CHANGES IN TRADING ACTIVITY FOLLOWING STOCK SPLITS AND THEIR EFFECT ON VOLATILITY AND THE ADVERSE INFORMATION COMPONENT OF THE BID-ASK SPREAD

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Abstract

We examine changes in trading activity around stock splits, and their effect on the volatility and the adverse information component of the bid-ask spread. Even after controlling for microstructure biases, we find a significant increase in the volatility after the split. Changes in total volatility and in its permanent component are positively related to changes in the number of trades. This suggests that both informed and noise traders contribute to changes in trading activity. Further, while the adverse information component of the spread increases unconditionally after the split, the change is negatively related to the change in trading activity. The results suggest that a crucial determinant of liquidity changes after a stock split is the success of the split in attracting new trades in the security.

I. Introduction

Stock splits per se do not alter either the cash flows of the firm or the claims of the security holders. Yet, in any given year, about 10 percent of the firms split their stock. Surveys of corporate managers by Baker and Gallagher (1980) and Baker and Powell (1993) reveal that the two most important reasons given by managers for undertaking a split are to bring the stock price into a better trading range and to improve its liquidity. Managers believe that the lower stock price makes it possible for wealth constrained "small" traders to purchase round lots. Based on their survey, Baker and Powell argue that the managerial view of enhanced liquidity is this increase in the diversity and number of shareholders. Lamoureux and Poon (1987) and Maloney and Mulherin (1992) document an increase in the number of shareholders after the stock split, and their evidence is therefore consistent with the managerial motivations for stock splits.

However, other studies find that after a stock split, there is an increase in the proportional bid ask spread (Copeland (1979) and Conroy, Harris, and Benet (1990)), a decrease in the split-adjusted trading volume (Copeland (1979) and Lamoureux and Poon (1987)), and an increase in the volatility of the stock's returns (Ohlson and Penman (1985) and Dubofsky (1991)). A post-split increase in the number of shareholders does not, by itself, provide any explanation for these changes in the characteristics of the stock. However, they are likely a result of changes in the incentives for trading that occur after a stock split. Even though we cannot directly observe these changes in trading incentives, we can observe the resultant changes in trading activity and in microstructure. Therefore, in this study, we examine the relation between changes in trading activity following splits and changes in the volatility and spreads.

Two widely recognized motives for trading are information and liquidity. Prior studies suggest theoretical reasons why these motivations might change after the split. For example, Black (1986) argues that noise traders prefer low-priced stocks to high-priced stocks. If they do, the lower per-share price after a split would attract noise traders. On the other hand, Brennan and Hughes (1991) argue that the lower per-share price after the split might give analysts the incentive to collect more information on firms. They provide evidence that the number of analysts following a firm increases after the firm announces a stock split. This suggests the presence of a larger number of informed traders in the security after the split. Admati and Pfleiderer (1988) argue that both noise and informed traders may increase after the split. In their model of strategic trading with costly information acquisition, the number of informed traders is determined endogenously. A higher number of noise traders results in a higher number of informed traders as well. In the context of stock splits, if lower post-split share prices attract noise traders, the level of informed traders would increase endogenously.

A change in the motivations for trading after the split would manifest itself as a change in the trading activity in the stock. We provide evidence consistent with this hypothesis. We find a significant increase in the number of trades and a significant decrease in the average turnover per trade (trading volume per trade, normalized by outstanding shares) after the split. However, since we cannot directly observe trader types, we cannot distinguish between changes in informed and liquidity trading.[1] Consequently, we rely on microstructure models to infer the change in the mix of trader types. Specifically, we examine the relation between changes in trading activity and the volatility and the adverse information component of the bid-ask spread.

Jones, Kaul, and Lipson (1994) find that volatility is primarily and positively related to the number of trades. Since previous studies document that volatility increases after the split, this

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1 Our definition of liquidity traders includes those who trade on noise as if it were information. We do so since we cannot distinguish between liquidity and noise traders empirically. We refer to the combined class of traders as noise traders in this paper.

would be consistent with an increase in the number of trades after the split. Following the argument in Jones, Kaul, and Lipson, we expect a positive relation between the change in the number of trades and the change in the volatility. An increase in trading by either type of trader would increase the volatility. By decomposing the volatility into a transient (short-lived) component and a permanent (or fundamental) component, we can draw conclusions about changes in trader types. An increase in noise trading would primarily affect the transient component, while an increase in informed trading would increase the permanent component of the volatility. In this study, we use multiday volatilities and variance ratios to examine changes in the two components of the volatility.

Further, while previous studies examine changes in the total volatility around stock splits, Ohlson and Penman (1985) and Dravid (1988) argue that microstructure biases inflate volatility estimates. Particularly, both bid-ask bounce and price discreteness induce upward biases in volatility estimates based on transaction prices, and these biases are exacerbated after the split due to the lower share prices. We avoid the bias due to bid-ask bounce by using returns based on bid-bid prices (see Kaul and Nimalendran (1990)) and the correction for price discreteness follows the model in Ball (1988).

We find that the volatility of the stock increases after the split, even after we adjust for these microstructure biases. Further, both the transient and the permanent component of the volatility increase significantly after the split. This is consistent with an increase in both noise and informed traders in the stock after the split. We also find a significant positive relation between the change in the number of trades and the change in the permanent volatility. As in Jones, Kaul, and Lipson (1994), trades appear to be the primary vehicle for bringing information into the market, and consequently affect the permanent volatility.

We also investigate the effect of changes in trading activity on the adverse information component of the bid-ask spread. An increase in noise trading (holding informed trading constant) reduces the adverse information component, while an increase in informed trading (holding noise trading constant) increases this component of the spread. The effect on the adverse information component of the spread of an increase in both types of traders is more complex. Admati and Pfleiderer (1988) argue that the effect on the adverse information component depends on the degree of competition between informed traders. Competition between these traders increases if all traders receive identical signals, and this increase in competition reduces the adverse information component even if the number of informed traders increases. Conversely, if the signals received by the informed traders are diverse and sufficiently precise, information asymmetry could increase even if the number of noise traders in the market increases. Thus, a net increase in the adverse information component is not inconsistent with an increase in the level of noise trading after the split.

We use the methodology in George, Kaul, and Nimalendran (1991) to extract the adverse information component from the total bid-ask spread. We then relate changes in this component to changes in the number of trades after the split. On average, both the proportional spread and the adverse information component of the spread increase after the stock split. The increase in the adverse information component of the spread is particularly significant since our analysis of volatility changes indicates that noise trading increases after the split, and an increase in noise trading would bias against finding an increase in this component of the spread. Our results therefore suggest that informed trading has increased as well.

We also find a negative correlation between the change in the adverse information component and the change in the number of trades. A large increase in the number of trades tends to reduce the adverse information component of the spread. Since we find that both noise and informed trading increase after the split, this negative correlation suggests one or both of the following. First, a large increase in noise trading causes the adverse information component to decrease. Second, as Admati and Pfleiderer (1988) point out, if informed traders receive correlated signals, competition among these traders increases. This too would decrease the adverse information component.

