IMPACT OF STOCK SPLITS ON SIGNALING, LIQUIDITY AND INFORMATION ASYMMETRY ON THE STOCK EXCHANGE OF THAILAND

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ผลกระทบของการแตกหุ้นต่อการส่งสัญญาณ สภาพคล่อง และ ความไม่เท่าเทียมกันของข้อมูล ในตลาดหลักทรัพย์แห่งประเทศไทย

นายวรุณ บุญรำลึกถนอม

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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วรุณ บุญรำลึกถนอม : ผลกระทบของการแตกหุ้นต่อการส่งสัญญาณ สภาพคล่อง และความไม่เท่าเทียมกันของข้อมูล ในตลาดหลักทรัพย์แห่งประเทศไทย . (IMPACT OF STOCK SPLITS ON SIGNALING, LIQUIDITY AND INFORMATION ASYMMETRY ON THE STOCK EXCHANGE OF THAILAND) อ.ที่ปรึกษาวิทยานิพนธ์หลัก : อ.ดร.อนันต์ เจียรวงศ์, 75 หน้า.

งานวิจัยฉบับนี้ศึกษาผลกระทบของการแตกหุ้นในตลาดหลักทรัพย์แห่งประเทศไทย ในช่วงปี 2002 ถึง 2009 โดยศึกษาจากการเปลี่ยนแปลงของกิจกรรมการซื้อขาย สภาพคล่อง และความไม่เท่าเทียมกันของข้อมูล ในช่วงวันที่ประกาศวันแตกหุ้น และ ช่วงวันที่การแตกหุ้นมีผล ผลที่ได้พบว่าการประกาศวันแตกหุ้นเป็นการส่งสัญญาณที่ดีไปยังนักลงทุน นอกจากนั้นยังพบว่า ตัววัดสภาพคล่องโดนส่วนใหญ่มีค่าเพิ่มขึ้น ซึ่งผลดังกล่าวสอดคล้องกับสมมติฐานการส่งสัญญาณ และ สมมติฐานระยะราคาการซื้อขายหุ้น อย่างไรก็ตามผลการศึกษาของอัตราส่วนระหว่างอัตราผลตอบแทนต่ออัตราการหมุนของหุ้น ซึ่งเป็นหนึ่งในตัววัดความไม่มีสภาพคล่อง มีค่าเพิ่มขึ้นอย่างมีนัยสำคัญ ซึ่งขัดแย้งกับหลักฐานการเปลี่ยนแปลงสภาพคล่องอื่นๆ สำหรับผลการศึกษาในเรื่องความไม่เท่าเทียมกันของข้อมูล พบว่ามีค่าลดลงเล็กน้อยหลังจากวันที่การแตกหุ้นมีผล งานวิจัยฉบับนี้ยังสามารถสนับสนุนการตัดสินใจของนักลงทุนในการทำกำไรจากข่าวของการแตกหุ้น และการตัดสินใจเปลี่ยนแปลงยุทธวิธีการลงทุนเมื่อพบหุ้นที่มีสภาพคล่องเพิ่มขึ้นหลังจากการแตกหุ้น

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This research explored an impact of stock splits on the Stock Exchange of Thailand during the period of 2002 to 2009 by examining the changes of trading activity, liquidity and information asymmetry during both stock split announcement date and effective date. It was found that stock split announcements signals good news to the investors. Almost all measures of liquidity indicated increasing liquidity after stock splits. These results are consistent with both signaling hypothesis and trading range hypothesis which are frequently used to explain stock splits. However, one of illiquidity measure which is price impact ratio (return to turnover ratio) has had a significantly positive change after splits. Liquidity evidence of price impact ratio opposes the other evidences of the liquidity improvement. Moreover, information asymmetry evidences were mildly decreased after splits. This research also implies the benefits of stock split news and liquidity improvement of stocks which could have impact on investor's investment strategy.

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CHAPTER I

INTRODUCTION

1.1. Background and Problem Review

Stock splits increase number of shares outstanding and decrease price of each share proportionally. Hence, there should be no change in overall firm's value after splits and no motivation that drives firms to split stocks. Although the firms do stock split, there should be no abnormal trading reaction from the investors. To explain the rationale stock split, the motivation of stock splits is needed to study further.

From the past empirical evidences, there are two main motivations that support stock splits. First, stock split announcements generate positive return. Grinblatt, Masulis, and Titman (1984), Lamoureux and Poon (1987) and Arbel and Swanson (1993) concluded that stock split announcements may be the signal for higher expected firms' future cash flow. Consequently, stock split announcements can be interpreted as good news. A group of investors that believes in the good news buys the stocks and generates positive return around the stock split announcement days. However, Asquith, Healy and Palepu (1989) found the evidence that stock split announcements do not contain good news for investors.

Second, the lower stock price after splits generally attracts small investors. Consequently, stocks have higher liquidity after splits due to trading of small investors as proposed by Maloney and Mulherin (1992) and Elfakhani and Lung

(2003). But, Copeland (1979) found the contrast liquidity evidence of stock splits. He found that bid-ask spread increases after splits and concluded that liquidity decreased. Moreover, Conroy, Harris, and Benet (1990) proposed that post-split liquidity changes depend on liquidity measures. Hence, the effect of stock splits remain inconclusive, thus further study is imperative.

Moreover, signaling and liquidity impact from stock split events also affect information asymmetry. If stock split announcements contain good news to investors as concluded by Grinblatt, Masulis, and Titman (1984) then it signals for firms' better performance in the future. Consequently, stock split announcement terminate information leakage and information asymmetry should decrease. Second, liquidity also affects information asymmetry. Desai, Nimalendran, and Venkataraman (1998) found that adverse information component is negatively related to trading volumes. So, it can be roughly concluded that information asymmetry may decreases as liquidity increase. On the other hand, Easley, O'Hara, and Saar (2001) did not find any significant change in adverse selection problem after splits. Additionally, they found that information asymmetry does not change and percentage spread increases after splits. Hence, evidence of information asymmetry changes after stock splits is still inconclusive from the past researches.

Apart from previous literatures, findings of stock splits in Thai's stock market are affected by its specific characteristics. Thailand has smaller size of the stock market, smaller numbers of investors and less money involved in comparison to developed markets. Hence, stock trading in Thailand should have less liquidity than those in developed markets. Consequently, illiquidity problems are much more severe and it is more probable that managers might use stock splits to enhance liquidity more than in developed market.

This research of stock splits on the Stock Exchange of Thailand is interesting in two aspects. First, past empirical evidences of stock splits are shown in different results in the topic of signaling, liquidity and information asymmetry. It is interesting to investigate further about stock splits evidences in Thailand. Second, liquidity needs in Thailand is higher than other developed markets. Hence, liquidity plays more important role in the Thai stock market. Investors not only concern about the return that they can gain from investment, but also pay attention to the ability to convert to cash (liquidity). As lower liquidity presence in the market, investor would seek for the higher liquidity stocks to invest efficiently. However, illiquid stocks compensate liquidity premium to attract investors to invest in the low liquidity stock. Stock splits make stock prices lower which is attractive to small investors. Consequently, stock liquidity improves and liquidity premium is expected to decrease. I expected that liquidity needs in Thailand to produce different results of stock split compare to developed market.

Impact of stock splits in the Stock Exchange of Thailand might be a result of signaling, liquidity or both. Signaling evidence might help investors to have better reaction to the good news of stock splits. This means that market efficiency would be enhanced. Existence of liquidity improvement evidence might help investors face less liquidity risk. However, stock splits do incur costs; managers must compare their intention to do stock splits and the stock split reaction.

1.2. Research Questions

1. Motivation of stock splits on the Stock Exchange of Thailand: signaling, liquidity or both?
2. Are there any improvements in liquidity level and liquidity risk after stock splits? And do the results hold across different liquidity measures?
3. Do stock splits reduce information asymmetry?

1.3. Objectives

This research aims to investigate the market reaction of stock splits on the Stock Exchange of Thailand that contributes to investors and managers decision. Due to signaling, investor might find abnormal return around stock splits. If the motivation of stock splits is liquidity, stock splits will result in liquidity improvement. Because of signaling and liquidity improvement, information asymmetry might decrease after stock splits. Consequently, investors may plan their strategy better and make more efficient investment decision. Managers might be able to predict the tentative post-split results and decide whether they should do stock split or not.

1.4. Research Hypotheses

The impacts of stock splits apart from price reduction and number of shares increase are signaling, liquidity and also information asymmetry. Additionally, the signaling motive and liquidity motive may exist independently of each other. For the first impact, I hypothesize that investors might buy the stocks around the stock split announcement date due to their interpretation of stock splits as good news. Consequently, positive abnormal return around stock split announcement date is expected.

From past empirical evidences, stock splits in some developed countries result in no liquidity improvement such as Danish stock market (Bechmann and Raaballe (2007)) and Greece stock market (Leledakis, Papaioannou, Travlos and Tsangarakis (2009)). However, as mentioned in the background section that illiquidity problem of stocks in Thailand is more severe than developed market, I hypothesize that the effect of stock split in Thailand may result in liquidity improvement. Therefore, improvement of trading activities, increasing in liquidity level and reduction of liquidity risk might be found after stock splits.

Lastly, information asymmetry may decrease for two reasons. Stock split announcements eliminate leakage information of good news, information asymmetry may decrease. And, it may also decrease due to the presence of small traders (uninformed traders) who are attracted by lower price of stocks.

1.5. Organization of the Papers

Remaining chapters are organized as follows. Chapter 2 is literature review. Data and methodology is presented in chapter 3. Results and discussion are in chapter 4. Lastly, conclusion are provided in chapter 5.

CHAPTER II

LITERATURE REVEW

This research aims to study three effects from stock splits: signaling, liquidity change and information asymmetry change. In this chapter, the research reviews of these three effects from stock splits are separated into three sections. Signaling evidence, liquidity evidence and information asymmetry evidence will be presented in the section 2.1, 2.2 and 2.3 respectively.

2.1. Signaling Evidence

In the perfect capital market, stock split is the event that directly increases number of shares and decreases stock price. Consequently, there is no change in the total firm's value. However, stock split announcements provide positive abnormal returns in many countries. For example, Grinblatt, Masulis, and Titman (1984) studied the signaling effect of the common stock listed in the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from 1967 to 1976. They found that stock price positively react to stock dividend and stock split announcement which is indicated by significantly positive excess return around the ex-date of stock dividends and stock split. They conclude that some information content of stock dividends and splits are directly related to firms' future cash flows.

Consistent with previous research, Lamoureux and Poon (1987) tested a model of market reaction to stock splits. They also studied abnormal return and trading volume of pre- and post-split announcement. Stock split samples are based on both NYSE- and AMEX-listed firms in the period from July 1962 to December 1985. They found positive cumulative abnormal return from the stock split announcements. The number of transactions and number of shares traded also increase after stock splits. Additionally, signaling evidence was confirmed by using pure stock split announcements by Arbel and Swanson (1993). Pure stock split announcements are defined as stock split announcements with no other firm specific news for 6 days around the announcement day. They studied the stock split announcement effects by using over-the-counter stocks as the representative of information-poor stocks and stock traded on NYSE and AMEX as the information-rich stocks. Consequently, both information-poor stocks and information-rich stock adjust their price to the good news of pure stock split announcements. In addition, the price adjustment process or market reaction to the announcement for information-poor stocks is incomplete and slower than information-rich stocks.

Apart from NYSE and AMEX, signaling effects of stock split announcement were explored in many countries such as Toronto Stock Exchange by Elfakhani and Lung (2003), Tokyo Stock Exchange by Guo, Zhou and Cai (2008), Athens Stock Exchange by Leledakis, Papaioannou, Travlos and Tsangarakis (2009) and London Stock Exchange by Kalotychou, Staikouras and Zagonov (2009).

In contrast to earlier study of signaling, Asquith, Healy and Palepu (1989) showed that the NYSE and AMEX firms during 1970 to 1980 have temporarily increased earnings in the period before splits. This means that firms do not permanently increase earnings after splits. Hence, stock split announcements are not consistent with the expectation of investors that firms will have higher future earnings after splits.

