The Impact of Clientele Changes: Evidence from Stock Splits[*]

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Abstract: We examine the trades of individual and professional investors around stock splits and find that splits bring about a significant shift in investor clientele. We find that a higher fraction of post-split trades are made by less sophisticated investors, as individual investors increase and professional investors reduce their aggregate buying activity following stock splits. This behavior supports the common practitioners' belief that stock splits help attract new investors and improve stock liquidity. The shift in clientele also influences return properties, price discovery, and asset prices: stocks exhibit stronger serial correlation after splits; stocks co-move more with the market index; and the introduction of new investors explains part of the positive post-split drift puzzle.

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ABSTRACT

We examine the trades of individual and professional investors around stock splits and find that splits bring about a significant shift in investor clientele. We find that a higher fraction of post-split trades are made by less sophisticated investors, as individual investors increase and professional investors reduce their aggregate buying activity following stock splits. This behavior supports the common practitioners' belief that stock splits help attract new investors and improve stock liquidity. The shift in clientele also influences return properties, price discovery, and asset prices: stocks exhibit stronger serial correlation after splits; stocks co-move more with the market index; and the introduction of new investors explains part of the positive post-split drift puzzle.

The widely-held view among investors is that stock splits are a positive event for the company. On the other hand, neo-classical financial theory suggests that splits are simply numeraire changes that should have no impact on the market value of the firm. Several studies over the years have addressed this apparent contradiction and discovered empirical regularities associated with stock splits. In particular, splits are related to changes in the risk, return, volume and liquidity characteristics of the stock. One explanation for these empirical effects is that splits change the stock's clientele and thus affect trading activity. To date, however, clientele changes and investor trading activity must either be inferred from annual data (Lamoureux and Poon 1987), changes in trade sizes (Schulz 1999), or institutional holdings. Reseachers have thus not been able to closely examine the changes in clientele around splits, and test a full range of their empirical effects.

In this paper, we examine the trading of individual and professional investors around stock splits using a panel dataset of individual investor trades and a separate data set of trades made by professional money managers. Our data include representative individual and institution trades and can further be broken down by investor sophistication within the individual investor class. We study changes in the demographic characteristics of traders before and after the split announcement date as well as before and after the split ex-date, and we contrast the effect of a split upon the trading habits of professional investors to its effect upon more naïve investors.

We find strong evidence that a change in investor clientele accompanies a stock split. Following the announcement of a split, individual investors increase their trading of the split stocks by more than 50 percent and also considerably increase their buying intensity. In contrast, our sample of professional traders reduces both their aggregate order flow and the ratio of buy orders to sell orders. Furthermore, less sophisticated individuals, such as investors in non-professional occupations or with lower incomes, comprise a larger fraction of individual investor ownership after stock splits, a phenomenon consistent with the contrast between individuals and institutions.

We also study in some detail the micros-structure effects of clientele changes. We find that both the price impact of trades, and the bid-ask spread decrease after split execution, indicating improved liquidity after splits. We also find that the clientele shifts and changes in trading behavior are associated with regime changes in asset price dynamics. Stocks co-move more with the market index after splits, become more volatile, and exhibit stronger serial correlation after splits. Our cross-sectional analysis suggests that documented clientele differences are significantly related to beta shifts, volatility shifts, and the post-split drift.

The rest of the paper is organized as follows: section 2 reviews the current literature and presents the hypotheses to be tested; Section 3 describes the data used in this paper; Section 4 presents the findings on clientele change after splits; Section 5 investigates the impact of the clientele shift on liquidity; Section 6 examines the impact on asset prices; and Section 7 concludes.

2. Literature Review and Hypothesis Development

A. Documented Empirical Regularities

Previous research has found that splits have significant liquidity effects (cf. Copeland 1979; Lakonishok and Lev, 1987; Brennan and Copeland, 1988; Conry, Harris and Benet, 1990; Han, 1995; Angel, 1997; Amihud, Mendelson and Uno, 1999; Schultz, 2000; Easley, O'Hara and Saar, 2001; and Anshuman and Kalay, 2002) and also have apparent signaling effects (cf. McNichols and Dravid, 1990; Bajaj and Vijh, 1995; Ikenberry, Rankine and Stice, 1996; Muscarella and Vetsuypens, 1996; Prabhala, 1997; Nayak and Prabhala, 2001; Kadiyala and Vetsuuypens, 2002).

Most evidence suggests that these microstructure and signaling effects in turn influence price dynamics. In particular, splits are associated with a post-split risk-adjusted drift in prices (Grinblatt, Masulis and Titman 1984, Conrad and Conroy 1994, and Ikenberry et al. 1996, 2002)[1], increased volatility (Ohlson and Penman, 1985) and increased market betas (Lamoureux and Poon 1987). On the other hand, Byun and Rozeff (1993) argue that these documented effects are due in part to the choice of sample period and the focus by researchers upon split ratios near 2:1, as well as upon the risk adjustment procedures employed. While we do not directly address their concerns, we are able to shed some light on the argument that some of these effects are spurious. On balance previous, past results suggest that the distribution of returns change following splits, although there is some dispute about whether these effects apply in all time periods and for splits of small magnitude.

B. Clientele Change around Splits

Companies apparently split stocks to make their shares more attractive to individual investors and thus expand the investor base. Baker and Gallagher (1980), for example, survey public company CFOs and find that more than 80 percent of them believe stock splits make it easier for small investors to purchase shares and thus increase the number of shareholders (Baker and Powell, 1993). Academic tests of this proposition, however, have been limited by the lack of individual and institutional trade data. Lamoureux and Poon (1987) use annual data to document clientele changes. Schulz (1999) used trade sizes. The annual data do not allow Lamoureux and Poon (1987) to determine the timing around the split of the clientele shift. On the other hand, the Schultz study using high-frequency data is not able to distinguish the characteristics of the traders before and after the split. In order to test certain hypotheses about the effects of stock splits, it is important to be able to understand the timing of clientele changes as well as investor characteristics.

Our study uses two sources of data. The first is a database of detailed trading records of individual investors from a large discount brokerage. The second is a large sample of trades by a group of large institutional traders. This gives us the advantage of directly examining a large and varied clientele sample around stock splits. The marketability hypothesis predicts that individual investors will make up a higher fraction of the shareholders post-split. We hypothesize that individuals will increase and institutions will decrease their overall trading and buying intensity of split stocks around the split dates. Within the individual investor group, we expect less sophisticated investors to increase and more sophisticated investors to decrease their overall trading and buying intensity, thus extending the hierarchy seen between individual and institutional investors. Finally, we examine whether the clientele shift is temporary or persistent following splits. In sum, we will test the following hypotheses:

H1A: Individuals and institutions do not change their trading intensity after splits.

H1B: Individual and institutions do not change their buying intensity after splits.

H1C: The individual investor base does not increase after splits.

H1D: The average level of individual investor sophistication for those holding the stock of a firm does not change after splits.

B. Clientele Shift and Liquidity

In addition to the expansion of the investor base following a split, managers also cite improved liquidity and a more desirable trading range as reasons for splitting their stocks (c.f. Baker and Gallagher, 1980; Baker and Powell, 1993). Interestingly, empirical studies do not entirely agree on whether liquidity increases following a split. Many authors have used trading volume as a proxy for liquidity, as it is negatively correlated with the bid-ask spread (Demsetz, 1968; Benston and Hagerman, 1974). No consensus emerges from these studies. Maloney and Mulherin (1992) find that trading volume increases after splits, which they take to be evidence of increased liquidity. Copeland (1979) finds that volume increases following a split, although not proportionally to the split factor and thus the average daily dollar volume traded decreases following a split. He concludes that splits decrease liquidity. On the other hand, Lakonishok and Lev (1987) show that relative volume decreases following split, but a matched control group shows that volume for split stocks was abnormally high prior to the split. Following the split, volume returns to a more normal range. They conclude that splits do not exert a permanent effect upon the volume of trade, but may affect other aspects of marketability (such as the composition of stockholders).

Another approach in the literature centers on direct measures of liquidity. Conroy, Harris, and Benet (1990) measure the bid-ask spread and find that while spreads decrease following a split, the spread percent increases due to the price effect. They attempt to separate the split effect on liquidity from the price effect and determine that, controlling for the change in price, splits have a positive but not statistically significant effect upon liquidity. Desai, Nimalendran, and Venkataraman (1995) decompose the bid-ask spread and measure changes in information-based trading. They find adverse selection risk increases following splits and accounts for a significant part of the increased proportional spreads following splits. They argue that the split increases both the level of noise traders as well as the level of informed traders. However, lacking trade-level information, they cannot directly substantiate this hypothesis.