Our results provide an explanation for the previously documented changes in the characteristics of the stock after the split. Increases in volatility are not solely driven by microstructure biases. Changes in trading activity in the stock are positively related to changes in the bias corrected volatility. Our evidence on volatility changes also suggests that both noise and informed traders increase after the split. Finally, we document that while spreads (total, as well as the adverse information component) increase from before to after the split, firms that experience a substantial increase in the number of trades have a smaller increase in spreads relative to other firms.

II. Data and Sample Characteristics

Data

The initial sample consists of NASDAQ-NMS firms that announced stock splits and are listed in the CRSP 1990 data base. We confine our sample to NASDAQ-NMS firms because CRSP presently provides bid-ask spreads (inside quotes), daily trading volume, and number of trades only for these firms. Further, since transaction prices and bid-ask spreads for NMS securities are available in the CRSP data base on a regular basis only after November 1982, we restrict our sample to announcements of splits during the period January 1983 to December 1990.

There are 980 splits announced by 739 firms meeting the above screens.

We estimate the pre-split microstructure variables for the sample (such as volatility, spreads, trading intensity, etc.) over the 180 day period ending 21 days before the announcement of the split. The post-split characteristics are estimated over the 180 day period beginning from 21 trading days after the stock first trades ex-split. We exclude the period from 20 days before the announcement to 20 days after the stock trades ex-split to avoid any contamination due to information effects around the announcement day and the transient microstructure effects around the ex-split date. We require that all relevant data items be available during the pre-split and the post-split estimation periods. Finally, we exclude from our initial sample all observations that have either a stock split or a stock dividend within 400 days of each other. This screen ensures that our estimation period data are not contaminated by events similar to the ones examined in this study. The final sample consists of 366 stock splits announced by 341 firms.

In our sample of 366 split announcements, 147 are 3-for-2 splits (a split factor of 0.5) and 138 are 2-for-1 (a split factor of 1.0). Sixty-three announcements are for splits smaller than 3-for-2, while eighteen are for splits greater than 2-for-1. Previous studies suggest that there is a difference between the motives of firms issuing small versus large stock splits. Elgers and Murray (1985) document a positive relation between firm size and the split factor, and also between pre-split share prices and the split factor. Further, small split factors may be motivated by a desire to signal optimistic expectations, while larger split factors are motivated by liquidity reasons. Baker and Powell (1992) find a significant difference between the preferred trading ranges for the small (< 2-for-1) versus large (≥ 2-for-1) splits. Thus there appears to be differences between the motives for small versus large splits. Moreover, larger splits may have a more pronounced effect on some of the effects of splits examined in this study. Consequently, we partition our sample into two subsamples: a small split factor subsample of 3-for-2 splits and smaller, and a large split factor subsample of 2-for-1 splits and greater.

Sample Characteristics

Table 1 reports sample characteristics for some selected variables (market value, number of shares, price, and number of market makers) for the entire sample, and for the two subsamples based on the split factor. There is a significant difference in the median pre-split market values of the equities of the firms in the two subsamples. The median value of equity in the small split factor subsample is $85 million compared to $182 million for the large split factor subsample. Since the difference in the median pre-split outstanding shares is not statistically significant, the difference in firm size is driven by the higher pre-split share price for the large split factor subsample ($37.7 versus $21.8). There is no statistical difference in the number of market makers between the two groups in the pre- and post-split periods.

[Insert Table 1 here]

We report statistics for microstructure variables and measures of trading activity in Table 2. The table reports pre- and post-split means and medians for the proportional bid-ask spread, the daily volatility corrected for microstructure biases, the average daily number of trades, the average volume turnover, the average volume turnover per trade.

[Insert Table 2 here]

First, the median values of both the pre- and post-split proportional spreads are higher for the small split factor subsample than for the large split factor subsample. This is consistent with a smaller market value and lower pre-split share prices for the small split factor subsample compared to the large split factor subsample. Next, there is a significant increase in the proportional spread after the stock split for the total sample as well as for each subsample. This increase in the post-split spreads is consistent with the findings of Copeland (1979) and Conroy, Harris, and Benet (1990). The median ratio of the post-split to the pre-split proportional spread is 1.08 for the small split factor subsample, and 1.45 for the large split factor subsample. While both these values are significantly greater than 1.0, the median change in the spread is obviously much greater for the large split factor subsample.

Our estimates of the bias-corrected volatility in the pre-split and the post-split periods are also presented in Table 2. Previous studies document a significant increase in the transaction price based volatility of the stock. However, Ohlson and Penman (1985), Dravid (1988), and Dubofsky (1991) argue that the larger bid-ask spread and the larger effect of price discreteness on lower priced stocks after the split may account for part of the increase in the volatility based on transaction prices.

Roll (1984) shows that in an efficient market, if the probability of the transaction price being at the bid or the ask is equally likely, then using transactions prices to estimate the true volatility of the stock returns would induce spurious volatility equal to $s^2/2$, where s is the percentage bid-ask spread.[2] This bias could be particularly significant in estimating the volatility change around stock splits since the bid-ask spread increases after the split. Following Kaul and Nimalendran (1990), we avoid this bias due to the bid-ask bounce by estimating the volatility of returns based on bid-to-bid prices.[3]

Further, Gottlieb and Kalay (1985) and Ball (1988) examine the effect of price discreteness on the inflation in the volatility estimates. Ball shows that if stock prices follow a

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2 For example, Kaul and Nimalendran (1990) show that for a portfolio of small market value NASDAQ-NMS firms, this spurious volatility could be as high as 50 percent of the underlying true volatility. Even for the largest firms, this proportion could, on average, be as high as 23 percent.

Geometric Brownian motion with an instantaneous true underlying variance σ^2, and price P, then the bias induced by price discreteness can be approximated by $d^2/6P^2$, where d is the minimum price change (typically, \$0.125). We apply this correction to the volatility measure to obtain an unbiased estimator.

Table 2 presents our estimates of the volatility of the stock, corrected for both the bid-ask bounce and price discreteness. The estimator, $\sigma^2_{B,D}$, is computed using equation A-1 in the Appendix. Even after we correct for these microstructure biases, the volatility of the stock increases significantly after the split. In our total sample, the median volatility increases from 2.75×10^{-4} to 4.61×10^{-4}. The median ratio of the post-split volatility to the pre-split volatility is 1.81. Thus, the volatility of the stock increases by 81 percent after the split.[4]

Our estimates of changes in the bias corrected volatility indicate that microstructure biases arising from bid-ask bounce and price discreteness alone cannot account for the previously documented increase in the volatility after stock splits. Moreover, the estimates of volatility changes for each subsample indicate that the increase is even more dramatic for the large split factor subsample. While the median volatility increases by 42 percent in the small split factor subsample, it increases by 118 percent in the large split factor subsample.