Although there are evidences to support signaling hypothesis, signaling is not the only motivation of stock splits. Next section, another stock split motivation which is liquidity improvement will be presented.

2.2. Liquidity Evidence

Liquidity evidence of stock splits is investigated in many countries by different liquidity indicators. However, the conclusions of these studies do not always agree. First is the evidence of liquidity decay after stock splits. The earliest evidence by Copeland (1979) studied the stock split events on the NYSE. He proposed that firms use stock splits to keep their stocks remain at the certain price range. There are two benefits of certain price range adjustment. First, specific kind of traders is attracted by the certain price range that is small traders or uninformed traders. Second, ownership of company is better dispersed after splits. However, liquidity decreases after splits indicated by decreasing in trading volume and increasing in bid-ask spreads. The reason that liquidity decay after splits can be explained by the following reasons: rate of information is lower after splits, and lower volume of stocks is needed to reach the desired portfolio weights.

Second conclusion of liquidity evidence is inconclusive liquidity evidence. Conroy, Harris, and Benet (1990) showed the reduction in liquidity after splits of NYSE-listed companies. They used percentage spreads and absolute spreads as liquidity measures. Absolute spreads decrease after splits. In contrast, percentage spreads increase after splits. Hence, the liquidity evidence is inconclusive due to the different results from two liquidity measures. Muscarella and Vetsuypens (1996) also found the inconclusive liquidity evidence for the American Depository Receipts (ADRs) splits. They found liquidity improvement that is evident by higher trading volume and higher proportion of trading volume especially for small trades, greater total transaction value and lower liquidity premium after splits. In contrast, the sign of liquidity deterioration is indicated by higher relative liquidity premium. Consequently, liquidity evidence cannot be concluded due to one of the liquidity measures contradict to others. Bechmann and Raaballe (2007) also found inconclusive liquidity evidence in Danish stock's market. Liquidity indicators are the number of days when the stock is traded and average daily stock turnover. They found improvement of stock trading continuity. In contrast, the insignificant decreasing in turnover ratio after splits pointed in different view of liquidity evidence. Additionally, Leledakis, Papaioannou, Travlos and Tsangarakis (2009) studied liquidity evidence of stock splits on Athens Stock Exchange. They found insignificant change in relative trading volume and total trading volume (in Euros) after splits.

Table 1 Summary liquidity evidence from past researches

This table shows the difference results of liquidity change according to stock splits in different market and various liquidity indicators.

Researcher	Data source	Liquidity changes after splits	Liquidity indicator
Copeland (1979)	NYSE	Reduction	Wider bid-ask spread Lower trading volume
Conroy, Harris, and Benet (1990)	NYSE	Inconclusive result	Narrower Absolute spreads Wider percentage spreads
Muscarella and Vetsuypens (1996)	ADRs	Inconclusive result	Higher trading volume Greater proportion of small trading volume More total transaction value Lower liquidity premium Higher relative liquidity premium
Bechmann and Raaballe (2007)	Denmark	Inconclusive result	Higher trading continuity Steady turnover ratio
Leledakis, Papaioannou, Travlos and Tsangarakis (2009)	Greece	Inconclusive result	Insignificant change of relative trading volume and total trading volume (in Euros)
Lamoureux and Poon (1987)	NYSE and AMEX	Improvement	Higher number of transactions Greater trading volume
Maloney and Mulherin (1992)	NASDAQ	Improvement	Bigger number of shareholders Higher number of trades Greater dollar volume Narrower bid-ask spreads
Lin, Singh, and Yu (2009)	NYSE	Improvement	Better trading continuity Lower liquidity risk
Elfakhani and Lung (2003)	Canada	Improvement	Narrower bid-ask spread, Greater trading volume Higher number of transactions
Guo, Zhou and Cai (2008)	Japan	Improvement	Greater number of trades Narrower absolute effective spread Smaller relative effective spread
Schultz (2000)	NASDAQ, NYSE and AMEX	Improvement	Higher numbers of transaction of small buy orders

Last is liquidity improvement evidence. Lamoureux and Poon (1987) investigated the stock splits of firms listed in NYSE and AMEX. They showed that both daily number of transactions and raw trading volume increase after splits. Raw trading volume is the average trading volume adjusted for the splits compare relative to market trading volume. Moreover, Maloney and Mulherin (1992) studied the sample of NASDAQ firms. They found the improvement of trading activity as indicated by greater number of shareholders, higher number of trades and more dollar volume after stock splits. Furthermore, illiquidity measure is provided to show the liquidity evidence. The study showed that bid-ask spread is narrower after splits. Lin, Singh, and Yu (2009) used Liu's measure (LM12) (2006) to test liquidity around splits and study the difference of liquidity premium of NYSE-listed firms. They found that trading continuity increases, and liquidity risk decreases. In addition, firms that face more trading discontinuity are able to gain more liquidity as they use higher split factors.

Liquidity improvement was found not only companies listed in American Stock Exchange including NYSE and AMEX, but also Canadian stocks on the Toronto Stock Exchange as shown by Elfakhani and Lung (2003). Bid-ask spread, trading volume and number of transactions are used as liquidity indicators. Consequently, they found narrower bid-ask spread, higher trading volume and greater number of transactions. These results can be used to confirm the liquidity improvement. Guo, Zhou and Cai (2008) provided the evidence of liquidity improvement in Tokyo Stock Exchange. They found higher number of trades, narrower absolute effective spread and lower relative effective spread after splits. However, trading volume adjusted split factors is insignificantly changed after splits.

In addition, liquidity may be enhanced by the liquidity providers who are attracted by higher relative bid-ask spread after splits. Schultz (2000) studied the benefits of liquidity providers after stock splits in NASDAQ, NYSE and AMEX. He found that effective spreads increase for almost every split stock. Consequently, liquidity providers gain higher benefits through their limit order submission. Percentage of limit order use is also higher because of the liquidity provider benefits.

In summary, there are many difference consequences of stock splits shown in previous researches due to the results are presented from different markets and various liquidity indicators. Table 1 is provided to clearly classify the difference of results.

2.3. Information Asymmetry Evidence

Both signaling and liquidity can have impact information asymmetry. First, signaling impact on information asymmetry. Grinblatt, Masulis, and Titman (1984) explained that stock split announcement is used by the managers which transfer the good news of higher firms' future earnings to investors. Stock split announcements eliminate leakage information of higher firms' future earnings. Hence, it would result in the reduction of the information asymmetry between the managers and investors after stock split announcement. Moreover, Desai, Nimalendran, and Venkataraman (1998) studied effect of liquidity to information asymmetry. They examined the stock split evidence on the NASDAQ and National Market System (NMS) during the period from 1983 to 1990. They found that volatility and trading volume increases after splits. Furthermore, they proposed that the effect of adverse information component with respect to liquidity is affected by two components. Noise traders would decrease the adverse information component. On the other hand, informed traders would increase this component. They found that both numbers of trades by noise traders and informed traders increase after splits. Moreover, adverse information component is negatively related to trading volumes due to proportion of noise traders dominates informed trader in total trading volume.

In another strand, Easley, O'Hara, and Saar (2001) studied information asymmetry around stock split announcements by using probability of informed traders (PIN). They found that stock splits of the NYSE stocks attract both uninformed and informed trading. Consequently, probability of informed traders is not significantly decreases after splits and adverse selection problem remains unchanged. In contrast, Guo, Zhou, and Cai (2008) also investigated information asymmetry changes around stock splits in the Japanese stock market using adverse selection costs and probability of informed trading (PIN). They showed that stock splits can lower information asymmetry and lower probability of informed trading due to the small traders attracted by the lower stock price after splits.

2.4. Summary

This section concludes reviews from empirical evidences of stock splits in three aspects. First from signaling evidence, Asquith, Healy and Palepu (1989) proposed that stock splits signal for only temporary higher firms' earning. In contrast, signaling was found in many countries even in the country that have temporary higher earning evidence. This research expects to find the signaling evidence as one of the motivation for stock splits in Thai's stock market. However, expectation of signaling evidence in Thailand is not as strong as liquidity improvement evidence which will be mentioned below.

Second from liquidity evidence, there are various results from different markets as shown in Table 1. The expected result of stock splits in Thailand is liquidity improvement due to the special characteristic of emerging market such as smaller size of market, lower numbers of investors and less money efforts compare to developed market. This research strongly expects that there will be an improvement of trading activities, deterioration of illiquidity measures and reduction in liquidity risk after the stock splits of companies listed in Stock Exchange of Thailand.

Finally, information asymmetry might decrease due to the presence of signaling and liquidity improvement. This research expects to investigate the reduction of information asymmetry evidence in the SET which will be indicated by asymmetric information component, probability of informed trading and adjusted probability of informed trading.

CHAPTER III

DATA AND METHODOLOGY

3.1. Sample and Data

3.1.1. Sample

Stock splits and stock split announcements data are obtained from the SET Smart. Sample includes all SET-listed companies which have stock split from January 1, 2002 to December 31, 2009. The total number of stock splits and stock split announcements is 189 days each.

3.1.2. Data

Required data is presented as follow. Data of firms listed in the stock exchange of Thailand is obtained from DataStream including daily close price, daily data on the opening and closing of bid-ask share prices, daily trading volume, number of shares outstanding, 1-month Treasury bill as the risk-free rate, annual book value, and annual market value from January 1, 2000 to December 31, 2011.

Moreover, intra-day data from the SET database including every transaction. Data in each transaction consists of security symbol, date, time, transaction type, trading volume, trading price, the best bid price, the best ask price, bid size and ask size.

3.2. Hypothesis Development

In this research, I have three research questions as mentioned above. This section aims to develop hypothesis in order to answer these three questions. There are some important hypotheses related to stock splits event. First, signaling hypothesis assumes that there is information asymmetry between managers and traders about the firm's expected future performance. Stock split announcements eliminate this information asymmetry and stock price increases due to the stock split announcement contain good news to investors. Fama, Fisher, Jensen, and Roll (1969) provided this evidence of signaling hypothesis that they found abnormal return around stock split announcement date. Grinblatt, Masulis, and Titman (1984) also confirmed this hypothesis. They found positive abnormal return around stock dividend and stock split announcements which can be concluded that stock dividends and splits contain information about firms' future cash flows. Lamoureux and Poon (1987) found abnormal return around stock split announcement and also increasing in trading volume of post-split announcement. From these empirical evidences, positive abnormal return around announcement date and positive abnormal trading volume is the good indication of signaling hypothesis. In conclusion, this research develops two hypotheses to support signaling hypothesis as follows:

Hypothesis 1 There is the positive abnormal return around split announcements.

Hypothesis 2 There is the positive trading volume around split announcements.

Second is trading range hypothesis. Copeland (1979) proposed that firms used stock splits to reduce stock price to the certain price range. He explained that small traders or uninformed traders are attracted by this certain price range. The main benefits of the presence of small traders are liquidity increase and trading cost of the stocks decrease. Maloney and Mulherin (1992) found that stock splits lead to liquidity improvement as measured by narrower bid-ask spreads. Muscarella and Vetsuypens (1996) also found that trading volume increases significantly especially for small trades. This can be confirmed that small traders are attracted by certain trading range of stock splits. Furthermore, Lin, Singh, and Yu (2009) discovered that liquidity level increases and liquidity risk decreases after splits. From trading range hypothesis, I decide to measure the changes of liquidity by three ways. First, trading activities that are trading volume and effective spread are investigated in the pre- and post-split period for various trade sizes. Due to the trading range hypothesis, trading volume for small trade size should increase and effective spread should decrease. Second, liquidity level that can be estimated by liquidity measures should be higher. In other word, illiquidity level should be lower. Third, liquidity risk of stocks should be lower. Trading range hypothesis development is summarized as below:

Hypothesis 3 Trading activity significantly increases after splits.

Hypothesis 4 Proportion of trade for small trade significantly increases after splits.

