous empirical results of other researchers.

First, the trading activity change has been studied. The main measures adopted in this study are quotations and trades. In details, the number of quotations, number of trades, trade sizes, and daily trading volume are investigated. The results show that both the number of quotations and the number of trades increase significantly after stock splits, while the trade sizes decreases significantly and there is no significant change on the daily trading volume. Meanwhile, the quoted depths decrease significantly. The findings imply that the stocks are traded more actively only on small trades after stock splits. The results on the trading activity support the trading range hypothesis and tick size hypothesis, which states that small traders will be attracted by the lower price following stock splits.

Second, the liquidity effects of the stock split are investigated with the measures of the bid-ask spreads and quoted depths. Three types of bid-ask spreads are examined: the absolute spread, the effective spread, and the relative spread. The quote depths are studied both at the ask side and the bid side. The results show that all the bid-ask spreads decrease significantly after stock splits, while the quoted depths at both sides decrease significantly. The two opposite effects of the spread and depths are combined by the quality index to measure the liquidity change. The result shows that the liquidity is enhanced after stock splits. So the liquidity enhancement assumption predicted by the trading range hypothesis is supported by the empirical evidence.

Next, the information asymmetry is studied. The adverse-selection component of the bid-ask spread is adopted to measure the information asymmetry change around the stock splits. The results show that the adverse-selection component decreases significantly after the stocks splits, which supports the signaling hypothesis that predicts the reduction of information asymmetries due to the revelation of private information to the public after split events. Though different from the existing findings of other researchers, the result can be explained by their arguments that the increase in noise trading will reduce the adverse-selection component, while the increase in informed trading will increase this component.

Finally, estimation is made on the parameters of a sequential trade model to investigate the change in the investors' behaviors. The investors are divided into uninformed traders and informed traders. The results show that the appearance of both kinds of traders increases significantly after stock splits. This finding supports the trading range hypothesis. The fact that the probability of informed trades (PIN) decreases can explain the previous effects on trading activity, liquidity, and information asymmetry. Although the informed trades increase after the stock splits, their proportion to total trades decreases significantly. So the increase in the information asymmetry caused by the informed trades are offset or overwhelmed by the decreasing effects caused by the uninformed trades. As the information asymmetry and the probability to meet the informed trades are reduced, the market makers are facing less risk compared to that during pre-split period. This decreased risk is reflected on the decrease in volatility and bid-ask spread. So all the empirical results are consistent and can be explained soundly from the viewpoint of the investors' behavior change.

This paper provides a comprehensive study on the effects of stock splits by investigating the case of Tokyo Stock Exchange. The findings indicate that the events of stock splits really affect the quality of splitting stocks. And it is the change in the investors' behavior that causes the change in the market characteristics of the splitting stocks. The existent hypotheses are supported by the empirical results in this study.

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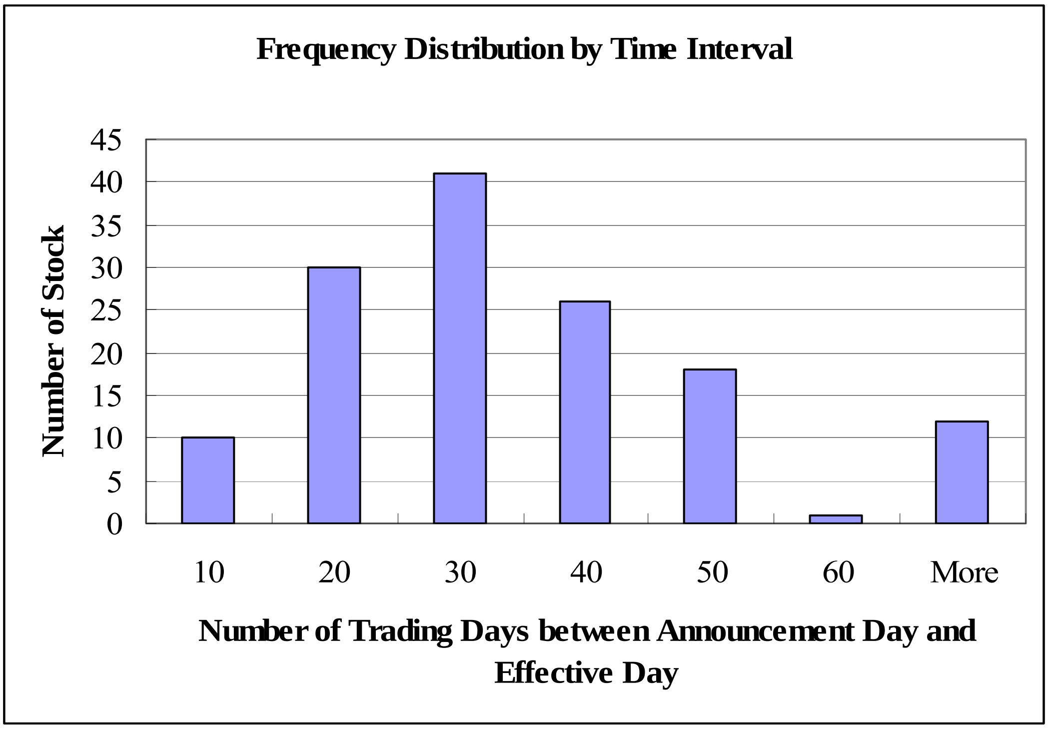
Figure 1