In addition to spreads and volatility, we also examine changes in trading activity. In the total sample, the median increase in the number of trades is 28 percent, and this increase is significantly different from zero at the 1 percent level. The median increases for the two

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[3] The CRSP data base gives closing bid and ask prices in addition to the closing transactions price for NASDAQ-NMS firms. We construct return series based on bid prices by adjusting for dividends and distributions on ex-days.

[4] We also estimated the volatility based on transaction prices, and based on bid-to-bid prices alone. A comparison of these estimates to the volatility corrected for both biases indicates that the bid-ask bounce inflates volatility estimates by about 40 percent and price discreteness inflates it by about 4.5 percent. Details of these comparisons are available from the authors.

subsamples are 12 percent and 37 percent respectively, and again both are significantly different from zero at the 1 percent level.

The observed increase in the number of trades after the split is consistent with an increase in the number of shareholders and a change in the motivations for trade. Holding investor trading strategies constant, an increase in the number of shareholders directly implies a greater number of trades in the stock. This is consistent with Lamourex and Poon (1987), who document an increase in the number of shareholders after the split. However, the motivation for trade, and hence investor trading strategy, could also change after the split. This would also lead to a change in the number of trades after the split. This would be consistent with the arguments presented in Black(1986), Brennan and Hughes (1991) and Admati and Pfleiderer (1988).

To discriminate between these two reasons for the observed increase in the number of trades, we examine the trade size adjusted for the split. Specifically, we examine changes in the average turnover (defined as the trading volume normalized by outstanding shares) and the average turnover per trade. Holding trading strategies constant, a mere increase in the number of shareholders would not change the average turnover per trade (i.e., the trade size). However, if noise traders are likely to trade in smaller quantities, an increase in noise traders after the split would result in a decrease in the trade size.

In the total sample, there is no significant change in the average turnover. It increases by 7 percent for the small split factor subsample and decreases by 7 percent for the large split factor subsample, with the latter being statistically insignificant. This is consistent with the findings of Murray (1985) and Lakonishok and Lev (1987) who find that splits do not appear to exert a permanent effect on volume. However, the average turnover per trade decreases significantly after the split. In the total sample, the median reduction in the trade size is 23 percent. The difference in the changes in the median turnover per trade is even more dramatic when we examine the subsample statistics. While the median turnover per trade declines by 18 percent for the small split subsample, it declines by 35 percent for the large split subsample. All of these changes in the average turnover per trade are significantly different from zero at the 1 percent level.

Since the average turnover does not change after the split, the increase in the number of trades decreases the average turnover per trade. This decrease is consistent with an increase in noise traders who are likely to trade smaller quantities. While we cannot rule out an increase in informed trading based on these measures, the results presented in Table 2 suggest that the increase in the number of trades is driven, at least in part, by an increase in noise traders. This change in the trader mix leads to a change in trading strategies after the split. In the next section, we examine the effect of this change in trading strategies on the volatility of the stock's returns.

III. Changes in Volatility Following Stock Splits

To examine the effect of the change in the trader mix after the split on the change in the volatility estimates, we need to estimate changes in trader types after stock splits. Since it is not possible to directly identify the trader types, we analyze stock return dynamics and market microstructure variables to infer the changes in the types of traders.[5] We decompose the change in the volatility into changes in the permanent (information driven) component and the transient (noise driven) component.

[5] We investigated using insider trades as a proxy for informed trades. However, since trading on insider information is prohibited, it is likely that these traders do not alter their trading strategies around important corporate announcements. Consistent with this argument, we find that in our sample, the number of insider trades does not change significantly from before the split to after. Consequently, we do not use information on these trades in our analysis.

Changes in Permanent Volatility

French and Roll (1986) argue that, if the effects due to noise trading (i.e., pricing errors) are subsequently corrected, then the volatility based on longer period returns reflects the permanent component. Thus we estimate the volatility based on multiday returns. Due to the limited number of observations in each estimation period, we use overlapping data and the estimator in Lo and MacKinlay (1988). This estimator, given in equation A-2 in the Appendix, corrects for the effects on volatility of both the bid-ask bounce and price-discreteness.

Table 3 reports these multiperiod volatility estimates for cumulating intervals up to 30 days for the total sample and for subsamples based on the split factor. For the total sample, the median 30-day return volatility increases by 57 percent after the split, and this increase is statistically significant at the 1 percent level. This indicates that a significant component of the increase in volatility is permanent. The one day return volatility however, increases by 81 percent for this sample (see Table 2). The larger increase in the one-day volatility relative to the increase in the 30-day volatility suggests that there is also a large component of the increase in volatility that is transient and attributable to noise. We obtain similar results for the subsamples based on the split factor. However, for the small split factor group, the increase in the permanent component of the volatility (based on 30-day returns) is only 32 percent compared to 81 percent for the large split factor group.

[Insert Table 3 here]

These results indicate that for our sample, there is a substantial increase in volatility that is permanent, in addition to a significant increase that is transient. The significant increase in the multiday volatility is consistent with Dubofsky's (1991) finding of an increase in the post-split volatility of weekly returns for stocks listed on the NYSE. However, Dubofsky finds no increase in weekly returns for AMEX listed stocks. He argues that this difference between his results for NYSE and AMEX listed stocks may be due to differences in one or more of several exchange listed factors. In particular, he notes differences in firm size, price range, size of the bid-ask spread, specialist behavior and ownership clientele factors between NYSE and AMEX stocks. Since our sample consists of NASDAQ-NMS firms, these factors could potentially explain the differences between our results and those of Dubofsky for AMEX listed stocks.

Changes in Volatility due to Noise Trading

The variance ratio, defined as the ratio of the variance of k-period returns to k times the variance based of one-period returns, can also be used as an alternative metric to determine the relative contribution of noise trading to the total volatility of a security's returns. The presence of noise trading induces negative autocorrelation in the returns, thereby reducing the variance based on multiperiod returns. The variance based on one period returns is unaffected by this negative autocorrelation if mispricing is corrected over more than one period. Consequently, French and Roll (1986) argue that one minus the variance ratio reflects the fraction of the one period volatility that is attributable to noise.

While noise trading introduces negative autocorrelation in returns, Kaul and Nimalendran (1990) find that at short lags there is also significant positive autocorrelation of returns. In their study, the average autocorrelation of returns on bid-to-bid prices at lag one is 0.15, and this is much larger than the negative autocorrelations at higher lags. This positive autocorrelation could result in variance ratio estimates that are greater than one leading to infeasible estimates of the noise component of the volatility.[6]

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[6] Lo and MacKinlay (1988) show that the variance ratio can be written as the weighted sum of the autocorrelations):

In our sample, we find positive and significant autocorrelations at lags one and two that are similar to the numbers reported in previous studies.[7] At higher order lags, the autocorrelations are small and insignificantly different from zero. To mitigate the effects due to large positive autocorrelations at short lags, we define one period of time as being three days. We compute our long run measure of variance using 30-day returns (i.e., 10 periods). Estimates of the variance ratios based on these returns provide feasible estimates for the effects of noise.