There are good reasons to suspect that splits will increase liquidity if they successfully attract more noise traders into the market. Black (1986) notes that an increase in noise trading (which he assumes comes from individual investors) should improve liquidity, but also that "as the amount of noise trading increases, it will become more profitable for people to trade on information, but only because the prices have more noise in them." This pattern is consistent with strategic models of market trading. In Kyle (1985), an increase in noise trading improves liquidity because informed traders are better able to camouflage their trades amongst the noise, thus reducing the price impact of each trade. In a similar setting, Admati and Pfleiderer (1988) endogenize informed trading and show that the improved liquidity brought on by increasing noise can, in turn, increase the level of informed trading. However, the effect upon liquidity is unclear; it depends upon the current level of informed trading and whether the informed traders have similar information (in which case they compete, and can increase liquidity) or monopolistic information. We test the following liquidity hypotheses:

Hypothesis 2A: The price impact of trade does not change around splits.

Hypothesis 2B: The bid-ask spread does not change around splits.

C. Clientele Shifts and Asset Prices

Barberis and Shleifer (2001) and Barberis, Shleifer and Wurgler (2002) show that clientele changes affect asset co-movement – inducing “style” effects or co-movement among securities in the S&P 500 index. In particular, using data on index additions and deletions, Barberis et al. (2002) find a higher correlation between individual stock returns and the index, which they attribute to changes in investors’ trading patterns. If the individual investor base expands around splits, we suspect there may be a similar pattern: split stocks “co-move” more with the market.

To this end, we test for changes in split stocks’ R^2 from CAPM regressions. An increase in the R^2 in a CAPM regression indicates that the market index can explain a higher fraction of a stock return’s variance and is a clear indication of how closely individual stocks move with the market index. Campbell et al. (2002) document a secular decrease over the last decade in the average R^2 for the returns to individual stocks regressed on the market index. While they do not offer a complete explanation, they suspect that improvements in information access and decreases in trading costs over recent years has increased price discovery. Morck et al. (2002) examine international data and find that R^2 in CAPM regressions are significantly higher in less developed financial markets, consistent with the conjecture that higher R^2 is associated with poorer price discovery.

If a stock split brings more noise traders to the market and hampers price discovery, we would expect ex-split stocks to co-move more with the market index. This leads to two testable hypotheses: following a stock split, R^2 from a CAPM regression should increase, and the beta from a CAPM regression should also increase.

Hypothesis 3A: The CAPM R^2 does not change around stock splits.

Hypothesis 3B: The CAPM beta does not change around stock splits.

We also explore whether a clientele shift may explain the post-split irregularities found in the literature, such as changes in market beta, volatility, and autocorrelation around splits (Lamoureux and Poon, 1987; Brennan and Copeland, 1988; Ohlson and Penman, 1985, Dubovsky, 1991, etc.). More interestingly, we will test whether clientele shifts around stock splits have an impact on asset prices. In a similar vein, Kalay (1982) and Booth and Johnston (1984) find that the ex-dividend day price drop is associated with a tax-induced clientele effect. Although stock splits do not have the same tax consequences as dividends, it is possible that asset prices will be similarly influenced by a change in investor clientele.

Separately, Foerster and Karolyi (1999) find that changes in market beta are positively correlated with an increase in the investor base. In particular, we will examine whether the increase in betas and R^2 is cross-sectionally associated with an increase in the less sophisticated investor clientele, investors in non-professional occupations and with lower income.

Hypothesis 4A: Post-split drift is not associated with clientele shift around splits.

Hypotheses 4B: Changes in market beta and R^2 are not associated with clientele shift around splits.

Implicitly, both of these hypothesis provide indirect evidence on the Byun and Rozeff critique that returns effects conditional upon splits may be spurious artifacts of sample selection. If we find evidence that the shift in various measures depend upon clientele effects predicted by theory, it would support the argument that these changes are due to real economic effects.

Of course, all of our hypotheses are not observationally independent. In particular, liquidity changes may affect measurement of betas and R^2 , as well as expected return. Our empirical test design, and interpretation of our results must therefore take into account these joint effects.

3. Data

Our individual investor data comes from a large U.S. discount brokerage firm and includes daily trades and monthly position statements for a total of 77,995 households. Of these, 62,387 have traded common stocks during the sample period between January 1991 and November 1996. For each trade, we have information on the date, direction, size, and commission of the trade.

The brokerage house also provided to us a demographic file compiled by Infobase Inc. (dated June, 1997). This file includes information on the age, gender, income, and profession of more than half the investors in the sample. We do not always have all types of personal information for a given individual. Consequently, we have a slightly different sub-sample when focusing on investors' income and on their profession in our study. About half of the households hold more than one account with this brokerage, generally one taxable and one tax-deferred. We aggregate accounts to the household level in our analysis.

Descriptive statistics of the data are presented in Table 1. In an average month, individual investors in our sample hold \$2.18 billion worth of securities in their portfolios. The average investor holds four stocks (median=3) worth \$35,629 (median=\$13,869) in their portfolio. The average monthly turnover is 7.59 percent over the 6-year period (although the median investor turns over her portfolio at a much slower rate of 2.53 percent per month).

To verify the representativeness of our individual investor sample, we compare our average investor portfolio with national averages. The Survey of Consumer Finance (Federal Reserve 1992, 1995) reports the median stock portfolio size is \$15,300 and \$16,900 in 1992 and 1995, respectively. These numbers match closely to the median portfolio size for our sample investors. We obtain similar results by comparing portfolio sizes for investors of different age groups. More than 80 percent of sample individuals trade split stocks at least once between 1991 and 1996. The sub-sample of individual investors has a very similar demographic profile to the entire sample.

To analyze the trading practices of professional investors, we use a data set compiled by the Plexus Group, an advisory service to institutional clients. This includes the trades made by 43 professional money managers from January 1992 to March 1996. Not all managers are included in the sample for the entire period; we include a manager's trades for a given stock only if his trading history spans the entire event window for that split event. In our sample period, these managers entered 1,520,270 buy orders worth an average value of $658,683 and 1,173,634 sell orders worth an average value of $708,627.

Data on split events between 1991 and 1996 are obtained from CRSP. For each split, we obtain information on the split announcement date, split ex-date, split ratio and share price before and after the split. Daily stock returns also come from CRSP. For each split event, the entire split event window is divided into three periods: the first period (Period 1, hereafter) consists of the three months before the announcement date. The second period (Period 2, hereafter) is the period between the announcement date and the split execution date, excluding both dates. We exclude the split announcement date and the ex-date because of the existing empirical evidence of unusual returns on these two dates. The third period (Period 3, hereafter) is the three-month period following the split ex-date. Thus, the length of the event window varies for different splits. For a single split, the length of period 2 and the other two periods will also likely be different. To address this problem, we compute all of our statistics on a daily basis, avoiding the potential bias induced by comparing results over different period lengths.

A split event must satisfy the following requirement to be included in our sample: (1) All of the above information is available from CRSP; (2) the split factor is 1.5-for-1 or 2-for-1; (3) our investors trade the stock at least once during Period 1, 2, and 3. We restrict our attention to events where the split ratio is between 1.5 and 2.0 to avoid any differences induced by the split factor, and because these splits make up more than 80 percent of all split events.

The sample individual investors have traded 2,723 split stocks. The above filtering rules reduce the sample to 1,524 splits for the individual investors, and 638 splits for the professional investors. Summary statistics are provided in Table 2.

4. Clientele Shift after Splits

A. Trading Intensity for Individuals and Institutions

Lamoureux and Poon (1987) report that the number of shareholders increases following a split. Their findings are based upon annual data from COMPUSTAT and thus cannot pinpoint an investor base change exactly around splits, nor can their study differentiate whether the split announcement or the execution causes the increase. Our database enables us to distinguish whether it is the information event (announcement) that brings in new investors, or the numeraire event (the split itself) that does so. Increased trading activity could result from splits carrying a positive signal (which would manifest itself at the announcement date and not the ex-date) or from attention effects (which would show up on both dates) or as a result of lower share prices allowing greater participation by small investors (which is solely a numeraire effect).

We first look at the trading intensity around splits for individuals and institutions. Panel A of Table 3 reports that the average number of individual investors trading split stocks increases monotonically across the periods, from 0.175 to 0.245 to 0.308 per day, reflecting 40 and 75 percent increases in individual traders from period 1 to period 2 and period 2 to period 3. These findings support both the signaling hypothesis (from period 1 to period 2) and the marketability hypothesis (from period 2 to period 3). Panel B of Table 3 depicts a different pattern for institutions. The number of professional traders first increases by about 80 percent from period 1 to period 2, and then decreases by about 40 percent to a level slightly above that in period 1. Institutions seem to temporarily increase their trading activity in the split stock -- perhaps due to the positive signal given by the split announcement -- but disregard the split execution itself.

We further examine buying and selling trades separately. This approach contrasts individual and institutional trading patterns around splits. For individuals, the increase in traders is primarily driven by the increase in the number of buyers. The number of investors making buying trades increases monotonically from period 1 to period 3, and more than twice as many investors buy split stocks in period 3 than in period 1. Consistent with both the signaling and the market microstructure literature, the split announcement and the execution of the split have separate impacts on individual investor trading decisions and both attract investor interest. Splits have a far smaller impact on sales. The number of individuals selling split stocks remains largely unchanged from period 1 to period 2 and then increases by about 20 percent in period 3. This may be partly because individuals have considerably increased their position in split stocks during period 2 and trade for liquidity reasons in period 3. Overall, however, individuals exhibit heavier buying than selling throughout the split events.