Hypothesis 5 Illiquidity level is lower after splits.

Hypothesis 6 Liquidity risk falls after splits.

Third, tick size hypothesis is defined that tick size of stocks is optimized by stock splits. Angel (1997) proposed that companies used stock splits to keep minimal tick size of their stocks or optimal relative tick size defined as tick size divided by stock price. Consequently, liquidity providers that previously not invest in these stocks are attracted by the optimal tick size. Number of shareholders should increases after splits as the presence of more liquidity providers that is consistent with Lamoureux and Poon (1987) and Maloney and Mulherin (1992) study. Furthermore, Schultz (2000) found that trading cost (effective spread) increase after splits. Liquidity providers would gain higher benefits after stock splits by limit order submission. In addition, the presence of more liquidity providers that generally trade by using limit orders is considered to be uninformed traders. In order to find the consistency of tick size hypothesis, results must show higher proportion of using limit orders and lower information asymmetry because of the presence of uninformed traders. Hence, research can be hypothesized as follows:

Hypothesis 7 Limit order uses are higher after splits.

Lastly is information asymmetry argument. Grinblatt, Masulis, and Titman (1984) found that there is good information content of stock splits to traders. To explain the information asymmetry with stock splits, I assumed that there is no stock split and information-leakage occurs. Hence, informed trader would make benefits from this information. After stock split announcements, information becomes public and information asymmetry should be reduced. Desai, Nimalendran, and Venkataraman (1998) found increasing in trading volume after splits. If higher trading volume comes from noise traders, the adverse selection component should decrease. In contrast, if trading volume is higher due to informed traders, adverse selection component should increase. This means that adverse information component is negatively related to proportion of noise traders. Easley, O’Hara, and Saar (2001) provided alternative way to study information asymmetry by using probability of informed traders (PIN). They found that probability of informed traders is not significantly decreases after splits and adverse selection problem remains unchanged. In my research, I decide to construct hypothesis that information asymmetry, probability of informed traders (PIN) and adjusted probability of informed traders (APIN) should decrease due to the presence of either signaling or liquidity. Information asymmetry component can be estimated by the movement of the stock mid price. Finally, hypotheses in this research for information asymmetry argument are shown below:

Hypothesis 8 Information asymmetry is lower after split announcements.

Hypothesis 9 Information asymmetry is lower after splits.

Hypothesis 10 Probability of informed trading and adjusted probability of informed trading are lower after split announcements.

Hypothesis 11 Probability of informed trading and adjusted probability of informed trading are lower after splits.

3.3. Methodology

In this research, methodology consists of 7 parts; signaling from announcement, trading activities, liquidity measures, asset pricing tests, information asymmetry, probability of informed traders and adjusted probability of informed traders.

3.3.1. Signaling from Announcement

Signaling evidence can be provided by abnormal returns of stock around the stock splits announcement date. Abnormal returns can be estimated by two methods following Brown and Warner (1985). The first method, market adjusted return is return of each stock minus market return. The second method, OLS market model is the return of each stock minus estimated stock return in that time by its systematic risk to the market. Systematic risk can be estimated by using estimation window in the period of 244 day to 6 day before the announcement day. Event window is from the 5 day before announcement day to 5 day after announcement day. Multi-day interval tests are also used to find accumulated abnormal return effect of split announcements. Abnormal returns, standard deviation, test statistic calculation and multi-day test are as shown below,

Market adjusted returns

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{1}$$

OLS market model

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t} \tag{2}$$

Where $AR_{i,t}$ is abnormal return of stock i at time t, $R_{i,t}$ is return of stock i at time t and $R_{m,t}$ is market return of stock i at time t.

Test statistic

$$t_{AR,t} = \overline{AR}_t / \hat{S}(\overline{AR}_t) \tag{3}$$

Where

$$\overline{AR}_t \ = 1/N_t \sum_{i=1}^{N_t} AR_{i,t} \tag{4}$$

$$\hat{S}(\overline{AR}_t) \ = \sqrt{\sum_{t=-244}^{-6} (\overline{AR}_t - \overline{\overline{AR}})^2 \,/238} \tag{5}$$

$$\overline{\overline{AR}} = \frac{1}{239} \sum_{t=-244}^{-6} \overline{AR}_t \tag{6}$$

Multi-day test

$$t_{CAR,t} = \sum_{t=-5}^{5} \overline{AR}_t \,/ \sqrt{\sum_{t=-5}^{5} \hat{S}^2(\,\overline{AR}_t)} \tag{7}$$

Where $\overline{AR}_t$ is the average abnormal return at time t, $\overline{\overline{AR}}$ is the average abnormal return from -244 day to -6 day before split announcements and $\hat{S}(\,\overline{AR}_t)$ is standard deviation of the average abnormal return in estimation window period.

There are 189 stock split announcements in the period during 2002 to 2009. Firms that have no trade in estimation period for 24 firms are excluded. Moreover, 16 firms are excluded because date are unavailable due to they are excluded from SET or suspended. Event study samples of signaling effect are left with 149 events in total.

The sample of 149 events is used to find the signaling effect indicated by abnormal return in the event window period. The hypothesis testing of signaling effect by abnormal return in each day is given as follow;

$H_0{:}\,\overline{AR}_t \leq 0$

(The abnormal return around split announcements in day t is not positive)

$H_1: \overline{AR}_t > 0$

(The abnormal return around split announcements in day t is positive)

Where, t is the day in the event window from -5 day to 5 day around stock split announcement date.

Moreover, cumulative abnormal return is tested to reveal the accumulate effect of signaling effect by stock split announcements. The hypothesis testing of signaling effect by cumulative abnormal return is shown as follow

$H_0: \overline{CAR}_{[-5,t]} \leq 0$

(The cumulative abnormal return around split announcements in the period from -5 day to t day is not positive)

$H_1: \overline{CAR}_{[-5,t]} > 0$

(The cumulative abnormal return around split announcements in the period from day -5 day to t day is positive)

Where, t is the day in the event window from -5 day to 5 day around stock split announcement date.

In addition, the test statistics of hypothesis testing of abnormal return and cumulative abnormal return is provided in the equation (3) and (7) respectively.

3.3.2. Trading activities

Signaling Evidence Support based on trading volume

Trading volume is provided in order to support the signaling hypothesis and to reveal the attention of investors to stock split announcement. Summary statistics of trading volume and cumulative abnormal trading volume around stock split announcement days are provided below:

Abnormal trading volume

$$ATV_{i,t} = TV_{i,t} - \overline{TV}_i \tag{8}$$

Where $ATV_{i,t}$ is abnormal trading volume of stock i at time t, $TV_{i,t}$ is trading volume of stock i at time t and $\overline{TV}_t$ is the average trading volume of stock i.

Test statistic

$$t_{ATV,t} = \overline{ATV}_t / \hat{S}(\overline{ATV}_t) \tag{9}$$

Where

$$\overline{ATV}_t = 1/N_t \sum_{i=1}^{N_t} ATV_{i,t} \tag{10}$$

$$\hat{S}(\overline{ATV}_t) = \sqrt{\sum_{t=-244}^{-6} (\overline{ATV}_t - \overline{\overline{ATV}})^2 / 238} \tag{11}$$

$$\overline{\overline{ATV}} = \frac{1}{239} \sum_{t=-244}^{-6} \overline{ATV}_t \tag{12}$$

Multi-day test

$$t_{CATV,t} = \sum_{t=-5}^{5} \overline{ATV_t} \,/ \sqrt{\sum_{t=-5}^{5} \hat{S}^2(\,\overline{ATV_t})} \tag{13}$$

Where $\overline{ATV_t}$ is the average abnormal trading volume at time t, $\hat{S}(\,\overline{ATV_t})$ is standard deviation of the average abnormal trading volume in estimation window period and $\overline{\overline{ATV}}$ is the average abnormal trading volume from -244 day to -6 day before split announcements.

The sample of 149 events is used to find the signaling effect indicated by abnormal trading volume in the event window period. The hypothesis testing of signaling effect by abnormal trading volume in each day is given as follow:

$H_0: \overline{ATV_t} \leq 0$

(The abnormal trading volume around split announcements in day t is not positive)

$H_1: \overline{ATV_t} > 0$

(The abnormal trading volume around split announcements in day t is positive)

Where, t is the day in the event window from -5 day to 5 day around stock split announcement date.

Multi-day test of cumulative abnormal trading volume is also studied to reveal the accumulate effect of signaling effect of stock split announcements. The hypothesis testing of signaling effect by cumulative abnormal trading volume is provided as follow:

H_0: $\overline{CATV}_{[-5,t]} \leq 0$

(There is no cumulative positive abnormal trading volume around split announcements in the period from -5 day to t day)

H_1: $\overline{CATV}_{[-5,t]} > 0$

(There is the cumulative positive abnormal trading volume around split announcements in the period from day -5 day to t day)

Where, $\overline{CATV}_t$ is the average of cumulative abnormal trading volume in day t, which t is the day in the event window from -5 day to 5 day around stock split announcement date.

Test statistics of hypothesis testing of abnormal trading volume and cumulative abnormal trading volume is presented in the equation (9) and (14) respectively.

However, a numbers of average abnormal trading volume may be overwhelmed by high number of share outstanding companies. To enlighten on abnormal trading volume of split stock, abnormal trading volume of each split firm is individually tested.

Liquidity Evidence Support

From trading range hypothesis and tick size hypothesis, I expect the liquidity improvement which will manifest through trading activity. The trading activity includes (A) trading volume for various trade sizes, (B) Proportion of trades for various trade sizes, (C) Effective spread, (D) Relative spread, (E) Proportion of limit order and (F) Proportion of time of stock trading within each spread.

Liquidity evidence is shown by testing the difference of these trading activities between the period before stock splits (pre-split) and the period after stock splits (post-split). The pre-split period is in the range of -69 day to -10 day before stock split announcement. The post-split period is in the range of +10 day to +69 day after stock split. To determine whether liquidity is improved after splits, the hypothesis testing of liquidity effect by trading activities and test-statistic of the difference between two periods (post-split minus pre-split) is determined by Welch's t-test as follow:

Hypothesis testing

$H_0: \bar{X}_{i,post-splits} = \bar{X}_{i,pre-splits}$

(Trading activity in the post-split period is the same as pre-split period)

$H_1: \bar{X}_{i,post-splits} \neq \bar{X}_{i,pre-splits}$

(Trading activity in the post-split period is not the same as pre-split period)

Where, $\bar{X}_i$ are the average of trading activities including trading volume for small trades, proportion of small trades, effective spread, relative spread, proportion of limit order and proportion of time of stock trading within each spread.

Welch's t-test

$$t = \frac{\bar{X}_{Post} - \bar{X}_{Pre}}{\sqrt{\frac{S^2_{Post}}{N_{Post}} + \frac{S^2_{Pre}}{N_{Pre}}} \qquad (14)$$

Where, $\bar{X}_{Post}$ is the mean of each trading activity variable of post-split period, $\bar{X}_{Pre}$ is the mean of each trading activity variable of pre-split period, S^2_{Post} is the variance of each trading activity variable of post-split period, S^2_{Pre} is the variance of each trading activity variable of pre-split period, N_{Post} is the number of observation of the post-split period (60 days) and N_{Pre} is the number of observation of the pre-split period (60 days).

A. Trading Volume for Various trade sizes (in baht)

Trading volume of each trade size (in baht) is determined by the number of shares traded multiplied by deal price in the intraday data deal files. Trading volume in each transaction is summed up into daily trading volume for each trade size. Trading volume of pre-split value is obtained from averaging of daily trading volume in the range of -69 day to -10 day before stock split announcement. Trading volume of post-split value is obtained from averaging of daily trading volume in the range of +10 day to +69 day after stock split.

The various trade sizes are classified into small trades, medium trades and large trades. Due to the ability to afford the money into market is constrained by the investor's budget, I classified the small trades as lower than 30th percentile of the overall retail investors' trading volume from year 2001 to 2009. Mid trades is the trading volume from 30th to less than 70th percentile and the rest is large trades.

