SIGNALING VIA STOCK SPLITS: EVIDENCE FROM SHORT INTEREST

Fabricio Perez,[†] Andriy Shkilko,* and Tony Tang[†]

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*Contact author: Wilfrid Laurier University, School of Business and Economics, SBE 3255, Waterloo, ON N2L 3C5, Canada; phone: 519.884.0710 ×2462; fax: 519.884.0201; e-mail: ashkilko@wlu.ca.

[†] Perez: 519.884.0710 ×2532; Tang: 519.884.0710 ×2479

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ABSTRACT

We test the split signaling hypothesis by studying sophisticated investors' reaction to stock split announcements. Return-based tests of signaling used in earlier studies produce conflicting results and have been recently criticized as unreliable. We bypass this criticism by focusing on long-term post-split behavior of short sellers who are generally recognized as sophisticated investors. Upon controlling for alternative hypotheses and conventional short selling determinants, we show that short interest permanently declines in reaction to split announcements. Furthermore, consistent with signaling, the degree of the decline is positively related to signal strength and to the splitter's level of information asymmetry. Overall, our results are consistent with the view that firms use stock splits to relay positive value-relevant signals.

1. Introduction

The literature on split motives mainly focuses on two hypotheses: (i) signaling and (ii) catering. The signaling hypothesis suggests that companies use splits to send positive value-relevant signals to the market (Grinblatt, Masulis, and Titman, 1984; Brennan and Copeland, 1988; Ikenberry, Rankine, and Stice, 1996). Alternatively, the catering hypothesis posits that firms split (a) to attract small investors (Baker and Gallagher, 1980), (b) to reward liquidity providers (Angel, 1997), and (c) to time investors' time-varying preferences for low-priced stocks (Baker, Greenwood, and Wurgler, 2009). The literature is, however, still far from an agreement as to whether the two abovementioned hypotheses sufficiently explain cross-asset pervasiveness and historical persistence of stock splits. For instance, the discussion in Weld, Michaely, Thaler, and Benartzi (2009) casts doubt on both signaling and catering explanations and argues that splitting to lower prices is merely a societal norm.

Studies that promote the signaling hypothesis base their conclusions on the positive return reaction to split announcements (Grinblatt et al., 1984; McNichols and Dravid, 1990). They posit that the announcement return reflects positive changes in the opinion of the marginal investor; hence, splits must relay positive signals about firms' prospects. The criticism of this conclusion is implied by a growing body of research on inefficient information processing by some investors. In particular, Busse and Green (2002), Barber and Odean (2008), and Hou, Peng, and Xiong (2009) argue that the market may overreact to information in a corporate announcement if the announcement attracts unusual level of investor attention to the stock. Thus, if the positive split announcement return represents a temporary overreaction to a sudden increase in firm's visibility, conclusions based on the positive announcement returns may be innately spurious.

Sidestepping this shortcoming of announcement returns, a group of split signaling studies focuses on long-term post-split performance. The shift to long-term measures is logical, considering the market's ability to correct overreactions over time. If splits relay a positive signal, these studies expect to find evidence of improved long-term post-split performance. Notable in this group are papers by Lakonishok and Lev (1987), Asquith, Healy, and Palepu (1989), and Byun and Rozeff (2003) who find no evidence of increases in earnings and no evidence of positive long-term returns after stock splits, thus undermining the signaling hypothesis. In the meantime, studies that use alternative techniques to measure long-term post-split returns (Ikenberry et al., 1996; Desai and Jain, 1997; Ikenberry and Ramnath, 2002) find evidence of positive abnormal returns, consistent with signaling. In a way, the split signaling debate is at an impasse due to a disagreement as to the proper way to measure long-term returns.

We innovate by testing the split signaling hypothesis from a new angle that does not rely solely on short-term or long-term return measurements. Instead, we focus on the post-split behavior of sophisticated investors, as represented by short sellers. Our focus on short selling is prompted by the growing literature that argues that short sellers possess superior investment skills (Dechow, Hutton, Meulbroek, and Sloan, 2001; Akbas, Boehmer, Erturk, and Sorescu, 2008; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2010).

Our results are consistent with the hypothesis that stock splits are interpreted by sophisticated investors as positive signals. In particular, short interest usually decreases by more than 25% in reaction to a split announcement (Figure 1). Furthermore, the decline in short interest is larger when the split signal is stronger. Specifically, short interest declines more in reaction to (i) large splits and (ii) splits that bring stock prices to a level that is lower than that achieved by the previous split – two characteristics that the literature recognizes as amplifiers of positive signals (McNichols and Dravid, 1990; Conroy and Harris, 1999). In addition, split signals have a more prominent effect when they are sent by firms with higher information asymmetries.

We study 5,014 splits that occur during a 17-year period from February 1990 through December 2006. Our results corroborate the signaling hypothesis throughout the entire sample period. Notably, the evidence consistent with signaling is considerably stronger in the post-decimalization years. This finding is expected considering Angel's (1997) suggestion that stock splits may be a way of catering to intermediaries (i.e., specialist and dealer firms) by way of increasing profits from intermediation.[1] In exchange for higher profitability, market makers reward splitters with better liquidity and exert more effort to promote the firm's stock.[2]

Angel suggests that the importance of catering-to-intermediaries motive should diminish upon reduction in the minimum tick size. Whereas a 2-for-1 split has potential to double market making revenues under any tick size regime; the amount of revenue being doubled is much smaller under decimals than it is under the eighths or the sixteenths. Consistent with this prediction, we find that the number of splits declines significantly in 2001 and remains at the new lower level in the subsequent years. In the meantime, the signaling effect becomes considerably more evident in 2001. This result is consistent with existence of multiple split motives, neither of which explains the entirety of split decisions. While the incidence of splits motivated by catering-to-intermediaries declines after decimalization, the splits motivated by signaling start dominating the sample. This intertemporal feature of the splits data might explain

[1] Angel (1997) notes that splits increase the tick-to-price ratio, thus increasing potential revenue from market making. In addition, by increasing the number of shares required to transact a particular dollar amount, splits increase profits from intermediating institutional trades, as institutional trading fees are a function of the number of transacted shares.
[2] Schultz (2000) reports evidence consistent with such promotional activity.

why earlier research (Kadiayala and Vetsuypens, 2002) does not find sufficient evidence of changes in short interest in reaction to split announcements.

We test our result for robustness to alternative split motives, namely, the catering-to-small-investors hypothesis of Baker and Gallagher (1980) and the catering-to-temporal-preferences hypothesis of Baker et al. (2009). The catering-to-small-investors hypothesis states that splits are meant to attract individual investors into stock ownership by making shares nominally more affordable. Schulz (2000), Easley, O'Hara, and Saar (2001), and Dyl and Elliott (2006) provide evidence consistent with post-split increases in shareholdings of individual investors. Given that individual investor activity exacerbates idiosyncratic volatility (Brandt, Brav, Graham, and Kumar, 2009) and thus increases arbitrage costs (Duan, Hu, and McLean, 2009), short sellers may tend to avoid recent splitters.[3] Thus, the decline in short interest that we document may be driven by short sellers' aversion to trading alongside small investors. We show that changes in individual investor activity do not drive our results using three proxies for this activity; those of Easley et al. (2001), Hvidkjaer (2008), and Kaniel, Saar, and Titman (2008).

The signaling explanation also survives testing against the catering-to-temporal-preferences hypothesis of Baker et al. (2009), who propose that managers of firms-splitters attempt to time investors' time-varying preferences for cheap and small firms. Baker et al. show that, in years when investors assign a premium to low-priced stocks or stocks of small firms, more firms split their shares, and splits bring prices to lower levels. Testing for robustness to this hypothesis is important in our setting. If timing of investor preferences attracts sentiment-driven traders to the stock, short sellers may choose to reduce their positions to avoid going "against the grain" (DeLong, Shleifer, Summers, and Waldmann, 1990; Shleifer and Vishny,

[3] Alternatively, Ben-David, Glushkov, and Moussawi (2010) find that hedge funds tend to allocate more capital to stocks with high idiosyncratic risk, implying that short positions may increase post-split.

1997; Wurgler and Zhuravskaya, 2002; Brunnermeier and Nagel, 2004). Our findings are robust to the sentiment timing explanation. Specifically, when we re-estimate the results separately for years with high and low sentiment timing incentives, the evidence of signaling persists.

Our results are also robust to controlling for the conventional short interest determinants, such as institutional holdings, returns, liquidity, and return volatility. In addition, we conduct a set of robustness tests that eliminate confounding events that may (i) affect the strength and the clarity of the split signal or (ii) affect short interest independently of the split signal. Namely, we test the results for dependence on (a) option listings and delistings and (b) inclusions to and exclusions from the S&P 500 index. Considering that short selling is often used by option market makers and by index arbitrageurs, we seek to prevent these events from affecting our results. Our findings are also robust to elimination of dividend changes that occur simultaneously with split announcements and thus may contain signals of their own (Nayak and Prabhala, 2001).

Finally, we ask whether short sellers are successful at anticipating post-split long-term returns. We show that the splits associated with the largest declines in short interest are followed by positive returns in the calendar time abnormal return framework of Buyn and Rozeff (2003). Meanwhile, the remaining splits are followed by non-positive returns. This result holds for both strong and weak split signals. Thus, although our evidence suggests that short sellers react to the known split signal amplifiers, their understanding of the signal seems to be enhanced by the ability to analyze information beyond that revealed in the split announcement. This result is consistent with recent research by Akbas et al. (2008) and Engelberg et al. (2010) who suggest that short sellers' trading performance is related to their ability to process publicly available information better than an average investor.

We view our contribution to the literature as threefold. First, we show that sophisticated investors infer positive signals from split announcements. As such, our approach avoids relying solely on return measurements that have produced conflicting results in earlier studies. Second, we show that short sellers' reaction to split announcements is more consistent with signaling after decimalization, most likely due to weakening of Angel's catering-to-intermediaries split motive. Thus, our results are consistent with existence of a time-variant set of split motives. We propose that the lack of consistent evidence on split signaling in earlier studies may be due to the fact that pre-decimalization samples contain a number of splits that were initiated for non-signaling reasons. Finally, we find some evidence that short sellers' opinions of splitting firms may be already improving before the split, and that the decline in short interest may be based on information that is beyond that derived from the conventional amplifiers of split signals. As such our results are consistent with research that argues that short sellers' possess superior ability to process value-relevant information.

2. Background

The finance literature identifies two most likely motives for stock splits: (i) signaling and (ii) catering to investors and/or intermediaries. The literature, however, is far from a consensus as to whether the two motives are able to explain cross-asset pervasiveness and historical persistence of stock splits (Rozeff, 1998; Weld et al., 2009). Although the motives behind split decisions are somewhat unclear, there is abundant evidence of nontrivial costs associated with stock splits. Among these are direct administrative/legal cost, the costs of getting a split approved by the shareholders, the additional per-share listing and maintenance fees levied by some stock exchanges, and the per-share franchise taxes levied by the states of incorporation.

Together, these costs may often add up to millions of dollars. Also notable are higher trading costs and lower liquidity in the post-split months (Conroy, Harris, and Benet, 1990; and Kadapakkam, Krishnamurthy, and Tse, 2005) that may have an adverse effect on the cost of capital.[4] Thus, with the obvious costs and unclear benefits, stock splits remain one of the less understood corporate decisions.

Surveyed CFOs cite the expansion of the shareholder base as the main split motive (e.g., Baker and Gallagher, 1980). The per-share price reduction that results from a split makes the stock more affordable to small investors, attracting them in the realm of stock ownership. Schulz (2000), Easley et al. (2001) and Dyl and Elliott (2006) find empirical evidence consistent with this proposition, showing that, respectively, the numbers of (i) small transactions, (ii) uninformed traders, and (iii) small shareholders increase post-split. On the other hand, Weld et al. (2009) examine a long time series of splits and argue that the clientele explanation is not sensible when one takes into account changes in individual nominal incomes. Additionally, attempts to attract small shareholders are unable to explain mutual fund splits (Rozeff, 1998). Mutual fund shares are infinitely divisible, therefore splitting them is not necessary to make the fund affordable to small investors. Yet mutual funds regularly split their shares.

Muscarella and Vetsuypens (1996) and Angel (1997) propose a different angle to the catering hypothesis. They suggest that firms split to increase the tick-to-price ratio and hence the profits from making the market in their stock. Responding to higher profit potential, market makers exert more effort at providing liquidity. Yet another angle on catering is proposed in a recent study by Baker et al. (2009), who suggest that splitters attempt catering to investors' time-

[4] The direction of liquidity changes subsequent to stock splits is subject to debate. Whereas Conroy et al. (1990), Easley et al. (2001), and Kadapakkam et al. (2005) argue that liquidity, as measured by bid-ask spreads, declines post-split, Lin, Singh, and Yu (2009) show that, if measured as incidence of no trading, liquidity increases post-split.

varying preferences for small and/or low-priced stocks. When small-stock premium and/or low-price premium are high, more firms choose to split and end up splitting to relatively low prices.