We report sample statistics for the variance ratios in Table 4. These variance ratios are computed using the estimator given by equation A-3 in the Appendix. The median differences in the ratios (computed as the median of the matched difference in the post-split and pre-split variance ratios) are significantly negative for the entire sample and also for the two subsamples based on the split factor. These ratios suggest that the fraction of volatility attributable to noise trading is higher after the split relative to the pre-split level for all three samples. Further, since the total one-day volatility is also increasing for these groups, it suggests that the volatility due to noise trading after the split is substantially higher relative to the pre-split level.

[Insert Table 4 here]

Decomposition of the volatility

Since one minus the variance ratio reflects the fraction of the one-period volatility that is attributable to noise, we use these variance ratios to decompose the volatility into the permanent

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$$VR(k) = 1 + \sum_{j=1}^{k-1} \frac{2(k-j)}{k} \hat{\rho}_j$$

where $\hat{\rho}_j$ denotes the estimate of the j^{th} order autocorrelation of daily returns. The effects of large positive autocorrelations at lag one could therefore results in a variance ratio estimate that is greater than one even if the autocorrelations at higher lags are negative.

and transient components. We then examine the change in each of these components of volatility. To avoid the effects due to large positive autocorrelations at short lags, we decompose the bias corrected volatility of three day returns. Further, we use the median variance ratios of size based portfolios in the decomposition.[8]

Specifically, we divide our total sample of 366 stock splits into three size based portfolios, where firm size is measured by the market value of the equity prior to the split. For each portfolio, we estimate the median variance ratios in both the pre- and the post-split periods. The permanent component of the volatility for each firm i in period j is then the product of that firm's 3-day return volatility (corrected for microstructure biases) in period j and the median variance ratio in period j for the portfolio in which this firm belongs. The transient or noise component of the volatility is the product of the firm's 3-day bias corrected volatility and one minus the corresponding variance ratio. Table 5 reports the median estimates of the total 3-day bias corrected volatility and its components.

[Insert Table 5 here]

Both the noise and the permanent components of the bias corrected volatility increase significantly after the split. For the total sample, the total volatility increases by 5.65×10^{-4}, representing a 70 percent increase from the pre-split value. The noise component of the volatility increases by 2.23×10^{-4} (a 564 percent increase) and the permanent component increases by 3.48×10^{-4} (a 50 percent increase). These results suggest that about 62 percent of the increase in the total volatility is due to the increase in the permanent component. We can draw qualitatively

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7 For example, in the total sample and for the pre-split period, the median autocorrelations at lag one and two are 0.15 and 0.04 respectively. In the post-split period, the corresponding values are 0.11 and 0.02 respectively. Details are available from the authors.

8 We use the median variance ratio for the size based portfolio since using individual variance ratios for each firm results in a reduction in sample size due to estimation errors.

similar conclusions by examining the increase in the volatility for the subsamples classified by the split factor.

The results in Table 5 indicate that there is a significant increase in both the noise and the permanent components of the volatility after the split. Further, as indicated in Table 2, the total number of trades increases, on average, after the split. Note that the total number of trades consists of trades executed by both noise and informed traders. Thus, an increase in both components of the volatility, coupled with an increase in the total number of trades, is consistent with the argument that the level of both noise and informed trading increases after a split. In the next section, we investigate this further using a cross-sectional regression framework.

Cross-sectional Analysis of Volatility Changes

Trading activity can be measured by either the number of transactions or the size of the trade (i.e., the turnover volume). Earlier studies document a positive relation between volatility and trading volume (see Karpoff (1987) for a review). However, Jones, Kaul, and Lipson (1994) conclude that it is the number of transactions per se, and not their size, that generates volatility. That is, the effect of trade size is subsumed in the number of transactions. Given their conclusions, we use the change in the number of trades as our measure of the change in trading activity.[9]

First, we investigate the relation between the change in the total bias corrected volatility (based on 3-day returns) and the change in the number of trades. Specifically, we estimate the following model using ordinary least squares regression:

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[9] Jones, Kaul, and Lipson include both the number of trades and volume in their cross-sectional analysis of volatility. In our study, we are interested in the change in trading activity. We find that in our sample, the change in the number of trades is highly correlated with the change in turnover volume: the correlation coefficient between these two variables is 0.79. Thus, including both measures of changes in trading activity results in the usual problems associated with multicollinearity in the independent variables.

$$\ln\left(\frac{\sigma^2_{B,D,2}}{\sigma^2_{B,D,1}}\right)_i = \alpha_0 + \alpha_1 \ln\left(\frac{NTRD_2}{NTRD_1}\right)_i + \varepsilon_i \qquad \textbf{(1)}$$

where $\sigma^2_{B,D,j}$ is the bias corrected volatility in period j (j equals 1 for the pre-split period and 2 for the post split period), and $NTRD_j$ is the number of trades in period j. We estimate this model for the total sample and for the subsamples based on the split factor.[10] We report the estimates of the parameters of this model and the associated statistics in Table 6.

[Insert Table 6 here]

We find a significant and strong positive relation between the change in the number of trades and the change in the total volatility. In the total sample, the estimate of α_1 is 0.52 with a t-statistic of 6.24. The estimates of α_1 for the two subsamples are 0.62 and 0.30 respectively, and both are statistically significantly different from zero.

These results extend the findings of Jones, Kaul, and Lipson (1994). They find a significant positive relation between volatility and the number of trades. Our results indicate that this positive relation also applies to changes in volatility and changes in the number of trades as well. Further, the results presented in Table 5 indicate that both the noise and the permanent component of volatility increase after the split. These increases may be due to an increase in noise and informed trading respectively. The interesting issue then is whether the increase in the number of trades affects the permanent component of volatility. French and Roll (1986) argue that a portion of the stock's volatility is due to trading by informed investors. Jones, Kaul, and Lipson (1994) argue that trading brings information in the market and affects prices, thereby leading to

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[10] Since volatility is likely to be related to firm size, we also estimated this model using firm size as an additional explanatory variable. The results from this estimation are qualitatively similar to those reported in Table 7. Inclusion of firm size in the right hand side of the model results in the intercept term being insignificantly different from zero. However, the estimates of the slope coefficients are significantly positive and of roughly the same magnitude.

volatility. Both of these studies suggest a positive relation between volatility and informed trading.

Since the total number of trades consists of both informed and noise trades, we cannot separate informed trades from this metric. However, if informed trading affects volatility, it would affect the permanent component of volatility. Therefore, we examine the relation between the change in the number of trades and the change in the permanent component of volatility. As in Table 3, we use the bias corrected volatility based on 30-day returns as the estimate of the permanent volatility. We then estimate the following model using ordinary least squares regression:

$$\ln\left(\frac{\Sigma^2_{B,D,2}}{\Sigma^2_{B,D,1}}\right)_i = \alpha_0 + \alpha_1 \ln\left(\frac{NTRD_2}{NTRD_1}\right)_i + \varepsilon_i \qquad \textbf{(2)}$$

where $\Sigma^2_{B,D,j}$ is the bias corrected volatility based on 30-day returns in period j (j=1 for the pre-split period and 2 for the post-split period). The estimates of the parameters of this model and associated statistics are also presented in Table 6. In the total sample, the estimate of α_1 is 0.4984 with a t-statistic of 5.16. The estimates of α_1 for the two subsamples are also positive and significantly different from zero.