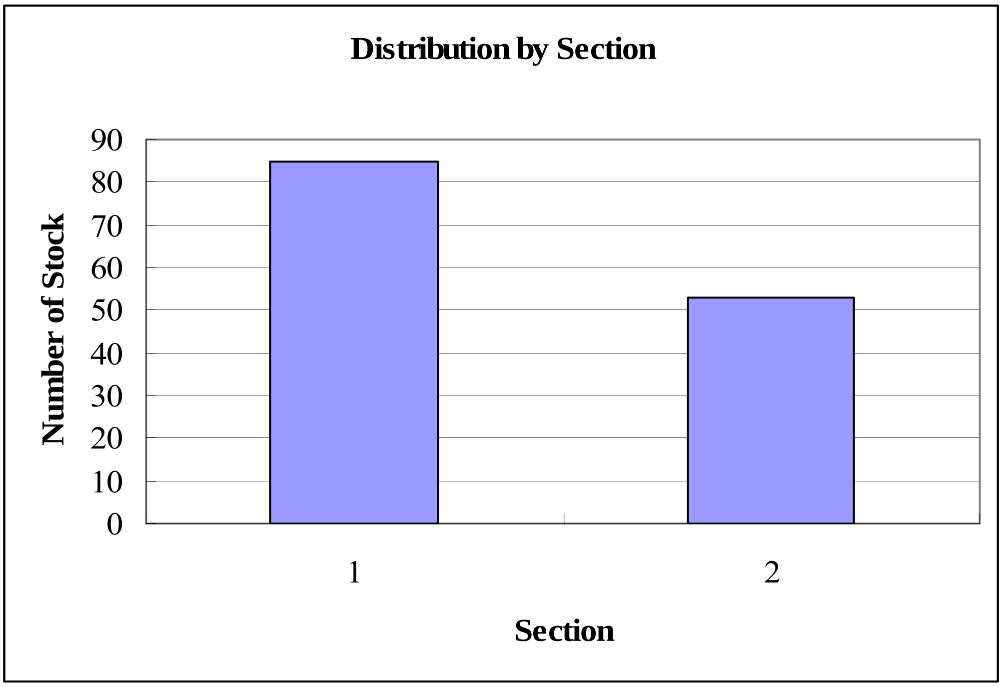
Frequency Distribution of Splits by Time Interval

This figure gives the illustration on distribution of the time interval between the announcement day (AD) and effective day (ED) of the total 138 sample.



10 (time interval≦ 10 trading days) : 10
20 (10 trading days ＜time interval≦ 20 trading days) : 30
30 (20 trading days ＜time interval≦ 30 trading days) : 41
40 (30 trading days ＜time interval≦ 40 trading days) : 26
50 (40 trading days ＜time interval≦ 50 trading days) : 18
60 (50 trading days ＜time interval≦ 60 trading days) : 1
More (60 trading days ＜time interval≦ 70 trading days): 12

Figure 2
Frequency Distribution of Splits by Section
This figure gives an illustration on the section distribution of the total 138 sample. The 1st Section of Tokyo Stock Exchange is for the largest, most successful companies; the 2nd Section is for smaller companies with lower trading volume levels.



Section 1: 85
Section 2: 53

Table 1
Summary of Splits
This table presents the distributions of stock splits by year and by factor. The sample includes 138 events of stock splits that took place between March 1996 and December 2005 at Tokyo Stock Exchange. The factor ranges from 1.5 to ≧10.