Signaling is another widely studied split motive. Return reaction to splits is usually positive, which Grinblatt et al. (1984) interpret as evidence that splits are positive signals. In a theoretical model by Brennan and Copeland (1988), undervalued firms credibly signal their higher quality by splitting the stock. McNichols and Dravid (1990) suggest that firms signal private information with their choice of a split factor, with larger splits being interpreted as more positive signals. Conroy and Harris (1999) show that seasoned splitters, and especially those seasoned splitters that split to lower prices than those achieved by their previous split, are able to send stronger signals.

According to Lakonshok and Lev (1987) and Weld et al. (2009), stock splits are merely mechanical adjustments toward a commonly accepted price benchmark. Such adjustments, although costly, are in line with Akerlof's (2007) proposition that a number of economic decisions are driven by societal norms. Weld et al. (2009) argue that, in North America, a nominal stock price around $40 per share is one of such norms. They conclude that the norms explanation is the only split motive that is able to explain splits persistence over time. Our results pose a challenge to norms as the only explanation for stock splits, as the decline in short interest in reaction to split announcements is not easily explained in the norms framework.

We are not the first to study short interest in relation to stock splits. Kadiyala and Vetsuypens (2002) carry out a similarly motivated investigation for a relatively small sample of 296 splitters during a 4-year period in the mid-1990s. Unlike us, Kadiyala and Vetsuypens do not find significant changes in short interest around splits. We are uncertain which stocks enter their sample, therefore we are unable to replicate their results precisely. When we follow their sample selection procedure, we find that signaling is supported (short interest declines in reaction to stock splits), albeit only marginally. Overall, this result is consistent with our general finding that signaling becomes more evident in the post-decimalization period when Angel's (1997) catering-to-intermediaries motive loses some of its appeal.

3. Data and sample

Our sample includes all NYSE and NASDAQ ordinary common shares (CRSP exchange codes 1 and 3 and share codes 10 and 11) from June 1988 through October 2007. For each security, we identify splits as distributions with the CRSP event code 5523. We exclude reverse splits and stock dividends that we identify as distribution events with split factors less than or equal to 0.25.

We obtain monthly short interest data from the NYSE and NASDAQ and then merge them with the CRSP file. A peculiar challenge in merging these datasets comes from the fact that short interest is collected in the middle of the reporting month,[5] making a conventional stock-month merge susceptible to errors. For instance, a split that is executed on July 25th will not be reflected in July's short interest because short interest data were collected by July 15th – prior to the split announcement. A correct merge of the datasets is essential for proper estimation of percentage short interest, $SI_{i,t}$, that is computed for each firm as the number of shares in short positions scaled by the number of shares outstanding. Short positions are scaled to facilitate comparison across stocks. An incorrect merge of the two datasets may lead to a downward error in *SI* estimates for those months when a stock split occurs after the short interest data have been collected, as in the example above. Fortunately, starting in 1995, short interest datasets provided

[5] During our sample period, the NYSE and NASDAQ collect short interest for a month t on the 15th of month t. If the 15th is a weekend day or a holiday, the collection date moves to the 14th or the 13th, if the 14th is a Saturday or a holiday.

by NASDAQ contain a *lagged short interest* field that reports short interest in month t as observed in month t+1. These lagged figures incorporate the mechanical increases in short interest due to splits, even if the previous month's record fails to do so. The NYSE does not perform a similar adjustment. We use NASDAQ's adjusted records when they are available. For the NYSE stocks during the entire sample period and for NASDAQ stocks prior to 1995, we multiply SI_t by [1 + *split factor*] if a split event occurs after the 15th of month t.[6]

Short interest data are available starting in June 1988 onwards.[7] Our tests require at least 20 months of short interest data before a split announcement, therefore the first announcement that is eligible to be included in the sample occurs in February 1990. We opt to stop collecting split data in December 2006 to avoid excessively relying on short interest during the financial crisis period. Because our tests require 10 months of short interest after a split announcement, the last month of short interest collection is October 2007.

In Table 1, for every sample year, we report the following statistics: (i) the number of splits, i.e., events with CRSP distribution code 5523 and split factors greater than 0.25; (ii) the percent of large splits in all splits, with large splits defined as 2-for-1 and larger; (iii) the percent of seasoned splitters defined as firms that have split at least once prior to the current split; and (iv) percent short interest, $SI_{i,t}$.

An average of 295 firms split their stock every year during our sample period. Notably, the number of splits considerably declines in 2001, concurrently with decimalization. We do not claim that decimalization is the only possible reason for this decline. Alternatively, the reduction in stock splitting activity may be attributed to the deflation of the tech bubble and the resulting market decline. We however note that the average number of splits does not return to the pre-

[6] This adjustment procedure takes into account weekends and holidays as described in the previous footnote.
[7] Short interest data are missing for all NASDAQ stocks in February and July of 1990. Similarly to earlier studies, we use linear extrapolation to estimate short interest for these two months.

2001 levels after the market rebounds in 2003, consistent with a structural shift that is independent of the market direction.[8] Generally, post-decimalization, the number of splits per year is lower than the average during the sample period. In untabulated results, we show that the percent of companies that split in a particular year declines from 5.51% pre-decimalization to 3.80% post-decimals, consistent with the weakening of the catering-to-intermediaries split motive proposed by Angel (1997). When the minimum tick size was \$0.125 or \$0.0625, splits had the potential to result in significantly higher per-share revenues for the market makers. When tick sizes were reduced, splitting stopped being a valuable catering incentive, and the number of splits declined.

Statistics in Table 1 also show that the percentages of large splits and seasoned splitters are relatively stable across sample years, both averaging about 56%. This sample feature benefits some of our subsequent tests that rely on stratifying the sample by these two characteristics. Finally, the statistics show that percent short interest, *SI*, increases steadily throughout the sample period, starting at 0.75% in 1990 and reaching 4.18% in 2006. This pattern is not surprising, as institutional trading, which is the primary driver of short selling activity (Boehmer et al., 2008), intensifies in later sample years (French, 2008), with some institutions (i.e., hedge funds) notorious for their reliance on short sales. Although not surprising, the strong time trend in short interest presents a methodological challenge. With the unconditional annual growth in short interest being 12.06% (Table 1), and our event-windows capturing close to two years of data, our tests must be carefully designed to avoid being influenced by the time trend.

To adjust for the time trend, we identify, for each splitter, a matched firm that does not split during the event window and has a set of split-relevant characteristics that closely resemble those of the splitter. Since short interest in all firms is affected by the positive trend, differencing

[8] Minnick and Raman (2011) document a similar decline in splitting activity in the 2000s.

*SI*s for splitters and matched non-splitters should eliminate the effect of the trend. In addition, the matched-firm approach should reduce possible endogeneity in the short sellers' decision to reduce positions and the firm's decision to split (Ellul and Panayides, 2009). To find suitable matches, we use the two-step propensity score methodology of Heckman, Ichimura, and Todd (1997). In the first step, we model the binary split decision as a function of observable split and short interest determinants, and in the second step, we use the predicted split probabilities to find matched non-splitters that have similar split propensities. Overall, the procedure works well; we find no significant differences between splitters and their non-splitting matches on the basis of the estimated propensity scores and on the basis of conventional split determinants. Appendix A. 1 contains the details of the matching procedure. Having paired splitters with their non-splitting matches, we proceed to inquire whether there is evidence of changes in short interest around split announcements.

4. Short interest around stock split announcements

4.1. Univariate analysis

To gain initial insight into short sellers' behavior around stock splits, we begin with the conventional event study methodology. For every splitter, we compute an abnormal short interest statistic, $ASI_{i,t}$, during a 21-month event window centered on the split announcement month. To compute *ASI*, short interest in the event window months is compared to the average short interest computed during the control period that spans months *t*-20 through *t*-11:

$$ASI_{i,t} = \left(SI_{i,t} - 10^{-1}\sum_{-11}^{-20} SI_{i,t}\right)/10^{-1}\sum_{-11}^{-20} SI_{i,t}, \quad (1)$$

where $SI_{i,t}$ is the short interest ratio of firm *i* in month *t*. Next, we compute *relative short interest*, $\Delta_{ij}SI_t$, as the difference between the abnormal short interest measures of the splitting firm *i* and its matching non-splitting firm *j*. To estimate the pure announcement effect, we limit the analysis to the splits, for which the announcement and the split event are separated by at least one month.[9] The results are organized in a [-10; +10]-month event window centered on the month of the split announcement, with the first post-split announcement collection of short interest occurring in month 0.

In Table 2 and Figure 1, we report cross-sectional means and medians of relative short interest. When evaluated at the means, short interest declines in the pre-split period, reaching a level 8.2% below that computed during the control period. The decline accelerates significantly in the month of the split announcement, reaching -16.2%, and stabilizes around -30% in the post-event period. When evaluated at the medians, the pre-announcement decline is not observed until month *t*-1, and short interest stabilizes around -25% in the post-event period.

Three observations emerge from the event study results. First, short sellers' behavior is consistent with split signaling, as stock splits result in a significant and permanent decline in short interest. The permanence of the decline suggests that changes in short positions are not attributable to temporary disruptions in the share lending market or short squeezes caused by share recalls (Lamont, 2004). Second, when evaluated at the means, there is some evidence of pre-split downward adjustment in short interest, suggesting that sophisticated investors gradually improve their opinion of the splitting firm even before receiving a split signal. The split signal, however, notably reinforces short sellers' positive views and results in a further (and a more rapid) decline in short interest. Third, both cross-sectional means and medians contain evidence consistent with early learning in the month before the split announcement. Such learning is expected in light of Christophe, Ferri, and Angel (2004) findings of leakages of corporate information in the pre-Reg. FD era. We re-estimate the results separately for the pre- and post-

[9] We relax this restriction in the regression models that follow, as these models focus on long-term split effects.

Reg. FD periods (not tabulated, but available upon request) and find that the pre-split month effect is not observed in the latter period.

Although the decline in short interest in the split announcement month and in the subsequent months is supportive of signaling, it may be alternatively attributed to, or partly influenced by, split-induced changes in commonly recognized short interest determinants. Although our matching procedure controls for the pre-split changes in these determinants, it does not control for the post-split changes. In Table 3 and Figure 2, we report pre- and post-split relative levels of the following short interest determinants: liquidity, volatility, institutional ownership, and abnormal returns. As with the relative short interest variable discussed earlier, the relative levels are computed as differences between abnormal levels of the respective variables for splitters and matched non-splitters.

The results presented in Table 3 and Figure 2 confirm our previous assertion that the matching procedure works well, as the relative levels of all covariates are insignificantly different from zero in the pre-split period. Meanwhile, the relative levels are significant in the post-split period for all variables but institutional ownership. In particular, corroborating Conroy et al. (1990) and Kadapakkam et al. (2005), post-split liquidity declines by more than 15%; whereas post-split volatility increases by about 14%, consistent with Koski (1998). In addition, we observe positive post-split buy-and-hold returns.

Considering that post-split changes in liquidity, volatility, and abnormal returns may affect short interest in the post-split period and, thus, may influence the univariate results reported earlier, we proceed to the multivariate tests of the signaling hypothesis. In Table 4, we report the estimated coefficients from the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1 POST_{i,t} + \beta_2 TREND_{i,t} + \beta_3 POST \times TREND_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t}, \qquad (2)$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t* estimated as the difference in abnormal short interest levels of the splitting firm *i* and its non-splitting match *j*; $POST_{i,t}$ is the indicator variable that equals to 0 in the pre-event months and equals to 1 in the event and the post-event months; and $TREND_{i,t}$ is the monthly trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables includes: (i) $\Delta_{ij}AR_t$ – the buy-and-hold abnormal return; (ii) $\Delta_{ij}INST_t$ – the relative institutional holdings; (iii and iv) $\Delta_{ij}LIQUID\ (GHT)_t$ and $\Delta_{ij}LIQUID\ (A)_t$ – the relative inverted effective tick of Goyenko et al. (2009) and the relative inverted Amihud (2002) liquidity measures; and (v and vi) $\Delta_{ij}VOLAT\ (JKL)_t$ and $\Delta_{ij}VOLAT\ (K)_t$ – the relative volatility measures obtained via Jones at al. (1994) and Koski (1998) methods.[10]

In specification [1] of Table 4, we begin by estimating equation (2) with only the intercept and the *POST* variable. Although subject to the omitted variable bias, this specification provides an initial illustration of the changes in relative short interest. Relative short interest declines by 25.7% post-split, similarly to the result obtained in the univariate tests. In specification [2], we expand the model to allow for a non-zero slope of the short interest function by adding the *TREND* variable and a term that interacts trend with the *POST* indicator, *POST*×*TREND*. The *TREND* variable has a negative coefficient, implying that relative short interest gradually decreases during the event window, corroborating the results in Table 2 and Figure 1. More importantly, we observe that the interaction term, *POST*×*TREND*, has a negative coefficient that is economically and statistically significant. Thus, the slope of the line that best describes post-split short interest is steeper than the slope of the line that best describes pre-split short interest. In other words, short interest begins to decline at a significantly faster pace in response to split announcements, consistent with signaling.

[10] We outline the estimation techniques used to obtain the liquidity and volatility measures in Appendices A. 1 through A.3.

In specifications [3] through [5], we use conventional short interest determinants to control for simultaneous effects. As the debate on proper liquidity and volatility measures has not yet been settled, we use two measures of each to eliminate the possibility that the results may be driven by our choice of estimators. We alternate between the liquidity estimates proposed by Amihud (2002) and Goyenko et al. (2009), and the volatility estimates of Jones et al. (1994) and Koski (1998).