The results presented in Table 6 indicate a strong positive relation between changes in the number of trades and changes in both the total volatility and the permanent component of volatility. This is consistent with the argument that noise and informed trading increases after the split and that this increase in trading activity generates the higher volatility. In the next section, we examine the effect of this change in trading activity on the bid-ask spread.

IV. Changes in Bid-Ask Spreads Following Stock Splits

The descriptive statistics presented in Table 2 indicate that, for the total sample, the proportional spread increases after the split by an average of 32 percent and that this increase is even higher for firms that employ a large split factor. Further, the results presented in the previous section indicate that the increase in the total number of trades is consistent with the hypothesis that trading by both noise and informed traders increases after the split. In this section, we decompose the total proportional spread in order to examine the effect of this change in trading activity on the information asymmetry in the market. The total spread consists of three components: order processing, adverse information, and inventory cost (Stoll (1989)). Since a change in the mix of trader types would affect the adverse information component of the spread, we focus our analysis on this component of the spread. Further, since our results suggest that both noise and informed trading increases after the split, we can only estimate the net effect on the adverse information component.

In order to extract the adverse information component of the spread, we use the methodology in George, Kaul, and Nimalendran (1991). This methodology allows us to decompose the total spread into the order processing component and the adverse information component. The part of the inventory cost component that decays within a day across a number of transactions is included in the order processing component, while that which does not decay within a day is included in the adverse information component (see Jagadeesh and Subrahmanyam (1993)). However, Stoll (1989) has found that the inventory cost component is a small fraction of the total spread (less than 10 percent). Madhavan and Smidt (1991) also find that inventory effects are economically and statistically insignificant.

George, Kaul, and Nimalendran use the difference in returns based on transaction prices and returns based on bid-to-bid prices to purge the bias due to changing expected returns and partial adjustment. In addition, by taking the difference between the two returns, the effects due to the unanticipated component of returns (which are a large fraction of the error) are eliminated. This substantially increases the efficiency of the estimates.

Let $R_{i,t}^{T}$ and $R_{i,t}^{B}$ represent the returns based on the closing transaction price and the closing bid price of firm i at time t respectively. Define $R_{i,t}^{D} = R_{i,t}^{T} - R_{i,t}^{B}$ as the difference in these returns. George, Kaul, and Nimalendran show that if S_i is the quoted spread, and π_i is the fraction of the quoted spread due to order processing costs (and 1- π_i is the fraction due to adverse information costs), then

$$C_i = 2\sqrt{-[\mathrm{Cov}(R_{i,t}^{D}, R_{i,t-1}^{D})]} = \pi_i S_i \qquad \textbf{(3)}$$

The relation in equation (3) is based on knowing whether the transaction occurred at the bid or the ask price. Since this cannot be directly observed with daily data, the true serial covariance is unobservable, and we can only obtain estimates of this covariance. These estimates could yield infeasible values of π_i.[11] However, the estimation errors are unlikely to be correlated with the true covariance since transactions at the bid and ask prices are equally likely. To circumvent this problem, we use the cross-sectional regression methodology proposed by George, Kaul, and Nimalendran.

If we assume that for a group of stocks the fraction of the quoted spread that is due to order processing costs (π_i) is constant and equal to π, then we can use the following cross-sectional model to estimate π:

[11] In our sample of 366 stock splits, estimation of the order processing component of the spread directly the serial covariance estimates yield infeasible values in 157 cases. We check the robustness of our results using the regression estimates below.

$$C_i = \pi_0 + \pi S_i + \varepsilon_i, \; i = 1, ..., N \qquad \textbf{(4)}$$

George, Kaul, and Nimalendran show that the ordinary least squares estimators of π are unbiased and efficient estimators of the order processing component of the spread. To estimate the parameters of this equation, we partition our sample of 366 splits into three portfolios based on firm size. We use firm size as the classification variable since smaller firms have larger proportional spreads on average (see Roll (1984) and Amihud and Mendelson (1986), for example).

For each portfolio, we estimate the model in equation (4) both in the pre-split and the post-split periods. S_i is the average proportional spread for firm i in the period used in the estimation. Using this procedure, we obtain 6 estimates of the order processing component (π). These portfolio estimates of π are then used to decompose the spread for each firm in each time period. The order processing cost as a percentage of the share price is computed as πS_i, and the adverse information cost is computed as $(1- \pi)S_i$.

In Table 7, we report the average values of the proportional spread, the order processing and the adverse information components in both the pre-split and the post-split periods. Average differences between the post-split and pre-split values and the average ratios of these two are also presented in Table 7. The statistics are reported for the total sample and for the two subsamples based on the split factor.

[Insert Table 7 here]

In the total sample, the proportional spread increases by 0.51, representing a 32 percent increase from the corresponding pre-split value. The adverse information component increases by 0.17, representing a 22 percent increase over the pre-split value. Further, one-third (=0.17/0.51) of the increase in the total spread is due to the increase in the adverse information component, with the rest being due to the increase in the order processing component. The statistics for the subsamples based on the split factor indicate similar increases in the total spread and the adverse information component. For the small split factor subsample, the total spread increases by 20 percent, while the adverse information component increases by about 11 percent. Further, about 18 percent of the increase in the total spread is due to the increase in the adverse information component. The results are even more dramatic for the large split factor subsample. The total spread increases by 49 percent and the adverse information component increases by 38 percent. About 41 percent of the increase in the total spread is due to the increase in the adverse information component.

The observed increase in the adverse information component is likely to be related to changes in informed trading for the following reason. If there were no change in informed trading, and noise trading decreased after the split, one might expect the adverse information component to increase. However, we find in the previous section that the temporary component of the volatility increases after the split, suggesting a post-split increase in noise trading. Thus, despite the increase in noise trading, the adverse information component increases, suggesting that the increase in the latter is related to an increase in informed trading.

The increase in the adverse information component in the presence of an increase in both noise and informed trading is consistent with the arguments presented by Admati and Pfleiderer (1988). In their model, information asymmetry increases even if the number of noise traders in the market increases. Diversity in the information received by the informed traders increases the amount of information in the market, thereby leading to an increase in the information asymmetry. Consequently, the adverse information component increases.