B. Proportion of Trades for Various trade sizes

Furthermore, liquidity evidence is not only shown by the trading volume, but also proportion of trades (especially in small size trade) is prepared to support the trading range hypothesis. Proportion of trades is calculated by the average of number of trades in each trade sizes divided by the total number of trades in each day. Each trade is classified into small trade, medium trade and large trade by the same method as above.

C. Effective Spread

Effective spread is defined as two times of absolute value of transaction price minus average of bid-ask price. Effective spread is obtained by intraday data. Instead of using only intraday data deal files, effective spread is considered by every transaction that may move the best bid price and the best ask price in order to calculate the average of bid-ask price.

Effective spread in pre- and post-split period are determined by four steps. First, effective spread in each transaction is determined. Second, it is averaged into one value for each stock and each single day in both periods ($Eff_{i,t}$). Third, the average of effective spread of each day (Eff_t) is computed. Finally, average of effective spread in pre-split ($Eff_{pre-splits}$) and post-split ($Eff_{post-splits}$) is the average of effective spread of their estimation window period that is [-69, -10] and [10, 69] respectively.

D. Relative Spread

Relative spread is prepared by the same methodology as effective spread. Relative spread is defined as effective spread divided by quote midpoint. The changes of relative spread after splits may result in decrease or increase which has a different explanation. Reduction of relative spread after stock splits shows the liquidity improvement. Investors would be attracted to take the transaction via market order uses by the lower transaction cost after splits. In contrast, group of liquidity providers who gain the portion of liquidity premium by using limit order would be attracted by the higher relative spread. Consequently, proportion of limit order is provided in the next trading activity estimation in order to support the increasing of relative spread evidence.

E. Proportion of limit order

As mentioned above, proportion of limit order in the period of pre- and post-split is determined to support tick-size hypothesis. Proportion of limit order can be determined by number of limit order divided by sum of limit order and market order. Market order and limit order are classified in the intraday data as follow. There are three possible order flag in the intraday data. First, flag (A) is the submitted order into the market including buy order and sell order. Second, flag (M) indicate the matched order. Third, flag (D) is the deleted order. The market order is classified by the order that is immediately matched (M) after sending order (A) into market. Limit order is the rest of (A) which is excluded by the (A) before matched line (M). To support the liquidity improvement as tick size hypothesis suggested, proportion of limit order would be higher after splits along with the higher relative spread.

F. Proportion of time of stock trading within each spread

According to trading regulations in the Stock Exchange of Thailand, bid-ask spread is different for each price range. Consequently, bid-ask spread and effective spread measures would not be appropriate to measure the liquidity changes around stock splits. In this research, numbers of tick is used in order to normalize the difference of bid-ask spread for each price range. However, numbers of tick cannot be directly summarized to show the liquidity improvement. In this research, I use the combination of numbers of tick and the function of time to show the liquidity improvement which is called proportion of time of stock trading within each spread.

Proportion of time of stock trading would be shown in the spread of one tick, two or three ticks and four or more ticks. Liquidity improvement after stock splits would be confirmed by the higher proportion of time of stock trading within low tick size.

3.3.3. Illiquidity Measures

Conroy, Harris, and Benet (1990) found that different liquidity measures provide different results of liquidity effect after splits. From past researches, there are 3 types of illiquidity measures: price-based measure (e.g., bid-ask spread), volume-based measure (e.g., turnover ratio), and price-and-volume based measure (e.g., illiquidity ratio by Amihud (2002)). This research provides three different types of liquidity measures to test and recheck liquidity impact after splits. In this research, there are four illiquidity measures including bid-ask spread (price-based measure), relative bid-ask spread (price-based measure), Liu's ratio (volume-based measure) and price impact ratio (price-and-volume based measure). Refer to the trading range hypothesis, illiquidity measures should be reduced after splits because of the lower stock price. This would be tested by the hypothesis below:

Hypothesis testing

$$H_0: \bar{X}_{i,post-splits} = \bar{X}_{i,pre-splits}$$

(Illiquidity measure in the post-split period is the same as pre-split period)

$H_1: \bar{X}_{i,post-splits} \neq \bar{X}_{i,pre-splits}$

(Illiquidity measure in the post-split period is not the same as pre-split period)

Where, $\bar{X}_i$ are the average of illiquidity measure including bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio.

Moreover, the test-statistic is determined by Welch's t-test which is mentioned in the trading activities section. Calculation of illiquidity measures is provided below;

Bid-ask Spread and Relative Bid-ask Spread (Price-based Measure)

Conroy, Harris, and Benet (1990) found that bid-ask spread decreases after splits, but relative bid-ask spread increases due to the price of stocks is also decreased after splits. Bid-ask spread and relative bid-ask spread are price-based measure of illiquidity. Relative bid-ask spread is determined as follow,

$$RBA = \frac{Ask - Bid}{0.5(Ask + Bid)} \quad (15)$$

Liu's Ratio (Volume-based Measure)

Liu (2006) defined the illiquidity measure of a security by using the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Liu's ratio is not only volume-based measure in illiquidity of stocks but also measure the trading continuity of stocks as shown in the first term in the equation below,

$$\text{Liu's ratio (LMx)} = [\text{Numbers of zero daily volumes in prior x months} + \frac{1/(x{-}month\ turnover)}{Deflator}] \times \frac{21x}{NoTD} \quad (16)$$

Where LMx, as the standardized turnover-adjusted number of zero daily trading volumes over the prior x months (x = 1; 6; 12), x-month turnover is calculated by sum of daily turnover over the x-month period, daily turnover is the ratio of number of shares traded on a day to the number of shares outstanding at the end of the day and NoTD is the total number of trading days in the market over the prior x months.

$$\text{Deflator is chosen such that } 0 < \frac{1/(x{-}month\ turnover)}{deflator} < 1 \text{ for all samples} \quad (17)$$

Price Impact Ratio (Price- and Volume-based Measure)

Florackis, Gregoriou, and Kostakis (2011) proposed new price impact ratio (return to turnover ratio) as an alternative illiquidity factor. Main strength point of this ratio is to eliminate size bias from illiquidity ratio of Amihud (2002) by adjusting the return with turnover ratio rather than trading volume. Price impact ratio is both price- and volume-based measure of illiquidity and it can be estimated as follow,

$$RtoTR = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}} \quad (18)$$

Where R_{itd} and TR_{itd} is return and Turnover Ratio of stock i at day d in month t, D_{it} is number of valid observation days in month t for stock i.

3.3.4. Asset Pricing and Liquidity Risk

Preliminary liquidity impact to stock splits is presented in trading activity section and liquidity measures section. In addition, this section provides more evidence about the liquidity risk of stocks after stock split which is the return-liquidity relationship. Liquidity risk can be estimated by the cross-sectional equation following Ball and Kothari (1989)[1] to compare the impact from splits as follow equation,

$$CAPML: R_{it} - R_{ft} = \alpha_0 + \alpha_1 D_t + (\beta_{m,0} + \beta_{m,1} D_t) MKT_t + (\beta_{l,0} + \beta_{l,1} D_t)\ LIQ_t + \varepsilon_t \quad (19)$$

Where R_{it} is the monthly return on stock i in month t, R_{ft} is risk free rate in month t, D_t is equal to one when t is in the post-split period, MKT_t is the excess market portfolio return in month t and LIQ_t is the mimicking portfolio return of liquidity factor in month t.

CAPML is estimated by using each illiquidity measure to construct mimicking portfolio of liquidity. Illiquidity measures are bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio.

Mimicking portfolio of liquidity is constructed followed Fama-French (1993) method. First, separate stocks into 2 groups by size (big and small) with value-

[1] Ball and Kothari (1989) proposed that the cross-sectional technique is better to measure risk which can shift in each event period.

weighted of 50:50. Second, separate stocks in each group into 3 subgroups by book to market ratio (high, medium and low) by the weight of 30:40:30 respectively. Finally, divide into 3 subgroups of liquidity (illiquid, moderately liquid and liquid) with value-weighted of 30:40:30 each division. In addition, this research uses 4 illiquidity measures as mentioned in the last section including bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio. Consequently, 18 portfolios were constructed for each illiquidity measures. All of the factors are annually rebalanced and mimicking portfolio returns of each factor can be estimated by value-weighted return as follow,

$$LIQ_t = R^{illiq}_{avg,t} - R^{liq}_{avg,t} \tag{20}$$

Where $R^{illiq}_{avg,t}$ is average return of illiquid portfolio at time t and $R^{liq}_{avg,t}$ is average return of liquid portfolio at time t.

The main estimator to capture the difference of liquidity risk between pre- and post-split period is $\beta_{l,1}$. Hence, the hypothesis testing which is tested by t-test is presented below:

Hypothesis testing

$H_0: \beta_{l,1} = 0$

(Liquidity risk is the same as after splits)

$H_1: \beta_{l,1} \neq 0$

(Liquidity risk is not the same as after splits)

Where, $\beta_{l,1}$ are liquidity risk difference from four illiquidity measures including bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio.

3.3.5. Information Asymmetry

Due to stock prices are dropped to the optimal trading range after splits, small traders are able to trade these stocks. Small traders usually are uninformed traders. Hence, level of information asymmetry may be lower due to the presence of uninformed trader. Madhavan, Richardson, and Roomans (1997) proposed that price changes are the function of asymmetric information component (a), autocorrelation of order flow (b) and transaction cost (c) as follow,

$$P_t - P_{t-1} = a(X_t - bX_{t-1}) + c(X_t - X_{t-1}) + \varepsilon_t \tag{21}$$

Where P_t is mid-price between bid price and ask price at time t, P_{t-1} is mid-price between bid price and ask price at time t-1, X_t is trade indicator that would equal to one for buy-initiated trade and equal to minus one for sell-initiated trade at time t, X_{t-1} is trade indicator that would equal to one for buy-initiated trade and equal to minus one for sell-initiated trade at time t-1, a is asymmetric information component, b is autocorrelation of order flow and c is transaction cost.

Since both signaling and liquidity can affect information asymmetry changes as mentioned by Grinblatt, Masulis, and Titman (1984) and Desai, Nimalendran, and Venkataraman (1998). Three estimation periods are provided to study the information asymmetry changes. Estimation period follows Conroy, Harris, and Benet (1990).

Pre-announcement period is in the range of -69 day to -10 day before the split announcements. Post-announcement period is in the range of +10 day to +69 day after the announcements to study the impact of signaling to information asymmetry. Post-split period is in the range of +10 day to +69 day after the ex-date to study the impact of signaling and liquidity or impact of doing stock splits to information asymmetry. Note that these three estimation windows also used to estimate the probability of informed trading (PIN) in the next section. The hypothesis testing which is examined by Welch's t-test is shown below:

Hypothesis testing

$$H_0: a_{before\ announcement} = a_{after\ announcement}$$

(Information asymmetry before announcement is the same as after stock split announcements)

$$H_1: a_{before\ announcement} \neq a_{after\ announcement}$$

(Information asymmetry before announcement is not the same as after stock split announcements)

$$H_0: a_{before\ announcement} = a_{after\ effective}$$

(Information asymmetry before announcement is the same as after stock split)

$$H_1: a_{before\ announcement} \neq a_{after\ effective}$$

(Information asymmetry before announcement is not the same as after stock split)

Where, $a_{before\ announcement}$ is the average of information asymmetry estimated in pre-announcement period, $a_{after\ announcement}$ is the average of information asymmetry estimated in the post-announcement period and $a_{after\ effective}$ is the average of information asymmetry estimated in the post-split period.