The estimated coefficients suggest that higher institutional ownership, higher liquidity, and higher volatility correspond to higher levels of short interest. The opposite relation holds for abnormal returns that are negatively related to short interest. These results corroborate conclusions of Asquith et al. (2005) with respect to institutional holdings, expectations of Kadiyala and Vetsuypens (2002) with respect to liquidity, and the findings of Diether et al. (2009) with respect to volatility. Meanwhile, the negative relation between short interest and returns and the positive relation between short interest and liquidity are different from those obtained by Dechow et al. (2001) and Diether et al. (2009). These differences are, most likely, due to the fact that we observe short interest around specific events whereas these two studies observe short sellers' behavior in unconditional panels. In addition, our results might be divergent due to different sets of controls and different data frequency.

In the meantime, the results are clear in that post-split decreases in short interest are not driven solely by the changes in conventional short interest determinants, corroborating the signaling explanation. In fact, the signaling result becomes stronger when the model includes short interest covariates as indicated by the larger coefficient of the $POST \times TREND$ variable in specifications [3] through [5] as compared to specification [2].

5. Tests of signaling

So far, our tests imply that short sellers' behavior is consistent with receiving a positive signal from stock splits. In this section, we look for additional confirmation of the signaling explanation by testing short interest changes in the signaling framework proposed by earlier studies. In particular, we rely on findings of McNichols and Dravid (1990) and Conroy and Harris (1999) who show, respectively, that larger splits and splits by seasoned splitters, (especially, to prices that are lower than those achieved through the previous split) are interpreted as stronger signals.

In addition, we test the generally accepted premise of the signaling theory that the reaction to a signal should be stronger for companies with higher information asymmetry. For such companies, the utility of the signal is higher and thus the reaction to the signal should be stronger. The literature proposes a number of information asymmetry proxies, from among which we choose: (i) the firm size, (ii) the number of analysts that follow the firm, (iii) the dispersion of analyst opinion, (iv) the firm's share of R&D expenses, and (v) the firm's percentage of intangible assets.

To test these expectations in our setting, we estimate the following equation:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1\delta_i + \beta_2 POST_{i,t} + \beta_3 TREND_{i,t} + \beta_4 TREND \times \delta_{i,t} + \beta_5 POST \times TREND_{i,t} + \beta_6 POST \times TREND \times \delta_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t} \quad (3)$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t*; δ_i is the indicator variable equal to 1 if a split characteristic or a splitting firm characteristic (the list of characteristics is provided shortly) is expected to cause a differential reaction to a split announcement. We consider the following characteristics: (i) *large split* (similarly to McNichols and Dravid (1990) and Byun and Rozeff (2003), we define large splits as 2:1 and larger); (ii) firm is a *seasoned splitter* (similarly to

Conroy and Harris (1999), firms that have executed a split prior to the current split are considered seasoned splitters); (iii) splitting to a *lower price* as compared to that achieved through the previous split; (iv) *large firm* (firms in the three upper deciles based on the NYSE market capitalization are considered large); (v) *large number of analysts* (firms in the three upper number of analysts deciles); (vi) *high dispersion* of analyst opinion (firms in the three upper deciles by dispersion); (vii and viii) *high R&D* expenses as a share of all expenses and *high intangible* assets as a share of total assets (firms in the three upper deciles by, respectively, R&D and intangibles). Control variables are defined as in specification [3] in Table 4. We do not report the estimated coefficients of the control variables to conserve space.

The estimated coefficients from various specifications of equation (5) are reported in Table 5. In the signaling context, our main variable of interest is the interaction term *POST*×*TREND*×δ that captures differences between post-announcement slopes for various split and firm characteristics as discussed above. For instance, a negative estimated coefficient on *POST*×*TREND*×δ, where δ is equal to 1 for large splits, indicates that an announcement of a large split has a stronger effect on short sellers' opinion than an announcement of a small split.[11]

The estimation results are, for the most part, consistent with our expectations. In particular, larger splits, splits by seasoned splitters, and splits to lower than previous prices have stronger negative effects on the post-announcement short interest, although the effect associated with seasoned splitters is rather marginal. When it comes to firm characteristics, all information asymmetry proxies acquire expected signs. Specifically, small firms, firms with just a few analysts, firms with high dispersion in analysts' opinion, firms with high R&D expenses, and

[11] To facilitate understanding of the results in Table 6. we provide stylized graphic interpretations of the estimated coefficients for *INTERCEPT*, δ, *POST*, *TREND*, *TREND*×δ, *POST*×*TREND*, and *POST*×*TREND*×δ, in Figure 3. The stylization forces control variables to zero, therefore the numerical distances between the lines in Figure 3 are meaningless. We therefore suppress the vertical axes values in the figure.

firms with high levels of intangible assets – all proxies for high information asymmetry – send stronger signals. Overall, these results are consistent with the signaling hypothesis.[12]

6. Alternative explanations, sub-period results, and confounding events

Baker and Gallagher (1980) report that managers most commonly cite attracting small investors as the main motive for splitting their firm's stock. Schulz (2000), Easley et al. (2001), and Dyl and Elliott (2006) find that small investor activity and ownership significantly increase after splits. Our study must therefore consider the possibility that the post-split decline in short interest is driven by changes in retail investor activity. On the one hand, higher individual ownership may result in more mispricing and higher profit opportunities from arbitrage. On the other hand, retail investors increase stock's idiosyncratic volatility (Brandt et al., 2009), and high idiosyncratic volatility increases short sellers' costs and leads to reductions in their positions (Duan et al., 2009).[13] Thus, it is imperative to test whether the decline in short interest that we document is affected (or is entirely driven) by the changes in the level of retail investor activity in the post-split environment.

Although the importance of controlling for retail investor activity is rather apparent, measuring this activity presents a significant empirical challenge. Public datasets do not differentiate small investor trades from other trades, whereas proprietary data do not span the entire sample period. To make our analysis as comprehensive as possible, we opt to use three measures of individual investor activity; those of Easley et al. (2001), Hvidkjaer (2008), and

[12] In unreported results, we re-estimate, separately for large and small splits, model specifications, in which δ represents firm characteristics. This additional test checks for the possibility that firms with higher information asymmetry may prefer sending stronger split signals based on split characteristics (e.g., these firms may prefer carrying out larger splits). The estimated coefficients of the $POST \times TREND \times \delta$ variable have expected signs and are statistically significant when the sample is stratified in this manner. Thus, endogeneity does not appear to present a significant concern in model (3).

[13] Contrary to Duan et al. (2009), Ben-David et al. (2010) suggest that savvy arbitrageurs may seek highly volatile stocks.

Kaniel et al. (2008). These measures have been shown to work well in previous studies; however, they have certain time-period and listing exchange limitations.

The measure used by Easley et al. (2001) is based on the probability of informed trading (PIN) methodology of Easley, Kiefer, and O'Hara (1996, 1997). The measure may be used to estimate the frequency of uninformed trader arrival, ε, in every month of the event window. Easley et al. (2001) show that ε increases after stock splits, corroborating catering-to-small-investors split motive.[14] The PIN framework is developed for a market with a central market maker, thus it may not be transplantable to stocks that trade in a dealer market such as NASDAQ. For this very reason, Easley et al. (2001) limit their sample to the NYSE-listed stocks. In the meantime, Chan, Menkveld, and Yang (2008) use the PIN model in the Chinese market that operates without active specialists, implying that PIN-based studies may not need to be limited to markets with single market makers. To avoid potential caveats related to the listing markets' structures, we estimate εs separately for the NYSE and NASDAQ stocks.

Hvidkjaer (2008) relies on small trades to gauge retail investor activity. To compute Hvidkjaer's measure, we sort stocks into quintiles based on the NYSE firm-size cutoff points. Then, we use the following small-trade cutoff points: $3,400 for the smallest firms, and $4,800, $7,300, $10,300, and $16,400 for the larger firms. Subsequently, we obtain the cutoff points in number of shares as the ratio of the dollar cutoff point to the share price rounded up to the nearest round lot. The share cutoff points are updated monthly based on the share price at the end of the prior month. Once defined, we use ISSM and TAQ data to compute the total volume from small trades in every month of the event window. Hvidkjaer notes that his measure loses precision after decimalization. Hence, we limit our use of this measure to 1988-2000 sub-period.

[14] We provide details on the computation of ε in Appendix A.4.

Kaniel et al. (2008) use Consolidated Audit Trail Data (CAUD) from the NYSE to identify retail orders. Their dataset covers years 2001 through 2006 and contains a flag for every order submitted by a retail trader in the NYSE-listed stocks. We use CAUD dataset to estimate the monthly aggregate individual investor volume during the event window.

In summary, difficulties in estimation of individual investor activity cause us to stratify the sample into two sub-samples based on the listing market (the NYSE and NASDAQ) and into two sub-samples based on the time period (pre-2001 and post-2001). To ensure that the signaling effect identified earlier is observed across the sub-samples, we re-estimate specification [1] from Table 5, with δ indicating large splits, and report the results in Panel A of Table 6.[15]

Several results in Panel A are of note. First, the signaling effect is stronger for NASDAQ firms. This result is perhaps expected, considering that Table 5 shows that signals from small firms are stronger. More importantly, the signaling effect is considerably stronger in the post-2001 sub-sample, with the coefficient of $POST \times TREND \times LS$ more than eight times larger than that estimated in the pre-2001 period. This result corroborates our proposition that catering-to-intermediaries motive proposed by Angel (1997) may have lost its significance in the post-decimalization environment and the visibility of the signaling motive increased as a result.

Panel B of Table 6 reports the estimated changes in individual investor activity between the pre-split and the post-split periods. All measures suggest an increase in retail investor trading, although the change in the PIN-based measure for NASDAQ stocks is only marginally significant. In Panel C of Table 6, we estimate equation (3), with δ indicating large splits. The model contains an additional control variable, $\Delta_{ij} INDIV$, that proxies for relative individual

[15] In unreported results, we also estimate the remaining specifications from Table 5 for each of the sub-samples. The results reported in Panel A of Table 6 persist in most cases. The triple interaction term loses statistical significance in the specifications that focus on seasoned NASDAQ splitters and in specifications that focus on NASDAQ stocks with high dispersion in analyst opinion and high R&D expenditures.

investor activity estimated as the difference between abnormal activity measures for splitters and their non-splitting matches. As previously, our focus is on the coefficient of the triple interaction term and, this time, on the coefficient of the $\Delta_{ij}INDIV$ control.

Controlling for changes in individual investor activity does not eliminate the evidence consistent with signaling. On the contrary, the newly estimated coefficients of the $POST \times TREND \times LS$ variable are larger than those estimated in Panel A specifications. Interestingly, the coefficients on the $\Delta_{ij}INDIV$ controls are positive, suggesting that individual investor trading tends to attract short sellers.

In the last two columns of Panel C, we test the signaling result for robustness to stratifying the sample into years of high and low investor sentiment as described in Baker et al. (2009). Relying on the logic of DeLong et al. (1990) and Shleifer and Vishny (1997), we reason that if in high sentiment years firms attract optimistic investors by splitting, the inflow of optimists may crowd arbitrageurs out of splitting stocks. If this effect is strong, our results may be attributable to the periods with high levels of low-price premium, P^{CME}. To examine this possibility, we divide sample years into three groups based on the magnitude of the P^{CME} measure and re-estimate the large split specification of equation (3) for the six out of 17 sample years with the lowest P^{CME} and for the six years with the highest P^{CME}. The results reported in the last two columns of Panel B of Table 6 indicate that the post-split decline in short interest is observed in all years, irrespective of the level of investor sentiment towards low-priced firms.

Having shown that changes in individual investor activity and the sentiment-driven investor activity do not eliminate the evidence of split signaling, we engage in a series of robustness checks to determine whether our main result is affected by confounding events. We identify the following three potentially confounding events: (i) option listings and delistings; (ii) inclusions in and exclusions from the S&P 500 index; and (iii) dividend changes.

It is a well-known fact that option market makers use short sales to hedge their positions. Similarly, short positions are extensively used by index arbitrageurs. Thus, if a split is accompanied by an option listing (delisting) or an index inclusion (exclusion), we expect a significant increase (decrease) in short positions of these market participants. We find (Panel A of Table 7) that option listings and inclusions in the S&P 500 index quite often occur during the 21-month event window that surrounds split announcements. In particular, about 15% of our sample splits are accompanied by an option listing; whereas about 2% are accompanied by an inclusion into the index. On the other hand, delistings and exclusions rarely occur during the event window, and we only observe, respectively, 15 and 5 of them.

Nayak and Prabhala (2001) caution that the magnitude of split signals may be misestimated because split announcements often occur simultaneously with the announcements of dividend changes. In our sample, 2,759 split announcements (about 55% of all splits) are adjacent to dividend changes. To ensure that our results are driven by split signals instead of dividend signals, we re-estimate the signaling model for the sub-sample of splits that are not accompanied by dividend changes.