On the other hand, the buying and selling patterns of institutions do not differ much around split events. The number of professionals buying as well as selling increases from period 1 to period 2, and then both decreases from period 2 to period 3. Professional traders increase their buying slightly more than their selling in period 2 but reverse this trend in period 3.

To summarize, we reject Hypothesis 1 that the trading activity does not change for individuals and institutions around split events. It clearly does change, and affects the two classes of investors in different ways.

B. Buying Intensity for Individuals and Institutions

To better understand the changes in trading intensity around splits, we examine both the order flow (in dollars) and the order imbalance (in number of trades). The average daily order flow is computed for each split as the aggregate dollar value of stock purchased during a given period minus the aggregate dollar value of stock sold during a given period, divided by the number of days in that period. The order imbalance for stock i in period p is defined as follows:

$$OI_{ip} = \frac{NB_{ip} - NS_{ip}}{NB_{ip} + NS_{ip}}$$

where NB_{ip} (NS_{ip}) is the number of buy (sell) orders submitted by the group of traders in stock i during period p.

The results in Table 4 show that individuals buy split stocks with much higher intensity in periods 2 and 3 compared to period 1. Order flow increases from –62.9 to 826.8 dollars per day, and the order imbalance more than quadruples from 0.0329 to 0.1761. It is interesting to note that both order flow and order imbalance are strongest during period 2, supporting the signaling hypothesis. Nevertheless, individuals' buying intensity remains much stronger in period 3 than in period 1.

In contrast to the trading habits of individual investors, Table 5 indicates that the professional investors severely reduce their net order flow following the announcement of a stock split. The professionals' average daily order flow decreases by 90 percent from period 1 to period 3. Most of this reduction comes from an increase in selling activity (as opposed to the individuals, who increase their selling activity slightly while sharply increasing their buys). While the average daily dollar value purchased remains relatively flat, the average daily dollar value sold increases by 34 percent from period 1 to period 3. Furthermore, it appears that the major impact upon professional investors occurs with the announcement of a split, while the numeraire event has very little effect: there is a large, significant change in order flow from period 1 to period 2 and a much smaller change from period 2 to period 3. The professional investors appear to greet the announcement of a split as new information, and treat the actual implementation of the split as a non-event.

The average order imbalance among professional traders also turns sharply lower following the announcement of a split. The average order imbalance drops from 24.3 percent to 9.3 percent from period 1 to period 3. Again, the largest effect is felt upon the announcement date, with a much smaller and generally insignificant effect felt following the ex-date. While the average number of buy orders per day remains fairly flat from period 1 to period 3, the average number of sell orders per day increases by 30 percent. It appears that the professional investors act, by and large, as profit takers. [2]

Both order imbalance and order flow remain positive following the announcement date and ex-date, so this sample of professional traders accumulated split stocks across all three periods. However, it is important to note that the professionals' order flow and order imbalance across all stocks during the sample period is quite positive. The aggregate order imbalance across all trades in our data set is 12.8 percent; the average daily order imbalance for split stocks in both period 2 and period 3 is well below this mark. Thus, these investors accumulated split stocks at a lower rate than they accumulated the average stock. In dollar terms, the professionals purchase $169 billion more than they sell in stocks during the sample period. Given these figures, it is not surprising that they still allocated a portion of their resources towards the stocks we study, albeit with far less enthusiasm than they did before the split event.

The results on order flow and order imbalance clearly reject Hypothesis 1B that buying intensity does not change for individuals and institutions around split events.

The use of net order imbalance in to test Hypothesis 1B naturally raises the question of how to account for the other side of the trades. In other words, while it appears that institutions may be buying the shares that individuals are selling, but we do not have a complete sample of the investor universe. We do, however, have some heterogeneity in our investor sample that allows us to investigate which sectors of the investor sample are buying while others are selling.

Our analysis indicates significant cross-sectional difference in order imbalance within individuals and institutions. In particular, individual investors who already hold split stocks before the announcement exhibit, on average, a negative order imbalance, while new individual investors who have not held the stocks exhibit particularly strong positive order imbalance. Thus the newcomers are buying from the current shareholders. We also find that different categories of institutions (i.e. diversified, momentum, and value investors) exhibit complementary order imbalances around stock splits. Although on net our sample of institutions is buying split stocks, we see that some styles tend to be sellers. One need not have exhaustive information about the market to draw inference from order imbalance provided there is some heterogeneity that allows an understanding of who is taking opposite sides of the trade.

C. Individual Investor Base around Splits

Because firms claim to split their stocks in part to attract small investors in the long run (Baker and Gallagher, 1980), we find it particularly interesting to study not only a short period around splits but also the long-term shift in investor clientele. We use the individual investor position statements to estimate the average number of shareholders for split stocks at different stages of the split. For each split and each period, we calculate the number of shareholders from the end-of-month position data. In addition to the three periods analyzed above, we also introduce a 6-month period following period 3 to trace any long-term shifts in shareholder base.

Similar to the findings on individual investor trading habits, the average number of shareholders also increases monotonically over time. In addition to the three periods immediately around splits, we also include period 4, 5, and 6 to detect splits' long-term impact. Period 4 is a from three to six months after split execution; period 5 is from six to nine months after split execution; and period 6 is from nine to twelve months after split execution. In Table 6, the average number of shareholders for split stocks increases 20 percent from 0.54 to 0.63 shareholders per day from before to twelve months after splits. This is largely in line with Lamoureux and Poon's finding that the shareholder base expands after splits. It seems that the individual investors are not merely trading in and out of these stocks around the splits. Hence, we reject Hypothesis 1C that the individual investor base does not change around splits.

D. Investor Sophistication around Splits

Having documented an increase in individuals' tendencies to trade and hold split stocks, we next seek to understand whether splits change the expectations of existing customers or attract new investors. It is possible that existing investors regard a stock split as positive signal and upwardly revise their opinions of its prospects. This could lead them to buy more shares.

Another possibility is that, as CFO's apparently hope, splits may attract new investors. In the past, splits enabled individuals to avoid odd-lot trades, which were costly to execute. In the sample period of 1991 to 1996, however, odd-lot trading was not significantly different in cost that round-lot trading. Still, individual investors tend to like trading in hundreds of shares (about 82 percent of all common stock trades are executed in round hundreds of shares lots) and cheaper stock prices enable them to increase portfolio diversification while still investing in round lots. Finally, splits may also attract individual investors due to a style preference (Barberis and Shleifer, 2003), or attention-grabbing effects (Barber and Odean, 2003).

To investigate the behavior of new versus existing investors, we first divide individuals into new and existing investors for periods 2 and 3. Existing investors are defined as those who have traded or held the split stock at least once before the split announcement date, even if they do not hold a current position in the stock. On the other hand, new investors are defined as those who have never traded the split stock during our sample period until the split announcement.[3]

The results in Table 7 indicate that the split event attracts new investors. More than 50 percent of traders in period 2 and period 3 are new investors, and the majority of new investors arrive between the split announcement date and split ex-date. Although the split announcement has a large effect on its own, the split execution further increases the fraction of new investors, indicating a separate marketability impact on the split ex-date.

The introduction of new investors has a similar impact on the fraction of shares traded. New investors make over 50 percent of the trades and account for more than 50 percent of the share volume in periods 2 and 3. Furthermore, the fraction of shares traded and trades executed by new investors increases significantly from period 2 to period 3, indicating that, apart from its signaling component, the split execution has a separate clientele impact. In contrast, panel B of Table 7 reports that splits tend not to attract new professional investors. Only 26 percent of professional traders (making 22 percent of the trades) in period 2 and 42 percent (making 31 percent of the trades) in period 3 are new investors.

In addition to the reduced relative presence of professional investors, a potential change in individual investor sophistication may also take place around stock splits. Our demographic data on individual investors allows us to identify investor characteristics such as investor income and profession. We classify individuals with annual incomes of $100,000 or more as high-income investors and individuals with annual incomes of $50,000 or less as low-income investors. Similarly, we classify those who claim to work in "administrative/managerial" and "professional/technical" as working professionals and those who report to work in “craftsman/blue collar”, “clerical/white collar”, and “sales/service” professions as non-professionals. We classify investors with high income and in professional occupations as more sophisticated investors.[4]

Table 8 shows that the fraction of trades by high-income investors decreases from 16 percent in period 1 to 13 percent in period 3. Meanwhile, the fraction of trades by working professionals decreases significantly from 18 percent in period 1 to 15 percent in period 3. As there is a strongly positive correlation between income and professional occupation, the patterns are similar for high-income investors and professionals. In each case, the trading volume by sophisticated investors decreases by about 20 percent from period 1 to period 3.[5] Most strikingly, the patterns found for sophisticated investors resembles the institutional traders more than the individuals as a whole. The fraction of sophisticated investors increases after split announcements and then decreases dramatically (more than 30 percent) after the ex-date. It appears that sophisticated individual investors are more likely than their unsophisticated counterparts to take advantage of the positive signal given by split announcements.

