A New Study On The Impacts Of Stock Split

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ABSTRACT

Stock splits are one of the common phenomena in the stock market. Three main theories are proposed to explain why firms split their stocks. They are liquidity, signaling, and optimal tick size theories. In this paper, we empirically test all three theories using some of the most recent methodologies. We use stock split data from 1962 to 2004. The empirical result is consistent with the signaling hypothesis in the sense that the firm-specific information has been found to decrease after the announcement of stock split. The liquidity has been found to decrease (increase) and the transaction cost has been found to increase (decrease) after the forward (reverse) split. Therefore, for the forward split, the empirical result is not consistent with the liquidity hypothesis which states that the liquidity should increase after the forward stock split. However, the evidence for the reverse split is consistent with the liquidity theory. Even though the increase in transaction cost is consistent with the optimal tick size hypothesis, the decrease in liquidity is not consistent with it. Therefore, the optimal tick size hypothesis is not fully supported by the empirical evidence.

1. INTRODUCTION

Stock splits are regular phenomenon in stock markets. There are mainly three theories that explain the reason behind stock split. In this section, we will briefly discuss these theories.

As pointed out by Lakonishok & Lev (1987), stock split is just like “a finer slicing of a given cake”. Since the change in number of shares does not involve changes to the future cash flow, in an efficient market with symmetric information, this event should be irrelevant to the value of the firm. In fact, stock split involves extra costs such as stock issuance taxes, listing fees, and mailing costs etc. (Sosnick (1961)). Despite of the transaction costs, managers are still enthusiastic about splitting their firms’ shares and stock splits are common events in reality. Therefore, the reasons behind stock split has been an interesting research topic in finance. There are three main theories which try to explain the stock split

1.1 Liquidity Theory

The first theory is the liquidity theory (or optimal trading range theory as suggested by Copeland (1979)). It states that there is an optimal price span for the stocks of a company in which trading is the most liquid, and managers adjust the stock price by splitting toward the optimal trading range in order to enhance the liquidity of the stocks. If the price is very high, large investors benefit because of low brokerage cost for their round lots. But small investors are discouraged to trade because of their limited money. Similarly, if the price is very low, large investors are not willing to invest in that stock. Therefore, the optimal price range is to equilibrate the preference of large investors and small investors so that the stock is most liquid.

Baker and Gallagher (1980) presents some evidence in support of this theory. In their survey of corporate managers’ motivation for stock splits, they find that managers tend to mention an optimal trading range to explain splits. The survey reports that 98% of chief financial officers admit that splits make it easier for small investors to purchase round lot and 94% of them believe that splits increase the number of investors and retain the stock prices in an optimal range.

As to the empirical evidence of stock split on liquidity, Copeland (1979) finds the residual trading volume to decrease after the stock split. Murray (1985) finds the trade volume after stock splits to decreases in short term, but, does not change in long term. Similar results are obtained by Lamoureux & Poon (1987) and Lakonishok & Lev (1987). Desai, Nimalendran & Venkataraman (1998) and Guirao & Sala (2002) and Wulff (2002) find an increase in trading frequency and percentage of trading days, but trade size significantly decreases after stock split.

In some other studies, bid-ask spread is used to indirectly measure the liquidity in the sense that lower bid-ask spread is associated with higher liquidity because it reflects the easiness of converting asset into cash.

Copeland (1979) finds a significant increase in percentage bid-ask spread following a split. However, Murray (1985) finds no evidence of a change in percentage spreads relative to a control sample.

Using NYSE-listed frims, Conroy, Harris, and Benet (1990) find that while absolute spreads significantly decrease following a split, the percentage spreads for the splitting firms increase after the stock split. Similar result is found by Dhar et al. (2003) when using NASDAQ-NMS firms. Desai, Nimalendran & Venkataraman (1998) study the major components of spread (order-processing costs and adverse-information costs) as well as the percentage bid-ask spread. They find both components significantly increase and the percentage spread also increases after the split. Kunz (2002) and Guirao & Sala (2002) also study the quoted percentage spread and effective bid-ask spread for non-US markets. And they also find that quoted percentage spread and effective percentage bid-ask spread increase significantly. Goyenko et al. (2005b) use effective tick suggested by Holden (2004) and round-trip transaction cost estimated using the model suggested by by Lesmond et al. (1999) and Goyenko et al. (2005a) to test the liquidity around stock split over long-time window. By comparing the variable in splitting and control firms, the percent effective spread for splitting firms is only temporarily higher than control sample after splitting and becomes significantly lower than that of control sample in long run. This result presents some evidence of the long-run benefit of split.

In addition to the trading volume and bid-ask spread, price impact of trade is also a good proxy of liquidity. Dhar et al. (2003) have used it to evaluate liquidity. They make use of Barclay & Warner (1993)'s conclusion that medium sized trades mainly impact the stock price. Based on the hypothesis, a lower frequency in medium sized trades implies the improved liquidity. Using the medium sized trade, thier result shows the liquidity increases following the split, but the increase is not significant.

Apart from the use of liquidity proxies to examine the theory, other methods are also applied. Easley, O'hara & Saar (2001) construct a sequential trade model and use maximum likelihood estimation to estimate parameters reflecting the liquidity. They find that the uninformed traders increase after the stock split. This evidence is considered to support the liquidity theory. Muscarella and Vetsuypens (1996) study the ADR 'solo-splits' (ADR that splits only in U.S. market). ADR 'solo-splits' cannot be motivated by managers' desire to signal, otherwise, the companies would have split the shares in the domestic market. They find that the liquidity increase significantly after ADR solo-splits where liquidity is measured by dollar trading volume, number of trades and liquidity premium. Dennis (2003) also disentangle the signaling effect from the liquidity effect of stock splits by studying the Nasdaq-100 Index Tracking Stock. Because the index is a market-capitalization weighted index of the 100 largest stocks on the Nasdaq, manager of the trust can not access the information of each stock in the index and signaling effect is excluded during the split. Various liquidity measures are examined for the 2-for-1 split of Nasdaq-100 Index Tracking Stock. He find that while daily turnover does not change and the relative bid-ask spread increases, the trading frequency, the share volume, and the dollar-volume of small trades all increase after the split. He interprets those results as improved liquidity.

In summary, the evidence on the liquidity impact of stock split is mixed. The adjusted trade volume has been generally found to decrease and the percentage bid-ask spread is usually found to increase after the split. However, in some cases, the trading frequency has been found to increase. Therefore, more studies are needed to examine the liquidity theory.

1.2 The Signaling Theory

The second explanation for the stock split is the signaling theory proposed by Brennan and Copeland (1988) where they develop a model to show that the managers communicate its private information about the firm's prospect to investors by means of a stock split announcement. Since the stock split is associated with transaction costs, this will prevent the firms with bad prospects from splitting their stocks. They find empirical evidence to support the signaling theory using the announcement day abnormal return.

Woolridge & Chambers (1983) study the abnormal return for reverse split and find negative abnormal return around announcement date. Grinblatt et al. (1984) exclude other simultaneous announcements when studying abnormal stock returns around announcement date and ex-date. They find an average of 3.3% increase in returns in two days around the split announcement date and abnormal returns of 1.9%-2.5% around ex-date. Ikenberry et al. (1996) also finds positive announcement return as well as post-split returns for 2-for-1 splits.

Signaling theory is also supported by a series of findings on splitting firms' long term performance: splitting firms continuously experienced higher growth in earnings and dividends. Lakonishok and Lev (1987) analyze the corporate performances by examining earnings growth and cash dividend growth. Specifically, they construct a sample of splitting firms and a control sample with matching firms with the same industry code and similar asset size and use chi-square test to test the difference in growth rates. They find that the splitting forms exhibit a higher growth in earnings and dividends than control firms after the split announcement. They also find a three to four percent abnormal stock price return around split announcement date. Asquith et al. (1989) also report that stock split is accompanied with superior earnings performance. Asquith et al. find that splitting firms have significantly higher earnings performance before the splits. And this favorable performance persists in the post-split period and remains significant even after adjusting for contemporaneous industry performance.