The preceding arguments suggest that changes in the adverse information component should be related to changes in the number of trades. However, since the total number of trades consists of trades by both informed and noise traders, it is difficult to predict the direction of the relation. Estimating this relation empirically will provide information about the effect of the change in number of trades on the adverse information component. We estimate the following model:

$$\ln\left(\frac{AS_2}{AS_1}\right)_i = \alpha_0 + \alpha_1 \ln\left(\frac{NTRD_2}{NTRD_1}\right)_i + \varepsilon_i \qquad \textbf{(5)}$$

where AS_j is the adverse information component of the spread in period j (j=1 for the pre-split period and j=2 for the post split period). We estimate this model for the total sample and for the two subsamples based on the split factor. Parameter estimates and associated statistics are presented in Table 8.

[Insert Table 8 here]

From Table 8, the estimate of α_1 is -0.378 for the total sample and this is significantly different from zero. The estimates of α_1 for the two subsamples are also negative and significantly different from zero.[12] These negative estimates, together with the observed increase in the adverse information component as reported in Table 7 suggest the following. Information asymmetry in the market increases unconditionally after the split due to an increase in the number of trades by informed traders. However, this increase is less pronounced when there is a large increase in the

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[12] To examine whether our portfolio approach to estimate the adverse information component introduces biases in our results, we used two alternative methodologies. First, we estimated the parameters of equation (5) using the adverse information component of the spread estimated directly from equation (3). Feasible values of the adverse information component were available for 209 splits (129 in the small split factor subsample and 80 in the large split factor subsample). We also estimated the relation between the difference in the pre- and post-split adverse information component of the spread (as opposed to the log of the ratio in equation (5)) and the change in the number of trades, using the total sample of 366 stock splits. Both methodologies yield conclusions identical to those that can be obtained from Table 8. This suggests that using equation (4) to estimate the adverse information component of the spread does not introduce any biases that affect our conclusions. Further details on these alternative methodologies are available from the authors.

number of trades. This large increase in the number of trades is likely due to a large increase in the number of noise traders, and the downward effect of these noise traders dominates the upward effect of an increase in informed traders.

V. Conclusions

This paper examines the impact of the change in trading activity after stock splits on the volatility and the spread. Our results show that the increase in volatility cannot be attributed solely to microstructure biases arising from the bid-ask bounce and price discreteness. Even after correcting for these biases, we find a significant increase in the volatility after the split. There is also an increase in the number of trades after the split, and the increase in the bias corrected volatility is positively related to this increase in the number of trades. We decompose the volatility into transient and permanent components, and find that both components of volatility increase after the split. To the extent that the transient volatility is driven primarily by noise traders, and permanent volatility by informed traders, our evidence suggests that trading by both types of traders increases after the split. We also find that a significant portion of the increase in the spread after the split is due to an increase in the adverse information component of the spread. Finally, this increase in the adverse information component is negatively related to the increase in the number of trades. This suggests that either the increase in the number of trades are predominantly noise motivated, or that there is an increase in competition between informed traders having substantially similar information.

Our results suggest that any analysis of the impact of stock splits on traditional measures of liquidity (like volatility and spreads) must first examine why different firms seem to be more or less successful in attracting additional trades to their security. The subsequent consequences for liquidity then seem to be consistent with existing theories on the way in which a change in trading activity affects liquidity. What distinguishes firms in terms of their ability to attract additional traders to their stock via a split remains an unresolved issue and is an interesting area for future work.

APPENDIX

Estimator of the Volatility Corrected for Price Discreteness

Ball (1988) shows that if stock prices follow a Geometric Brownian motion with an instantaneous true underlying variance σ^2 and price P, then the bias induced by price discreteness can be approximated as $d^2/6P^2$, where d is equal to 1/8. This approximation is valid for values of $d/\sigma P$ less than 2.50 (see Ball (1988), Table III). To correct for this bias, we need to estimate $1/P^2$. Since there is a price trend in the pre-split period, we use the average of $1/P_B^2$ from the estimation periods instead of one over the average of price squared. From Jensen's inequality, since $E(1/P^2) > 1/E(P^2)$, the estimated bias would bias it towards an upper value.

For the sample of firms in this study, the average value of $d/\sigma P$ is 0.34 and 99.9 percent of the estimates are less than 2.50 (based on an estimate of s using bid-to-bid prices and an estimate of P using the average bid price in the estimation period). Hence, Ball's approximation should be valid for our sample. We correct for the bias due to price discreteness by deflating the volatility estimate using bid-to-bid prices as follows:

$$\sigma_{B,D}^2 = \sigma_B^2 - \frac{d^2}{6(T_2 - T_1)} \sum_{t=T_1}^{t=T_2} \frac{1}{P_{B,t}^2} \quad \textbf{(A.1)}$$

where $\sigma_{B,D}^2$ is the volatility corrected for price discreteness, σ_B^2 is the volatility estimated using bid-to-bid prices, $(T_2 - T_1)$ is the range of the estimation period, and $P_{B,t}$ is the bid price at time t ($T_1 \leq t \leq T_2$).

Estimator of Multiperiod Volatility

We use the following estimator of the k-period volatility, based on Lo and MacKinlay (1988):

$$\sigma_c^2(k) = \frac{1}{m\left(1-\frac{k}{n}\right)} \sum_{t=1}^{n-k+1} \left(R_{B,t}^k - \hat{\mu}_k\right)^2 - \frac{d^2}{6T}\sum_{t=1}^{T}\frac{1}{P_{B,t}^2} \qquad \textbf{(A.2)}$$

where $\sigma_c^2(k)$ = estimate of k-period volatility based on bid-to-bid prices and with correction for price discreteness (the second term corrects for discreteness),

m = actual number of overlapping k-period observations,

n = number of one-period (daily) observations,

R_B^k = k-period return using overlapping one period returns based on bid-bid prices,

μ^k = the sample mean of overlapping k-period returns,

T = number of daily observations (= 180), and

$P_{B,t}$ = bid price on day t.

Estimator of the Variance Ratio

The variance ratio is defined as the ratio of the k-period volatility to k times the one-period volatility. The volatility estimates are corrected for the biases due to the bid-ask bounce and price discreteness. For each firm i, the variance ratio is given by:

$$VR(k) = \frac{Var\left(R_B^k\right) - \frac{d^2}{6P^2}}{k * \left[Var\left(R_B^1\right) - \frac{d^2}{6P^2}\right]} + \frac{2}{T-1}\sum_{j=1}^{k-1}\left(\frac{k-j}{k}\right) \qquad \textbf{(A.3)}$$

where $Var\left(R_B^k\right)$ is the k-period variance based on bid-to-bid returns. The quantity $[d^2/6P^2]$ in the RHS of the above equation is the adjustment for the bias die to price discreteness. The final term in the RHS of above corrects for the small sample bias in the expected value of the autocorrelation. Even if the returns are uncorrelated, the expected value of the autocorrelation is biased by -1/(T-1) (See Kendall and Stuart (1977)).