We also utilize the data on individual investors’ portfolio holdings to trace the long-term change in the sophistication of the shareholder base. Our results (not reported) indicate a similar change in the sophistication of the individual shareholder base for up to one year following the split announcement. These findings indicate that not only do new investors constitute a high fraction of the investor base after splits, but also these new investors tend to be less sophisticated than existing investors. Based on these findings, we reject Hypothesis 1D that there is no change in investor sophistication associated with stock splits.

In sum, in section 4 we find strong evidence that stock splits change the trading habits of both individuals and institutions around split events, induce long-run changes in the investor base, and also change the investor clientele.

5. Clientele Change and Liquidity

The way that stock splits change professional and individual trading habits closely resembles the Admati-Pfleiderer equilibrium, in which an increase in noise traders endogenously results in more informed trading. We find a strong increase in individual (noise) traders following a split, and a much smaller increase in the potentially informed professional traders. The noise traders tend to provide liquidity, while information-based trading will reduce liquidity. The net effect is an empirical question. We evaluate liquidity using two measures: the price impact of trade and the bid-ask spread.

5.1. The price-impact of trade

One of the primary measures of liquidity is the price impact of trade. We base our study on the work of Barclay and Warner (1993), who find that neither small-sized trades nor large-sized trades have much permanent impact upon the cumulative stock-price change. Rather, medium sized trades (between 500 and 10,000 shares) are most responsible for moving prices. Their “stealth trading” hypothesis assumes that informed investors strategically concentrate their trades in medium-sized lots in an attempt to minimize the price pressure of their trades. Large trades would reveal too much of their information at once, and small trades are too expensive in terms of trading costs. Evidence suggests that informed traders do indeed behave this way, and with some success. Cornell and Sirri (1992) find that their sample of insider traders make 78.2

percent of their trades in medium-sized blocks (for comparison, 38.4 percent of all trades in these stocks are of medium size).

Surprisingly, despite the smaller price movements associated with medium sized trades, recent empirical results show that these trades account for the largest cumulative price impact (because they are much more common than large block trades). Barclay and Warner report that, in a sample of NYSE firms undergoing tender offers, medium sized trades comprise 45.7 percent of all trades and 63.5 percent of total volume, but are responsible for 92.8 percent of the price movements prior to the tender offer announcement. Across all NYSE firms for the same time period, medium sized trades comprise 38.2 percent of trades and 55.1 percent of volume, but account for 82.9 percent of the cumulative price movements. Not only do medium sized trades appear to have the largest price impact, but the level of medium sized trades and their price impact increases when conditioning on events for which informed trading seems likely.

Furthermore, it appears that institutional traders have the most power to move prices, and the folk classification of individuals as noise traders is a realistic assumption. Chakravarty (2001) examines the trades of individual and institutional trades in a representative sample of 97 NYSE stocks with strong price appreciation over a three-month period. He confirms that institutions by far have the largest effect upon price movements; they are responsible for 93.5 percent of the cumulative price changes, and their medium sized trades are responsible for 79.2 percent of the movement. Individuals, by contrast, account for only 6.5 percent of the price change.

Our primary results in section 4 document a dramatic increase in noise trading and a slight increase in professional (possibly information-based) trading following a split. If the split successfully attracts enough noise traders to compensate for the possible increase in attention from informed traders, liquidity will likely improve. If the informed traders respond by stepping up their activity, and bring new information into the prices, liquidity could decrease or remain unchanged.

Following Barclay and Warner, we categorize the trades made by individuals and professionals into trades of small lots (less than 500 shares), medium (between 500 and 10,000 shares), and large (greater than 10,000 shares). Although we cannot directly measure the price impact of these trades, a decrease in medium sized trades following the split would indicate that the trades with the highest price impact are less common, and thus suggest improved liquidity.

For each split, we calculate for each group of investors the average daily trades for each period, the average share size per trade (adjusted for the split factor in the case of the post ex-date period), and the average number of small, medium, and large trades per period. We report cross-sectional averages for each split in which our investors make at least one trade in each period.

Our results strongly support the Admati-Pfleiderer model, in which splits promise to improve liquidity (as measured by a lower level of stealth trading) but professional investors then increase their frequency of price-moving trades to take advantage of this improved liquidity. Results are reported in Table 9. The individual investors increase their average daily trades from 0.47 to 0.85 from period 1 to period 3, and reduce their average trade size from 356 to 271 shares. Similarly, average trade size measured by the percentage of market cap per trade drops from 0.46 basis points to 0.33 basis points. Finally, the percentage of trades classified as small increases from 78.4 percent to 83.3

percent, and the percentage of medium-sized trades decreases from 21.5 percent to 16.7 percent.

The professional investors also step up their trading activity, and appear to take advantage of the improved liquidity to make more price-moving trades (thereby perhaps reducing liquidity). The professional investors increase their average daily trades from 1.38 to 1.72 from period 1 to period 3. The average number of shares traded drops from 15,005 to 9,780 and the percentage of market cap traded per order drops from 3.62 basis points to 3.21 basis points. The percentage of their trades classified as small increases from 10.5 percent to 17.3 percent, the medium trades increase from 53.5 percent to 56.4 percent, and their large trades decrease from 39.4 percent to 26.2 percent. Although the professional investors do increase their medium sized trades, they also greatly increase their small sized trades, and drastically reduce their large block orders.

Of course, the final change in liquidity can only be measured by examining the total order pool. While we cannot observe all orders in the marketplace, we do condition on the 478 stock splits in which both the professional and individual investors are active. The results from these pooled orders suggest that liquidity improves following the split. The average number of pooled trades increases from 2.11 to 2.91 per day; the average share size decreases from 11,580 to 7,515; the average percent of market cap per trade drops insignificantly, from 2.15 basis points to 2.01 basis points. The number of small trades increases from 28.5 percent to 35.2 percent, and the price-moving medium sized trades increase insignificantly, from 44.4 percent to 45.0 percent. The number of large trades drops from 27.1 percent to 19.8 percent. The main effect seems to be a replacement of large block trades (placed by the professionals) with small, probably noise-driven trades (placed by both individuals and institutions). We find little evidence in the combined order flow that medium sized trades increase; the reduced level of medium sized trades by individuals cancels out the increase in medium-sized trades by professionals.

If managers split their stocks in an attempt to broaden the base of traders and improve liquidity, it appears they are slightly successful. A split does indeed increase the level of noise trading in a stock. However, it also increases the level of professional trading in the stock, and perhaps the level of informed trading. Thus, liquidity may not improve as much as a manager may hope. It seems likely that informed traders seek out this improved liquidity and, in keeping with the stealth-trading hypothesis, break up their large trades into medium-sized trades in an attempt to disguise them amongst the increased noise. Our findings are consistent with Easley, O'Hara, and Saar (2001) who find that stock splits attract uninformed traders (individual investors) and increase informed trading at the same time.

Our investor data comprises only a small percentage of the daily volume for these stocks. As a robustness check, we focus on the subset of 831 NASDAQ-NMS firms that undergo splits during our sample period. We collect data on the number of daily trades, daily volume, and beginning-of-month market capitalization from CRSP. This allows us to analyze the average trade size and average trades per day. While this data does not enable us to differentiate between traders (or even identify the distribution of trades during a day), it does have the advantage of representing the complete set of trades made each day.

We calculate the average trade size for each split stock each day during our sample period and group them into small, medium, and large. We then investigate how the average trade size and number of trades differs across periods. Table 10 shows that the proportion of small sized trades nearly doubles from period 1 to period 3, and the proportion of medium and large sized trades decreases dramatically from period 1 to period 3. Additionally, the average number of trades per day increases from 97 before the split announcement to 151 after its execution, and the average number of shares per trade and average percentage of market cap traded per trade both decrease monotonically from period 1 to period 3.

There are two possible reasons for this change across periods: either the existing traders increase their trading around the split and change their trading behavior, or a stock split brings additional investors into the stock who behave differently than the pre-existing investors. Separating the behavior of existing and new investors can help illuminate how individual behavior shifts around splits. We find that the split event both causes a change in the trading behavior of existing investors and also gathers a new clientele with different behavior. Table 11 demonstrates that the trade size significantly decreases after split ex-date for both existing and new individual investors. We note that the trade size for new investors is significantly smaller than that of existing investors during each period. This indicates two reasons why trade size decreases after split ex-date. First of all, existing investors reduce their trade size after splits. Secondly, new investors make smaller trades and these smaller trades make up a significant fraction of post-split trades.

5.2. The bid-ask spread

The second major measure of liquidity is the size of the bid-ask spread. Most theoretical models (such as Glosten and Milgrom, 1985; Stoll, 1989) decompose the bid-ask spread into three components: the market maker's fixed costs, an inventory component, and an adverse selection component. If a stock split changes the bid-ask spread, at least one of these three components must change. The most likely candidate is the adverse selection component, as a split should not change either the fixed costs associated with making a market nor change the level of inventory risk faced by the market maker given there is little change in volume. If a split results in a clientele shift and brings more noise trading to the stock, the market maker's adverse selection costs should decline, and thus the bid-ask spread would narrow. If, however, the split also attracts more informed traders (as supported by our evidence in the previous section), the market maker may face a higher level of adverse selection, and compensate by widening the spread.