In Table 7, we re-estimate equations (2) and (3), with the latter equation estimated for large splits.[16] The results support our previous conclusions. In particular, in all cases, the model suggests that the slope of the line that best describes short interest becomes more negative after a split announcement. The slope is more negative as compared to that reported in Table 4 when we eliminate option listings and S&P 500 inclusions. The post-split slope estimated for the

[16] We also estimate a set of equations that control for individual investor activity. Because such estimation requires multiple specifications as described for Table 6, we do not report the results to save space. The main results remain qualitatively unchanged with these alternative specifications.

sample that excludes dividend changes is less negative than that reported in Table 4, consistent with the fact that some signals might be attributable to dividend announcements. The slope is still negative when we exclude all confounding events for a total of 1,960 remaining split announcements. The signaling results also hold when we exclude confounding events from estimation of equation (3) for large splits. Earlier results become stronger when we exclude confounding option listings and S&P 500 inclusions. The results become somewhat weaker, but remain statistically significant when we eliminate confounding dividend changes. Overall, the results that we earlier interpret as being consistent with the signaling hypothesis are robust to elimination of confounding events.

7. Post-split returns

Ikenberry and Ramnath (2002) use the buy-and-hold long-term return, BHAR, estimation technique of Barber and Lyon (1997) and find strong evidence that post-split long-term returns are positive. Using an, arguably, more robust methodology of calendar time abnormal returns, CTARs, Byun and Rozeff (2003) find that splits are usually not followed by long-term positive abnormal returns, thus undermining the signaling hypothesis. Our tests suggest that sophisticated investors behave consistently with signaling, as they reduce short positions in anticipation of positive post-split returns. If such positive returns do not ensue, our argument of short sellers' superior ability to analyze value-relevant information is untenable, at least in relation to stock splits.

Since Byun and Rozeff's CTAR approach produces more conservative return estimates as compared to those produced by the BHAR approach, we estimate CTARs to test short sellers' long-term return forecasting ability. In month t, $CTAR_t$ is the average abnormal return for all sample firms that have effected a split within the prior twelve months: $CTAR_t = R_{p,t} - E(R_{p,t})$, where $R_{p,t}$ is the monthly return on the portfolio of event firms, and $E(R_{p,t})$ is the expected return on the event portfolio. The expected return on the event portfolio is measured by the 4-factor model.[17] First, for each sample firm in month t, we estimate a time-series regression of the firm's excess returns on the four factors:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ is firm i's monthly return, including dividends, in month t; $R_{f,t}$ is the one-month Treasury bill return; and $R_{m,t}$ is the return on the CRSP value-weighted portfolio of all NYSE and NASDAQ stocks. The size and book-to-market factors are defined as in Fama and French (1993) and the momentum factor is defined as in Carhart (1997). The models are estimated during a 49-month period centered on month t. Estimated individual firm factor loadings are then averaged to obtain monthly portfolio factor loadings and monthly CTARs. Statistical significance of the estimates is computed based on time series of monthly CTARs.

As Byun and Rozeff, we estimate CTARs separately for large and small splits. Additionally, within split size groups, we estimate CTARs for all splitters in the sample and then, separately, (i) for splits followed by the largest declines in relative short interest in the five months following the split, $\Delta_{ij}SI_{t+5,30th}$, and (ii) for splits followed by the smallest changes in relative short interest in the five months following the split, $\Delta_{ij}SI_{t+5,70th}$. The largest (smallest) changes in short interest are defined as those below (above) the 30th (70th) percentile of all relative changes. We report estimated abnormal returns in annualized form.

The results reported in Table 8 are consistent with short sellers' ability to sort out noisy signals. We confirm the results in Byun and Rozeff (2003) that, in the cross-section, splits are

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[17] We use the 4-factor model, because stocks that split experience high returns before the split and thus price momentum may relate to subsequent returns.

not followed by abnormal long-term returns. Nevertheless, when we focus on splits that are followed by significant declines in short interest (columns titled $\Delta_{ij}SI_{t+5,30th}$), we find that short sellers are able to identify splits that represent the true positive signals. This result is evident for large and (in the value-weighted specification) for small splits. Overall, we conclude that long-term return evidence is consistent with signaling and with short sellers' superior ability to interpret split signals.

8. Conclusions

In this study, we test the split signaling theory of Brennan and Copeland (1988) from a new angle that avoids relying solely on return measurement. In particular, we focus on the post-split actions of sophisticated investors, short sellers, and ask whether their behavior is consistent with receiving a positive value-relevant signal from a stock split.

Our findings suggest that splits are interpreted by short sellers as positive signals, as short interest usually decreases by more than 25% in reaction to split announcements. The decline in short interest is larger when the split signal is stronger as represented by (i) larger split factors and (ii) lower post-split prices. In addition, split signals have a more prominent effect when they are sent by firms with higher information asymmetries.

We study 5,014 splits during a 17-year period from February 1990 through December 2006. Our results corroborate the signaling hypothesis throughout the entire sample period. The signaling explanation survives a series of robustness checks that account for split-related changes in individual investor activity and for investor sentiment. The results are also robust to controlling for the conventional short interest determinants such as abnormal returns, institutional holdings, liquidity, and volatility. In addition, the results are robust to eliminating a set of confounding events that may (i) affect the strength and the clarity of the split signal or (ii) affect short interest levels.

We also ask whether short sellers are successful at predicting long-term returns that follow split events. We show that split announcements that are associated with the largest declines in short interest are followed by positive abnormal returns in the CTAR framework of Buyn and Rozeff (2003). Meanwhile, splits that do not lead to a significant decline in short interest are followed by zero abnormal returns. This result holds for strong and weak split signals. Thus, although the evidence suggests that short sellers react to the known split signal amplifiers, their understanding of split signals seems to be enhanced by the ability to analyze information beyond that revealed in the split announcement.

We view our contribution to the literature as threefold. First, we show that sophisticated investors infer positive signals from split announcements. Our approach avoids relying solely on long-term return measures. Second, we show that short sellers' reaction to split announcements is more consistent with signaling after decimalization, most likely due to weakening of the catering-to-intermediaries split motive. Thus, our results are consistent with existence of a time-variant set of motives for firms' split decisions. We propose that earlier studies may have failed to find consistent evidence of split signaling because pre-decimalization samples contain a number of splits that may have been initiated for non-signaling reasons. Finally, we find some evidence that short sellers' opinions of splitting firms may be already improving before the split, and that the decline in short interest may be based on information that is beyond that derived from the conventional amplifiers of split signals. As such our results are consistent with research that argues that short sellers' possess superior ability to process value-relevant information.

Appendices: Matching and Estimation Techniques

A.1. Propensity score matching

To identify the composition of the split decision model, we refer to the existing literature for guidance. We use a combination of the binary models of Lakonishok and Lev (1987), Nayak and Prabhala (2001), and Baker et al. (2009) with a few alterations. In particular, we model split decisions as a function of (i) the price ratio – the relation of the firm's pre-split price to the average market price,[18] (ii) the pre-split price runup, (iii) the pre-split average monthly change in institutional ownership, (iv) the pre-split average monthly change in stock return volatility, (v) the pre-split average monthly change in stock liquidity, (vi) the level of investor sentiment toward low-price firms, (vii) the firm size, and (viii, ix) the tick size regime.

We offer the following reasoning for this model structure. As argued by Lakonishok and Lev (1987) and Weld et al. (2009), firms with high price ratios are likely to lower their prices by splitting. Such decision is often conditional on the relatively rapid price runup and on company size, with larger companies often opting for higher nominal prices, as suggested by Nayak and Prabhala (2001). More recently, Baker et al. (2009) add investor sentiment to the general split decision model. They also introduce volatility as a split determinant, arguing that firms with high volatility should be reluctant to force their prices down. To allow firms' split decision criteria to change with tick size, we also add indicator variables that distinguish between three tick size regimes: eighths, sixteenths, and decimals.

Since short interest is our main variable of focus, we require that the splitters and their matches have similar conditions for establishing short interest positions. Hence, in addition to the split determinants, we control for the conventional short interest determinants: institutional

[18] Lakonishok and Lev's (1987) results are not significantly affected when they replace the denominator of the price ratio with the average price of stocks in the firm's industry. Since we use industry affiliation as one of matching characteristics, we opt to use the average market price in the denominator of the price ratio metric.

holdings and liquidity. Institutional ownership is often used as a proxy for short selling constraints (Asquith, Pathak, and Ritter, 2005), whereas liquidity is deemed to be an important short selling determinant, although the direction of the relation is not yet settled in the literature. Whereas Diether, Lee, and Werner (2009) view short sellers as short-term liquidity providers who seek out illiquid stocks, Kadiyala and Vetsuypens (2002) suggest that, in the long run, short sellers tend to avoid illiquid stocks due to higher risk of unwinding positions in such stocks.

In summary, as the first step of the propensity score matching procedure, we estimate the following logistic regression:

$$\begin{aligned} \Pr(split_{i,t} = 1) = \alpha + \beta_1 PRATIO_{i,t-1} + \beta_2 AR_{i,[t-10;\, t-1]} + \beta_3 \Delta INST_{i,[t-10;\, t-1]} + \\ \beta_4 \Delta VOLAT_{i,[t-10;\, t-1]} + \beta_5 \Delta LIQUID_{i,[t-10;\, t-1]} + \beta_6 P^{CME}{}_t + \\ \beta_7 NYSED_{i,t} + \beta_8 SIXTNTHS_t + \beta_9 DECIMALS_t + \varepsilon_{i,t}, \end{aligned} \qquad \text{(A1)}$$

where the binary dependent variable $split_{i,t}$ is equal to 1 if firm i announces a split in month t and is equal to 0 otherwise; $PRATIO_{i,t-1}$ is firm i's price ratio computed as its price in the pre-split announcement month divided by the average price for all sample stocks other than i; $AR_{i,[t-10;t-1]}$ is the buy-and-hold abnormal return that represents the price runup; $\Delta INST_{i,[t-10;t-1]}$ is the mean monthly change in institutional ownership of stock i during the 10-month pre-split announcement period; $\Delta VOLAT_{i,[t-10;t-1]}$ is the monthly change in stock i's daily volatility; $\Delta LIQUID_{i,[t-10;t-1]}$ is the mean monthly change in stock i's liquidity; $P^{CME}{}_t$ is the log difference in the average market-to-book ratios of low- and high-priced stocks as in Baker et al. (2009); $NYSED_{i,t}$ is the NYSE market capitalization decile that firm i belongs to; and $SIXTNTHS_t$ and $DECIMALS_t$ are indicator variables that identify minimum tick size regimes, with the eighths being the base regime. Institutional ownership is computed as the number of shares in institutional holdings reported via 13-F filings and scaled by the number of shares outstanding. Daily stock volatility is estimated, similarly to Jones, Kaul, and Lipson (1994), as the absolute value of the residual from the following model:

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{k,t} + \sum_{\tau=1}^{12} \beta_j R_{i,t-\tau} + \varepsilon_{i,t}, \quad \text{(A2)}$$

where $R_{i,t}$ is the return of stock i on day t; $D_{k,t}$ are the five day-of-the-week dummies; and τ denotes the lag operator for lagged returns. Liquidity is estimated as the inverse *effective tick* measure described in Goyenko et al. (2009).[19]

Specification [1] of Table A.1 reports the marginal effects obtained from the estimated coefficients. Although the economic interpretation of split determinants is not the main focus of this study, we briefly discuss them to highlight similarities with prior research. Split likelihood increases in the price ratio, price runup, investor sentiment, and liquidity. Split likelihood declines upon the switch to sixteenths and, further, upon the switch to decimals. Changes in institutional holdings and volatility are only marginally relevant for firms' split decisions. Finally, large firms are less likely to split, consistent with the cross-sectional pattern, in which large firms tend to maintain higher prices. Overall, the estimated effects corroborate prior research and our expectations.

Before continuing with the matching procedure, we take a brief detour to discuss an issue that is directly related to our logistic model; however, has not been settled in prior research. In particular, we ask whether pre-split increases in short interest systematically induce split decisions. Our interest in this issue is triggered by previous research (Lamont, 2004) and some media reports that suggest that firms may use stock splits to combat rapid increases in short positions. Under certain conditions, stock splits may result in temporary disruptions in the

[19] Appendix A. 2 contains the computational details of the Goyenko et al. (2009) measure.

supply of lendable shares or in share recalls, thus constraining opening of new short positions or forcing closeouts of existing positions (short squeezes).

Anecdotal evidence on stock splits as short seller repellents is relatively scarce. Such scarcity is not surprising, as management is unlikely to publicly admit to an imprudent practice of forced elimination of pessimistic investors. Instead, firms usually cite more sensible reasons for splitting, among which diversifying the shareholder base is the most popular (Baker and Gallagher, 1980). One of the well-publicized split-induced short squeezes is that of Gruene, Inc. that openly admitted that its 4-for-3 stock split was a measure to "combat naked short-selling."[20] Gruene's split process involved a stock recall that drained short positions and induced a short squeeze. Gruene case occurred more than 20 years ago. We searched for similar media stories using Factiva and found no mentioning of similar events in more recent years.[21] The absence of similar events may indicate that Gruene case is unique, or that firms are reluctant to admit that splits are, at times, used to curtail recent increases in short interest. Our logistic model is uniquely suited to inquire whether abnormal growth in short interest is a systematic split determinant, as the model controls for conventional split determinants and short selling conditions.