McNichols and Dravid (1990) provide evidence that firms signal their private information about future earnings by their choice of split factor. They regress split factor on stock price, market value, return run-up and analysts' earnings forecast error. The coefficient of forecast error is found to be significantly positive even after controlling for other factors, showing that split factor reflects the management's private information about future earnings. Conroy & Harris (1999) also use regression to investigate the relationship among split factor, split announcement return and revisions of analysts' earnings forecasts. They find a positive relationship between abnormal return and unexpected change in split factor and a positive relationship between proportional changes in earnings forecasts and unexpected change in split factor. Both results are significant even after controlling for other factors and thus support the signaling theory: the unexpected change in split factor is a signal of future prospects, and the signaling effect is reflected in abnormal return.

In addition to above studies, signaling theory is also tested by Easley, O'hara & Saar (2001) through their sequential trade model. Although they find a slight decrease in probability of informed trading (PIN) as implied by the signaling theory, an increased overall transaction cost is not consistent with the theory that implies a reduction in adverse selection costs. On balance, this theory is not supported. Easley et al. admit that the model is only a good tool in testing the effects related to trades. If the signaling effects are reflected in stock prices immediately so that they are not reflected in trades, it's reasonable to find unreliable results. On balance, this model has potential flaw when testing signaling theory.

1.3 The Optimal Tick Size Theory

The second theory, proposed by Angel (1997), claims that firms split their shares to maintain optimal relative tick size for the stocks. This argument is analogous to that in liquidity theory because it considers liquidity as well. The difference lies in two aspects. The first one is that it represents a tradeoff between the benefits to investors and dealers. If tick size is too small, investors are not willing to make limit orders thus lengthen the time on bargaining and dealers have no passion to form a liquid market. On the contrary, if tick size is too large, the small investors would suffer and the dealers would benefit, thus the stock's liquidity also decreases. The second difference of the optimal tick size theory is that it clearly states the possibility of coexistence of higher liquidity and higher quoted bid-ask spread.

The prominent advantage of this theory over the previous two is that it partly explains the substantial difference in stock prices across countries and the relatively stable stock price in each country. When studying the 22 equity markets in the world, Angel (1997) finds that both stock prices and tick rules in these markets are apparently different. Specifically, the median U.S. stock sells for about $40, while London stock sells for about £5 and Hong Kong stock is only about $2. And tick size in these countries also varies. However, tick size as percentage of stock price seems remarkably consistent across the countries. In other words, there is much less dispersion in relative tick sizes than in share prices. Therefore, these results potentially support the optimal tick size theory, in which relative tick size lead to decision on splitting.

Easley, O'Hara & Saar (2001)'s sequential trade model also tests this theory. As stated in the optimal tick size theory, the relative tick size is small before the split so that the investors are not willing to place limit order. When relative tick size increases through (forward) splitting, limit order trading should increase after the ex-date. Therefore, the actual overall transaction cost should decrease because more limit orders improve the overall quality of execution of orders even with larger quoted bid-ask spread. However, their findings are not consistent with the optimal tick size theory. They find an increase in the intensity of limit order trading. But the increase is not sufficient to compensate the uninformed population for the increase in the bid-ask spread. Goyenko et al. (2005b)'s study finds a decrease in the effective spread for splitting firms compared to the control firms in the long run. This evidence partially supports this theory.

2. METHODOLOGY

In this paper, we test all three theories of stock split using relatively new measures which has not been used in the previous studies. The new measure as discussed below.

2.1 Liquidity Measure

As discussed before, liquidity is one of the important issue in stock split. In this paper, we used the relatively new measure of liquidity and illiquidity proposed by Amihud (1999) liquidity measure and its adjusted liquidity measure.

Amihud's illiquidity measure is the average ratio of absolute return and dollar volume. This measure is supposed to capture the impact of per dollar trade on the stock return. Smaller the impact means lower the illiquidity or higher liquidity.

This is a reasonable measure of liquidity because of its significant positive correlation with microstructure based illiquidity measures like price impact and the fixed-cost component of bid-ask spread (see Brennan & Subrahmanyam (1996)). Furthermore, this measure is superior to other liquidity proxies such as trading volume and trading frequency, because those measures fail to incorporate the price impacts. Operationally, the average illiquidity for the pre and post split period is calculated using the following formula for each stock:

$$ILLIQ = \frac{1}{T}\sum_{t=1}^{T}\frac{|R_t|}{Vol_t}, \quad Vol_t > 0$$

where R_t is the daily return for day *t*, Vol_t is the dollar trading volume for day *t* and *T* is the total number of valid trading days in the sample period.

The average liquidity is computed in the similar way:

$$LIQ = \frac{1}{T}\sum_{t=1}^{T}\frac{Vol_t}{|R_t|}, \; R_t \neq 0$$

We can use the above measures of illiquidity and liquidity to test for the changes in these measure in the post-split and pre-split periods using paired t-test for means. In addition, the non-parametric Wilcoxon signed rank test for medians would also be applied.

Since Hasbrouck (2005) states that sample distributions of LIQ often exhibit extreme values, we follow his suggestion and calculate an adjusted LIQ and ILLIQ as given below:

$$ILLIQ = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{|R_t|}{Vol_t}}, \quad Vol_t > 0$$

$$LIQ = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{Vol_t}{|R_t|}}, \; R_t \neq 0$$

2.2 Information Content

To test the signaling theory, the firm-specific information is studied. The firm-specific information is suggested by Roll (1988) and used by Durnev, Morck & Yeung (2004). In Roll's paper, the variation in stock return is considered to be due to economic factors, industry information and firm-specific information. With all the information, the stock return should be fully predictable. But actually, firm-specific information is not public. Therefore, the R-square in a regression only measures the stock price variation explained by systematic economic factor and public information. Thus, the complement of R-square measures the firm-specific information. According to signaling theory, some unobserved information is revealed by the split announcement. Therefore, the firm-specific information contained in stock price should decrease as a result of the split announcement if the announcement has any signal component.

This method of testing the firm-specific information is fairly new. Traditional method of testing signaling mainly tests the relationship between split factor or target price and abnormal return. A strong relationship implicitly supports the theory. The firm-specific information test, however, directly describe whether more information becomes public after the announcement date.

Specifically, three models are used to compute the firm-specific information content. They are the market model, Fama-French's three factor model and Carhart (1997)'s four factor model which includes an additional momentum term. They are listed below:

Market model: $R_{jt} = \alpha + \beta_j * R_{mt} + \varepsilon_t$

Fama-French model: $R_{jt} - R_f = \alpha + \beta_j * (R_{mt} - R_f) + s_j SMB_t + h_j HML_t + \varepsilon_t$

Carhart model: $R_{jt} - R_f = \alpha + \beta_j * (R_{mt} - R_f) + s_j SMB_t + h_j HML_t + m_j PR1YR_t + \varepsilon_t$

where R_{jt} is the stock j's return on day t, R_{mt} is CRSP's value-weighted market return on day t, and R_{ft} is the Treasury bill return. Furthermore, SMB_t, the size factor, is the return of small size portfolio minus that of large size portfolio, HML_t, the book to market ratio factor, is the return difference of high and low BE/ME portfolios. These two factors are included because they haven found to explain the stock returns. Finally $PR1YR_t$, the momentum factor, is the returns difference of two equally weighted portfolios which previously have the highest and the lowest returns during t-12 to t-2. This factor is added to isolate momentum effect related to stock returns.

In the study, the time-series regression is based on daily data. As information of stock price may vary a lot just near the announcement day, we exclude two days around the announcement event. That is, both pre-announcement period and post-announcement period have 250 days observations. The firm-specific information is given by $1 - R^2$ calculated from each of the three regression equations. The firm-specific information is computed for each stock for each period (pre-split and post-split announcement periods). Then the two values are compared using paired t-test and Wilcoxon signed rank test. According to signaling theory, the firm-specific information would significantly decrease after the announcement date.