Distribution by Year and Factor

	Factor					
Year	1.5	2	3	4	≧10	**Total**
1996					1	1
1999	6	7				13
2000	7	6				13
2001	8	9				17
2002	4	9	2		1	16
2003	3	10			1	14
2004	8	29	2	1	1	41
2005	4	15	3	1		23
Total	40	85	7	2	4	**138**

Table 2
Description of Stocks
This table presents the frequency distribution of the studied sample by the industry they are classified into. The Tokyo Stock Exchange divides the stocks into 9 main industries. The splits cover 7 of them.

Industry	**No. of Stocks**
Construction	1
Manufacturing	46
Wholesale and Retail	39
Financial and Insurance	6
Real Estate	10
Transportation and Communication	1
Service	35
Total	**138**

Table 3
The Number of Quotes
This table presents the cross-sectional means and medians of the average daily number of quotes, of bid and of ask. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The opening and closing trades and the quotes before the opening trade or after the closing trade are excluded. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last column.

A. Daily Number of Quotes

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff. (p-value)
Mean	654.87	925.05	8.55		0.388(0.00)
Median	430.43	685.73		3,416	0.384(0.00)

B. Bid Quotations

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff. (p-value)
Mean	327.44	462.52	8.55		0.388(0.00)
Median	215.22	342.87		3,416	0.384(0.00)

C. Ask Quotations

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff. (p-value)
Mean	327.43	462.43	8.54		0.388(0.00)
Median	215.22	342.87		3,415	0.384(0.00)

Table4

Number of Trades, Trading Size and Trading Volume

This table presents the means and medians of average daily number of trades, trade sizes and trading volume. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The trading size and daily trading volume of post-split are factor adjusted or divided the split factor. The opening, post-closing and closing contracts are excluded. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last two columns.

A. Number of Trades

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff.
Mean	132.44	182.18	7.48		0.409	0.00
Median	69.62	121.67		3038	0.424	0.00

B. Trade Sizes (Factor Adjusted)

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	575.18	360.3	-21.28		-0.464	0.00
Median	343.91	204.21		-4612	-0.454	0.00

C. Daily Volume (Factor Adjusted)

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	85,513	84,508	-0.759		-0.048	0.450
Median	23,733	22,665		-179	-0.004	0.700

Table 5
The Transaction Direction Change after AD and ED
This table presents the change on the ratio between the number of transaction at bid and the number of transaction at ask during 10 trading days after the announcement day (AD) and effective day (ED). The estimation window is [-69, -10] relative to AD, and the studied period is [+1, +10] relative to AD and ED. The percentage change of the ratio, the test value on mean and median, and the p-value of corresponding test are given in the consequent columns.

		AD		
Relative Day		Change (Log-Diff)	Statistic	p-value
+1	Mean	-0.58	-12.88	0.00
	Median	-0.56	-3,066	0.00
+2	Mean	-0.36	-8.4	0.00
	Median	-0.33	-2,792	0.00
+3	Mean	-0.33	-7.11	0.00
	Median	-0.32	-2,778	0.00
+4	Mean	-0.36	-7.48	0.00
	Median	-0.33	-3,030	0.00
+5	Mean	-0.29	-5.8	0.00
	Median	-0.27	-2,497	0.00
+6	Mean	-0.36	-6.87	0.00
	Median	-0.28	-2,820	0.00
+7	Mean	-0.33	-7.15	0.00
	Median	-0.32	-2,814	0.00
+8	Mean	-0.31	-6.48	0.00
	Median	-0.31	-2,735	0.00
+9	Mean	-0.33	-6.82	0.00
	Median	-0.31	-2,774	0.00
+10	Mean	-0.32	-5.57	0.00
	Median	-0.38	-2,497	0.00

Table 6

Number of Trades at Ask, and at Bid

This table presents the means and medians of average daily numbers of trades at ask and at bid. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The opening, post-closing and closing contracts are excluded. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last two columns.

A. Number of Trades at Ask

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff.
Mean	68.94	91.73	6.18		0.346	0.00
Median	35.32	58.59		2719	0.333	0.00

B. Number of Trades at Bid

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	64.27	90.53	8.26		0.428	0.00
Median	33.85	61.08		3252	0.43	0.00

Table 7
Quoted Depth at the Bid and at Ask
This table presents the mean and median of quotation sizes at the bid and ask in number of shares. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The depth of 'Post' is factor adjusted which means it is divided by the split factor. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last two columns.