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TABLE 1. Sample Characteristics for 366 Stock Split Announcements Made by NASDAQ-NMS Firms Between January 1983 and December 1990, for the Total Sample, and for Subsamples Classified by the Split Factor.[a]

Variable	Total Sample		Small Split Factor Subsample (SFAC ≤ 0.5)		Large Split Factor Subsample (SFAC ≥ 1.0)		p-value [b]
	Mean	Median	Mean	Median	Mean	Median	
N	366		210		156		
SFAC	0.72	0.50	0.41	0.50	1.14	1.00	
MVAL	259	123	176	85	371	182	< 0.001
NSHR	7.36	4.38	6.52	4.10	8.50	4.93	0.110
P_1^{AV}	25.80	22.80	19.65	17.51	34.14	31.61	< 0.001
P_1^{B}	30.50	27.50	23.30	21.80	40.30	37.70	< 0.001
P_2^{AV}	17.70	16.50	16.50	15.50	19.30	18.0	0.001
P_2^{B}	18.20	17.70	16.90	15.90	19.90	19.0	< 0.001
$NMMK_1$	7.80	6.00	7.30	6.00	8.40	7.0	0.12
$NMMK_2$	7.00	6.00	6.70	6.00	7.50	6.0	0.32

[a] N is the number of observations in each subsample; SFAC is the announced split factor; MVAL is the market value of equity (in $ millions), measured two days before the announcement of the split; NSHR is the number of outstanding shares, in millions, as of two days before the announcement of the split; P_1^{AV} and P_2^{AV} are the average bid prices in the pre-split and the post-split estimation periods, respectively; P_1^{B} and P_2^{B} are the closing bid prices two days before the announcement of the split and two days after the ex-split day, respectively; and $NMMK_1$ and $NMMK_2$ are the average number of market makers in the pre-split and post-split periods.

[b] p-value is for the Wilcoxon sign rank sum test of differences in medians between the two subsamples.

TABLE 2. Changes in Samples Estimates of the Proportional Spread, Bias Corrected Daily Volatility, and Measures of Trading Activity for 366 Stock Split Announcements Made by NASDAQ-NMS firms Between January 1983 and December 1990.

Variable, Subscript 1 = Pre-Split, Subscript 2 = Post-Split		Total Sample		SFAC ≤ 0.5		SFAC ≥ 1.0	
		Mean [a]	Median [b]	Mean [a]	Median [b]	Mean [a]	Median [b]
Sample Size (N)		366		210		156	
Proportional Spread	S_1	3.11	2.32	3.36	2.68	2.78	1.77
	S_2	3.62	2.79	3.64	3.09	3.61	2.48
	S_2 / S_1	1.32**	1.23††	1.20**	1.08††	1.49**	1.45††
Bias Corrected Volatility of Daily Returns (x 10^4)	$\sigma^2_{BD,1}$	4.01	2.75	4.09	2.98	3.91	2.38
	$\sigma^2_{BD,2}$	7.29	4.61	6.90	4.19	7.82	5.25
	$\sigma^2_{BD,2} / \sigma^2_{BD,1}$	2.88**	1.81††	2.88**	1.42††	2.89**	2.18††
Average Number of Daily Trades	NT_1	21.56	9.37	15.88	7.76	29.21	10.96
	NT_2	32.33	12.00	20.77	9.95	47.90	17.56
	NT_2 / NT_1	1.53**	1.28††	1.39**	1.12††	1.71**	1.37††
Average Volume Turnover (x 10^3)	VT_1	3.40	2.50	3.24	2.52	3.69	2.49
	VT_2	3.80	2.30	3.81	2.41	3.90	2.13
	VT_2 / VT_1	1.19**	1.00	1.24**	1.07††	1.11	0.93
Average Volume Turnover per Trade (x 10^4)	$(VT / NT)_1$	3.19	2.64	3.45	3.00	2.83	2.09
	$(VT / NT)_2$	2.53	1.92	2.81	2.44	1.89	1.41
	$(VT / NT)_2 / (VT / NT)_1$	0.83**	0.77††	0.93*	0.82††	0.68**	0.65††

[a] Significance levels for the hypothesis that the mean ratio equals one are indicated as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

[b] Significance levels for the Wilcoxon sign rank test for the hypothesis that the median ratio equals one are indicated as follows: † indicates significance at the 10% level, †† at the 5% level, and ††† at the 1% level.

TABLE 3. Median Estimates of Multiperiod Return Volatilities in the 180 Day Pre-Split and Post-Split Periods, for the Total Sample and for Subsamples Classified by the Split Factor.[a]

Number of Days	Pre-Split Volatility ($x\ 10^4$)	Post-Split Volatility ($x\ 10^4$)	Median Difference [b] ($x\ 10^4$)	Median Post-Split Volatility/Pre-Split Volatility [c]
		Total Sample, N = 366		
5	18.38	28.43	9.26**	1.62††
10	37.29	57.36	18.11**	1.58††
20	68.43	102.74	28.20**	1.54††
30	95.76	139.17	34.33**	1.57††
		SFAC ≤ 0.5, N = 210		
5	19.06	27.19	5.69**	1.37††
10	38.09	53.17	10.65**	1.32††
20	75.79	97.96	12.11**	1.29††
30	102.10	126.52	11.87**	1.32††
		SFAC ≥ 1.0, N = 156		
5	16.76	32.33	12.85**	2.00††
10	36.29	64.71	25.04**	2.08††
20	61.51	111.56	47.74**	1.96††
30	77.24	146.57	55.65**	1.81††

[a] The estimator used is

$$\sigma_c^2(k) = \frac{1}{m(1 - k/n)} \sum_{t=1}^{n-k-1} \left(R_B^k - \hat{\mu}_k\right)^2 - \frac{d^2}{6T} \sum_{t=1}^{T} \frac{1}{P_{B,t}^2}$$

where, m is the actual number of overlapping k-period observations, n is the number of one period (daily) observations, R_t^k is the k-period return using overlapping one period returns based on bid-bid prices, μ^k is the sample mean of the overlapping k-period returns, and P_{Bt} is the bid price on day t.

[b] Significance levels for the Wilcoxon matched pair sign rank test for the hypothesis that the median difference equals one are indicated as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

[c] Significance levels for the test of the hypothesis that the median ratio equals one are indicated as follows: † indicates significance at the 10% level, †† at the 5% level, and ††† at the 1% level.

TABLE 4. Median Estimates of Variance Ratios During the 180 Day Pre-Split Period and the 180 Day Post-Split Period, for the Total Sample and for Subsamples Classified by the Split Factor.[a]

	Pre-Split	Post-Split	Difference [b]
Total (N = 366)	0.94	0.79	-0.13**
SFAC ≤ 0.5 (N=210)	0.95	0.88	-0.12**
SFAC ≥ 1.0 (N=156)	0.93	0.75	-0.15**

[a] The estimator for the variance ratio is

$$VR = \frac{Var\left(R_B^k\right) - \frac{d^2}{6P^2}}{k \times \left(Var\left(R_B^1\right) - \frac{d^2}{6P^2} \right)} + \frac{2}{T-1}\sum_{j=1}^{k-1}\left(\frac{k-j}{k}\right)$$

where, $Var\left(R_B^1\right)$ is the 1-period (3-day) day return variance based on bid-to-bid returns, and $Var\left(R_B^k\right)$ is the k-period (30-day) return variance based on bid-bid prices, and k is equal to 10. The quantity $[d/6P^2]$ is the adjustment for the bias due to price discreteness', where d is equal to 1/8 th., and P is the price of the stock. The final term in the equation corrects for the small sample bias in the expected value of the autocorrelation, and T is the number of one-period returns used.