2.3 Transaction Cost

Since the transaction cost is related to the optimal tick size and, indirectly, to liquidity, we estimate the transaction cost using the Gibbs-sampler method suggested by Hasbrouck (2004) as well as the Limited Dependent Variable model suggested by Lesmond et al. (1999). We also extend Lesmond et al.'s model by including Fama-French factors.

A. Gibbs-sampler Method

This method of estimating the transaction cost is based on model suggested by Roll (1984). According to Roll's model, log efficient price follows a normal random walk, which can be stated as:

$$m_t = m_{t-1} + u_t$$
$$p_t = m_t + cq_t$$

where m_t is the log efficient price, p_t is the log trading price, u_t is i.i.d. $N(0, \sigma_u^2)$, c is the effective transaction cost and q_t is the buy/sell indictor. Thus,

$$\Delta p_t = m_t + cq_t - (m_{t-1} + cq_{t-1}) = c\Delta q_t + u_t$$

It can be shown that the effective cost is given by $c = \sqrt{-\operatorname{cov}(\Delta p_t, \Delta p_{t-1})}$

Therefore, the transaction cost can be calculated from the autocovariance of the log price changes. However, if the covariance of price changes is positive, this method cannot be applied. This situation of positive autocovariance can be eliminated using the Bayesian method suggested by Hasbrouck.

In this method, the parameters c, σ_u^2 in Roll's model are treated as random variables. Other unknowns include buy/sell indictors $(q_1, q_2, \ldots q_T)$ and the log efficient prices $(m_1, m_2, \ldots m_T)$. Because the density for posterior of parameters and other unknowns $f(c, \sigma_u, q | p)$ is not represented in closed-form, it is characterized through a simulation method. Therefore, Gibbs-sampler, an iterative method, is applied to estimate these parameters as well as buy/sell indicators. This iterative procedure starts with initial value for c, σ_u^2 and q, which is denoted as $\{c^{(0)}, \sigma_u^{(0)}, q^{(0)}\}$. Specifically, Gibbs-sampler involves the three steps:

i) estimate $c^{(1)}$ given $\sigma_u^{(0)}, q^{(0)}, p$

ii) estimate $\sigma_u^{(1)}$ given $c^{(1)}, q^{(0)}, p$

iii) estimate $q^{(1)}$ given $c^{(1)}, \sigma_u^{(1)}, p$

After each cycle (or sweep), a simulated value of $\{c^{(i)}, \sigma_u^{(i)}, q^{(i)}\}$ is generated.

This method is attractive, because it is based on market microstructure theories and it has some advantages over the traditional moment method. Specifically, effective cost estimates can be restricted to be positive for the prior in the framework. Besides, the posterior is an exact small sample distribution.

In this study, 1000 sweeps are run and only the latter 800 sweeps are accepted in order to exclude the start up effect, i.e., the first 200 sweeps are discarded as burn out sample. Again, the paired sample t-test for means and Wilcoxon signed rank test for medians are used to test the change in transaction cost.

According to optimal tick size theory, it is possible for liquidity and transaction cost to increase at the same time. Therefore, if the transaction cost is found to increase significantly after the ex-date, this is consistent with the optimal tick size theory.

B Limited Dependent Variable Method

Lesmond et al. (1999)'s Limited Dependent Variable (LDV) model calculates the roundtrip transaction cost based on frequency of zero return. The basic idea behind this model is that the informed traders would trade only when the return from informed trading exceed the total round-trip cost. The model can be written as:

$$R_j^* = \beta_j R_m + \varepsilon_j$$

where

$$\begin{aligned} R_j &= R_j^* - \alpha_{1j} && \text{if} \quad R_j^* < \alpha_{1j} \\ R_j &= 0 && \text{if} \quad \alpha_{1j} < R_j^* < \alpha_{2j} \\ R_j &= R_j^* - \alpha_{2j} && \text{if} \quad R_j^* > \alpha_{2j} \end{aligned}$$

R_j^* is unobserved true return for stock j, R_j is the observed return, R_m is the market return. α_1 and α_2 are the transaction cost thresholds. By assumption, the common market model is the correct model of stock returns. As the intercept term is just additive to each alpha term, the suppression of it will not affect the estimates. So, the intercept term is not included in the model. Since α_1 is expected to be negative, the roundtrip transaction cost is given by $\alpha_2 - \alpha_1$. The resulting likelihood function of the above equation is developed as follows:

$$\begin{aligned} L(\alpha_{1j}, \alpha_{2j}, \beta_j, \sigma_j | R_j, R_m) &= \prod_{R_i^* < 0} \frac{1}{\sigma_j} \phi \left[\frac{R_j + \alpha_{1j} - \beta_j * R_m}{\sigma_j} \right] \\ &* \prod_{R_i^* > 0} \frac{1}{\sigma_j} \phi \left[\frac{R_j + \alpha_{2j} - \beta_j * R_m}{\sigma_j} \right] \\ &* \prod_{R_i^* = 0} \left[\Phi \left(\frac{\alpha_{2j} - \beta_j * R_m}{\sigma_j} \right) - \Phi \left(\frac{\alpha_{1j} - \beta_j * R_m}{\sigma_j} \right) \right] \end{aligned}$$

where ϕ the standard normal density function, Φ standard cumulative density function.

The maximum likelihood parameter is estimated by maximizing above likelihood function with respect to parameters α_1, α_2, β_j and σ_j. Once the parameters are estimated, the transaction cost is estimated by (α_2-α_1) for each stock.

As the maximum likelihood method is a numerical method, there are possibilities that the method would not converge. We drop those that do not converge from further analysis. Then as before, the paired sample t-test and Wilcoxon signed rank test would be used to test the transaction cost hypothesis.

*C. Limited Dependent Variable Method*I

Since Lesmond et al. (1999) introduced this method, Goyenko (2005) has recently used it to estimate transaction cost in his empirical study. However, the one factor market model may not sufficiently describe the return generating process. Therefore, we extend the Lesmond's model by using the Fama-French model to describe the return generating process. As described earlier, the intercept term and risk-free return are just additive to each alpha term, the suppression of them will not affect the estimates. So, the intercept term is not included in the model. Specifically, the model can be written as:

$$R_j^* = \beta_j * (R_m - R_f) + s_j SMB + h_j HML + \varepsilon_j$$

where

$$R_j = R_j^* - \alpha_{1j} \quad \text{if} \quad R_j^* < \alpha_{1j}$$
$$R_j = 0 \quad \text{if} \quad \alpha_{1j} < R_j^* < \alpha_{2j}$$
$$R_j = R_j^* - \alpha_{2j} \quad \text{if} \quad R_j^* > \alpha_{2j}$$

This model leads to the following likelihood function:

$$L(\alpha_{1j}, \alpha_{2j}, \beta_j, \sigma_j | R_j, R_m) = \prod_{R_i^* < 0} \frac{1}{\sigma_j} \phi\left[\frac{R_j + \alpha_{1j} - \beta_j * (R_m - R_f) - s_j SMB - h_j HML}{\sigma_j}\right]$$
$$* \prod_{R_i^* > 0} \frac{1}{\sigma_j} \phi\left[\frac{R_j + \alpha_{1j} - \beta_j * (R_m - R_f) - s_j SMB - h_j HML}{\sigma_j}\right]$$
$$* \prod_{R_i^* = 0}\left[\Phi\left(\frac{\alpha_{2j} - \beta_j * (R_m - R_f) - s_j SMB - h_j HML}{\sigma_j}\right) - \Phi\left(\frac{\alpha_{1j} - \beta_j * (R_m - R_f) - s_j SMB - h_j HML}{\sigma_j}\right)\right]$$

where ϕ the standard normal density function, Φ standard cumulative density function.