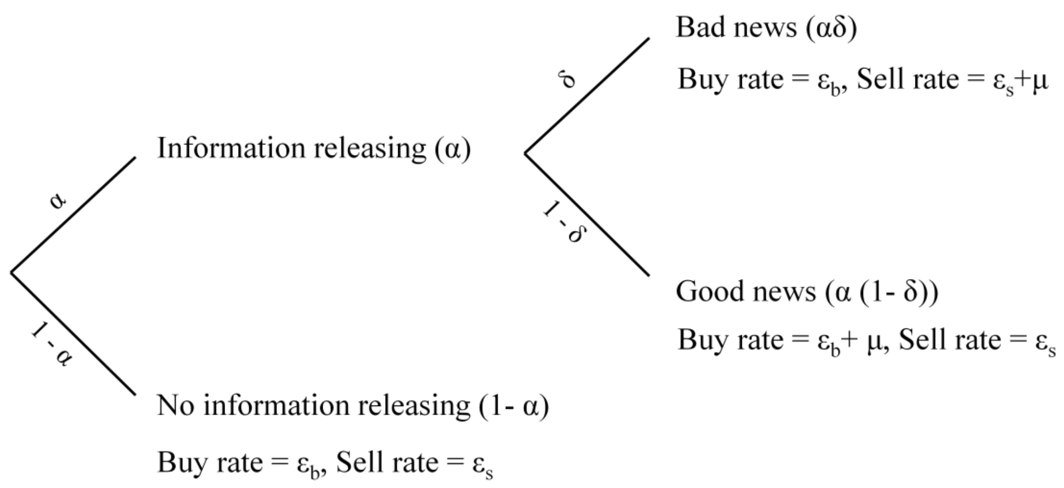
3.3.6. Probability of Informed Trading (PIN)

In the last section, MRR model (1997) study information asymmetry by spread decomposition. In this section, information asymmetry would be studied by arrival rate of orders when information arrives.

Basically, transactions in the stock market are set by two mains type of traders. First, uninformed traders who have only fundamental and technical information of the company decide to invest within these levels of information accessible. Second are informed traders who trade with non-public information. PIN can estimate the proportion of the informed traders to overall traders.

In this research, I estimate PIN by following Easley, Kiefer and O'Hara (1996). PIN diagram is presented in figure 1. PIN can be estimated by these following concepts. Let ε_b and ε_s are the arrival rates of noise traders who submit buy and sell order respectively. Information event occur in the probability of α. Information event

Figure 1 Probability of informed trading diagram



can be occurred as bad news and good news in the probability of δ and 1-δ respectively. So probability of no information occurrence is 1- α. Moreover, when information occurs as bad news with probability of $\alpha\delta$, traders prefer submitting sell order. Hence, the arrival rates of sell order become $\varepsilon_s + \mu$ and arrival rates of buy order remain ε_b. In contrast, when information occurs as good news with probability of $\alpha(1-\alpha)$, traders prefer submitting buy order. Consequently, the arrival rates of buy order become $\varepsilon_b + \mu$ and arrival rates of buy order remain ε_s. Let $\theta = \{\varepsilon_b, \varepsilon_s, \alpha, \delta, \mu\}$. The likelihood function for one trading day can be estimated as follows,

$$L(\theta|B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^S}{S!} + \alpha(1-\delta)e^{-(\varepsilon_b+\mu)}\frac{(\varepsilon_b+\mu)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \quad (22)$$

Where B is the numbers of submitted buy orders and S is the numbers of submitted sell orders for one trading day.

To estimate θ in the above model that including $\varepsilon_b, \varepsilon_s, \alpha, \delta$ and μ, trading information of 60 days as estimation window in the information asymmetry section is used to maximize the likelihood function as below,

$$V = L(\theta|B,S) = \prod_{\mathrm{j=1}}^{\mathrm{j=60}} L\left(\theta\middle|B_j, S_j\right) \tag{23}$$

Probability of informed trading (PIN) for each stock in 60 days period can be measured by following equation,

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{24}$$

Since probability of informed trading (PIN) is an alternative to show the quantity of information asymmetry, PIN is prepared to demonstrate the information asymmetry changes by the effect from stock split events. PIN of the three periods are estimated including pre-announcement period, post-announcement period and post-split period as suggested in the last section. Two factors needed to estimate PIN are numbers of submitted buy orders and numbers of submitted sell orders. They can be constructed by the frequency of sending buy and sell orders of each stock in each day by using deal files of intraday data.

To examine to difference of three periods, the null hypothesis which is examined by Welch's t-test is shown below:

Hypothesis testing

$$H_0: PIN_{before\ announcement} = PIN_{after\ announcement}$$

(Probability of informed trading before stock split announcement is the same as after stock split announcement)

$$H_1: PIN_{before\ announcement} \neq PIN_{after\ announcement}$$

(Probability of informed trading before stock split announcement is not the same as after stock split announcement)

$$H_0: PIN_{before\ announcement} = PIN_{after\ effective}$$

(Probability of informed trading before stock split announcement is the same as after stock split)

$$H_1: PIN_{before\ announcement} \neq PIN_{after\ effective}$$

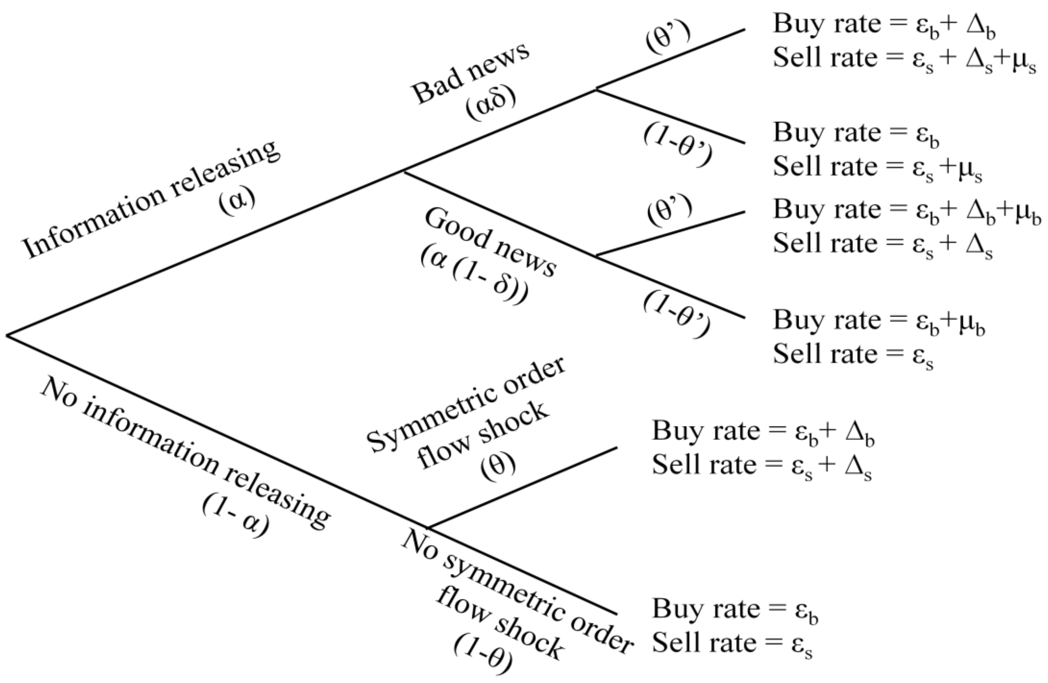
(Probability of informed trading before stock split announcement is not the same as after stock split)

Where, $PIN_{before\ announcement}$ is the average of probability of informed trading estimated in pre-announcement period, $PIN_{after\ announcement}$ is the average of probability of informed trading estimated in the post-announcement period and $PIN_{after\ effective}$ is the average of probability of informed trading estimated in the post-split period.

3.3.7. Adjusted Probability of Informed Trading (APIN)

The probability of informed trading (PIN) is widely used in many previous literatures. In addition, adjusted probability of informed trading (APIN) was constructed by Duarte and Young (2009) to extend the PIN model in two conditions. First, as the good news or bad news occur, the arrival rate of buy orders and sell orders are μ_b and μ_s respectively instead of the same arrival rate in PIN (μ). Second, symmetric order-flow shock is added due to the different variation in buy order flow (Δ_b) and sell order flow (Δ_s). APIN diagram is shown in the Figure 2.

Figure 2 Adjusted probability of informed trading diagram



The likelihood function of APIN is provided below:

$$\begin{aligned} L(\theta|B,S) = {} & (1-\alpha)(1-\theta)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \\ & + (1-\alpha)\theta e^{-(\varepsilon_b+\Delta_b)}\frac{(\varepsilon_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\Delta_s)}\frac{(\varepsilon_s+\Delta_s)^S}{S!} \\ & + \alpha\delta(1-\theta^{'})e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-(\varepsilon_s+\mu_s)}\frac{(\varepsilon_s+\mu_s)^S}{S!} \\ & + \alpha\delta\theta^{'}e^{-(\varepsilon_b+\Delta_b)}\frac{(\varepsilon_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\mu_s+\Delta_s)}\frac{(\varepsilon_s+\mu_s+\Delta_s)^S}{S!} \\ & + \alpha(1-\delta)(1-\theta^{'})e^{-(\varepsilon_b+\mu_b)}\frac{(\varepsilon_b+\mu_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \\ & + \alpha(1-\delta)\theta^{'}e^{-(\varepsilon_b+\mu_b+\Delta_b)}\frac{(\varepsilon_b+\mu_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\Delta_s)}\frac{(\varepsilon_s+\Delta_s)^S}{S!} \end{aligned} \tag{25}$$

where α is the probability of information event occur, ε_b and ε_s are the arrival rates of noise traders who submit buy and sell order respectively, δ is the probability of information event occur as bad news, 1-δ is the probability of information event occur as good news, B is the numbers of submitted buy orders, S is the numbers of submitted sell orders for one trading day, θ is the symmetric order flow shock for no information occur event, $\theta^{'}$ is the symmetric order flow shock for information occur event, Δ_b is the arrival rate of buys due to the event of symmetric order-flow shock, Δ_s is the arrival rate of sells due to the event of symmetric order-flow shock, μ_b is the arriving rate of buys of informed traders by good news and μ_s is the arriving rate of sells of informed traders by bad news.

To estimate parameter vector in the above model that including $\varepsilon_b, \varepsilon_s, \alpha, \delta, \theta, \theta', \mu_b, \mu_s, \Delta_b$ and Δ_s, trading information of 60 days as estimation window in the information asymmetry section is used to maximize the likelihood function as equation 24.

Adjusted probability of informed trading (APIN) for each stock in 60 days period can be measured by following equation,

$$APIN = \frac{\alpha(\delta\mu_s+(1-\delta)\mu_b)}{\alpha(\delta\mu_s+(1-\delta)\mu_b)+(\Delta_b+\Delta_s)(\alpha\theta'+(1-\alpha)\theta)+\varepsilon_b+\varepsilon_s} \qquad (26)$$

By extending PIN, APIN is an alternative to show the quantity of information asymmetry. APIN is prepared to demonstrate the information asymmetry changes by the effect from stock split events. APIN of the three periods are estimated including pre-announcement period, post-announcement period and post-split period. Data used to estimate APIN are numbers of submitted buy orders and numbers of submitted sell orders. They are constructed by the frequency of sending buy and sell orders of each stock in each day by using intraday data.

To examine to difference of three periods, the null hypothesis which is examined by Welch's t-test is shown below:

Hypothesis testing

$$H_0: APIN_{before\ \ announcement} = APIN_{after\ \ announcement}$$

(Adjusted probability of informed trading before stock split announcement is the same as after stock split announcement)

$H_1: APIN_{before\ announcement} \neq APIN_{after\ announcement}$

(Adjusted probability of informed trading before stock split announcement is not the same as after stock split announcement)

$H_0: APIN_{before\ announcement} = APIN_{after\ effective}$

(Adjusted probability of informed trading before stock split announcement is the same as after stock split)

$H_1: APIN_{before\ announcement} \neq APIN_{after\ effective}$

(Adjusted probability of informed trading before stock split announcement is not the same as after stock split)

Where, $APIN_{before\ announcement}$ is the average of adjusted probability of informed trading estimated in pre-announcement period, $APIN_{after\ announcement}$ is the average of adjusted probability of informed trading estimated in the post-announcement period and $APIN_{after\ effective}$ is the average of adjusted probability of informed trading estimated in the post-split period.