In specifications [2] and [3] of Panel A in Table A.1, we add average monthly changes in short interest in, respectively, ten and five pre-split months as an explanatory variable in model (A1). The estimated effects are marginally significant and have a negative sign. Thus, the data show that short interest does not have a ceteris paribus positive effect on stock split decisions. In Panel B, we report the results from a series of robustness checks that re-estimate the model in specification [2] separately for (i) large and small firms, (ii) large and small splits, and (iii)

[20] "Gruene Inc. Declares 4-for-3 Split, Citing 'Naked Short-Selling'", *The Wall Street Journal*, June 1, 1989.
[21] We searched for combinations of the following: *stock split*, *short selling*, *short squeeze* and their variations.

seasoned and first-time splitters. Short interest does not have a positive effect on split probability in either specification.

Having estimated the propensity to split for each firm in each sample month, we continue to the second step of Heckman et al. (1997) procedure that involves finding suitable matches for the splitting firms. We match (without replacement) every firm *i* that announces a split in month *t* with a non-splitting firm *j* whose estimated propensity to split in month *t*-1 is the closest to that of firm *i*'s. To be eligible for matching, firm *j* must have the same Fama-French (1997) industry classification as firm *i* and must not split during the 10 months before or during the 10 months after the split by firm *i*. Once a unique match is found, we compare the estimated propensity scores and the pre-split split determinants (e.g., *PRATIO*, *AR*, *INST*, *VOLAT*, and *LIQUID*) for splitters and matched non-splitters. All variables match well, with the difference between the splitters and non-splitters being statistically insignificant.

A.2. Goyenko, Holden, and Trzcinka (2009) effective tick measure

In a recent paper, Goyenko et al. (hereafter, GHT) develop a proxy for the effective spread measure that may be estimated from daily trade data without relying on intraday datasets. The measure is based on the assumption that trade prices cluster to minimize negotiation costs between traders. The authors let S_t be the realization of the effective spread at the closing trade of day t. Then they assume that this realization is randomly drawn from a set of possible spreads s_j, $j = 1, 2, \ldots, J$ that arise with corresponding probabilities γ_j, with the possible effective spreads ordered from smallest to largest. GHT further assume that price clustering is determined by spread size, implying that the frequency with which closing prices occur in particular price clusters can be used to estimate the spread probabilities $\hat{\gamma}_j$. Then, they let N_j be the number of trades on prices corresponding to the j^{th} spread using only positive-volume days and let F_j be the empirical probabilities of trades on prices corresponding to the j^{th} spread computed as $F_j = N_j / \sum_{j=1}^{J} N_j$. They let U_j be the unconstrained probability of the j^{th} spread defined as

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots J - 1 \\ F_j - F_{j-1}, & j = J. \end{cases} \tag{A3}$$

To account for the possibility of reverse price clustering, GHT add constraints to generate proper probabilities. In particular, they define $\hat{\gamma}_j$ as constrained probability of the j^{th} spread as follows:

$$\hat{\gamma}_j = \begin{cases} min\left[max\{U_j, 0\}, 1\right], & j = 1 \\ min\left[max\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right], & j = 2, 3, \dots, J. \end{cases} \tag{A4}$$

Finally, the effective tick measure is a probability-weighted average of each effective spread size divided by $\bar{P}_i$ – the average price in time interval i: $effective\ tick = \sum_{j=1}^{J} \hat{\gamma}_j s_j \Big/ \bar{P}_i$.

A.3. Amihud (2002) illiquidity measure

Amihud (2002) develops an illiquidity measure that is meant to capture the "daily price response associated with one dollar of trading volume." In particular, he estimates $illiquidity = mean(|r_t| / dolvol_t)$, where r_t is the stock return on day t and $dolvol_t$ is the dollar volume on day t.

A.4. PIN-based uninformed trading measure of Easley, Kiefer, and O'Hara (1996, 1997)

The probability of informed trading (PIN) model assumes that informed traders receive a private signal about the value of an asset at the start of a trading day with probability α. Conditional on the arrival of this signal, bad news arrives with probability δ and good news arrives with probability (1-δ). Furthermore, buy (sell) orders from uninformed (liquidity) traders arrive at rates ε_b (ε_s), and, conditional on the arrival on new information, orders from informed traders arrive at rate μ. Informed traders buy when they receive a positive signal and sell when they receive a negative signal.

The PIN model makes use of observable trade and quote data on the number of buys and sells to make inferences about unobservable information events and the frequency of informed and uninformed trades. In the estimation, each day is considered as a trading period and the normal level of buys and sells indicates information-based transactions, which are used to identify μ. The number of days for which there are abnormal buys or sells is used to identify α and δ. Using a maximum likelihood estimation procedure and assuming a Poisson arrival process for the informed and uninformed traders, the likelihood function for a single day is

$$L(\vartheta|B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!}$$
$$+ \alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}, \qquad (A5)$$

where B and S indicate the total number of buys and sells, respectively, and $\vartheta = (\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$ is the parameter vector. The estimates are obtained by maximizing the likelihood function

$$L\big(\vartheta|\{B_t, S_t\}_{t=1,\ldots,T}\big)$$
$$= \prod_{t=1}^{T}\Bigg((1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^{B_t}}{B_t!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_t}}{S_t!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^{B_t}}{B_t!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^{S_t}}{S_t!}$$
$$+ \alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^{B_t}}{B_t!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_t}}{S_t!}\Bigg), \qquad (A6)$$

where B_t and S_t indicate the total number of buys and sells on day t. To determine the level of retail investor activity, we average ε_b and ε_s estimates as in Ellul and Panayides (2009).

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Table 1
Sample statistics
The table contains sample statistics for an 17-year sample period (February 1990 through December 2006). We report [1] the number of splits; [2] percent of large splits; [3] percent of splits by seasoned splitters; and [4] short interest, SI. Following Baker et al. (2009), splits are defined as distributions with CRSP event codes 5523. We exclude reverse splits and stock dividends by restricting CRSP split factors to at least 0.25. For splits, for which CRSP does not report announcement dates, we search Factiva for the earliest reported announcement. Large splits are defined, as in Byun and Rozeff (2003), as those with the CRSP split factor of at least 1 (i.e., 2:1 and larger splits). Seasoned splitters are defined, as in Conroy and Harris (1999), as firms that have split at least once prior to the current split. Short interest, $SI_{i,t}$, is defined, for each sample stock i, as the number of shares in short positions in month t, $SS_{i,t}$, scaled by the number of shares outstanding, $SO_{i,t}$; namely, $SI_{i,t} = 100 \times SS_{i,t}/SO_{i,t}$. Short positions are collected in the middle of the month, whereas the number of shares outstanding is collected at the end of the month. Thus, for splits that occur in the second half of the month, $SI_{i,t}$ metric must be adjusted to avoid measurement error. In particular, $SI_{i,t}$ should be estimated as $(1 + split\ factor) \times SS_{i,t}/SO_{i,t}$. NASDAQ's short interest datasets provide a *lagged short interest* field that contains short interest in month t as observed in month t+1. These lagged figures incorporate the mechanical increases in short interest due to splits, even if the previous month record fails to do so. We use these records to adjust $SS_{i,t}$ figures in split event months. The NYSE does not perform a similar adjustment. Therefore, for the NYSE stocks, we multiply $SI_{i,t}$ by $(1 + split\ factor)$ if a split event occurs after the 15th of month t.

Year	*# of splits*	*% large splits*	*% seasoned splitters*	*SI, %*
1990	149	61.07	49.66	0.75
1991	221	50.68	60.18	0.94
1992	375	48.53	55.20	0.91
1993	428	51.87	54.21	0.98
1994	296	56.08	48.31	1.19
1995	406	57.39	49.26	1.15
1996	460	57.39	52.61	1.14
1997	443	55.08	52.60	1.42
1998	389	62.21	60.67	1.64
1999	365	70.96	50.96	1.51
2000	349	79.37	54.44	1.57
2001	149	41.61	65.10	2.08
2002	163	49.08	64.42	2.73
2003	180	45.00	57.78	2.81
2004	232	57.33	59.48	2.95
2005	232	60.78	65.09	3.39
2006	177	59.89	58.76	4.18
Mean	295	56.72	56.40	1.84
Median	296	57.33	55.20	1.51
Total	5,014			
% annual growth				12.06

Table 2
Short interest around split announcements: Event study
The table contains monthly estimates of mean differences in relative short interest around split announcements. First, we compute (for splitters and matched non-splitters, in each event-window month) the abnormal short interest metric, $ASI_{i,t}$, as follows: $ASI_{i,t} = \left(SI_{i,t} - 10^{-1}\sum_{-11}^{-20} SI_{i,t}\right) / 10^{-1}\sum_{-11}^{-20} SI_{i,t}$, where $SI_{i,t}$ is the number of firm *i*'s shares in short positions in month *t* scaled by the number of shares outstanding. Second, we compute *relative short interest*, $\Delta_{ij}SI_t$ as the difference between the abnormal short interest of a splitting firm *i* and a matching non-splitter *j*. To estimate the pure announcement effect, we limit the analysis to the splits, for which the announcement and the split event are separated by at least one month. The results are organized in a [-10; +10]-month event window centered on the month of the split announcement, where month 0 contains the first post-split announcement collection of short interest. *p*-Values in parentheses denote the results of statistical significance tests for means (medians).

	mean $\Delta_{ij}SI_t$	*t-test p-value*	*median* $\Delta_{ij}SI_t$	*Wilcoxon p-value*
-10	1.3	(0.20)	**5.2**	(0.00)
-9	-2.3	(0.61)	4.5	(0.10)
-8	**-1.4**	(0.01)	0.1	(0.51)
-7	**-2.2**	(0.00)	2.8	(0.73)
-6	**-3.2**	(0.00)	0.1	(0.52)
-5	**-3.6**	(0.00)	-4.1	(0.11)
-4	**-4.6**	(0.00)	0.8	(0.19)
-3	**-5.1**	(0.00)	0.1	(0.06)
-2	**-5.7**	(0.00)	0.1	(0.10)
-1	**-8.2**	(0.00)	**-2.7**	(0.02)
0	**-16.2**	(0.00)	**-5.9**	(0.00)
+1	**-22.4**	(0.00)	**-11.0**	(0.00)
+2	**-27.6**	(0.00)	**-17.8**	(0.00)
+3	**-31.3**	(0.00)	**-23.8**	(0.00)
+4	**-27.9**	(0.00)	**-21.4**	(0.00)
+5	**-33.4**	(0.00)	**-24.4**	(0.00)
+6	**-27.7**	(0.00)	**-19.7**	(0.00)
+7	**-31.8**	(0.00)	**-24.8**	(0.00)
+8	**-33.1**	(0.00)	**-26.0**	(0.00)
+9	**-30.2**	(0.00)	**-26.3**	(0.00)
+10	**-28.0**	(0.00)	**-23.3**	(0.00)

Table 3
Short interest and covariates around split announcements
The table contains mean differences in the following covariates: (i) $\Delta_{ij}LIQID$ computed as the mean difference in abnormal effective tick measures between splitters and matched non-splitters; (ii) $\Delta_{ij}VOLAT$ computed as the mean difference in abnormal daily volatility measures of Jones et al. (1994); (iii) $\Delta_{ij}INST$ computed as the mean difference in abnormal institutional holdings; (iv) $\Delta_{ij}AR$ is computed as Ikenberry and Ramnath's (2002) BHAR. The results are computed as monthly mean differences between splitters and matched non-splitters in the [*t*-5; *t*+5]-month window and in the [*t*-10; *t*+10]-month window. The pre-announcement period is identified as *pre*, and the post-announcement period – as *post*. *p*-Values in parentheses denote statistical significance of mean differences.

		[*t*-5; *t*+5]		[*t*-10; *t*+10]	
$\Delta_{ij}LIQID$	*pre*	0.57	(0.92)	0.61	(0.84)
	post	**-15.00**	(0.00)	**-15.36**	(0.00)
$\Delta_{ij}VOLAT$	*pre*	-0.62	(0.16)	-0.80	(0.18)
	post	**14.67**	(0.00)	**13.52**	(0.00)
$\Delta_{ij}INST$	*pre*	0.90	(0.21)	0.49	(0.31)
	post	0.00	(0.39)	-1.64	(0.25)
$\Delta_{ij}AR$	*pre*	1.48	(0.14)	0.79	(0.21)
	post	**2.33**	(0.00)	**1.45**	(0.01)

Table 4

Post-split changes in short interest: multivariate framework

The table contains estimated coefficients from a set of panel regressions of changes in relative short interest between the pre-announcement and post-announcement periods. We estimate the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1 POST_{i,t} + \beta_2 TREND_{i,t} + \beta_3 POST \times TREND_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t},$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t* estimated as the difference in abnormal short interest between a splitting firm *i* and its non-splitting match *j*. $POST_{i,t}$ is the indicator variable equal to 0 in the pre-event months and equal to 1 in the event and post-event months; and $TREND_{i,t}$ is the trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables includes: (i) $\Delta_{ij}AR_t$ – the relative BHARs computed as the difference in returns between splitters and their non-splitting matches; (ii) $\Delta_{ij}INST_t$ – the relative abnormal institutional holdings computed as a difference between splitters and their non-splitting matches; (iii and iv) $\Delta_{ij}LIQUID\ (GHT)_t$ and $\Delta_{ij}LIQUID\ (A)_t$ – the relative abnormal inverted effective tick and abnormal inverted Amihud's liquidity measures computed as differences between splitters and their non-splitting matches; (v and vi) $\Delta_{ij}VOLAT\ (JKL)_t$ and $\Delta_{ij}VOLAT\ (K)_t$ – the relative abnormal volatility measures obtained via Jones at al. (1994) and Koski (1998) methods computed as differences between splitters and their non-splitting matches. The models are tested and adjusted for firm fixed effects and heteroskedasticity using Newey-West estimator. *p*-Values and in parentheses.