As before, the maximizing likelihood method is used to estimate the parameters $\alpha_1, \alpha_2, \beta_j, \sigma_j$. Then, the transaction cost is given by (α_2-α_1). As before, those which fail to converge would be excluded from the analysis. The change in transaction cost is tested using paired sample t-test and Wilcoxon signed rank test.

If the transaction cost is found to increase significantly after the ex-date, then optimal tick size theory is partly supported.

In addition to the above tests to compare the transaction cost in pre and post period, we use other rules to test the transaction cost shift. That is to count the number of firms with significantly changed transaction cost.

Firstly, we calculate the t-statistic of paired transaction costs for each firm. The paired transaction costs are estimated transaction cost in pre-period ($\alpha_2^b - \alpha_1^b$) and in post-period$(\alpha_2^a - \alpha_1^a)$. The null hypothesis is that the transaction cost of a firm does not change after stock split, i.e.,

$$H_0 : \alpha_2^b - \alpha_1^b = \alpha_2^a - \alpha_1^a$$

t-statistic for paired difference is given by:

$$t = \frac{\alpha_2^b - \alpha_1^b - \alpha_2^a + \alpha_1^a}{\sqrt{\sigma_{11}^b - 2\sigma_{12}^b + \sigma_{22}^b + \sigma_{11}^a - 2\sigma_{12}^a + \sigma_{22}^a}}$$

Where $\sigma_{ij}^k = Cov\left(\alpha_i^k, \alpha_j^k\right), \quad i, j = 1,2 \quad \& \quad k = a, b$

If t-statistic of a firm is larger than 1.96, then we reject the null hypothesis and conclude the transaction cost is significantly decreased after the split. If t-statistic is less than -1.96, we also reject the null hypothesis and conclude the transaction cost is significantly increased after the split.

Based on the rule, we count the number of significantly positive t and significantly negative t for each sub-sample. If majority of the firms have positive t-statistic, then the firms' transaction costs are believed to decrease after the split. If majority of the firms have negative t-statistic, then the firms' transaction costs are believed to increase.

3. IMPIRICAL RESULTS:

3.1 Data

The initial sample includes 3,686 stock splits and 3,392 stock announcements events for stocks listed on NYSE between July, 1962 and December, 2004. In the empirical analysis, we study one year before and one year after the ex-date or announcement date. The difference in the number of actual splits and announcements has to do with the use of non-overlapping events. The data are obtained from CRSP.

The initial sample is filtered by considering the split factor (the ratio of new share number over old share number minus one) and the number of non-trading days. Firstly, all the events with negative split factors (reverse split) are included in the study. The stock splits and stock dividends with split factors larger than or equal to 0.25 are also included in the study. The stock dividend and stock split with split factor less than 0.25 are excluded from the analysis. This is consistent with the previous studies such as Dravid (1987). Secondly, this sample is further checked for the number of trading days. Those events which have more than 20 non-trading days for either pre-split period or post-split period are discarded. This is done in order to increase the reliability of the statistics used in the tests. The filtering processes lead to 3,199 valid splits and 2926 valid announcements. All further analyses are based on the filtered sample.

As the filtered sample includes forward split and reverse split which may have different characteristics, the sample is further segmented into forward split subgroup and reverse split subgroup. Of the 3199 valid splits, 3084 of them are forward split, 115 of them are reverse split. In addition, since majority of the forwards splits have split factor of 1 (2-for-1) and 0.5 (3-for-2), the two representative subgroups will also be studied separately. The same subgroups are also studied when dealing with announcement events.

3.2 Empirical Analysis

A. Summary Statistics

The frequency and relative frequency of stock splits across years are summarized in Table 1. During the 42 years, the number of splits in each five-year interval increases steadily except for the last interval. However, the relative frequency over all firms shows that there is quit variation over time

<insert table 1>

Table 2 summarizes the split frequency by month of the year. The number of splits in May and June has been found to be about twice the number of splits in other months. Table 3 displays the distribution of splits across industries. About 35% of splits of all the splits belong to the six largest groups. Thus, it seems that firms in certain industries are more likely to split their stocks than firms in others industries.

<insert table 2 andtable 3 >

Table 4 also presents the distribution of split events by split factor, where split factor is the ratio of new shares over old shares minus one. Of all valid splits, most of them are forward split, and only 115 of them are reverse split. For forward split, most of the split factor equals 1 (2-for-1) or 0.5 (3-for-2). To study the effects of stock split in more details, the full sample and the sub-samples are examined. And the split announcement events are also grouped into sub-samples to facilitate the following study on the firm-specific information. And the sub-samples and their sample size are reported in Table 5.

<insert table 4 and table 5>

Table 6 and Table 7 display the descriptive statistics of share prices for forward and reverse splitting firms. Pre-split row is presents the closing prices one day before the ex-date and post-split row is presents the closing prices on the ex-date. For the forward split, the median share price decreases from $53.38 to $28.25 after the stock split, and the share prices in post-split period is much less dispersed. Median share price for reverse split, however, increases from $2.5 to $10.25. Its standard deviation also mildly decreases. Therefore, the tables present such an interesting phenomenon: no matter how different are the share prices, the firms' share prices are always adjusted in a certain range once split is executed. This is consistent with optimal trading range hypothesis. The distribution of prices before and after the split for forward split is shown in Figure 1 and the same for the reverse split is shown in Figure 2. From Figure 4, the optimal trading range seems to be between $20 and $30.

<insert table 6 and table 7>

<insert Figure 1 and Figure 2>

In addition, We computed the abnormal excess return of splitting firms over NYSE/AMEX/NASDAQ value weighted index over one year period just before the split announcement. This gives some idea about whether the firms experiencing a high excess return are more likely to split their stocks. The results are presented in Table 8. For the forward split, the excess return is significantly positive. Whereas, for the reverse split, the excess return is negative but not significant.

B. Liquidity Effect

Firstly, Table 9 reports the changes in Amihud's liquidity and illiquidity ratio both before and after the stock split. The first four columns are related to the paired sample t-test and the next four columns are related to the Wilcoxon signed rank test. A positive t-statistics means measure decreases after the event, and a negative t-statistics indicates measure increases after the event. Regarding to the Wilcoxon signed rank test, the first two columns show the number of positive difference and negative difference. z-value is also based on pre measure minus post measure. Accordingly, more positive differences mean decreases and more negative differences mean increases. P-value is also shown in the fourth column. Actually, the following Table 10, 11, 12 and 13 have identical layout, so the above statements are also applicable to those tables.

<Insert table 9>

From Table 9, we find the values of ILLIQ are extremely small and LIQ are extremely large. And the t-statistics of LIQ are always insignificant, showing the LIQ may not reflect the changes in liquidity. These insignificant LIQ results are probably due to the sknewness of LIQ measure (Hasbrouck (2005)) and the skewness makes the tests less reliable. Therefore, we rely mostly on the adjusted ILLIQ and adjusted LIQ measures to be discussed next.

Table 10 reports the results for adjusted liquidity ratio for pre-split and post split periods. Both the t-test and Wilcoxon test indicate similar evidence. For the forward split and 2-for-1 split, the liquidity is found to significantly decrease and illiquidity is found to significantly increase after the split. The reverse is the case for reverse split, where the liquidity is found to significantly increase and the illiquidity is found to significantly decrease. However, no significant changes are found for the 3-for-2 split. It is not clear as to why we get such insignificant results for 3-for-2 split.

<Insert table 10>

It seems clear that the liquidity only increases for the reverse split. However, since the sample size for the reverse split is quite small, this result should be interpreted with care.

From my result it is clear that the liquidity decreases after forward stock split. This is inconsistent with both the liquidity theory and optimal tick size theory. However, when it comes to reverse split the liquidity increases after the split. This result is consistent with Han (1995) who finds that the reverse split enhance the liquidity of stock (decrease in percentage spread and number of non-trading days and increase in adjusted share volume) and treats this as a motivation for firms to reversely split.