CHAPTER IV

RESULTS AND DISCUSSION

From last chapter, I design the methodology to answer research questions. To reveal the evidence of three main research questions, this chapter is organized into three sections respectively: 1) signaling evidence, 2) liquidity evidence, and 3) information asymmetry evidence.

4.1. Signaling Evidence

Since stock split announcements do not change the overall firm's value, they should result in no surprising changes of stock return. However, the following results tell a different story. In Tables 2, 3 and 4 the summary statistic of abnormal returns from OLS market return, abnormal returns from market adjusted model and abnormal trading volume around stock split announcements are presented, respectively. Moreover, t-statistic is provided in Tables 2, 3 and 4 to test the null hypothesis 1 and 2: the abnormal return around split announcements is not positive, and the abnormal trading volume around split announcements is not positive, respectively.

Mean of abnormal stock return from OLS market model and mean of abnormal return from market adjusted return on the announcement date are 1.06% (t-statistic 4.59) and 1.15% (t-statistic 4.64) respectively. Consequently, the null hypothesis testing of abnormal return is rejected at stock split announcement date.

Moreover, cumulative abnormal return especially in the period from -5 day to +5 day of announcement date from OLS market model and market adjusted return are 4.85% (t-statistic 6.35) and 7.01% (t-statistic 8.54). The null hypothesis testing of abnormal return is rejected around the stock split announcement date.

Mean of abnormal trading volume on the announcement date is 13363 shares (t-statistic 1.65). This also rejects the null hypothesis that the abnormal trading volume at split announcements is not positive. Cumulative abnormal trading volume are 116570 shares (t-statistic 4.35) that rejects the null hypothesis of the abnormal trading volume around split announcements is not positive. In order to recheck that average abnormal trading volume is not overwhelmed by high number of shares outstanding companies, abnormal trading volume of each firm is individually tested. Consequently, there are 117 firms which significantly have abnormal trading volume around stock split announcements from totaling 149 firms. This means that investors strongly pay attention to the 79 percent of the stock split announcement event.

Rejection of null hypothesis of abnormal return and trading volume are consistent with the findings of Grinblatt, Masulis, and Titman (1984) and Lamoureux and Poon (1987). Presence of abnormal return and abnormal trading volume around the stock split announcements suggest that investors consider the stock split announcement as good news as suggested by signaling hypothesis. Hence, signaling evidence in Thailand is in line with evidence from other markets such as Toronto Stock Exchange by Elfakhani and Lung (2003), Tokyo Stock Exchange by Guo, Zhou and Cai (2008), and London Stock Exchange by Kalotychou, Staikouras and Zagonov (2009).

Cumulative abnormal return and cumulative abnormal trading volume is in Table 2, 3 and 4 provide further support to the signaling hypothesis. The cumulative abnormal return and cumulative abnormal trading volume are significantly positive especially in the period from -3 day to 0 day of announcement date. The cumulative abnormal returns from OLS market model, the cumulative abnormal returns from market adjusted model and cumulative abnormal trading volume around stock split announcements in the period from -3 day to 0 day of event day are 3.46% (t-statistic, 7.51), 4.16% (t-statistic 8.41) and 66843 shares (t-statistic, 4.14) respectively. Results show that the stock price is adjusted to the higher price in the short-run after good news announcement (within day 0 of stock split announcement). This shows consistency of semi-strong form efficient market hypothesis[2]. In addition, the results show the significance of abnormal return and abnormal trading volume in the period before stock split announcement (from -3 day to -1 day before announcement date). These mean that there is a group of informed traders who interpret the leakage news of stock split announcement as good news.

In summary, stock splits are good news to investors. Hence, stockholder, informed traders and traders would benefit from stock splits by holding or buying the stocks around stock split announcements.

[2] Semi-strong form of efficient market hypothesis suggests that as good news are known as public; the value of that asset would adjust to the good news immediately.

4.2. Liquidity Evidence

Apart from the signaling effect, stock splits also have impact on liquidity. Trading activities, alternative illiquidity measures and liquidity risk are considered in the period before stock split announcement date and after stock split effective date to exhibit the liquidity evidence.

4.2.1. Trading Activities

The summary of trading activities changes is demonstrated in Table 5. Panel A shows trading volume for various trade sizes. Panel B reports proportion of trades for various trade sizes. Panel C displays effective spread, relative spread and proportion of limit order. Panel D exhibits proportion of time of stock trading within each spread. Panel A is constructed to test the null hypothesis 3: trading volume in the post-split period is the same as pre-split period. Panel A shows the rejection of the null hypothesis especially for small trade size. The aggregate trading volume of small trades significantly increases for 118.75% (from 0.98 to 2.14 million baht) after splits. This result indicates that investors do pay attention to the split stock especially for small investors. It is consistent with the trading range hypothesis with the following mechanism. Stock price is reduced into the certain trading range after splits. Consequently, small investors who can afford only a small amount of money are able to trade these lower stock prices after splits.

The proportion of trades for various trade sizes is used to demonstrate the liquidity evidence of stock splits. The proportion of trades for various trade sizes is presented in Panel B which is used to test the null hypothesis 4: proportion of trades for various trade sizes in the post-split period is the same as pre-split period. The rejection of the null hypothesis 4 is indicated in the Panel B by the reduction in proportion of medium- and large-trades and the increasing in proportion of small trades after stock splits. Like Panel A, results in Panel B are also consistent with trading range hypothesis and with previous researches such as Lamoureux and Poon (1987) and Muscarella and Vetsuypens (1996) who found that the trading volume increases for all trade size, especially highly increase for 138.3% in small trade size.

Panel C exhibits three trading activities including effective spread, relative spread and proportion of limit order to test null hypothesis 5 and 7: effective spread and relative spread in the post-split period are the same as pre-split period and proportion of limit order premium in the post-split period is the same as pre-split period.

From Panel C, effective spread significantly falls for more than 600% due to stock price reduction after splits. However, relative spread is not significantly changed after splits as the increasing of 0.17% per trade (t-statistic 0.80) and proportion of limit order almost remain unchanged after splits. Consequently, the null hypothesis of effective spread in the post-split period is the same as pre-split period is rejected. However, the remaining is failed to reject at 5% significance level.

From tick-size hypothesis, higher relative spread could attract liquidity providers to trade by placing limit orders. From the results, relative spread is not significantly change after stock splits. Hence, it fails to attract the liquidity provider after stock splits that is also shown by no change in proportion of limit order.

Consequently, there is no change of liquidity supported by tick-size hypothesis. Moreover, the total trading volume shows in Panel A increase. This implies that the stock split can attract investors both liquidity providers and liquidity takers because of its price reduction.

On the other hand, effective spread and relative spread can be viewed in liquidity measure perspective. Effective spread per transaction shows that there is the liquidity improvement after splits. In contrast, relative spread does not show significantly liquidity improvement after splits. However, mildly relative spread improvement may occur because of manager intend to maintain the optimal relative tick size as suggested by Angel (1997). Liquidity improvement is also demonstrated by proportion of time of stock trading within each spread in Panel D. Proportion of time of stock trading within each spread is used to test null hypothesis 5: liquidity level in the post-split period are the same as pre-split period. The proportion of time of stock trading within one tick significantly increases for 5.70% (t-statistic 2.31). Null hypothesis of liquidity level in the post-split period are the same as pre-split period is rejected. Hence, there is an improvement of liquidity level after stock splits.

4.2.2. Illiquidity Measures

Illiquidity measures including bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio are illustrated in Table 6. Illiquidity measures are used to examine the liquidity change by the null hypothesis 5: illiquidity measure in the post-split period is the same as pre-split period. Results show rejection of null hypothesis at 5% significance level for three illiquidity measures including relative bid-ask spread, Liu's ratio and price impact ratio. Bid-ask spread does not change significantly after splits, it is only 0.03 (t-statistic -0.66) lower after splits. Moreover, relative bid-ask spread and Liu's ratio decline after splits for 1.29% (t-statistic -1.85) and 30.39 (t-statistic -3.74) respectively. In contrast, price impact ratio rises for 335.79 (t-statistic 3.78) after splits. Turnover ratio which is a denominator part of price impact ratio also significantly falls around three times after splits.

From the above results, alternative liquidity measures give different liquidity evidence. Bid-ask spread shows mild improvement of liquidity. Relative bid-ask spread and Liu's ratio reveal higher liquidity level. On the contrary, price impact ratio and turnover ratio imply liquidity deterioration. These results seem to be concluded that the liquidity changes depend on the illiquidity measure which is consistent with Conroy, Harris, and Benet (1990).

However, there might be some bias in the calculation of price impact ratio and turnover ratio. Price impact ratio and turnover ratio ignore the trading discontinuity since they are calculated only on the days with a valid observation. This may leads to the bias in the pre-splits period which have high amount of non-valid observation day. Hence, price impact ratio is not a good illiquidity measure then it is excluded from illiquidity measures. It can be conclude that liquidity is improved after splits This makes result consistent with many finding such as Copeland (1979) and Lin, Singh, and Yu (2009).

Moreover, trading volume (in baht) shown in Panel A Table 5 increases after stock splits is opposed by turnover ratio result. However, Table 7 shows the summary statistics of stock price changes around stock splits that can further explain the contradicting results. There are 23 observations of 2-for-1 splits, 40 observations of 5-for-1 splits and the largest portion of 97 observations of 10-for-1 splits. Stock price before splits of 2-for-1 splits is 2.24 times of stock price after splits (t-statistic -46.76). Stock price before splits of 5-for-1 splits is 4.79 times of stock price after splits (t-statistic -49.40). The highest portion which could strongly affect the increase in trading volume is 10-for-1 splits; its stock price before is 7.95 times of stock price after splits (t-statistic -38.13). Trading volume which is determined by stock price multiplied by number of shares traded. Due to stock price increase during the stock split announcement period (signaling effect), it can offset the lower number of shares traded and result in higher trading volume.

4.2.3. Liquidity Risk

Last liquidity evidence is demonstrated by the changes of the liquidity risk. There are four alternatives illiquidity measures plugged into standard capital asset pricing model (CAPM) to form the liquidity-augmented capital asset pricing model (CAPML). Moreover, the dummy variable of after splits (D_t) is added to estimate the changes by stock split effect in each independent variables which is shown in Table 8. In this section, main objective is to test the null hypothesis 6: liquidity risk in the post-split period is the same as pre-split period. Consequently, I found the rejection of null hypothesis from most of the illiquidity measures except bid-ask spread. From Table 8, changes in liquidity risk which can be indicated by average excess return from liquidity $\beta_{il,1}$ of alternative illiquidity measures including bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio are -0.02, -0.56,-0.49 and -0.90 (t-statistic are -0.26, -3.35, -2.19 and -3.08) respectively. Most of results show the significant decreasing in liquidity risk ($\beta_{il,1}$) after splits that is consistent with the earlier results of trading activities improvement and illiquidity measures deterioration. Moreover, even the negative liquidity risk premium ($\beta_{il,0}$) contradict to the hypothesis of return-liquidity relationship, but it is still consistent with earlier finding of return-liquidity relationship in the Stock Exchange of Thailand by Worasuttipisit (2006)[3].

4.3. Information Asymmetry Evidence

4.3.1. Information Asymmetry

Components of price changes including asymmetric information component, autocorrelation of order flow and transaction cost is presented in Table 9. Asymmetric information component is prepared in three periods including pre-announcement, post-announcement and post-split are used to test the null hypothesis 8 and 9: information asymmetry in the post-announcement period is the same as pre-announcement period and information asymmetry in the post-split period is the same as pre-split period. Table 8 implies the rejection of the null hypothesis. Asymmetric information component significantly decreases in the period of post-announcement and post-split for 0.07 baht (t-statistic -3.07) and 0.18 baht (t-statistic -6.49) respectively.