A fourth factor may also affect the bid-ask spread: price discreteness. *Ceteris paribus*, lower priced stocks will have a smaller spread in dollar terms but a larger spread in percentage terms. During our sample period, the minimum tick size is 1/8. Additionally, collusion amongst the NASDAQ market makers to avoid the odd-eighths during this time period widened the spread artificially, and with a greater percentage impact upon lower-priced stocks. Given that a split stock will always have a lower price after the split, this price discreteness problem will have a negative effect upon liquidity following stock splits. We attempt to focus upon the liquidity effects of the clientele shift, controlling for the price effect.

To examine the bid-ask spread, we focus on the 831 NASDAQ-NMS firms in our sample. We collect data on the closing price, daily volume, and bid and ask quotes for each stock from 63 days before the split announcement to 63 days after the split ex-date. We calculate spread percent as the ratio of the spread to the bid-ask midpoint.

Splits bring about a significant change in the bid/ask spread. Results are presented in Table 12. The average spread first widens from 76 cents before the announcement to 83 cents, and then narrows to 66 cents after the execution. The spread percentage, on the other hand, first narrows from 2.87 percent to 2.69 percent, then widens to 3.51 percent after the split execution. Since both the spread and the spread percent measure liquidity, it seems puzzling that an event could impact each measure in a different direction. Undoubtedly, this results from the price discreteness problem.

To isolate the price effect from the clientele shift effect, we run the following regression on our pooled data:

$$SPREAD_{it} = \alpha + \beta_1 PRICE_{it} + \beta_2 VOLUME_{it} + \beta_3 PER\_2_{it} + \beta_4 PER\_3_{it}$$

We regress both the actual spread and the percentage spread upon these four explanatory variables. In addition to price, we also control for daily volume, which has a significant effect upon liquidity and changes following the split. The dummy variable PER_2 (and PER_3) are set to 1 if stock *i* is in period 2 (or period 3) on date *t*, and 0 otherwise. These will pick up any liquidity changes that are due to the announcement and execution of the split. The results are reported in Table 13. All four variables are statistically significant at the 1 percent level in both models. As expected, price has a strongly negative effect on the spread percent and a strongly positive effect upon the spread, due to the price discreteness problem. Volume has a strongly negative effect upon both the spread and the spread percent. Once these variables are controlled for, we see that spreads in period 2 are, on average, 6.1 cents wider than those in period 1 and the spread percent is 0.21 percent wider. But spreads in period 3 are 5.7 cents *narrower* than those in period 1, and the spread percent is 0.05 percent narrower than in period 1. The split reduces liquidity after the announcement, but then increases liquidity following the ex-date. Although the results are statistically significant, the magnitude is rather small. This agrees with our analysis of the price impact measure: the long-run effect of a split on liquidity is mildly positive.

Based on our evidence in this section we reject Hypothesis 2A and 2B and conclude that stock splits and the associated clientele change can lead to improved liquidity.

6. Impact of Clientele Change and Asset Prices

6.1. Return Properties around Stock Splits

Similar to the index inclusion/exclusion events found by Barberis et al. (2002), we observe an increase in the co-movement between individual stock returns and the market index after splits.[6] Table 14 shows that the R^2 in our CAPM regressions significantly increase after a split, indicating that the proportion of the variance attributable to security-specific news decreases following the split. Individual prices reflect less idiosyncratic risk. As a related indication of increased co-movement, the CAPM beta increases by about 0.20 after stock splits. Both results imply that individual stock prices reflect less idiosyncratic risk and efficiency may decrease after splits.

Another traditional gauge of efficiency is the serial dependence of stock returns. Properly anticipated stock prices should fluctuate randomly. Improved information revelation should reduce serial dependence, and thus increase the weak-form efficiency of stock prices. We find some evidence consistent with this conjecture. The autocorrelation of returns decreases significantly from –0.0195 to –0.0441 following a split. On the other hand, the absolute value of serial correlation in individual stock return increases considerably from 0.0855 to 0.1154 after splits, both results indicating greater predictability and lower informational efficiency. These findings are consistent with the beta and R^2 results: stock returns become slightly more predictable and accordingly less efficient.

An important caveat is the Wiggins (1992) critique, which attributes the lower pre-split beta to asynchronicity between daily returns for the stock and daily returns for the market. Using the Scholes-Williams correction for asynchronous trading, Wiggins finds little difference between pre and post split betas, partly due to the limited power of the test with less frequent data. The potential implication of his finding is that the increased trading activity following splits generates timely price observations at the beginning and the end of the day for post-split stocks and this improves the explanatory power of the market model regressions.

To address this concern, we reproduce our results using returns from bid-ask quote midpoints. We generate the return time series from computing the difference in the bid-ask quote midpoint at 4PM of each trading day. While the last trade price can vary at different times for different stocks, the quotes are binding commitments prevailing at the market close. By requiring a complete time-series of bid-ask quote midpoints to compute the new return series, we substantially reduce our sample to 191 split events. We report the results from the alternative approach in Table 14, Panel B. The changes in R^2, beta, and autocorrelation only become stronger, fully supporting our above results.

Leaving aside the Wiggins critique, we can still examine whether the shifts in betas and R^2 are cross-sectionally associated with differences in clientele changes. We find some evidence that co-movement measures increase when a higher fraction of unsophisticated investors participate in buying split stocks. Table 15 reports the documented change in beta on the change in the increase in unsophisticated investor clientele from period 1 to the period 3. The beta increase is significantly greater when high-income investors make up a smaller fraction of the buying trades after split ex-dates. Similarly, the increase in R^2 is greater when high-income investors make up a smaller fraction of buying trades after splits ex-dates (significant only at the 10 percent level, however). The relationship between the change in co-movement measure and the change in professional occupation exhibits a similar yet statistically weaker pattern. Our results are consistent with Foerster and Karolyi's (1998) findings that shifts in the investor base can lead to meaningful changes in asset prices and risk exposures.

According to the logic in Wiggins (1992), this would suggest only that cross-sectional differences in changes in the asynchronicity of price observations might be attributed to clientele changes. But if the Wiggins critique is only part of the story, then the clientele shifts – namely, the introduction of noise traders – may genuinely affect prices. The introduction of less-sophisticated investors may actually decrease the timely revelation of firm-specific information, even while improving estimates of beta through more timely incorporation of market-level information. [7]

In sum, we find that stocks experience lower price efficiency after splits. Our findings reject Hypothesis 3A and 3B and support our conjecture that splits have a meaningful impact on asset return properties.

6.2. Clientele Shift and Asset Prices

Grinblatt et al. (1984) and Ikenberry and Ramnath (2002) document positive excess returns after stock splits, under various time horizons and measurements. The latter authors attribute this post-split drift to market under-reaction to news announcements. We find that clientele shifts after splits can, in part, explain the positive excess return after splits. We compute cumulative abnormal returns (CARs) by regressing individual stock returns on the value-weighted market index within each period. To control for the change in risk around splits, we separately use pre-split and post-split (not reported) beta in computing the CAR, and the two methods produce virtually the same results. We then regress the CAR during period 2 and 3 on the incremental percentage change in the number of investors in period 2 and 3, respectively. We report the results in Table 16. For each period, the increase in the number of investors is positively priced in the CAR within the corresponding period. The CAR during period 3 increases when there are more investors during period 3 but decreases when there are more investors during period 2.[8]

Similarly, we also regress the excess returns on changes in investor sophistication around splits. The coefficients on the change in the fraction of high-income investors and professionals are negative and significant. This indicates that the cumulative excess return is significantly higher when unsophisticated investors make up a larger fraction of the buying pool following announcement dates and ex-dates.

Both results are consistent with the hypothesis that the cross-sectional differences in the under-reaction of stocks to the release of value-relevant information are associated with a higher proportionate increase in unsophisticated investors.

7. Conclusion

This study exploits panel data on individual investor and professional investor trading behavior around splits to investigate the effects of clientele changes on known empirical regularities associated with splits. Our results support previous findings that splits increase liquidity. We also find evidence in favor of the signaling hypothesis for splits. Purchases increase after split announcements, confirming the conjecture that split announcements signal favorable information about the company's future prospects. We also find some evidence that individual investor trading volume increases significantly after a split execution, an event for which there is no new information release. More interestingly, this change in trading volume is driven by two separate changes, an increase in the number of trades executed, and a decrease in the average number of shares per trade.

Splits also apparently make stocks more accessible to lower-income investors, and thus increase the number of shareholders in a company and change the demographic composition. Individual investors who never previously traded split stocks make up more than half of the individual purchases after split announcements. Further, they constitute a significantly greater fraction of investors after the split date than they did between the split announcement and split date. Professional investors sell stocks far more frequently following splits, while their buying habits remain relatively unchanged. The introduction of this new clientele of investors can largely explain the higher trade frequency and smaller trade size observed after the split date. Sophisticated investors, characterized by high-income individuals and individuals in professional occupations, make up a significantly smaller fraction of the investor base after splits. Interestingly, we show that such addition of naïve investors is positively priced during a 6-month period right after split ex-dates.