C. Signaling Effect

Table 11 reports the firm-specific information content in stock price (measured by $1-R^2$) during the pre and post split announcement date for various sub-samples and models. As information of stock price may vary a lot just near the announcement day, we exclude two days around the announcement event. That is, both pre-announcement period and post-announcement period have 250 days observations.

<insert table 11>

Panel A presents the firm-specific information estimated from the market model. The t-statistics indicates that the firm-specific information content is significantly decreased for all splits including the reverse split. The Wilcoxon signed rank tests also suggest that the firm-specific information content is significantly decreased for all splits including the reverse split. This is consistent with the signaling hypothesis.

Panel B shows the results estimated from the Fama-French's three factor model. Both the t-statistics and Wilcoxon signed rank tests indicate that the firm-specific information content is significantly decreased for all splits.

Panel C shows the results from Carhart's four-factor model. Again, both the t-statistics and Wilcoxon signed rank tests indicate that the firm-specific information content is significantly decreased for all splits.

In summary, different models and tests points to the same conclusion. That is, the firm-specific information significantly decreases after split announcement. This result is quite robust in the sense that both t-statistics and Wilcoxon signed rank tests when applied to the market model, Fama-French 3-factor model and Carhart's 4-factor model points to the same conclusion. Although the signaling theory only explains forward splits, the findings of decreased information for reverse split indicate that the split announcement (either forward or reverse) contains some private information. For the forward split, this information may be related to the future abnormal earnings. However, it is not clear whether the information for the reverse split is also related to the future earnings. Further investigation is required to answer this question.

D. Changes in Transaction Cost

D.1 Gibbs Sampler Method

Table 12 reports the transaction cost estimated from Gibbs sampler method. As Table 9, the statistics are also based on pre-split measure minus post measure. The value in column 2 and column 3 is the cross-sectional average transaction cost.

<Insert table 12>

For forward split, mean transaction cost is found to significantly increases with t-statistic equal to -36.11. The same is true for the 2-for-1 and 3-for-2 sub-samples. When it comes to the reverse split sub-sample, the transaction cost is found to significantly decreases with t-statistics equal to 12.13.

Similar result is obtained using the Wilcoxon sign rank tests, i.e., the transaction cost increases for forward split and decreases for reverse split.

D.2 LDV Method

Table 13 reports the transaction cost estimated from LDV model. The results with the market model are presented in Panel A and the results with extended Lesmond's method are presented in Panel B.

<Insert table 13>

For forward split, the mean transaction cost is found to significantly increase with the t-statistics equal to -27.04. For 2-for-1 and 3-for-2 sub-samples, as the main components of forward splits, the round-trip transaction costs have been found to significantly increase. Whereas, for the reverse split, the transaction cost is found to significantly decreases with t-statistics equal to 9.78.

When the changes of transaction cost are further tested with Wilcoxon sign rank test, similar results are obtained. Similar results are found based on the extended model given in Panel B.

In summary, the transaction costs are found to increase for the forward split and decrease for the reverse split. Furthermore, it is important to note that the results are highly significant.

In addition to the paired t-test and Wilcoxon signed rank test of LDV measures, we count the number of significant changes on firm basis.

<Insert table 14>

Firstly, t-statistic, based on roundtrip cost before the split minus that after the split, has been calculated for each firm. Then, the number of significant t-statistics (at 5% significance level) is counted. The significant t-statistics can be positive or negative. A positive t-value means a decrease in the transaction cost and negative t-value indicates an increase in transaction cost after the split. From Panel A, it is clear that most of the changes are negative for forward split and positive for reverse split. The results from Fama-French model, shown in Panel B, are also similar in nature. In summary, the transaction cost for forward split is found to increase and the transaction cost for the reverse split is found to decrease.

we can summarize the results as it applies to the three theories discussed before as follows:

Liquidity Theory:

The results for the reverse split supports this theory in the sense that the reverse split is associated with the higher liquidity. However, when it comes to the forward split, the liquidity is found to decrease instead of increase. Therefore, the liquidity theory is not supported by the results associated with forward split.

Some researchers have considered transaction cost as part of liquidity measure in the sense that higher liquidity is associated with lower transaction cost. If we use this argument, then only the reverse split seems to support the liquidity theory because only for the reverse split the transaction cost has been found to decrease. But, this theory is not supported by the evidence regarding forward split where the transaction cost is found to increase after the stock split.

Signaling Theory:

Since the firm-specific information content in stock price has been found to decrease for both the forward as well as the reverse split during the post-split announcement period, the signaling theory is strongly supported by the evidence.

Optimal Tick Size Theory:

According to this theory, the transaction cost should increase and liquidity should also increase. The evidence regarding forward split indicates a significant increase in transaction cost but at the same time a significant decrease in liquidity. When it comes to the reverse split, the transaction cost is found to decrease and liquidity is found to significantly increase. Therefore, the evidence does not seem to support the optimal tick size theory.

4. SUMMARY AND CONCLUSION

In this dissertation, we investigate the consistency of three main theories of stock split with the empirical evidence. The three theories are liquidity theory, signaling theory and optimal tick size theory. In order to get a clearer picture regarding the impacts of stock splits, we use recently proposed methods as well as extend some existing methods.

We find that liquidity significantly decreases after forward stock splits and significantly increases after reverse splits. This evidence of decreased liquidity for forward split is inconsistent with the Liquidity theory. However, the increased liquidity for the reverse split is consistent with the liquidity hypothesis.

As to the signaling theory, the firm-specific information content in a stock price is measured by 1 minus R-squared in a regression using market model as well as extended market model. The results indicate that the firm-specific information content significantly decreases after the announcement of the stock split including reverse split. Thus, these results strongly support the signaling theory that split announcements convey managers’ private information to the public. For the forward split, this information may be related to the future abnormal earnings. However, it is not clear whether the information for the reverse split is also related to the future earnings. Further investigation is required to answer this question.

Finally, we also estimated the effect of split on the transaction cost. It is found that the round-trip transaction cost significantly increases after forward split and significantly decreases after reverse split. This result is consistent regardless of the methods used. This shows the robustness of the result. Therefore, for the forward split, it is found that the transaction cost increases but the liquidity decreases. As to the reverse split, the liquidity increases but the transaction cost is found to decrease. Therefore, the optimal tick size theory, which predicts both the transaction cost as well as the liquidity to increase after the split, is not consistent with the empirical evidence.

In conclusion, liquidity theory is not supported except for the reverse split. The optimal tick size theory is also not supported for both the forward split and reverse split. Only the signaling theory is fully supported. However, what signal the reverse split conveys is unknown. Future research is required to answer this question.

It would be interesting to see if the similar result holds using high frequency data. We would suggest this for the future research.

REFERENCES

Angel, James J. (1997), Tick size, share prices, and stock splits, Journal of Finance, Vol. 52, No. 2, PP. 655-681

Amihud, Yakov (2002), Illiquidity and stock returns: cross-section and time-series effects, Journal of Financial Markets, Vol. 5, PP. 31-56

Amihud, Yakov & Haim Mendelson (1987), Trading mechanisms and stock returns: an empirical investigation, Journal of Finance, Vol. 42, 533-553

Asquith, P., P. Healy and K. Palepu (1989), Earnings and stock splits, The Accounting Review, 64, 3, 387-404

Baker, H. Kent and Patricia L. Gallagher (1980), Management's view of stock splits, Financial Management, 9, 73-77

Bar-Yosef, Sasson, Lawrence D. Brown (1977), A reexamination of stock splits using moving betas, The Journal of Finance, Vol. 32, No. 4, PP. 1069-1080

Brennan, Michael. J., Thomas. E. Copeland (1988a), Stock splits, stock prices, and transaction costs, Journal of Financial Economics, Vol. 22, PP. 83-101

Brennan, Michael. J., Thomas. E. Copeland (1988b), Beta changes around stock splits: A note, Journal of Finance, Vol. 43, No. 4, 1009-1013

Carhart, Mark M. (1997), On persistence in mutual fund performance, Journal of Finance, Vol. 52, 57-82

Conrad, Jennifer S., Robert Conroy (1994), Market microstructure and the ex-date return, the Journal of Finance, Vol. 49, No. 4, PP. 1507-1519

Conroy, Robert M, Robert S. Harris (1999), Stock splits and information: the role of share price, Financial Management, Vol. 28, 28-40 (FM, 1999 event study- event date is take from CRSP – is this the announcement date).