	[1]	[2]	[3]	[4]	[5]
INTERCEPT	-0.003	0.009	-0.001	0.001	-0.002
	(0.17)	(0.50)	(0.97)	(0.96)	(0.90)
POST	-0.257***	0.171***	0.215***	0.203***	0.218***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TREND		-0.002***	-0.001***	-0.001***	-0.001***
		(0.00)	(0.00)	(0.00)	(0.00)
POST×TREND		-0.014***	-0.021***	-0.020***	-0.021***
		(0.00)	(0.00)	(0.00)	(0.00)
$\Delta_{ij}AR$			-0.082***	-0.089***	-0.081***
			(0.01)	(0.01)	(0.01)
$\Delta_{ij}INST$			0.303***	0.292***	0.030***
			(0.00)	(0.00)	(0.00)
$\Delta_{ij}LIQUID\ (GHT)$			0.034***		0.030***
			(0.00)		(0.00)
$\Delta_{ij}LIQUID\ (A)$				0.081***	
				(0.00)	
$\Delta_{ij}VOLAT\ (JKL)$			0.031***	0.048***	
			(0.00)	(0.00)	
$\Delta_{ij}VOLAT\ (K)$					0.067***
					(0.00)
Adj. R^2, %	26.99	32.30	35.69	35.00	35.57

Table 5
Tests of the signaling hypothesis
The table contains coefficient estimates from a set of panel regressions of changes in relative short interest between the pre-announcement and post-announcement periods. We estimate the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1\,\delta_i + \beta_2 POST_{i,t} + \beta_3 TREND_{i,t} + \beta_4 TREND \times \delta_{i,t} + \beta_5 POST \times TREND_{i,t} + \beta_6 POST \times TREND \times \delta_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t},$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t* estimated as the difference in abnormal short interest between a splitting firm *i* and its non-splitting match *j*; δ_i is the indicator variable equal to 1 if a split characteristic or a splitting firm's characteristic (the list of characteristics is provided shortly) is expected to cause differential reaction to a split announcement. We consider the following characteristics: (i) *split size* (similarly to Byun and Rozeff (2003), 2:1 and larger splits are considered large); (ii) firm's *splitting experience* (similarly to Conoy and Harris (1999), firms that have split prior to the current split are considered seasoned splitters); (iii) splitting to a *lower price* that that achieved through a previous split; (iv) *firm size* (firms are divided into deciles based on the NYSE market capitalization; firms in the 3 lowest deciles are considered small, whereas firms in the 3 highest deciles are considered large); (v) *number of analysts* (firms in the 3 lowest deciles by the number of analysis versus firms in the 3 highest deciles); (vi) *dispersion of analyst opinion* (firms in the 3 lowest dispersion deciles versus firms in the 3 highest deciles); (vii and viii) *R&D expenses and the ratio of intangible assets to total assets* (firms in the 3 lowest R&D and relative intangibles deciles versus firms in the 3 highest deciles). $POST_{i,t}$ is the indicator variable equal to 0 in the pre-event months and equal to 1 in the event and post-event months; and $TREND_{i,t}$ is the trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables (estimated but not tabulated) includes: (i) $\Delta_{ij}AR$ – the buy-and-hold return, BHAR; (ii) $\Delta_{ij}INST_t$ – the relative abnormal institutional holdings computed as a difference between splitters and their non-splitting matches; (iii) $\Delta_{ij}LIQUID_t$ – the relative abnormal inverted effective tick measure computed as the difference between splitters and their non-splitting matches; (iv) $\Delta_{ij}VOLAT_t$ – the relative abnormal volatility measure obtained via Jones at al. (1994) method computed as the difference between splitters and their non-splitting matches. The models are tested and adjusted for firm fixed effects and heteroskedasticity using Newey-West estimator. *p*-Values and in parentheses.

	large split	*seasoned splitter*	*seasoned to lower price*	*large firm*	*large # of analysts*	*high dispersion*	*high R&D*	*high intangibles*
INTERCEPT	-0.008* (0.06)	-0.027 (0.37)	-0.042 (0.30)	-0.001** (0.52)	-0.049* (0.06)	0.011** (0.02)	0.001 (0.70)	-0.169 (0.30)
δ	0.003* (0.08)	0.038 (0.32)	0.003* (0.06)	0.076 (0.13)	0.009** (0.03)	0.026* (0.05)	-0.045 (0.36)	0.077 (0.37)
POST	0.190*** (0.00)	0.198*** (0.00)	0.185*** (0.00)	0.246*** (0.00)	0.021*** (0.00)	0.146*** (0.00)	0.231*** (0.00)	0.214*** (0.00)
TREND	-0.001*** (0.00)	-0.001*** (0.00)	-0.001*** (0.00)	-0.001*** (0.00)	-0.001** (0.03)	-0.001*** (0.00)	-0.001*** (0.01)	-0.001*** (0.00)
TREND×δ	0.004 (0.43)	0.007 (0.22)	0.010 (0.12)	0.004 (0.56)	-0.003 (0.60)	-0.004 (0.56)	-0.003 (0.62)	-0.001 (0.91)
POST×*TREND*	-0.016*** (0.00)	-0.020*** (0.00)	-0.022*** (0.00)	-0.023*** (0.00)	-0.023*** (0.00)	-0.021*** (0.00)	-0.022*** (0.00)	-0.033*** (0.00)
POST×*TREND*×δ	-0.008** (0.02)	-0.001* (0.07)	-0.012** (0.03)	0.017*** (0.01)	0.013** (0.02)	-0.014* (0.06)	-0.012** (0.02)	-0.013** (0.04)
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2, %	35.63	35.66	35.64	35.63	35.66	33.61	34.16	35.20

Table 6
Tests of alternative hypotheses
The table contains coefficient estimates from a set of panel regressions of changes in relative short interest between the pre-announcement and post-announcement periods. We estimate the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1 LS_i + \beta_2 POST_{i,t} + \beta_3 TREND_{i,t} + \beta_4 TREND \times LS_{i,t} + \beta_5 POST \times TREND_{i,t} + \beta_6 POST \times TREND \times LS_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t},$$

where $\Delta_{ij}SI_t$ is the relative short interest in month t estimated as the difference in abnormal short interest between a splitting firm i and its non-splitting match j; LS_i is the indicator variable equal to 1 for 2:1 and larger splits and is equal to 0 otherwise; $POST_{i,t}$ is the indicator variable equal to 0 in the pre-event months and equal to 1 in the event and post-event months; and $TREND_{i,t}$ is the trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables (estimated but not tabulated) includes: (i) $\Delta_{ij}AR$ – the buy-and-hold return BHARs; (ii) $\Delta_{ij}INST_t$ – the relative abnormal institutional holdings computed as the difference between splitters and their non-splitting matches; (iii) $\Delta_{ij}LIQUID_t$ – the relative abnormal inverted effective tick measure computed as differences between splitters and their non-splitting matches; (iv) $\Delta_{ij}VOLAT_t$ – the relative abnormal volatility measures obtained via Jones at al. (1994) method computed as the difference between splitters and their non-splitting matches. In Panel A, we stratify the main sample into the NYSE and NASDAQ sub-samples and into sub-periods, 1989-2000 and 2001-2006. This is done to facilitate comparisons to the results in Panel B that contains proxies for changes in trading by individual investors, some of which are unavailable for NASDAQ stocks and/or for one of the time sub-periods. We use the following three proxies for individual trader activity: (i) Hvidkjaer's (2008); (ii) CAUD-based (as in Kaniel et al., 2008); and (iii) PIN-based (as in Easley et al., 2001). To compute Hvidkjaer's measure, stocks are sorted into quintiles based on the NYSE firm-size cutoff points. Then, the following small-trade cutoff points are used: \$3,400 for the smallest firms, and \$4,800, \$7,300, \$10,300, and \$16,4000 for the larger firms. Subsequently, the cutoff points in number of shares are obtained as the ratio of the dollar cutoff point to the share price rounded up to the nearest round lot. The share cutoff points are updated monthly based on the share price at the end of the prior month. Once defined, we compute the total volume from small trades in every month of the event window. Hvidkjaer notes that this measure loses precision after decimalization. Hence, we limit our use of this measure to 1989-2000 sub-period. The PIN-based measure estimates ε - the rate of arrival of uninformed traders from the probability of informed trading, PIN, model of Easley et al., (1996, 1997). CAUD data are limited to the NYSE stocks in 2001 through 2006. We estimate the PIN-based measure for the NYSE and NASDAQ stocks separately due to a debate on the applicability of PIN model to NASDAQ stocks. Upon estimation, we compute abnormal statistics for the individual trading activity measures and compute the differences in these abnormal statistics between splitters and their non-splitting matches. The resulting relative monthly individual investor activity measure, $\Delta_{ij}INDIV_t$, becomes a component of the control vector $\boldsymbol{x_{i,t}}$. In Panel B, we report the estimated percentage changes in individual trading measures computed as the difference between the pre-split and the post-split averages. Finally, in Panel C, we test the catering hypothesis of Baker et al. (2009) by dividing the sample into splits that were announced in years of above-median low-price premium, P^{CME}, and years of below-median premium. The models are tested and adjusted for firm fixed effects and heteroskedasticity using Newey-West estimator. *p*-Values and in parentheses.

Panel A: Sub-samples and sub-periods

	NYSE	*NASDAQ*	*1989-2000*	*2001-2006*
INTERCEPT	0.024	-0.018*	-0.008	-0.073
LS	-0.033	0.035	0.012	0.130
POST	0.129*	0.159***	0.208***	0.167
TREND	-0.001**	-0.001**	-0.001**	-0.002***
TREND×LS	0.003	0.001	-0.000	0.005*
POST×TREND	-0.011**	-0.023***	-0.017***	-0.013**
POST×TREND×LS	-0.007***	-0.010**	-0.006**	-0.049***
CONTROLS	Yes	Yes	Yes	Yes

Panel B:Effects of split-related changes in trading by individual investors

	PIN-ε, NYSE	*PIN-ε, NASD*	*Hvidkjaer*	*CAUD*
% change	34.84 (0.00)	10.82 (0.08)	28.39 (0.00)	23.97 (0.00)

Panel C:Effects of split-related changes in trading by individual investors

	PIN-ε: NYSE, all years	*PIN-ε: NASD, all years*	*Hvidkjaer: 1989-2001*	*CAUD: NYSE, 2001-2006*	*high P^{CME}*	*low P^{CME}*
INTERCEPT	0.013	-0.019*	-0.078*	0.035	0.301	0.424
LS	-0.032	0.034	0.014*	-0.058	-0.054	-0.068
POST	0.132**	0.141**	0.208***	0.023*	0.200	0.150*
TREND	-0.001**	-0.001**	-0.001***	-0.001***	-0.001***	-0.001***
TREND×LS	0.003	0.002	0.004	0.004	-0.001	-0.007*
POST×TREND	-0.012**	-0.021***	-0.018***	-0.009**	-0.014**	-0.018**
POST×TREND×LS	-0.011**	-0.013**	-0.008**	-0.032***	-0.007**	-0.008***
Δ_{ij}*INDIV*	0.014**	-0.031	0.064***	0.021***		
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Elimination of confounding events
The table contains coefficient estimates from a set of panel regressions of changes in relative short interest between the pre-announcement and post-announcement periods. We estimate the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1 LS_i + \beta_2 POST_{i,t} + \beta_3 TREND_{i,t} + \beta_4 TREND \times LS_{i,t} + \beta_5 POST \times TREND_{i,t} + \beta_6 POST \times TREND \times LS_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t},$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t* estimated as the difference in abnormal short interest between a splitting firm *i* and its non-splitting match *j*; LS_i is the indicator variable equal to 1 for 2:1 and larger splits and is equal to 0 otherwise; $POST_{i,t}$ is the indicator variable equal to 0 in the pre-event months and equal to 1 in the event and post-event months; and $TREND_{i,t}$ is the trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables (estimated but not tabulated) includes: (i) $\Delta_{ij}AR$ – the buy-and-hold abnormal return; (ii) $\Delta_{ij}INST_t$ – the relative abnormal institutional holdings computed as the difference between splitters and their non-splitting matches; (iii) $\Delta_{ij}LIQUID_t$ – the relative abnormal inverted effective tick measure computed as differences between splitters and their non-splitting matches; (iv) $\Delta_{ij}VOLAT_t$ – the relative abnormal volatility measures obtained via Jones at al. (1994) method computed as the difference between splitters and their non-splitting matches; (v) $\Delta_{ij}INDIV_t$ – the relative abnormal individual trading activity computed as in Hvidkjaer (2008) for the 1989-2000 sub-period and as in Kaniel et al., (2008) for the 2001-2006 sub-period. In this table, we control for the following confounding effects: (i) listings and de-listings of options, (ii) inclusions and exclusions from the S&P 500 index, and (iii) dividend changes. Panel A contains the number of splits that are accompanied by events of each kind and the total number of confounding events. Throughout the table, we eliminate confounding events one-by-one to gauge their influence on the main result. The models are tested and adjusted for firm fixed effects and heteroskedasticity using Newey-West estimator. *p*-Values and in parentheses.