Another advantage of our database is that it allows us to examine demographic factors that might affect cross-sectional differences in post-split performance. We find that the previously documented changes in beta and R^2 are associated in the cross-section with increases in the individual investor base and the fraction of less sophisticated investors. While we do not directly test whether these changes are due solely to increased liquidity and decreased effects of asynchronous trading, we find that post-event drift is, in part, a function of clientele changes. Taken together, the cross-sectional evidence is consistent with timely price discovery of market-wide information, but delayed price-discovery of firm-specific information.

Footnotes

1. Lamoureux and Poon (1987) and Brennan and Copeland (1988) note changes in beta around splits. Ohlson and Penman (1985), Koski (1998), Dubovsky (1991), and Sheikh (1989) identify increases in volatility following a split. Byun and Rozeff (2003) use long-run split data and find that the positive post-split drift may be due to selection of particular sample, specification, and abnormal return measures.

2. We create control group for the split stocks based on size, book-to-market, and past-year return and compare the order imbalance/flow for split and control stocks. Individual investors exhibit much stronger order imbalance for split stocks than for control groups after split announcement and split execution. At the same time, professional traders exhibit weaker order imbalance for split stocks than for control groups. The results are consistent with the pattern that we document so far.

3. Our sample investors may have made trades before the start of January 1991, when our data starts. It is thus possible that an investor may have traded split stocks before our sample starts. To check for robustness, we divide our data into two sub-samples: 1991 to 1993 and 1994 to 1996. The results of the sub-periods are very similar.

4. This is not a comment upon investor capabilities, but rather a definition based upon probable familiarity with investing. The SEC defines a sophisticated investor based upon wealth and income. We also include profession because it may relate to differing degrees of familiarity with financial assets and institutions. Dhar and Zhu (2002) define investors

with high income and in professional occupations as sophisticated investors. They find that sophisticated investors exhibit a significantly weaker disposition effect. Using a similar definition, Zhu (2002) find that more sophisticated investors exhibit weaker bias towards geographically closer companies and Goetzmann and Kumar (2002) find that more sophisticated investors have more diversified portfolios.

5. We can also compute the fraction of trading volume by "Low-income" and "Non-professional" investors. "Low-income" investors are defined as investors with annual income less than $40,000 and "non-professional" investors are defined as investors whose occupation fall in "white collar/clerical", "blue collar/craftsman" or "service/sales". We did not take that approach because there are much more observations of trades made by high-income investors and professionals. The fraction of trades by low-income investors increases from 5.96 percent to 6.96 percent and the fraction of trades by non-professional investors increases from 7.53 percent to 8.99 percent. These patterns mirror the change in the fraction of trades made by sophisticated investors. Note that we do not have demographic information on a large fraction of individuals and therefore the fraction of volume by "high-income" and "low-income" investors do not sum to 1.

6. We use the CRSP NYSE/AMEX/Nasdaq value-weighted return as proxy for market portfolio. We regress the CRSP daily stock return on the market return for a 6-month window before split announcement and after split execution to compute the R-square, Beta of the CAPM regression before and after the splits. CAR is calculated by using the

pre-split beta. We have also performed similar study using post-split beta and our results remain virtually the same.

7. Another potential way to address the Wiggins' critique is to divide stocks by their pre-split trading frequency. If asynchronicity has significant impact on the changes in beta and R^2, we would expect considerably smaller changes for frequently traded stocks. To test this, we divide our observations by the number of shares traded in the three-month period before split announcement. For the frequently traded stocks, the increase in beta, R^2, and volatility is 0.19, 0.0054, and 0.005 respectively. These results are virtually the same as the results for the less frequently traded stocks. These results offer additional support that the change in market efficiency around splits is not driven by measurement error.

8. We also use alternative specification by including the change in trading volume and spread percent around splits and our results remain the same. The results should not be surprising given the mixed evidence on changes in trading volume and spread percent around splits (Conroy, Harris, and Benet 1990, Conroy, Harris, and Benet 1990, Lakonishok and Lev 1987, and Maloney and Mullerin 1992).

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Table 1. Data Description

The primary dataset contains individual investor data from a large U.S. discount brokerage firm between 1991 and 1996. The dataset contains three files: (1) Positions file contains the end-of-month portfolios of all investors; (2) Trades file contains buy and sell transactions executed by all investors; (3) Demographics file contains key demographic information, such as income, occupation, age, and geographical location (5-digit zip code) for a subset of investors.

Panel A: Positions	
Average account size	\$35,629 (Median = \$13,869)
Average number of stocks in the portfolios	4 (Median = 3)
Average portfolio turnover	7.59% (Median = 2.53%)
Panel B: Trades	
Total number of trades	2,886,912
Total number of trades in stocks	1,854,776
Average number of trades	41 (Median = 19)
Average holding period	187 days (Median = 95)
Panel C: Households	
Number of households	79,995
Number of households trading equities	62,387
Panel D: Demographics	
Average income	\$59,097 (Median = \$50,000)
Average age	50 (Median = 48)

Table 2. Descriptive Statistics of Split Events

There are a total of 1,524 split events for the individual investors and 615 split events for the professional investors. Split factor is defined as the number of shares after split divided by the number of shares before split.

Panel A: Individual Investors

Summary statistics

	Max	Min	Mean	Median
Split factor	2	1.5	1.73	1.5
Event Window	60	3	34.31	33
Pre-split price	95.75	2.625	22.97	22.50

Splits by Year

	1991	1992	1993	1994	1995	1996
Num. of Splits	147	242	307	208	273	347

Panel B: Professional Investors

Summary statistics

	Max	Min	Mean	Median
Split factor	2	1.5	1.78	1.0
Event Window	86	3	25.07	22.0
Pre-split price	154.38	9.44	46.00	41.62

Splits by Year

	1991	1992	1993	1994	1995	1996
Num. of Splits	0	0	207	159	247	2

Table 3. Average Number of Investors around Split Events

The average number of traders every day is computed for three periods around split events: (1) before the split announcement date; (2) between the split announcement and the split execution date; and (3) after the split execution date. For each period, the average number of traders per day is computed as the total number of traders within each period divided by the total number of days within that period. T-statistics are provided in parentheses.

Panel A: Individual Traders

	All	**Buy**	**Sell**
Before (1)	0.175	0.110	0.089
Between (2)	0.248	0.186	0.087
After (3)	0.308	0.241	0.112
(2)-(1)	0.072 (3.72)***	0.076 (5.07)***	-0.002 (0.39)
(3)-(1)	0.133 (4.88)***	0.130 (5.79)***	0.023 (2.22)**
(3)-(2)	0.059 (2.03)**	0.055 (2.21)**	0.025 (2.53)***

Panel B: Professional Traders

Before (1)	0.1038	0.0788	0.0640
Between (2)	0.1845	0.1301	0.1061
After (3)	0.1171	0.0874	0.0764
(2)-(1)	0.0807 (21.08)***	0.0512 (16.33)***	0.0421 (16.01)***
(3)-(1)	0.0133 (8.64)***	0.0086 (5.65)***	0.0124 (9.17)***
(3)-(2)	-0.0674 (-17.70)***	-0.0426 (-13.51)***	-0.0297 (-11.16)***

*, **, and *** indicate significant at 10, 5, and 1 percent level, respectively.

Table 4. Trading Activity of Individual Investors Around Split Announcements

The average daily order flow (in dollars) and order imbalance (in number of trades) are computed for three periods around split events: (1) before the split announcement date; (2) between the split announcement and the split execution date; and (3) after the split execution date. The average daily order flow is computed for each split as the aggregate dollar value of stock purchased during a given period minus the aggregate dollar value of stock sold during a given period, divided by the number of days in that period. The average daily order imbalances are calculated as the average number of buys per day minus the average number of sells per day, divided by the average daily number of trades. T-statistics are provided in parentheses.

Panel A: Dollar Value

	All	Buy	Sell
Period (1)	-62.9	3237.1	3300.0
Period (2)	1000.3	5488.9	4488.6
Period (3)	826.8	5569.8	4743.0
(2)-(1)	937.4 (5.27)***	2251.8 (3.83)***	1188 (2.02)**
(3)-(1)	889.7 (3.98)***	2332.7 (3.99)***	1443 (2.17)**
(3)-(2)	-173.5 (-1.41)	80.9 (0.089)	254.4 (0.31)

**, and *** indicate significant at 5, and 1 percent level, respectively.

Panel B: Trade Order Imbalances

	Order Imbalance	Buy Orders/day	Sell Orders/day
Period 1	0.0329	0.135	0.105
Period 2	0.2424	0.201	0.093
Period 3	0.1761	0.293	0.140
(2)-(1)	0.210 (10.63)***	0.066 (2.48)**	-0.012 (-0.92)
(3)-(1)	0.143 (8.82)***	0.158 (5.14)***	0.035 (2.25)**
(3)-(2)	-0.0663 (-2.71)***	0.092 (2.88)***	0.047 (2.66)***

*, **, and *** indicate significant at 10, 5, and 1 percent level, respectively.