Copeland, Thomas E. (1979), Liquidity changes following stock splits, Journal of Finance, Vol. 34, No.1, PP. 115-141

Conroy, Robert M., Robert S. Harris, Bruce A. Benet (1990), The effects of stock splits on Bid-ask spreads, The Journal of Finance, Vol. 45, No. 4, PP. 1285-1295

Desai, Anand S., M. Nimalendran, S. Venkataraman (1998), Changes in trading activity following stock splits and their effect on volatility and the adverse-information component of the bid-ask spread, Journal of Financial Research, Vol. XXI, 159-183

Dravid, Ajay R. (1987), A note on the behavior of stock returns around Ex-dates of stock distributions, The Journal of Finance, Vol. 42, 163-168

Dubofsky, David A. (1991): volatility increases subsequent to NYSE and AMEX stock splits, Journal of Finance, Vol. 46, 421-431

Durnev, Art, Randall Morck, Bernard Yeung (2004), Value-enhancing capital budgeting and firm-specific stock return variation, The Journal of Finance, Vol. LIX, No. 1

Durnev, Art, Randall Morck, Bernard Yeung (2003), Does greater firm-specific return variation mean more or less informed stock pricing?, Journal of Accounting Research, Vol. 41, No. 5

Dennis, Patrick (2003), Stock splits and liquidity: the case of the Nasdaq-100 Index Tracking Stock, The Financial Review, Vol. 38, PP. 415-433

Dhar, Ravi, William N. Goetzmann, Shane Shepherd, Ning Zhu (2003), The impact of clientele changes: evidence from stock splits, working paper

Easley, David, Maureen O'hara, Gideon Saar (2000), How stock splits affect trading: a microstructure approach, The Journal of Financial and Quantitative Analysis, Vol. 36, No. 1, PP. 25-51

French, DW, DA Dubofsky (1986), Stock splits and implied stock price volatility, Journal of Portfolio Management,

French, Dan W., Taylor W. Foster (2002), Does price discreteness affect the increase in return volatility following stock splits?, The Financial Review, Vol. 37, 281-294

Fama, Eugene F., Lawrence Fisher, Michael C. Jensen, Richard Roll (1969), The adjustment of stock prices to new information, International Economic Review, Vol. 10, No. 1, PP. 1-21

French & Dubofsky (1986), Stock splits and implied stock price volatility, Journal of Portfolio Management, Vol.12, Iss. 4; pg. 55

GUIRAO JOSÉ YAGÜE, J. CARLOS GÓMEZ SALA (2002), Transaction size, order submission and price preference around stock splits, working paper

Goyenko Ruslan, Craig W. Holden, Christian T. Lundblad, Charles A. Trzcinka (2005a), Horseraces of monthly and annual liquidity measures, working paper from Indiana University

Goyenko Ruslan Y., Craig W. Holden, Andrey D. Ukhov (2005b), Do stock splits improve liquidity?, working paper from Indiana University

Grinblatt Mark S., Ronald W. Masulis, Sheridan Titman (1984): the valuation effects of stock splits and stock dividends, Journal of Finanacial Economics, Vol. 13, PP. 461-490

Han Ki C. (1995), The effects of reverse split on the liquidity of the stock, Journal of Financial and Quantitative Analysis, 30, 159-169

Hasbrouck Joel (2004), Liquidity in the futures pits: Inferring Market Dynamics from incomplete data, Journal of Financial and Quantitative Analysis, Vol. 39, No. 2

Hasbrouck Joel (2003), Trading costs and returns for US equities: the evidence from daily data, working paper

Huson Mark R., Gregory MacKinnon (2003), Corporate spinoffs and information asymmetry between investors, Journal of Corporate Finance, Vol. 9, PP 481-503

Ikenberry David L., Graeme Rankine, Earl K. Stice (1996), What do stock splits really singal?, The Journal of Financial and Quantitative Analysis, Vol. 31, No. 3, PP. 357-375

Klein L.S, and D.R. Peterson, 1989, Earnings Forecast Revisions Associated with Stock Split Announcements, Journal of Financial Research 12, No. 4, pp. 319-328.

Koski Jennifer Lynch (1998), Measurement effects and the variance of returns after stock splits and stock dividends, the review of financial studies, Vol. 11, 143-162

Lakonishok Josef, Baruch Lev (1987), Stock splits and stock dividends: why, who and when, Journal of Finance, Vol. 42, 913-932

Lamoureux Christopher G., Percy Poon (1987), The market reaction to stock splits, Journal of Finance, Vol. 42, 1347-1370

Lesmond David A., Joseph P. Ogden, Charles A. Trzcinka (1999), A new estimate of transaction costs, Review of Financial Studies, Vol. 12, No. 5, PP. 1113-1141

Lipson Marc L. (1999), Stock splits, liquidity and limit orders, working paper

Murray, Dennis (1985), Further Evidence on the Liquidity Effects of Stock Splits and Stock Dividends, The Journal of Financial Research, Vol. 8, Iss. 1; p. 59-68

Muscarella Chris J., Michael R. Vetsuypens (1996), Stock splits: signaling or liquidity? The case of ADR ‘solo-splits’, Journal of Financial Economics, Vol. 42, 3-26

Ohlson James A., Stephen H. Penman (1985), Volatility increases subsequent to stock splits, Journal of Financial Economics, Vol. 14, 251-266

Pastor Lubos, Robert F. Stambaugh (2003), Liquidity risk and expected stock returns, Journal of Political Economy, Vol. 111, No. 3

Roll, R. (1984), A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, Journal of Finance, 39, 1127-1139.

Roll Richard (1988), R2, Journal of Finance, Vol. 43, No. 3, PP 541-566

Sheikh Aamir M. (1989), Stock splits, volatility increases, and implied volatilities, The Journal of Finance, Vol. 44, No. 5, PP. 1361-1372

Schultz Paul (2000), Stock splits, tick size, and sponsorship, The Journal of Finance, Vol. LV, No. 1

Woolridge Randall J., Donald R. Chambers (1983), Reverse splits and shareholders wealth, Financial Management, Vol. 12, No. 3

Wulff Christian (2002), The market reaction to stock splits-evidence from Germany, Schmalenbach Business Review, V54, 270-297

Wiggins James B. (1992), Beta changes around stock splits revisited, The Journal of Financial and Quantitative Analysis, Vol. 27, No. 4, PP. 631-640

Table 1: Frequency and relative frequency of split events in each 5-year interval

Year	62-65	66-70	71-75	76-80	81-85	86-90	91-95	96-00	01--04
# of splits	84	348	232	324	399	543	496	623	150
% over all splits	2.6	10.9	7.3	10.1	12.5	17.0	15.5	19.4	4.7
% over all firms	5.8	19.1	12.8	16.6	19.3	22.4	15.9	14.9	4.4

Table 2: Frequency of Split Events by Month

Month	Jan.	Feb.	Mar.	Apri.	May	Jun.
# of splits	198	170	278	219	429	494
Month	July	Aug.	Sep.	Oct.	Nov.	Dec.
# of splits	290	217	232	211	206	255
total	3199					

Table 3: Frequency of Split Events by Industry

Industry Major Group Code	20	28	35	36	49	60	Others industries
# of splits	145	252	198	153	223	144	2084
relative %	4.53	7.88	6.19	4.78	6.97	4.50	65.15

The six industries which have most split events:
20: Food and Kindred Products
28: Chemicals and Allied Products
35: Industrial and Commercial Machinery and Computer Equipment
36: Electronic and Other Electrical Equipment and Components, Except Computer Equipment
49: Electric, Gas, And Sanitary Services
60: Depository Institutions
From the split frequency, it seems that certain industries are more likely to conduct split.