Panel A: The number of confounding events				
	option listings & delistings	S&P500 inclusions & exclusions	dividend changes	total confounding events
	758 & 15	117 & 5	2,759	3,054

Panel B: Elimination of confounding events	no option (de)listings		no S&P500 in- or exclusions		no dividend changes		no confounding events	
INTERCEPT	-0.002	-0.005*	0.000	-0.080	-0.021	-0.085	0.023	-0.046
	(0.91)	(0.06)	(0.99)	(0.30)	(0.24)	(0.10)	(0.25)	(0.11)
LS		0.002*		0.009**		0.015**		0.008*
		(0.08)		(0.04)		(0.02)		(0.06)
POST	0.163***	0.163***	0.198***	0.201***	0.103**	0.215***	0.029	0.139***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.55)	(0.00)
TREND	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
TREND×LS		0.003		0.004		-0.003		-0.004
		(0.53)		(0.37)		(0.52)		(0.38)
POST×TREND	-0.028***	-0.020***	-0.022***	-0.018***	-0.018***	-0.018***	-0.023***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
POST×TREND×LS		-0.015**		-0.009**		-0.005**		-0.009**
		(0.01)		(0.02)		(0.04)		(0.02)
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2, %	36.60	36.62	35.76	35.81	34.33	35.63	37.24	37.83

Table 8

Calendar-time abnormal returns, CTARs

The table contains calendar-time abnormal returns computed similarly to Byun and Rozeff (2003). At month t, $CTAR_t$ is the average abnormal return for all firms that have split within the prior 10 months, $CTAR_t = R_{pt} - E(R_{pt})$, where R_{pt} is the monthly return on the portfolio of splitters at time t, and $E(R_{pt})$ is the expected return on the event portfolio at time t. The expected return on the event portfolio is measured by the factor model as follows. First, for each sample firm in a monthly portfolio, we estimate a four-factor model over a 49-month period centered on that month:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is firm i's monthly return, including dividends, in month t, $R_{f,t}$ is the one-month Treasury bill return, and $R_{m,t}$ is the return on the CRSP value-weighted portfolio of all NYSE, AMEX, and NASDAQ stocks. The size and book-to-market factors are defined as in Fama and French (1993), and the momentum factor is defined as in Carhart (1997). Estimated individual firm factor loadings are then averaged to obtain monthly portfolio factor loadings and monthly CTARs. Reported p-values are computed from time series monthly CTARs. As Byun and Rozeff, we estimate CTARs separately for large splits (2:1 and larger) and small splits. Additionally, within split size groups, we estimate CTARs for all splitters in the sample and then separately (i) for splits followed by the largest declines in short interest in the 5 months following the split, $\Delta_{ij}SI_{t+5,\ 30th}$, and (ii) for splits followed by the smallest changes in short interest in the 5 months following the split, $\Delta_{ij}SI_{t+5,\ 70th}$. Largest changes in short interest are defined as those below the 30th percentile of all changes. Smallest changes are defined as those above the 70th percentile.

	large split			*small split*		
	all	$\Delta_{ij}SI_{t+5,\ 30th}$	$\Delta_{ij}SI_{t+5,\ 70th}$	*all*	$\Delta_{ij}SI_{t+5,\ 30th}$	$\Delta_{ij}SI_{t+5,\ 70th}$
EW	1.25	2.98**	-0.46	-0.21	0.64	-0.94
	(0.28)	(0.03)	(0.12)	(0.84)	(0.40)	(0.26)
VW	2.61	3.41***	1.64*	0.51	1.04**	0.22
	(0.18)	(0.00)	(0.07)	(0.57)	(0.04)	(0.89)

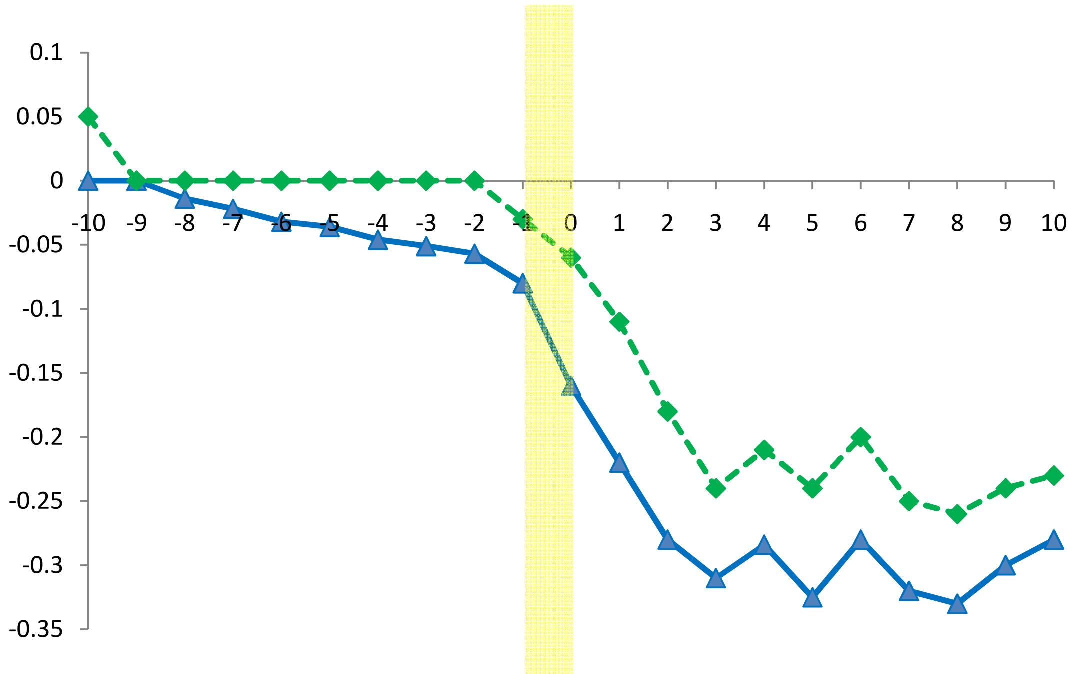

Figure 1. Abnormal short interest around split announcements

For this analysis, we first estimate the propensity to split as the predicted value from the following panel logistic regression:

$$Pr\ (split = 1)_{i,t} = \alpha + \beta_1 PRATIO_{i,t-1} + \beta_2 AR_{i,[t-10;\ t-1]} + \beta_3 \Delta INST_{i,[t-10;\ t-1]} + \beta_4 \Delta VOLAT_{i,[t-10;\ t-1]} + \beta_5 \Delta LIQUID_{i,[t-10;\ t-1]} + \beta_6 P^{CME}_t + \beta_7 NYSED_{i,t} + \beta_8 SIXTNTHS_t + \beta_9 DECIMALS_t + \varepsilon_{i,t};$$

where the binary dependent variable $split_{i,t}$ is equal to 1 if firm i announces a split in month t and is equal to 0 otherwise; $PRATIO_{i,t-1}$ is firm i's price in month $t-1$ divided by the average price for all sample stocks excluding firm i; $AR_{i,[t-10;\ t-1]}$ is the mean monthly abnormal return estimated as Ikenberry and Ramnath's BHARs during months $t-10$ through $t-1$ preceding the split announcement month t; $\Delta INST_{i,[t-10;\ t-1]}$ is the mean monthly change in institutional ownership in stock i during the 10-month pre-split period; $\Delta VOLAT_{i,\ [t-10;\ t-1]}$ is the monthly change in stock i's volatility during the 10-month pre-split period computed as in Jones et al. (1994); $\Delta LIQUID_{i,[t-10;t-1]}$ is the mean monthly change in stock i's liquidity during the 10-month pre-split period computed as an inverted effective tick measure in Goyenko et al. (2009); P^{CME}_t is the log difference in the average market-to-book ratios of low- and high-priced stocks as in Baker et al. (2009); $NYSED_{i,t}$ is the NYSE market capitalization decile of firm i; and $SIXTNTHS_t$ and $DECIMALS_t$ are indicator variables that identify minimum tick size regimes. Having obtained predicted values for propensity to split, $\widehat{Pr}(split\ =\ 1)_{i,t}$, we match (without replacement) every firm i that announces a split in month t with a non-splitting firm j whose propensity to split in month t-1 is the closest to that of firm i's. To be eligible for matching, firm j cannot have split in the 10 months preceding or the 10 months following the split by firm i. Upon matching, we compute (for splitters and matched non-splitters, in each event-window month) the abnormal short interest metric, $ASI_{i,t}$, as follows: $ASI_{i,t} = \left(SI_{i,t} - 10^{-1}\sum_{-11}^{-20} SI_{i,t}\right)/10^{-1}\sum_{-11}^{-20} SI_{i,t}$, where $SI_{i,t}$ is the number of i's shares in short positions in month t scaled by the number of shares outstanding. Finally, for each splitter/non-splitter pair, we compute the difference between abnormal short interest statistics for every month in the event window. These differences (denoted in the text as relative short interest, $\Delta_{ij} SI_t$) are potted in the figure. The blue solid line denotes mean differences, and the green broken line denoted median differences. The yellow shaded area indicates the month of the split announcement, and time 0 represents the first post-split announcement collection of short interest.

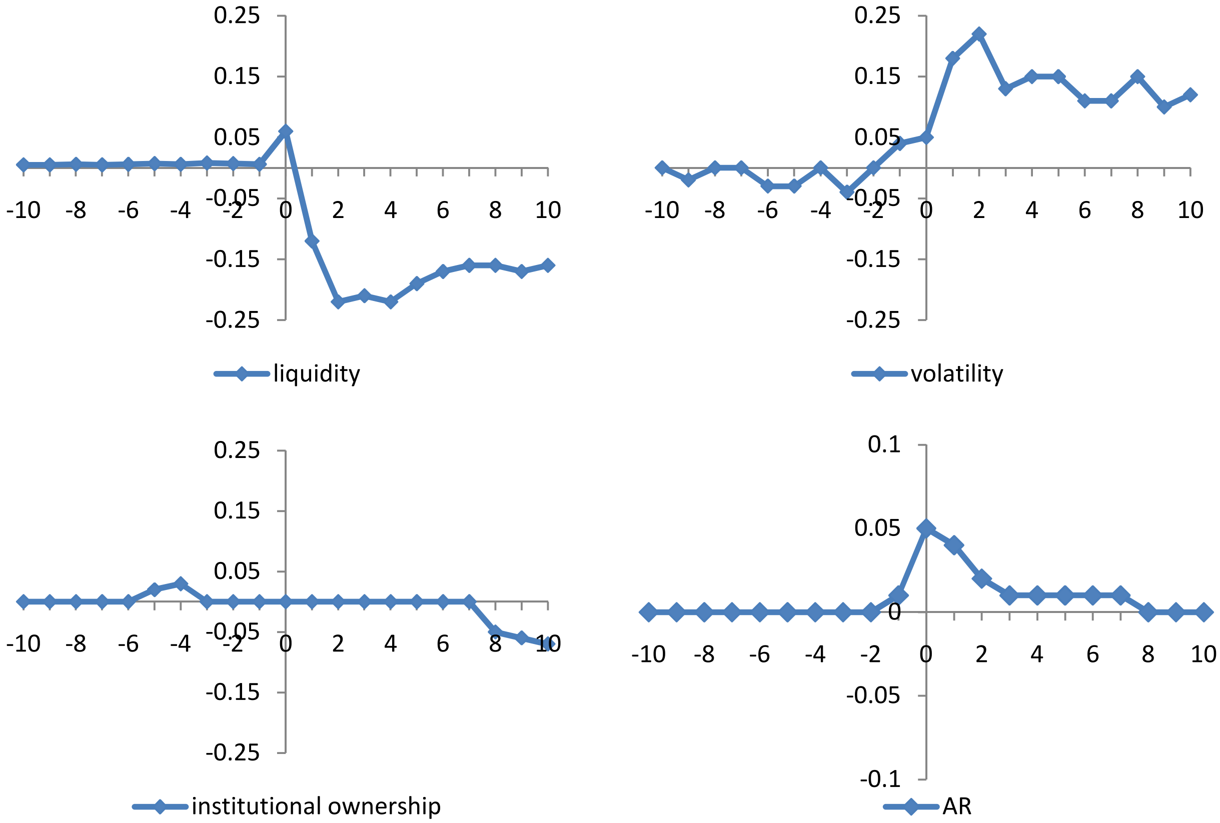

Figure 2. Short interest determinants around split announcements
The figure contains event-window time series of short interest covariates in the [-10; +10]-month event window centered on the split announcement month. We consider the following covariates: (i) $\Delta_{ij}LIQID$ computed as the mean difference in abnormal effective tick measures between splitters and matched non-splitters; (ii) $\Delta_{ij}VOLAT$ computed as the mean difference in abnormal daily volatility measures of Jones et al. (1994); (iii) $\Delta_{ij}INST$ computed as the mean difference in abnormal institutional holdings; and (iv) $\Delta_{ij}AR$ computed as abnormal buy-and-hold returns. Estimates that are not statistically different from zero are forced to zero in the plots.