Table 5. Trading Activity of Professional Investors Around Split Announcements

This table examines the 638 splits in which the Plexus investors executed at least one trade in each of the three event periods. The average daily order flow (in dollars) and order imbalance (in number of trades) are computed for three periods around split events: (1) before the split announcement date; (2) between the split announcement and the split execution date; and (3) after the split execution date. The average daily order flow is computed for each split as the aggregate dollar value of stock purchased during a given period minus the aggregate dollar value of stock sold during a given period, divided by the number of days in that period. Order imbalances are calculated as the average number of buys per day minus the average number of sells per day, divided by the total average daily trades. T-statistics are provided in parentheses.

Panel A: Dollar Value

	Order Flow	**Buys**	**Sells**
Period 1	114,544 (5.11)***	364,988	250,444
Period 2	37,098 (1.46)	337,958	300,860
Period 3	11,177 (0.46)	346,579	335,402
(2)-(1)	-77,445 (-2.11)**	-27,029 (-1.23)	50,415 (1.73)*
(3)-(1)	-103,366 (-3.06)***	-18,408 (-0.85)	84,958 (3.38)***
(3)-(2)	-25,920 (-0.81)	8,621 (0.43)	34,542 (1.05)

Panel B: Trade Order Imbalances

	Order Imbalance	**Buy Orders/day**	**Sell Orders/day**
Period 1	0.2427 (13.22)***	0.3942	0.2780
Period 2	0.1153 (4.91)***	0.3926	0.3042
Period 3	0.0930 (5.25)***	0.4366	0.3621
(2)-(1)	-0.1273 (-4.75)***	-0.0016 (-0.14)	0.0262 (2.90)***
(3)-(1)	-0.1496 (-5.99)***	0.0423 (3.81)***	0.0841 (8.04)***
(3)-(2)	-0.0229 (-0.84)	0.0439 (3.46)***	0.0579(5.45)***

*, **, and *** indicate significant at 10, 5, and 1 percent level, respectively.

Table 6: Sample Individual Investor Base around Split Events

The average number of shareholders every day is computed for six periods around split events: (1) before the split announcement date; (2) between the split announcement and the split execution date; and (3) after the split execution date. In addition, we also include period (4), a three-month period between three and six months after the split execution, period (5) ,a three-month period between six and nine months after the split execution and period (6), a three-month period between nine and twelve months after split execution. For each period, the average number of individual shareholders per day is computed as the total number of shareholders within each period divided by the total number of days within that period. T-statistics are provided in parentheses.

Number of Individual Shareholders per Day

	Split Stocks	**Change from (1)**
Before (1)	0.5473	
Between (2)	0.5794	0.0321 (1.53)
After (3)	0.6108	0.0635 (2.00)**
After (4)	0.6276	0.0803 (2.24)**
After (5)	0.6316	0.0843 (2.41) **
After (6)	0.6394	0.0921 (2.83)***
(6)-(1)	0.0921 (2.83) ***	

** indicates significant at 5 percent level.

Table 7. Investment Activities by New Investors around Stock Splits

New investors are defined as investors who have never traded the split stocks before split announcement dates. For "shares", the measure is the fraction of total number of shares in each period traded by new investors; for "trades", the measure is the fraction of total number of trades in each period executed by new investors; for "investors", the measure is the fraction of total investors in each period who have not traded split stocks before announcements. T-statistics are provided in parentheses.

Panel A: Mean, Individual Investors

	All	**Buy**	**Sell**
Shares			
Between (2)	0.508	0.666	0.266
After (3)	0.609	0.712	0.449
(3)-(2)	0.101 (6.98)***	0.0461 (3.19)***	0.223 (10.44)***
Trades			
Between (2)	0.547	0.697	0.261
After (3)	0.637	0.729	0.453
(3)-(2)	0.0897 (6.95)***	0.0316 (2.47)**	0.191 (11.69)***
Investors			
Between (2)	0.585	0.721	0.279
After (3)	0.645	0.721	0.436
(3)-(2)	0.0606 (4.89)***	0.000600 (0.028)	0.158 (8.76)***

Panel B: Mean, Professional Traders

	All	**Buy**	**Sell**
Shares			
Between (2)	0.227	0.249	0.176
After (3)	0.315	0.384	0.227
(3)-(2)	0.0876 (6.24)***	0.1167 (7.30)***	0.0376 (2.26)**
Trades			
Between (2)	0.220	0.242	0.176
After (3)	0.314	0.371	0.244
(3)-(2)	0.0944 (7.84)***	0.1101 (8.01)***	0.0555 (3.89)***
Investors			
Between (2)	0.264	0.273	0.197
After (3)	0.425	0.432	0.321
(3)-(2)	0.1610 (13.96)***	0.2170 (14.07)***	0.1122 (7.81)***

, and * indicate significant at 5, and 1 percent level, respectively.

Table 8. Demographic Composition of Individual Investors Buying around Split events

"High-income" investors are defined as those who have annual income of greater than \$100,000. Professionals are those whose professions fall into "Professional/technical" or "Managerial/Administrative" categories. For each period, we compute the fraction of total volume of buying trades made by high-income investors or professionals.
T-statistics are provided in parentheses.

Panel A: Fraction of Investors Purchasing Split Stocks

	Fraction of "high-income" investors	**Fraction of professionals**
Before (1)	0.166	0.198
Between (2)	0.169	0.203
After (3)	0.148	0.155
(2)-(1)	0.003 (0.63)	0.005 (0.41)
(3)-(1)	-0.0218 (-3.71)***	-0.043 (-2.99)***
(3)-(2)	-0.021 (-4.58)***	-0.048 (-3.47)***

*, **, and *** indicate significant at 10, 5, and 1 percent level, respectively.

Table 9. Trade Size Change around Stock Splits (Sample Investors)

For each split, we compute, the average number of trades per day in each period, average number of shares per trade executed, the percent of market cap traded per trade (in basis points), and the percentage of orders that are classified as small (less than 500 shares), medium (between 500 and 10,000 shares) and large (greater than 10,000 shares). Cross sectional averages are reported for each period, with standard errors in parentheses.

Panel A: Individual Investors			
	Period 1	**Period 2**	**Period 3**
Trades/day	0.47	0.67	0.85
	(0.03)	(0.05)	(0.07)
Shares/trade	356.1	328.2	271.2
	(8.90)	(9.99)	(7.39)
Percent of	0.464	0.381	0.340
Market Cap	(0.026)	(0.019)	(0.023)
Small size	78.4%	79.7%	83.2%
	(0.67)	(0.76)	(0.573)
Medium size	21.5%	20.2%	16.7%
	(0.67)	(0.76)	(0.57)
Large size	0.03%	0.01%	0.02%
	(0.01)	(0.005)	(0.01)
Panel B: Institutional Traders			
	Period 1	**Period 2**	**Period 3**
Trades/day	1.38	1.39	1.72
	(0.076)	(0.077)	(0.091)
Shares/trade	15,005	19,022	9780
	(426.5)	(621.4)	(289.6)
Percent of	3.62	3.85	3.21
Market Cap	(0.37)	(0.41)	(0.31)
Small size	10.5%	9.9%	17.3%
	(0.42)	(0.55)	(0.55)
Medium size	53.5%	50.6%	56.4%
	(0.72)	(0.99)	(0.65)
Large size	39.4%	39.4%	26.2%
	(0.65)	(1.03)	(0.66)

Panel C: Combined Trades			
	Period 1	**Period 2**	**Period 3**
Trades/day	2.11	2.31	2.91
	(0.12)	(0.15)	(0.20)
Shares/trade	11,580	13,749	7515
	(362.9)	(483.4)	(243.4)
Percent of	2.15	2.18	2.01
Market Cap	(0.16)	(0.17)	(0.16)
Small size	28.5%	31.6%	35.2%
	(0.73)	(0.85)	(0.74)
Medium size	44.4%	39.9%	45.0%
	(0.61)	(0.76)	(0.60)
Large size	27.1%	28.5%	19.8%
	(0.68)	(0.81)	(0.55)

Table 10. Trade Size Change around Stock Splits (Market Level)

We pool data for each split with NASDAQ-NMS daily data and group the days by period. For each period, we report average number of shares per trade, percent of market cap traded per trade (in basis points), and the percentage of average daily trade size that fall into the small, medium, and large category. Standard errors are in parentheses.

NASDAQ-NMS Daily Trades			
	Period 1	**Period 2**	**Period 3**
Trades/day	97.7	124.1	151.5
	(1.18)	(2.70)	(2.25)
Shares/trade	1381	1214	900.6
	(7.03)	(9.83)	(4.42)
Percent of	2.37	2.07	1.61
Market Cap	(0.019)	(0.025)	(0.015)
Small size	17.73%	21.84%	33.97%
Medium size	81.80%	77.82%	65.85%
Large size	0.47%	0.34%	0.18%

Table 11. Average Trade Size around Splits for Existing and New Individual Investors.