Quote Depths in Daily Average Volume

at Bid (Factor Adjusted)

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	1,599.77	1,154.26	-5.013		-0.287	0.00
Median	857.44	574.91		-2691	-0.237	0.00

at Ask (Factor Adjusted)

Full Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	1,865.92	1,139.00	-5.098		-0.323	0.00
Median	947.21	648.33		-2986	-0.344	0.00

Table 8
Effective Spread, Absolute Spread and Relative Spread
This table presents the means and medians of the effective spread, absolute spread and relative spread. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The effective spread= │ price-(bid+ask)/2 │ *2, absolute spread=(ask-bid), relative spread=(absolute spread)/price. The last four columns report the t-value (mean test) and Sign-rank (median test), percentage change, and the corresponding p-value from t-tests and sign tests.

A. Effective Spread

Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	44.55	23.46	-14.31		-0.833	0.00
Median	15.30	7.35		-4646	-0.698	0.00

B. Absolute Spread

Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	63.73	35.39	-14.41		-0.832	0.00
Median	23.78	10.96		-4637	-0.693	0.00

C. Relative Spread

Sample (N=138)	Pre	Post	t value	Sign-rank	Log-Diff	p-value Post-Pre
Mean	0.01	0.008	-5.05		-0.002	0.00
Median	0.0068	0.0048		-3001	-0.001	0.00

Table 9
Quality Index
This table presents the mean and median of the quality index. The quality index is adopted to unit the effects of bid-ask spread and quotes on the liquidity and it is calculated by the equation: QI = [(depth at bid $_t$ + depth at ask $_t$)]/(percentage quoted spread $_t$ * split adjustment). The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The split-adjustment will be employed only on the 'Post'. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last two columns.

Quality Index

Sample (N=138)

	Pre	Post	t value	Sign-rank	Log-Diff	p-value Log-Diff
Mean	41,560	160,784	3.76		0.333	0.00
Median	3,118	4,982		1,893	0.342	0.00

Table 10

Components of the Bid-Ask Spread

This table change on the adverse selection component, the order-processing component, and the proportion of the adverse selection component of the bid-ask spread. The pre-split period ('Pre') is the [-69, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +69] window relative to the effective day (ED). The Glosten and Harris (1988) model is adopted to estimate components: $D_t = \alpha(Q_t - Q_{t-1}) + \beta Q_t V_t + \mu_t$, where α is the order processing cost; β is the adverse selection cost. Opening and closing trades are excluded in the regression. The selected stocks also must meet the requirement of at least 20 valid trading days where the valid trading day is defined as a trading day with at least five valid transactions. The log-difference (percentage change) and *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last two columns.

A. Percentage Adverse Selection Cost

Sample (N=138)	Pre	Post	t value	Sign-rank	Diff	p-value (Diff)
Mean	0.109	0.087	-3.59		-0.023	0.00
Median	0.087	0.072		-2628	-0.017	0.00

B. Percentage Order Processing Cost

Sample (N=138)	Pre	Post	t value	Sign-rank	Diff	p-value (Diff)
Mean	0.102	0.110	0.773		0.009	0.44
Median	0.081	0.075		-426	-0.002	0.36

C. Adverse Selection Proportion

Sample (N=138)	Pre	Post	t value	Sign-rank	Diff	p-value (Diff)
Mean	51.43	46.28	-2.28		-5.15	0.02
Median	52.42	48.53		-1679	-3.61	0.00

Table 11
Probability of Informed Trading
This table presents the cross-sectional means and medians of the probability of an information event (α), the arrival rate of uninformed traders (ε), the arrival rate of informed traders (μ), and the probability of information based trade (PIN). The pre-split period ('Pre') is the [-129, -10] window relative to the announcement day (AD). The post-split period ('Post') is the [+10, +129] window relative to the effective day (ED). Estimation on these parameters is based on the Easley, Kiefer, O'Hara, and Paperman's model (1996). The analysis is carried out for the sample of 136 stock splits. The *p*-value from t-tests (for mean) or sign tests (for median) are reported in the last column.

Mean and Median Estimates for the sample (N=136)

		Pre	Post	Post-Pre	t-value	Sign-rank	p-value
α	Mean	0.337	0.419	0.083	2.82		0.00
	Median	0.284	0.319	0.056		1499	0.00
ε	Mean	41.44	63.04	25.42	4.82		0.00
	Median	23.01	41.33	9.69		2980	0.00
μ	Mean	58.86	65.52	8.10	1.72		0.08
	Median	39.52	44.60	5.13		963	0.04
PIN	Mean	0.230	0.208	-0.023	-2.41		0.02
	Median	0.204	0.197	-0.023		-1572	0.00