[b] Significance levels of the Wilcoxon matched pair sign rank test for the hypothesis that the median difference equals zero are indicated as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

TABLE 5. Median Estimates of the Bias Corrected Total Volatility, the Volatility Due to Noise, and the Permanent Component of Volatility During the 180 Day Pre-Split Period and the 180 Day Post-Split Period, for the Total Sample and for Subsamples Classified by the Split Factor.[a]

Volatility Measure	Pre-Split	Post-Split	Difference[b]	Median Post-Split Volatility / Pre-Split Volatility[c]
		Total Sample (N = 366)		
Total Volatility	10.58	16.70	5.65**	1.70††
Noise Volatility	0.48	2.76	2.23**	6.64††
Permanent Volatility	9.83	13.58	3.48**	1.50††
		SFAC ≤ 0.5 (N = 210)		
Total Volatility	11.07	14.92	3.42**	1.46††
Noise Volatility	0.40	2.32	1.84**	6.88††
Permanent Volatility	10.51	12.87	1.84**	1.29††
		SFAC ≥ 1.0 (N = 156)		
Total Volatility	9.11	18.79	8.57**	2.07††
Noise Volatility	0.61	3.32	2.62**	6.27††
Permanent Volatility	8.59	14.14	5.37**	1.82††

[a] The total volatility is the volatility of 3-day returns. The component due to noise is estimated by multiplying the total volatility by one minus the median variance ratio for the size based portfolio to which the firm belongs. The permanent component is the total volatility times this variance ratio. All estimates of volatility are corrected for both bid-ask bounce and price discreteness, and are scaled by a factor of 10^4.

[b] Significance levels for the Wilcoxon matched pair sign rank test for the hypothesis that the median difference equals one are indicated as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

[c] Significance levels for the test of the hypothesis that the median ratio equals one are indicated as follows: † indicates significance at the 10% level, †† at the 5% level, and ††† at the 1% level.

TABLE 6. Ordinary Least Squares Estimates of the Model of the Relationship Between the Change in the Bias Corrected Volatility and the Change in the Total Number of Trades Following Stock Splits.[a]

Dependent Variable	Intercept	$\ln\left(\frac{NTRD_2}{NTRD_1}\right)$	Adjusted R^2
	Total Sample (N = 366)		
$\ln\left(\frac{\sigma^2_{B,D,2}}{\sigma^2_{B,D,1}}\right)$	0.3404 (6.59) ***	0.5171 (6.24)***	0.09
$\ln\left(\frac{\Sigma^2_{B,D,2}}{\Sigma^2_{B,D,1}}\right)$	0.1924 (3.19) ***	0.4984 (5.16) ***	0.07
	SFAC ≤ 0.5 (N = 210)		
$\ln\left(\frac{\sigma^2_{B,D,2}}{\sigma^2_{B,D,1}}\right)$	0.2166 (3.23) ***	0.6164 (5.36) ***	0.12
$\ln\left(\frac{\Sigma^2_{B,D,2}}{\Sigma^2_{B,D,1}}\right)$	0.0762 (0.99)	0.6241 (4.72) ***	0.09
	SFAC ≥ 1.0 (N = 156)		
$\ln\left(\frac{\sigma^2_{B,D,2}}{\sigma^2_{B,D,1}}\right)$	0.5703 (7.13) ***	0.2892 (2.43) **	0.03
$\ln\left(\frac{\Sigma^2_{B,D,2}}{\Sigma^2_{B,D,1}}\right)$	0.4078 (4.23) ***	0.2577 (1.80) *	0.01

[a] $\sigma^2_{B,D,j}$ is the bias corrected volatility of 3-day returns in period j (j=1 for the pre-split period and j=2 for the post split period); $\Sigma^2_{B,D,j}$ is the bias corrected volatility of 30-day returns in period j; SFAC is the announced split factor and $NTRD_j$ is the total number of trades in period j. t-statistics are in parenthesis. * indicates significance at the 10%, level; ** at the 5% level, and *** at the 1% level.

TABLE 7. Average Estimates of the Total Spread and its Order Processing and Adverse Information Components During the 180 Day Pre-Split Period and the 180 Day Post-Split Period, for the Total Sample and for Subsamples Classified by the Split Factor.

Spread Measure	Pre-Split	Post-Split	Difference [a]	Average Post-Split Volatility / Pre-Split Volatility [b]
Total Sample (N = 366)				
Total Spread	3.11	3.62	0.51***	1.32†††
Order Processing	1.63	1.97	0.34***	1.39†††
Adverse Information	1.48	1.65	0.17***	1.22†††
SFAC ≤ 0.5 (N = 210)				
Total Spread	3.36	3.64	0.28***	1.20†††
Order Processing	1.78	2.01	0.23***	1.26†††
Adverse Information	1.58	1.63	0.05	1.11†††
SFAC ≥ 1.0 (N = 156)				
Total Spread	2.78	3.61	0.83***	1.49†††
Order Processing	1.43	1.93	0.49***	1.56†††
Adverse Information	1.35	1.68	0.34***	1.38†††

[a] Significance levels for the Wilcoxon matched pair sign rank test for the hypothesis that the median difference equals one are indicated as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

[b] Significance levels for the test of the hypothesis that the median ratio equals one are indicated as follows: † indicates significance at the 10% level, †† at the 5% level, and ††† at the 1% level.

TABLE 8. Ordinary Least Squares Estimates of the Model of Determinants of the Change in the Adverse Information Component of the Bid-Ask Spread Following Stock Splits.[a]

Dependent Variable	Intercept	$\ln\left(\frac{NTRD_2}{NTRD_1}\right)$	Adjusted R^2
	Total Sample (N = 366)		
$\ln\left(\frac{AS_2}{AS_1}\right)$	0.2084*** (9.72)	-0.3778*** (-11.00)	0.25
	SFAC ≤ 0.5 (N = 210)		
$\ln\left(\frac{AS_2}{AS_1}\right)$	0.0866*** (3.47)	-0.3722*** (-8.72)	0.26
	SFAC ≥ 1.0 (N = 156)		
$\ln\left(\frac{AS_2}{AS_1}\right)$	0.4102*** (12.42)	-0.4834*** (-9.88)	0.38

[a] AS_j is the adverse information component of the bid-ask spread in period j (j equals 1 for the pre-split period and equals 2 for the post split period); $NTRD_j$ is the number of trades in period j, and SFAC is the announced split factor. t-statistics are in parenthesis. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.