New investors are defined as individual investors who have never traded the split stocks before split announcements. Existing investors are defined as investors who have traded the split stocks before split announcement. Average trade size is computed as the total number of shares traded in each period divided by the total number of trades in each period. T-statistics are provided in parentheses.

Panel A: All Trades

	Existing Investors	**New Investors**	**Difference**
Before (1)	362.56		
Between (2)	381.11	276.18	104.93 (5.55)***
After (3)	310.69	238.18	72.51 (4.79)***
(2)-(1)	18.55(0.97)		
(3)-(1)	-51.87 (-3.03)***		
(3)-(2)	-70.42 (-3.33)***	-38.00 (-2.93)***	193.23

Panel B: Buying Trades

	Existing Investors	**New Investors**	**Difference**
Before (1)	343.38		
Between (2)	369.94	261.27	108.67 (5.94)***
After (3)	265.98	217.29	48.69 (3.41)***
(2)-(1)	26.56 (1.33)		
(3)-(1)	-77.40 (-4.37)***		
(3)-(2)	-103.96 (-5.14)***	-43.98 (-3.37)***	135.69

Panel C: Selling Trades

	Existing Investors	**New Investors**	**Difference**
Before (1)	409.20		
Between (2)	414.81	390.53	24.28 (0.75)
After (3)	367.88	326.39	41.49 (1.77)*
(2)-(1)	5.61 (0.22)		
(3)-(1)	-41.32 (-1.84)*		
(3)-(2)	-46.93 (-1.67)*	-64.14 (-2.43)**	286.18

*, **, and *** indicate significant at 10, 5, and 1 percent level, respectively.

Table 12: Bid-Ask Spread Shift around Stock Splits

We pool data for each split with NASDAQ-NMS daily data and group the days by period. For each period, we report the average daily spread, average daily spread percent (ask minus bid divided by the bid/ask midpoint), average daily price, and average daily volume. Standard errors are in parentheses.

NASDAQ-NMS Bid-ask Spread			
	Period 1	**Period 2**	**Period 3**
Spread	0.76	0.83	0.66
	(0.002)	(0.004)	(0.002)
Spread percent	2.87	2.69	3.51
	(0.011)	(0.015)	(0.012)
Price	32.17	37.23	22.72
	(0.06)	(0.11)	(0.04)
Volume	144,295	160,801	234,460
	(1792)	(3600)	(3362)

Table 13. Determinants of Bid-Ask Spread around Stock Splits

OLS regression results with the daily spread or daily spread percent as the dependent variable and price, volume (in 1000s), and dummy variables for period 2 and period 3 as the independent variables. T-stats are in parentheses.

Regression results		
	Spread	**Spread %**
Intercept	0.69	5.40
	(158.3)	(282.8)
Price	0.0029	-0.077
	(25.1)	(-149.7)
Volume (1000)	0.00018	-0.00039
	(-74.5)	(-36.5)
Per2	0.061	0.214
	(13.8)	(11.0)
Per3	-0.056	-0.055
	(-16.2)	(-3.6)

Table 14. Return Properties around Stock Splits

"Before splits announcement**"** is the 120-day period before split announcements. "After split ex-dates" is the 120-day period after split ex-dates. R-Square is the R-square in the CAPM regression $R_{it} = \alpha + \beta * R_{mt} + \varepsilon_t$, where R_{it} is the return time series of split stocks before and after splits, respectively and R_{mt} is the return time series of market index during the same period. Beta is the market beta specified in above regression. Volatility is the standard deviation of returns during the two periods, respectively. Serial correlation is the daily auto-correlation(1) of stock returns and the absolute serial correlation is the absolute value of the daily auto-correlation(1) of stock returns during each period. There are 1,524 events when we use close price to calculate return time series in Panel A. There are 190 events when we use bid-ask midpoint price at 4PM to compute return series in Panel B. T-statistics of the null hypothesis that sample mean equals to zeros is reported in parentheses.

Panel A: Close Price

	Before Splits Announcements	**After Splits Ex-Dates**	**Pairwise Difference**
R-Square	0.0847	0.0903	0.0056 (1.641)*
Beta	1.0096	1.227	0.217 (6.12)***
Volatility of Return	0.0262	0.0424	0.0162 (3.50)***
Serial Correlation	-0.0195	-0.0441	-0.0246 (-3.44)***
Absolute Serial Correlation	0.1466	0.1557	0.0091 (1.97)**

Panel B: Mid-Point Price at 4PM

	Before Splits Announcements	**After Splits Ex-Dates**	**Pairwise Difference**
R-Square	0.0363	0.0519	0.0156 (3.14)***
Beta	1.272	1.887	0.615 (2.66)***
Volatility of Return	0.0150	0.0176	0.0026 (1.18)
Serial Correlation	-0.020	-0.124	-0.084 (-8.05)***
Absolute Serial Correlation	0.0855	0.1154	0.0683 (7.31)***

, and * indicate significant at 5, and 1 percent level, respectively.

Table 15. Changes in Comovement Measure and Clientele Sophistication.

There are a total of 1,524 splits. For each split, we define ΔBeta and ΔR-Square as the changes in market beta and R-square from pre-split to post-split period. Pre-split period is defined as 120 days prior to split-announcements and post-split period is defined as 120 days after split ex-dates. The market beta and R-square within each period is computed by running the CAPM regression $R_{it} = \alpha + \beta * R_{mt} + \varepsilon_t$, where R_{it} is the return time series of split stocks before and after splits, respectively and R_{mt} is the return time series of market index during the same period. ΔHigh-Income is the change in the fraction of buying trades made by high-income investors from pre-split to post-split period. ΔProfessional is the change in the fraction of buying trades made by professionals from pre-split to post-split period. Observations of ΔBeta and ΔR-Square are based on quartiles sorted on ΔHigh-Income and ΔProfessional, respectively. T-statistics are provided in parentheses.

Panel A: Changes in Beta and R-Squared Grouped by Changes in Fraction of Buying Trades Made by High-Income Investors

	ΔBeta	**ΔR-Square**	**ΔHigh-Income**
ΔHigh-Income			
1 (smallest)	0.384	0.0108	-0.501
2	0.308	0.00228	-0.030
3	0.261	0.00363	0.0778
4 (largest)	0.217	0.00182	0.435
Difference	0.167	0.0090	-0.936
1-4	(2.06)*	(1.87)*	(-25.55)***

* and *** indicate significant at 10 and 1 percent level, respectively.

Panel B: Changes in Beta and R-Squared Grouped by Changes in Fraction of Buying Trades Made by Professionals

	ΔBeta	**ΔR-Square**	**ΔProfessional**
ΔProfessional			
1 (smallest)	0.226	0.00747	-0.994
2	0.325	0.00159	-0.553
3	0.163	0.00411	0.0361
4 (largest)	0.112	0.00434	0.718
Difference	0.114	0.00310	-1.711
1-4	(0.68)	(1.14)	(-45.52)***

*** indicates significant at 1 percent level.

Table 16. Abnormal Excess Return and Incremental Investor Buying Around Splits

There are a total of 1,524 splits. For each event, Cumulative Abnormal Return (CAR) of period 2 and period 3 are Jensen's alpha in the CAPM regression model $R_{it} = \alpha + \beta * R_{mt} + \varepsilon_t$ within each period. CAR2 and CAR3 are cumulative abnormal returns during period 2 and period 3, respectively. DINV is the incremental number of new investors buying split stocks during period 2 and 3, respectively. Particularly, DINV(2) =NumBuyNew(2)/NumBuy(1) and DINV(3)=NumBuyNew(3)/NumBuy(1). NumBuyNew is the number of investors buying split stocks who have not traded the split stocks before announcement dates and NumBuy(1) is the number of investors buying split stocks during the 60-day period before splits announcements. ΔHigh-Income is the change in the fraction of buying trades made by "high-income" investors from pre-split to post-split period. ΔProfessional is the change in the fraction of buying trades made by professionals from pre-split to post-split period. T-statistics are provided in parentheses.

Panel A: Cumulated Abnormal Return in Period 2 and introduction of new investors

	CAR2	**CAR2**	**CAR3**	**CAR3**
Intercept	1.001	1.107	1.000	1.058
DINV (2)	0.000993 (4.334)***	0.0009675 (4.226)***		
DINV (3)			0.0002816 (3.126)***	0.0003318 (3.639)***
Split ratio	.000766 (1.054)	.000775 (1.069)	-0.000102 (-.218)	-.0000753 (-.162)
CAR 2				-.00585 (-3.118)***
CAR 3		-0.106 (-2.313)**		
Adjusted R-square	0.015	0.022	0.010	0.017

*** and ** in dicates significant at the 1 and 5 percent level.

Panel B: Cumulative Abnormal Return (CAR) and Changes in Investor Sophistication Composition

	CAR2	**CAR3**	**CAR2**	**CAR3**
Intercept	1.003	1.000	1.003	1.000
ΔHigh-Income	-.000528 (-.955)	-0.000940 (-2.55)**		
ΔProfessional			-0.000362 (-.705)	-0.00102 (-2.988)***
Adjusted R-square	0.001	0.011	0.001	0.015

* and ** indicate significant at 10 and 5 percent level, respectively.