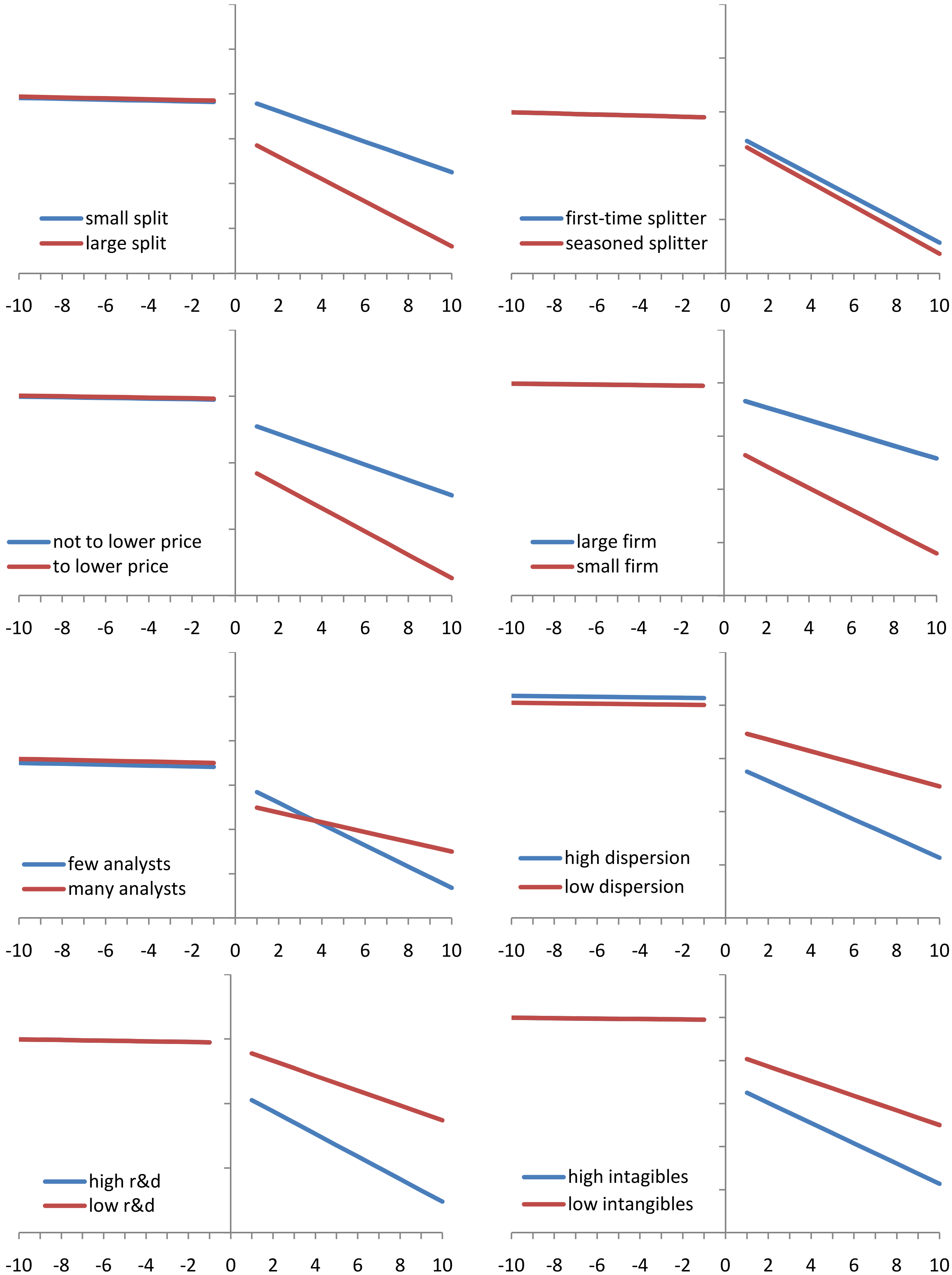
small split
large split
first-time splitter
seasoned splitter
not to lower price
to lower price
large firm
small firm
few analysts
many analysts
high dispersion
low dispersion
high r&d
low r&d
high intagibles
low intangibles
-10 -8 -6 -4 -2 0 2 4 6 8 10

Figure 3. Signal responses contingent on signal and company characteristics
The figure contains stylized event-window plots of relative short interest, $\Delta_{ij}SI_t$, obtained using estimated β coefficients from the following model:

$$\Delta_{ij}SI_t = \beta_0 + \beta_1\delta_i + \beta_2 POST_{i,t} + \beta_3 TREND_{i,t} + \beta_4 TREND \times \delta_{i,t} + \beta_5 POST \times TREND_{i,t} + \beta_6 POST \times TREND \times \delta_{i,t} + \boldsymbol{x_{i,t}\gamma} + \varepsilon_{i,t},$$

where $\Delta_{ij}SI_t$ is the relative short interest in month *t* estimated as the difference in abnormal short interest between a splitting firm *i* and its non-splitting match *j*; δ_i is the indicator variable equal to 1 if a split characteristic or a splitting firm's characteristic (the list of characteristics is provided shortly) is expected to cause differential reaction to a split announcement. We consider the following characteristics: (i) *split size* (similarly to Byun and Rozeff (2003), 2:1 and larger splits are considered large); (ii) firm's *splitting experience* (similarly to Conoy and Harris (1999), firms that have split prior to the current split are considered seasoned splitters); (iii) splitting to a *lower price* that that achieved through a previous split; (iv) *firm size* (firms are divided into deciles based on the NYSE market capitalization; firms in the 3 lowest deciles are considered small, whereas firms in the 3 highest deciles are considered lagre); (v) *number of analysts* (firms in the 3 lowest deciles by the number of analysis versus firms in the 3 highest deciles); (vi) *dispersion of analyst opinion* (firms in the 3 lowest dispersion deciles versus firms in the 3 highest deciles); (vii and viii) *R&D expenses and the ratio of intangible assets to total assets* (firms in the 3 lowest R&D and relative intangibles deciles versus firms in the 3 highest deciles). $POST_{i,t}$ is the indicator variable equal to 0 in the pre-event months and equal to 1 in the event and post-event months; and $TREND_{i,t}$ is the trend variable. The $\boldsymbol{x_{i,t}}$ vector of control variables (estimated but not tabulated) includes: (i) $\Delta_{ij}AR$ – the buy-and-hold abnormal return; (ii) $\Delta_{ij}INST_t$ – the relative abnormal institutional holdings computed as a difference between splitters and their non-splitting matches; (iii) $\Delta_{ij}LIQUID_t$ – the relative abnormal inverted effective tick measure computed as the difference between splitters and their non-splitting matches; (iv) $\Delta_{ij}VOLAT_t$ – the relative abnormal volatility measure obtained via Jones at al. (1994) method computed as the difference between splitters and their non-splitting matches. Once the model is estimated, we compute the stylized predicted value of $\Delta_{ij}SI_t$ from the equation above excluding the control variables. The estimated values are then plotted in the figure for every split or firm characteristic that may cause a differential response to a split signal.

Table A.1

Split decision determinants and propensity score estimation

The table contains the analysis of split determinants (specifications [1] and [2] of Panel A) and reports the model used for estimation of the propensity to split (specification [3] of Panel A). Predicted values from the propensity model are used in subsequent tests to match splitters with non-splitters. For the analysis of split determinants, we estimate the following logistic model:

$$
\begin{aligned}
Pr\,(split = 1)_{i,t} = \alpha + \gamma\, \Delta SI_{i,[t\text{-}\kappa;\, t\text{-}1]} &+ \beta_1\, PRATIO_{i,t\text{-}1} + \beta_2 AR_{i,[t\text{-}10;\, t\text{-}1]} + \beta_3 \Delta INST_{i,[t\text{-}10;\, t\text{-}1]} + \\
&\beta_4 \Delta VOLAT_{i,[t\text{-}10;\, t\text{-}1]} + \beta_5 \Delta LIQUID_{i,[t\text{-}10;\, t\text{-}1]} + \beta_6\, P^{CME}_{t} + \\
&\beta_7 NYSED_{i,t} + \beta_8\, SIXTNTHS_t + \beta_9\, DECIMALS_t + \varepsilon_{i,t},
\end{aligned}
$$

where the binary dependent variable $split_{i,t}$ is equal to 1 if firm i announces a split in month t and is equal to 0 otherwise; $\Delta SI_{i,[t\text{-}\kappa;\, t\text{-}1]}$, with $\{\kappa = 10$ or $\kappa = 5\}$ is the average rate of monthly change in short interest during the 10-month (or 5-month) pre-split announcement period (all changes in this table are computed as month-to-month continuous growth rates that are then averaged across the pre-split months); $PRATIO_{i,t\text{-}1}$ is firm i's price in the pre-split announcement month divided by the average price for all sample stocks excluding firm i as in Lakonishok and Lev (1987); $AR_{i,[t\text{-}10;\, t\text{-}1]}$ is the mean monthly BHAR estimated as in Ikenberry and Ramnath (2002) during months *t-10* through *t-1* preceding the split announcement month t; $\Delta INST_{i,[t\text{-}10;\, t\text{-}1]}$ is the mean monthly change in institutional ownership of stock i during the 10-month pre-split announcement period; $\Delta VOLAT_{i,[t\text{-}10;\, t\text{-}1]}$ is the monthly change in stock i's daily volatility during the 10-month pre-split announcement period computed as in Jones et al. (1994) (hereafter, JKL); $\Delta LIQUID_{i,[t\text{-}10;t\text{-}1]}$ is the mean monthly change in stock i's liquidity during the 10-month pre-split period computed as an inverted *effective tick* measure of Goyenko et al. (2009) (hereafter, GHT); P^{CME}_{t} is the log difference in the average market-to-book ratios of low- and high-priced stocks as in Baker et al. (2009); $NYSED_{i,t}$ is the NYSE market capitalization decile of firm i; and $SIXTNTHS_t$ and $DECIMALS_t$ are indicator variables that identify minimum tick size regimes. Abnormal returns are estimated as buy-and-hold returns in Barber and Lyon (1996, 1997). Institutional ownership is computed as the number of shares in institutional holdings reported via 13-F forms and scaled by the number of shares outstanding. Daily stock volatility is estimated as the absolute value of the residual from the following model:

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{k,t} + \sum_{\tau=1}^{12} \beta_j R_{i,t-\tau} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i on day t; $D_{k,t}$ are the five day-of-the-week dummies; and τ denotes the lag operator for lagged returns. Liquidity is estimated as the inverse *effective tick* (illiquidity) measure described in Goyenko et al. (2009) (see Appendix for the detailed description of the measure). Reported coefficients represent marginal effects, and p-values are reported in parentheses. In specification [1] of Panel A, we report the propensity score model. In specifications [2] and [3] of Panel A, we report models that test whether changes in short interest act as spread determinants. In Panel B, we re-estimate specification [1] separately for (i) large and small firms, (ii) large and small splits, and (iii) seasoned and first-time splitters. For these models, we report only the estimated marginal effects for the $\Delta SI_{[t\text{-}10;\, t\text{-}1]}$ variable.

Panel A: Split determinants			
	[1]	[2]	[3]
$\Delta SI_{[t-10;\ t-1]}$		-0.012*	
		(0.09)	
$\Delta SI_{[t-5;\ t-1]}$			-0.012**
			(0.04)
PRATIO	0.200***	0.200***	0.200***
	(0.00)	(0.00)	(0.00)
AR	0.780***	0.789***	0.828***
	(0.00)	(0.00)	(0.00)
$\Delta INST$	-0.051*	-0.050*	-0.054*
	(0.08)	(0.09)	(0.08)
$\Delta VOLAT$	-0.056*	-0.054*	-0.070**
	(0.06)	(0.07)	(0.04)
$\Delta LIQUID$	0.095***	0.095***	0.103***
	(0.00)	(0.00)	(0.00)
P^{CME}	0.651***	0.651***	0.651***
	(0.00)	(0.00)	(0.00)
NYSED	-0.428***	-0.428***	-0.429***
	(0.00)	(0.00)	(0.00)
SIXTNTHS	-0.080***	-0.080***	-0.083***
	(0.00)	(0.00)	(0.00)
DECIMALS	-0.098***	-0.097***	-0.098***
	(0.00)	(0.00)	(0.00)
pseudo-R^2, %	19.30	19.31	19.30
# obs.	338,166	338,166	338,166

Panel B: Alternative specifications, estimated marginal effects on $\Delta SI_{[t-10;\ t-1]}$			
	large mcap	*large split*	*seasoned splitter*
Yes	-0.016**	-0.010*	-0.016**
	(0.05)	(0.08)	(0.04)
No	-0.013	-0.016	-0.007
	(0.49)	(0.16)	(0.65)