[3] Worasuttipisit (2006) also found that liquidity risk premium on the Stock Exchange of Thailand is negative over the study period from 1995 to 2005.

The above results suggest that the information asymmetry falls 0.07 baht from the stock split announcement due to the absence of the leakage-information of good news. This result is in line with the signaling hypothesis. Moreover, the presence of small traders which is shown in the Panel A and Panel B of Table 5 continuously impact to decrease information asymmetry cost for another 0.11 baht. Hence, reduction of asymmetric information component in the post-split period can be explained by trading range hypothesis.

In addition, transaction cost components are negative significance of -0.13, -0.08 and -0.03 for before-announcement, after announcement and after effective respectively. This means that compensation of providing liquidity is negative. Negative compensation of providing liquidity is consistent with the evidence of Sweden stock market by Sandas (2001). Transaction cost components are less negative of 0.05 baht (t-statistic 4.00) and 0.10 baht (t-statistic 9.36) after stock splits announcement and after splits respectively. However, transaction cost stills negative after splits. Hence, negative compensation of providing liquidity supports the absence of liquidity providers attraction in Thai stock market as shown in the Panel C of Table 5.

4.3.2. Probability of Informed Trading

In Table 10, probability of informed trading (PIN) is demonstrated to test the null hypothesis 10 and 11: probability of informed trading in the post-announcement period is the same as pre-announcement period and probability of informed trading in the post-split period is the same as pre-split period. Results from Table 10 show no significance of probability of informed trading changes for both post-announcement period and post-split period. In other words, the null hypothesis is failed to reject in both periods. However, PIN changes after stock splits show mild evidence that the informed traders slightly decrease after splits for 3.27% (t-statistic -0.56).

Panel A of Table 5 displays the higher attention from all trade size after splits. Basically, lower stock price attract only the uninformed traders. However, results in this section show that stock splits attract both uninformed traders and informed traders. And stock splits can attract uninformed trader more than informed traders for only a small portion. This weak evidence also conforms to the suggestion of Desai, Nimalendran, and Venkataraman (1998) that proportion of noise traders dominate informed traders in total trading volume, hence adverse information component decreases after split.

4.3.3. Adjusted probability of Informed Trading

Adjusted probability of informed trading (APIN) is presented in Table 11. The null hypothesis 10 and 11 are adjusted probability of informed trading in the post-announcement period is the same as pre-announcement period and adjusted probability of informed trading in the post-split period is the same as pre-split period, respectively. The results from APIN model also show weak evidence of decreasing in portion of informed traders. Table 11 displays insignificant change of APIN for both after announcement and after effective of stock splits. Adjusted probability of informed trading (APIN) is decreased for 1.28% (t-statistic -0.24) and 1.70% (t-statistic -0.31) for the after announcement and after effective of stock splits respectively.

Due to the results of PIN and APIN is insignificantly changed and the trading volume for small trades increases significantly, it can conclude that the small traders (uninformed traders) are attracted to invest in the lower stock price. Consequently, informed traders gain profit by trading with higher number of uninformed traders.. Hence, informed traders would be the one who benefits from stock splits.

Table 2 Summary statistics of abnormal return by OLS market model method

This table shows the summary statistics including average of stock abnormal return and t-statistic from the abnormal return estimated by OLS market model method around the announcement period from -5 to +5 day around the stock split announcement date for totaling 149 times of stock splits in the period from 2002 to 2009. OLS market model method can provide the abnormal by following equation:

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}$$

where $AR_{i,t}$ is abnormal return of stock i at time t, $R_{i,t}$ is return of stock i at time t, $R_{m,t}$ is market return of stock i at time t, $\hat{\alpha}_i$ and $\hat{\beta}_i$ are intercept and slope respectively which are obtained from the estimation period from -244 to -6 day around the stock split announcement date.

Event day	Abnormal return (AR) (t-stat)		Cumulative abnormal return (t-stat)	
-5	0.25%	(1.08)	0.25%	(1.08)
-4	0.24%	(1.05)	0.49%	(1.50)
-3	0.84%**	(3.65)	1.33%	(3.34)
-2	0.86%**	(3.73)	2.19%**	(4.75)
-1	0.70%**	(3.05)	2.89%**	(5.61)
0	1.06%**	(4.59)	3.95%**	(7.00)
1	0.30%	(1.32)	4.26%**	(6.98)
2	-0.04%	(-0.16)	4.22%**	(6.47)
3	0.13%	(0.57)	4.35%**	(6.29)
4	0.16%	(0.71)	4.51%**	(6.19)
5	0.34%	(1.48)	4.85%**	(6.35)

** significant level at 1 percent

Table 3 Summary statistics of abnormal return by market adjusted returns method

This table demonstrates the summary statistics including average stock abnormal return and t-statistic from the abnormal return estimated by market adjusted returns method around the announcement period from -5 to +5 day around the stock split announcement date for totaling 149 times of stock splits in the period from 2002 to 2009. Market adjusted returns can be determined as follow:

$$AR_{i,t} = R_{i,t} - R_{m,t}$$

where $AR_{i,t}$ is abnormal return of stock i at time t, $R_{i,t}$ is return of stock i at time t and $R_{m,t}$ is market return of stock i at time t.

Event day	Abnormal return (AR) (t-stat)		Cumulative abnormal return (t-stat)	
-5	0.40%	(1.62)	0.40%	(1.62)
-4	0.52%*	(2.09)	0.92%*	(2.62)
-3	1.07%**	(4.31)	1.98%**	(4.63)
-2	1.04%**	(4.20)	3.02%**	(6.11)
-1	0.91%**	(3.66)	3.93%**	(7.10)
0	1.15%**	(4.64)	5.08%**	(8.38)
1	0.54%*	(2.18)	5.62%**	(8.58)
2	0.23%	(0.91)	5.84%**	(8.35)
3	0.30%	(1.22)	6.14%**	(8.28)
4	0.36%	(1.45)	6.50%**	(8.31)
5	0.51%*	(2.05)	7.01%**	(8.54)

* significant level at 5 percent
** significant level at 1 percent

Table 4 Summary statistics of abnormal trading volume

This table presents the summary statistics including average of stock abnormal trading volume and t-statistic around the announcement period from -5 to +5 day for totaling 149 times of stock splits in the period from 2002 to 2009 around the stock split announcement date which can be estimated as follow:

$$ATV_{i,t} = TV_{i,t} - \overline{TV_i}$$

where $ATV_{i,t}$ is abnormal trading volume of stock i at time t, $TV_{i,t}$ is trading volume of stock i at time t and $\overline{TV_i}$ is the average trading volume of stock i from -244 day to -6 day before split announcements.

Event day	Abnormal trading volume (t-stat)		Cumulative abnormal trading volume (t-stat)	
-5	8035	(1.00)	8035	(0.99)
-4	7223	(0.89)	15258	(1.34)
-3	12402	(1.53)	27661*	(1.98)
-2	13286*	(1.65)	40946*	(2.54)
-1	27792**	(3.44)	68739**	(3.81)
0	13363*	(1.65)	82102**	(4.15)
1	8213	(1.01)	90315**	(4.23)
2	13481*	(1.67)	103796**	(4.54)
3	4517	(0.56)	108313**	(4.47)
4	4097	(0.51)	112409**	(4.40)
5	4160	(0.52)	116570**	(4.35)

* significant level at 5 percent
** significant level at 1 percent

Table 5 Trading activities change around stock splits

This table shows the summary statistics including pre-split value, post-split value, difference between post- and pre-split, and their t-statistics. Panel A is aggregate trading volume shown in millions baht. Proportion of trades for various trade sizes is reported in Panel B. Trade sizes are classified by 0th to 30th percentile, 31st percentile to 70th percentile, and 71st to 100th percentile of retail investors' trading volume in the period from 2001 to 2009 as small trades, medium trades and large trades respectively. Effective spread which is determined by two times of the average of absolute value of transaction price minus mid-value of bid- and ask-price, average relative spread and average proportion of limit order for pre-split period (from day -69 to day 10 before stock split effective date, post-split period (from day 10 to day 69 after stock split effective date) and changes are presented in Panel C. Proportion of time of stock trading within each spread (one tick, two or three ticks and four or more ticks) is showed in Panel D.

	Pre-split (t-stat)		Post-split (t-stat)		Post – Pre split (t-stat)	
Panel A: Trading volume in various trade sizes (in millions baht)						
Small trades	0.98**	(7.74)	2.14**	(4.49)	1.16*	(2.35)
Medium trades	6.85**	(5.62)	12.23**	(5.06)	5.38*	(1.99)
Large trades	41.77**	(4.26)	50.70**	(5.00)	8.94	(0.63)
Panel B: Proportion of trades for various trade sizes (in percent)						
Small trades	33.74%**	(16.05)	55.35%**	(34.74)	21.61%**	(8.19)
Medium trades	44.39%**	(36.19)	34.30%**	(27.80)	-10.09%**	(-5.80)
Large trades	21.87%**	(15.30)	10.35%**	(14.25)	-11.52%**	(-7.18)
	Pre-split (t-stat)		Post-split (t-stat)		Post – Pre split (t-stat)	
Panel C: Effective spread (in baht), relative spread and proportion of limit order						
Effective spread	0.75**	(6.33)	0.12**	(9.49)	-0.63**	(-5.26)
Relative spread	1.31%**	(7.40)	1.48%**	(10.72)	0.17%	(0.80)
Proportion of limit order	83.73%**	(1099)	83.76%**	(1133)	0.03%	(0.28)
	Pre-split (t-stat)		Post-split (t-stat)		Post – Pre split (t-stat)	
Panel D: Proportion of time of stock trading within each spread						
Stock trading in one tick	79.07%**	(40.29)	84.78%**	(56.79)	5.70%*	(2.31)
Stock trading in two and three ticks	11.93%**	(8.13)	9.36%**	(8.11)	-2.57%	(-1.38)
Stock trading in four or more ticks	8.99%**	(4.43)	6.86%**	(4.07)	-2.13%	(-0.81)

* significant level at 5 percent

** significant level at 1 percent

Table 6 Illiquidity measures change around stock splits

This table demonstrates the summary statistics including pre-split value, post-split value, difference between post- and pre-split, and their t-statistics of four alternative illiquidity measures. Illiquidity measures are bid-ask spread, relative bid-ask spread, Liu's ratio, price impact ratio, turnover ratio. Pre-split period and post-split period used to calculate Illiquidity measures are -13th month to -1st month prior to stock split effective date and from 1st month to 13th month respectively. Liu's ratio and price impact ratio can be determined as follow:

$$\text{Liu's ratio (LMx)} = [\text{Numbers of zero daily volumes in prior x months} + \frac{1/(x\text{-}month\ turnover\ )}{Deflator}] \times \frac{21x}{NoTD}$$

where LMx, as the standardized turnover-adjusted number of zero daily trading volumes over the prior x months (x = 1; 6; 12), x-month turnover is calculated by sum of daily turnover over the x-month period, daily turnover is the ratio of number of shares traded on a day to the number of shares outstanding at the end of the day and NoTD is the total number of trading days in the market over the prior x months. And deflator is chosen such that $0 < \frac{1/(x\text{-}month\ turnover\ )}{deflator} < 1$ for all samples.

Price impact ratio is measured by

$$RtoTR = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}}$$

where R_{itd} and TR_{itd} is return and Turnover Ratio of stock i at day d in month t and D_{it} is number of valid observation days in month t for stock i.

	Pre-split (t-stat)		Post-split (t-stat)		Post – Pre split (t-stat)	
Bid-ask spread (baht)	0.20**	(6.76)	0.17**	(5.91)	-0.03	(-0.66)
Relative bid-ask spread	3.56%**	(5.70)	2.27%**	(7.37)	-1.29%*	(-1.85)
Liu's ratio	49.69**	(6.16)	19.30**	(21.96)	-30.39**	(-3.74)
Price impact ratio	378.86**	(13.72)	1185.43**	(55.97)	806.57**	(23.17)
Turnover ratio	0.022*	(2.59)	0.007	(1.04)	-0.015**	(-2.83)

* significant level at 5 percent
** significant level at 1 percent

Table 7 Stock price change around stock splits

This table shows the summary statistics of stock price in the pre-split period, post-split period and difference between post- and pre-split for three different stock split factors. Three stock split factors are 2-for-1 stock splits (23 observations), 5-for-1 stock splits (40 observations) and 10-for-1 stock splits (97 observations). Stock price in each period is determined by averaging stock price in the pre-split period (from day -69 to day 10 before stock split effective date and post-split period (from day 10 to day 69 after stock split effective date).