Table 4: Distribution of Split Events by split factor

Factor	<0	0.25	0.25~0.5	0.5	0.5~1	1	>1
	reverse split	5-for-4		3-for-2		2-for-1	
		Forward split					
# of splits	115	73	41	773	11	1970	216
total	115	3084					

Table 5: Samples studied in the paper

	original	total	forward	reverse	ftr=1	ftr=0.5
# of splits	3686	3199	3084	115	1970	773
# of announcements	3392	2926	2903	23	1834	747

Table 6: Descriptive statistics of stock prices for forward split

	Minimum	25%	Median	75%	Maximum	Mean	std. dev.
Pre-split	3.06	39.38	53.25	74.25	1370	60.85	41.83
Post-split	2.38	22.13	28.25	37.25	138	30.93	13.19

10 splits did not trade just before the split date and 3 splits which did not trade on the split date, so the prices on that non-trading day is shown as negative. The prices of these events are set as positive value of the negative price on that day (this is justified by the notation of CRSP data).

Table 7: Descriptive statistics of stock prices for reverse split

	Minimum	25%	Median	75%	Maximum	Mean	std dev.
Pre-split	0.09	1	2.5	3.94	93.44	4.9	10.19
Post-split	1.13	6.59	10.25	17.7	38.75	12.65	8.17

Table 8: Abnormal return of forward splits over NYSE/AMEX/NASDAQ value weighted index measured in one-year period just before the split announcement

	mean excess return	sample size	t value
forward	0.3596	2903	28.476
reverse	-0.1008	23	-0.593

Figure 1:

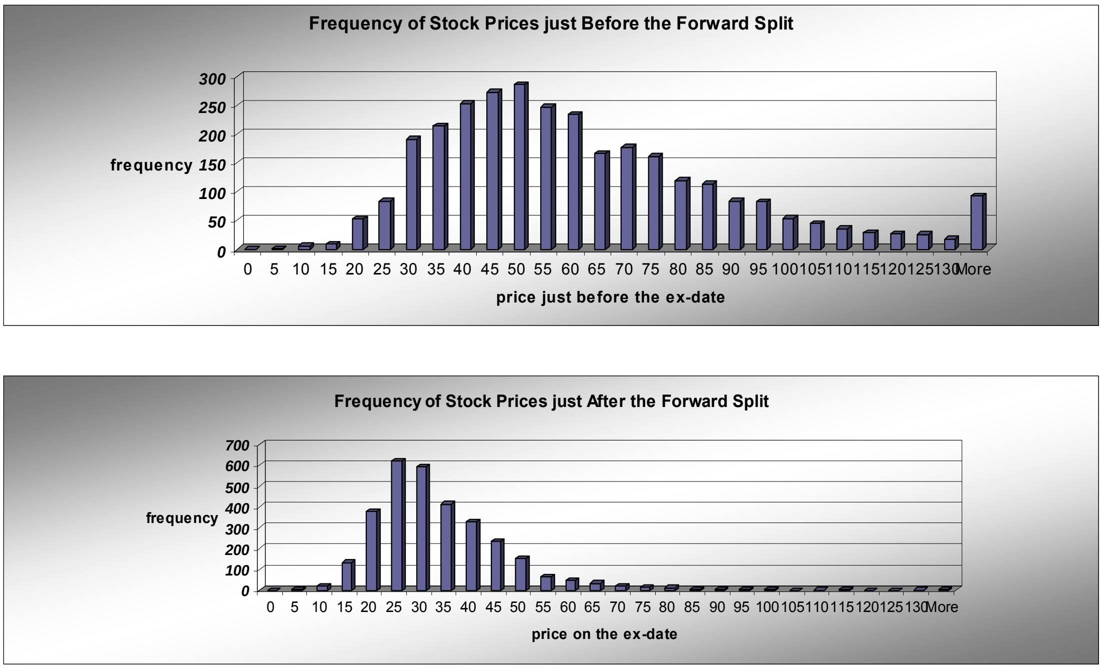

Figure 2:

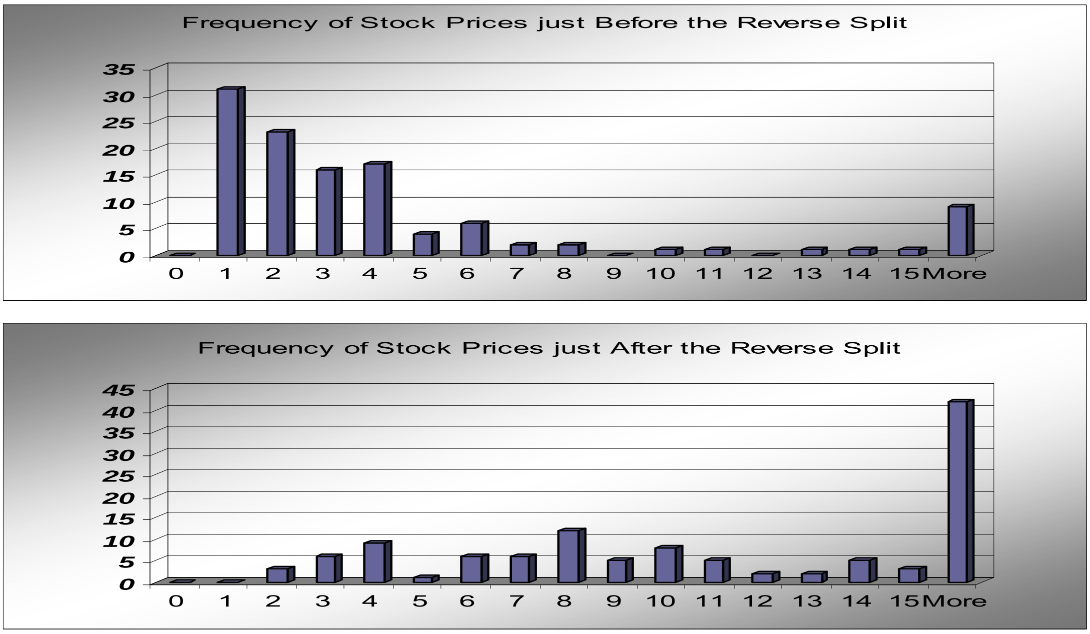

Table 9: Changes in the liquidity (measured by ILLIQ and LIQ) after the stock split

	Paired Sample t-test for Mean					***Wilcoxon Signed Rank Test for Median***			
	Average Pre-Split	Average Post-Split	**t-statistc** Pre Minus Post	**p-value**		**positive d**	**negative d**	**z-statistc**	**p-value (2-tailed)**
ILLIQ									
total	1.91E-07	1.54E-07	1.10	0.14		1510	1678	-2.35	0.02
forward split	9.64E-08	1.11E-07	-3.24	0.00		1428	1646	-3.89	0.00
reverse split	2.73E-06	1.30E-06	1.53	0.06		82	32	4.67	0.00
ftr=1	7.69E-08	1.02E-07	-4.36	0.00		863	1103	-6.19	0.00
ftr=0.5	1.44E-07	1.36E-07	0.98	0.16		426	343	2.25	0.02
LIQ									
total	1.46E9	1.41E9	1.21	0.11		1925	1268	10.46	0.00
forward split	1.51E9	1.45E9	1.21	0.11		1901	1177	11.22	0.00
reverse split	3.29E8	3.27E8	0.04	0.48		24	91	-5.15	0.00
ftr=1	1.67E9	1.67E9	-0.09	0.46		1282	684	10.68	0.00
ftr=0.5	6.35E8	6.53E8	-0.30	0.38		394	377	-0.36	0.72

$$ILLIQ = \frac{1}{T}\sum_{t=1}^{T}\frac{|R_t|}{Vol_t}, \quad Vol_t > 0$$

$$LIQ = \frac{1}{T}\sum_{t=1}^{T}\frac{Vol_t}{|R_t|}, \; R_t \neq 0$$

Both t-test and Wilcoxon signed rank test are based on the measure **before** split **minus** that **after** split.