	Pre-split (t-stat)		Post-split (t-stat)		Post – Pre split (t-stat)	
Stock price (2-for-1 splits)	45.91**	(89.34)	20.48**	(115.03)	-25.43**	(-46.76)
Stock price (5-for-1 splits)	47.27**	(62.73)	9.85%**	(127.59)	-37.41**	(-49.40)
Stock price (10-for-1 splits)	74.35**	(43.73)	9.35**	(77.70)	-65.00**	(-38.13)

** significant level at 1 percent

Table 8 Illiquidity risk change around stock splits

This table reports the relationship of excess return to market risk and alternative liquidity risk factors. Alternative liquidity risk factors are the liquidity return premium of mimicking portfolio of bid-ask spread, relative bid-ask spread, Liu's ratio and price impact ratio. Moreover, dummy variable is used to compare the difference of each risk factor between post- and pre-split period. The cross-sectional regression is provided as follow:

$$R_{it} - R_{ft} = \alpha_{i,0} + \alpha_{i,1}D_t + (\beta_{im,0} + \beta_{im,1}D_t)MKT_t + (\beta_{il,0} + \beta_{il,1}D_t)\ LIQ_t + \varepsilon_{it}$$

where R_{it} is the monthly return on stock i in month t, R_{ft} is risk free rate in month t, D_t is equal to one when t is in the post-split period, MKT_t is the excess market portfolio return in month t and LIQ_t is the mimicking portfolio return of liquidity factor in month t.

	$\alpha_{i,0}$ (t-stat)	$\alpha_{i,1}$ (t-stat)	$\beta_{im,0}$ (t-stat)	$\beta_{im,1}$ (t-stat)	$\beta_{il,0}$ (t-stat)	$\beta_{il,1}$ (t-stat)
Bid-ask spread	0.02**	-0.02**	0.36**	0.04	-0.44**	-0.02
	(9.39)	(-7.18)	(8.86)	(0.78)	(-10.94)	(-0.26)
Relative bid-ask spread	0.02**	-0.02**	0.44**	-0.29**	-0.47**	-0.56**
	(10.19)	(-7.35)	(7.53)	(-3.40)	(-4.65)	(-3.35)
Liu's ratio	0.02**	-0.02**	0.42**	-0.09	-0.81**	-0.49*
	(9.96)	(-7.77)	(8.15)	(-1.43)	(-5.68)	(-2.19)
Price impact ratio	0.02**	-0.02**	0.66**	-0.16**	-0.18	-0.90**
	(9.34)	(-7.23)	(18.33)	(-2.63)	(-0.95)	(-3.08)

* significant level at 5 percent
** significant level at 1 percent

Table 9 Effect of stock splits on the components of midpoint price changes

This table reports the relationship between midpoint price changes to the asymmetric information component (a), autocorrelation of order flow (b) and transaction cost (c) in the period of pre-announcement, post-announcement, post-split and the changes after announcement and splits. Information asymmetry estimation follows Madhavan, Richardson, and Roomans (1997) as equation below:

$$P_t - P_{t-1} = a(X_t - bX_{t-1}) + c(X_t - X_{t-1}) + \varepsilon_t$$

where P_t is mid-price between bid price and ask price at time t, P_{t-1} is mid-price between bid price and ask price at time t-1, X_t is trade indicator that would equal to one for buy-initiated trade and equal to minus one for sell-initiated trade at time t, X_{t-1} is trade indicator that would equal to one for buy-initiated trade and equal to minus one for sell-initiated trade at time t-1, a is asymmetric information component, b is autocorrelation of order flow and c is transaction cost.

	a	(t-stat)	b	(t-stat)	c	(t-stat)
Pre-announcement, -split	0.21**	(10.35)	0.70**	(14.49)	-0.13**	(-12.12)
Post-announcement	0.14**	(11.45)	0.72**	(21.09)	-0.08**	(-14.02)
Post-split	0.03	(1.86)	0.73**	(14.07)	-0.03**	(-8.95)
Post – pre announcement	-0.07**	(-3.04)	0.02	(0.36)	0.05**	(4.00)
Post – pre split	-0.18**	(-6.49)	0.03	(0.45)	0.10**	(9.36)

* significant level at 5 percent
** significant level at 1 percent

Table 10 The probability of informed trading

This table shows the probability of informed trading in the period of pre-announcement, post-announcement, post-split and the changes after announcement and splits. Probability of informed trading estimation follows Easley, Kiefer and O'Hara (1996) with the model as below:

$$L(\theta|B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} + \ \alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-\varepsilon_s+\mu}\frac{(\varepsilon_s+\mu)^S}{S!} +$$

$$\alpha(1-\delta)e^{-\varepsilon_b+\mu}\frac{(\varepsilon_b+\mu)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!}$$

where α is the probability of information event occur, ε_b and ε_s are the arrival rates of noise traders who submit buy and sell order respectively, δ is the probability of information event occur as bad news, 1-δ is the probability of information event occur as good news, B is the numbers of submitted buy orders, S is the numbers of submitted sell orders for one trading day and μ is the arriving rate of informed traders.

To estimate $\varepsilon_b, \varepsilon_s, \alpha, \delta$ and μ in order to calculate the probability of informed trading, maximum likelihood function and PIN calculation are provided as below:

$$V = L(\theta|B,S) = \prod_{\mathrm{j=1}}^{\mathrm{j=60}} L(\theta|B_j, S_j)$$

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s}$$

	PIN	(t-stat)
Pre-announcement, -split	24.87%**	(5.62)
Post-announcement	24.81%**	(5.74)
Post-split	21.60%**	(5.71)
Post – pre announcement	-0.06%	(-0.01)
Post – pre split	-3.27%	(-0.56)

** significant level at 1 percent

Table 11 The adjusted probability of informed trading

This table shows the adjusted probability of informed trading in the period of pre-announcement, post-announcement, post-split and the changes after announcement and splits. Adjusted probability of informed trading estimation follows Duarte and Young (2009) by the following model:

$$\begin{aligned} L(\theta|B,S) = {} & (1-\alpha)(1-\theta)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \\ & + (1-\alpha)\theta e^{-(\varepsilon_b+\Delta_b)}\frac{(\varepsilon_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\Delta_s)}\frac{(\varepsilon_s+\Delta_s)^S}{S!} \\ & + \alpha\delta(1-\theta')e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}\ e^{-(\varepsilon_s+\mu_s)}\frac{(\varepsilon_s+\mu_s)^S}{S!} \\ & + \alpha\delta\theta' e^{-(\varepsilon_b+\Delta_b)}\frac{(\varepsilon_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\mu_s+\Delta_s)}\frac{(\varepsilon_s+\mu_s+\Delta_s)^S}{S!} \\ & + \alpha(1-\delta)(1-\theta')e^{-(\varepsilon_b+\mu_b)}\frac{(\varepsilon_b+\mu_b)^B}{B!}\ e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \\ & + \alpha(1-\delta)\theta' e^{-(\varepsilon_b+\mu_b+\Delta_b)}\frac{(\varepsilon_b+\mu_b+\Delta_b)^B}{B!}\ e^{-(\varepsilon_s+\Delta_s)}\frac{(\varepsilon_s+\Delta_s)^S}{S!} \end{aligned}$$

where α is the probability of information event occur, ε_b and ε_s are the arrival rates of noise traders who submit buy and sell order respectively, δ is the probability of information event occur as bad news, 1-δ is the probability of information event occur as good news, B is the numbers of submitted buy orders, S is the numbers of submitted sell orders for one trading day, θ is the symmetric order flow shock for no information occur event, θ' is the symmetric order flow shock for information occur event, Δ_b is the arrival rate of buys due to the event of symmetric order-flow shock, Δ_s is the arrival rate of sells due to the event of symmetric order-flow shock, μ_b is the arriving rate of buys of informed traders by good news and μ_s is the arriving rate of sells of informed traders by bad news.

To estimate $\varepsilon_b, \varepsilon_s, \alpha, \delta, \theta, \theta', \Delta_b, \Delta_s, \mu_b$ and μ_s in order to calculate the adjusted probability of informed trading, maximum likelihood function and APIN calculation are provided as below:

$$V = L(\theta|B,S) = \prod_{j=1}^{j=60} L(\theta|B_j, S_j)$$

$$APIN = \frac{\alpha(\delta\mu_s + (1-\delta)\mu_b)}{\alpha(\delta\mu_s + (1-\delta)\mu_b) + (\Delta_b + \Delta_s)(\alpha\theta' + (1-\alpha)\theta) + \varepsilon_b + \varepsilon_s}$$

	APIN	(t-stat)
Pre-announcement, -split	19.53%**	(4.63)
Post-announcement	18.25%**	(5.35)
Post-split	17.83%**	(5.20)
Post – pre announcement	-1.28%	(-0.24)
Post – pre split	-1.70%	(-0.31)

** significant level at 1 percent

CHAPTER V

CONCLUSION

The three main findings of the impact of stock splits on the Stock Exchange of Thailand is explored by this research. First, there is signaling evidence confirmed by abnormal trading volume of 79 percent from all observations and average abnormal return of 1.06% at day 0 of stock split announcements. This implies that stock split announcements convey the information about good news to investor which is consistent with signaling hypothesis. Moreover, leakage of stock split announcement information is found indicated by the significant abnormal return in the period before the announcement day (day 0). From signaling evidence, it can be concluded that informed traders can generate abnormal return around stock split announcements from the belief of signaling hypothesis.

Second, there is a liquidity improvement after stock splits. Results exhibit the liquidity improvement after splits as expected by market characteristic of Thailand that need more liquidity than developed market. Supportive evidences of liquidity are the presence of small traders which are indicated by the higher proportion of small traders, the greater numbers of trading volume, the lower illiquidity measures, and the less liquidity risk after splits. These supportive evidences are in line with the trading range hypothesis: the certain range of the stock price after stock splits can attract small investors. Consequently, investors would have more choices to invest in higher liquidity stocks which could enhance their investment decision. However, one of illiquidity measures, price impact ratio, positively increases after splits. Since price impact ratio does not concern about non-valid observation days non-valid observation days, trading discontinuity is omitted from the measures. Hence, price impact ratio is not a good illiquidity measure then it is excluded from illiquidity measures. Consequently, liquidity improves after stock splits.

Stock split evidence in Thailand failed to support the tick-size hypothesis: relative spread (trading cost) is optimized after stock splits in order to attract the liquidity provider. From the results, relative spread is not significantly higher after stock splits. Since trading cost remains unchanged, stock splits fail to attract liquidity providers which is confirmed by insignificant change in proportion of limit order.

Third, information asymmetry is lower after stock splits. Regarding to the improvement of trading volume of small trade, the small traders (usually regarded as uninformed trader) are attracted by the stock splits. Significant decrease of adverse selection component, mild decrease of probability of informed trading and adjusted probability of informed trading also confirm the reduction of information asymmetry after stock splits. Results might benefit to informed traders as they have more number of uninformed counterparties.

In conclusion, my empirical evidences support the suggestion of signaling effect Grinblatt, Masulis, and Titman (1984), and Lamoureux and Poon (1987) and the liquidity improvement of stock splits also align with Maloney and Mulherin (1992) and Muscarella and Vetsuypens (1996). Moreover, the reduction in information asymmetry by the liquidity improvement is in line with Desai, Nimalendran, and Venkataraman (1998). These are the overall impact of stock splits on the Stock Exchange of Thailand.

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