Table 10: Changes in the liquidity (measured by adjusted ILLIQ and LIQ) after the stock split

	Paired Sample t-test for Mean					***Wilcoxon Signed Rank Test for Median***			
Adjusted	Average Pre-Split	Average Post-Split	**t-statistic** Pre Minus Post	**p-value**		**positiv e d**	**negative d**	**z-statistic**	**p-value (2-tailed)**
Panel A: ILLIQ									
total	1.90E-4	1.92E-4	-1.09	0.14		1493	1690	-3.10	0.00
forward split	1.73E-4	1.81E-4	-5.08	0.00		1412	1656	-4.50	0.00
reverse split	6.34E-4	4.85E-4	2.75	0.00		81	34	4.35	0.00
ftr=1	1.56E-4	1.69E-4	-6.63	0.00		854	1106	-6.63	0.00
ftr=0.5	2.17E-4	2.14E-4	0.86	0.19		415	354	1.85	0.06
Panel B: LIQ									
total	1.93E4	1.87E4	4.69	0.00		1868	1331	8.95	0.00
forward split	1.98E4	1.92E4	5.20	0.00		1842	1242	10.14	0.00
reverse split	6.02E3	7.38E3	-2.33	0.01		26	89	-5.43	0.00
ftr=1	2.19E4	2.13E4	4.14	0.00		1239	731	10.10	0.00
ftr=0.5	1.24E4	1.27E4	-1.34	0.09		383	390	-1.07	0.28

$$ILLIQ = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{|R_t|}{Vol_t}}, \quad Vol_t > 0$$

$$LIQ = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{Vol_t}{|R_t|}}, \ R_t \neq 0$$

Both t-test and Wilcoxon signed rank test are based on the measure **before** split **minus** that **after** split.

Table 11: Changes in the firm-specific information (measured by 1-R^2) after the announcement of stock split (excluding 2 days around announcement event)

	Paired Sample t-test for Mean					***Wilcoxon Signed Rank Test for Median***			
1-R^2 (2 days deleted)	Average Pre-Split	Average Post-Split	**t-statistic** Pre Minus Post	**p-value**		**positive d**	**negative d**	**z-statistic**	**p-value (2-tailed)**
Panel A: market model									
total	0.85	0.83	7.12	0.00		1635	1291	7.09	0.00
forward split	0.85	0.83	6.98	0.00		1618	1285	6.93	0.00
reverse split	0.96	0.92	2.41	0.01		17	6	2.71	0.01
ftr=1	0.84	0.82	6.29	0.00		1024	810	5.99	0.00
ftr=0.5	0.87	0.86	2.79	0.00		421	326	3.33	0.00
Panel B: FF model									
total	0.82	0.80	7.43	0.00		1651	1275	7.53	0.00
forward split	0.82	0.80	7.27	0.00		1635	1268	7.37	0.00
reverse split	0.94	0.88	2.39	0.01		16	7	2.34	0.02
ftr=1	0.81	0.79	6.70	0.00		1035	799	6.52	0.00
ftr=0.5	0.84	0.83	2.50	0.01		424	323	3.17	0.00
Panel C: four factor model									
total	0.81	0.79	7.21	0.00		1648	1278	7.35	0.00
forward split	0.81	0.79	7.04	0.00		1633	1270	7.18	0.00
reverse split	0.93	0.88	2.52	0.01		15	8	2.62	0.01
ftr=1	0.80	0.78	6.50	0.00		1039	795	6.40	0.00
ftr=0.5	0.83	0.82	2.41	0.01		420	327	3.00	0.00

Market Model: $R_{jt} = \alpha + \beta_j * R_{mt} + \varepsilon_t$

Fama-French Model: $R_{jt} - R_f = \alpha + \beta_j * (R_{mt} - R_f) + s_j SMB_t + h_j HML_t + \varepsilon_t$

Four Factor Model: $R_{jt} - R_f = \alpha + \beta_j * (R_{mt} - R_f) + s_j SMB_t + h_j HML_t + m_j PR1YR_t + \varepsilon_t$

Both tests are based on the firm-specific information **before** the announcement **minus** that **after** the announcement.

Table 12: Changes in the transaction cost (measured from Gibbs sampler method) after stock split

	Paired Sample t-test for Mean					***Wilcoxon Signed Rank Test for Median***			
	Average Pre-Split	Average Post-Split	**t-statistic** Pre Minus Post	**p-value**		**positive d**	**negative d**	**z-statistic**	**p-value (2-tailed)**
Gibbs sampler									
total	3.69E-3	4.41E-3	-8.81	0.00		683	2516	-30.53	0.00
forward split	2.87E-3	4.22E-3	-36.11	0.00		580	2504	-34.81	0.00
reverse split	2.57E-2	9.70E-3	12.13	0.00		103	12	8.57	0.00
ftr=1	2.56E-3	4.16E-3	-36.53	0.00		275	1695	-31.77	0.00
ftr=0.5	3.59E-3	4.27E-3	-8.65	0.00		232	541	-10.80	0.00

Both t-test and Wilcoxon signed rank test are based on the transaction cost **before** split **minus** that **after** split.

Table 13: Changes in the transaction cost (measured by α_2-α_1) after stock split

	Paired Sample t-test for Mean					*Wilcoxon Signed Rank Test for Median*			
	Average Pre-Split	Average Post-Split	t-statistic Pre Minus Post	p-value		positive d	negative d	z-statistic	p-value (2-tailed)
α2-α1									
Panel A: market model									
total	8.76E-3	8.65E-3	0.39	0.35		878	2288	-25.17	0.00
forward split	5.78E-3	7.69E-3	-27.04	0.00		778	2273	-29.09	0.00
reverse split	8.78E-2	3.40E-2	9.78	0.00		100	15	8.42	0.00
ftr=1	4.95E-3	7.10E-3	-27.76	0.00		411	1534	-27.42	0.00
ftr=0.5	7.78E-3	9.00E-3	-6.93	0.00		293	476	-7.63	0.00
Panel B: FF model									
total	8.74E-3	8.61E-3	0.46	0.32		881	2280	-25.14	0.00
forward split	5.75E-3	7.65E-3	-26.98	0.00		781	2265	-29.06	0.00
reverse split	8.76E-2	3.39E-2	9.79	0.00		100	15	8.42	0.00
ftr=1	4.93E-3	7.07E-3	-27.58	0.00		411	1533	-27.36	0.00
ftr=0.5	7.74E-3	8.95E-3	-6.96	0.00		298	469	-7.64	0.00

Market Model: $R_{jt} = \alpha + \beta_j * R_{mt} + \varepsilon_t$

Fama-French Model: $R_{jt} - R_f = \alpha + \beta_j * (R_{mt} - R_f) + s_j SMB_t + h_j HML_t + \varepsilon_t$

Both t-test and Wilcoxon signed rank test are based on the transaction cost **before** split **minus** that **after** split.

Table 14: Changes in the transaction cost after stock split by counting the number of significant changes

Number of significant changes

α2-α1	positive t	negative t	total no.
Panel A: market model			
total	208	866	3166
forward split	122	861	3051
reverse split	86	5	115
ftr=1	46	609	1945
ftr=0.5	64	145	769
Panel B: FF model			
total	209	862	3161
forward split	122	857	3046
reverse split	87	5	115
ftr=1	46	610	1944
ftr=0.5	63	142	767