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Stock Splits, Trading Continuity, and the Cost of Equity Capital

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Stock splits, trading continuity, and the cost of equity capital ☆

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A B S T R A C T

We hypothesize that managers use stock splits to attract more uninformed trading so that market makers can provide liquidity services at lower costs, thereby increasing investors' trading propensity and improving liquidity. We examine a large sample of stock splits and find that, consistent with our hypothesis, the incidence of no trading decreases and liquidity risk is lower following splits, implying a decline in latent trading costs and a reduced cost of equity capital. Further, split announcement returns are correlated with the improvements in both liquidity levels and liquidity risk. Our analysis suggests nontrivial economic benefits from liquidity improvements, with less liquid firms benefiting more from stock splits.

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1. Introduction

Managers often claim that stock splits are intended to attract more investors and to improve stock liquidity (Dolley, 1933; Baker and Gallagher, 1980; Baker and Powell, 1993). Muscarella and Vetsuypens (1996) examine ADR solo-splits and find evidence supportive of the liquidity improvement argument. Similarly, Amihud, Mendelson, and Uno (1999) show that, in Japan, a firm's investor base and stock liquidity increase significantly when the firm reduces its stock's minimum trading unit

(i.e., the number of shares in a round lot). However, many studies question whether liquidity improves after stock splits. In fact, Copeland (1979), Conroy, Harris, and Benet (1990), Easley, O'Hara, and Saar (2001), and Gray, Smith, and Whaley (2003) show that while splits lower stock price levels, they raise bid-ask spreads rather than improving the stocks' liquidity. Also, Copeland (1979) and Lamoureux and Poon (1987) find that turnover decreases following stock splits, which leads them to surmise that "splits induce permanent reductions in liquidity."

The findings intrigue Easley, O'Hara, and Saar (2001, p. 25), who note that "stock splits remain one of the most popular and least understood phenomena in equity markets… why a split per se is necessary is unclear… empirical research has documented a wide range of negative effects such as increased volatility, larger proportional spreads and larger transaction costs following the splits. On balance, it remains a puzzle why companies ever split their shares."

In this paper, we offer a new perspective on the issue. Our premise is that non-trading reflects illiquidity. This

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premise is motivated by Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), Liu (2006), and Bekaert, Harvey, and Lundblad (2007). In particular, Lesmond, Ogden, and Trzcinka (1999) argue that informed investors will trade only if the value of information exceeds trading costs. Similarly, liquidity traders might refrain from trading if trading costs outweigh the improvement in portfolio allocation. Hence, the trading decision is endogenous and a function of trading costs, which are directly related to market-making costs. We do not observe trading costs or market-making costs; but ex post we can observe whether trades have occurred, and we can then infer the latent trading costs. Holding other things constant, greater incidence of no trading implies higher (unobservable) trading costs and lower liquidity.[1]

While the bid-ask spread is conventionally used to measure trading costs, it has a limitation—the bid and ask quotes are often for small-size trades, whereas a larger transaction size might need to be negotiated. As Liu (2006, p. 631) points out, liquidity can be generally described as "the ability to trade large quantities quickly at low cost with less price impact." This suggests that liquidity is multifaceted and might not be well represented by the bid-ask spread, either before or after a stock split. Similarly, because of the endogeneity of the trading decision, standard measures such as Amihud's (2002) illiquidity measure and Kyle's (1985) lambda, which focus on the price impacts of trades, might not be able to fully capture the illiquidity of non-trading, either before or after a split.

Thus, we propose the trading continuity improvement hypothesis to explain how a stock split might improve liquidity and why it could be beneficial to the firm. Our hypothesis posits that, for a firm facing some possibility of trading discontinuity or no trading, managers have incentives to use a stock split to attract more uninformed traders to participate in trading. Indeed, Schultz (2000) shows a significant increase in small trades following the splits. Further, Easley, O'Hara, and Saar (2001) document more uninformed trades—and more informed trades as well—after stock splits.[2] More uninformed trading allows market makers to reduce their inventory holding costs and adverse information cost, which could lead to lower trading costs and liquidity improvements. In an improved liquidity environment, stock prices are less affected by shocks to market liquidity. Thus, our hypothesis predicts that, after stock splits, investors would face lower liquidity risk and require a lower liquidity premium, which in turn would reduce the cost of equity capital for the firm and increase firm value.

We use a large sample of NYSE/AMEX/Nasdaq stock splits to test our hypothesis. To measure the degree of trading discontinuity on each sample stock, we use Liu's (2006) LM12, the standardized turnover-adjusted number of days with zero trading volume over the prior 12 months. Similar to Fama and French's (1996) size and book-to-market factors, Liu constructs a mimicking liquidity factor, LIQ, as the return difference between a low-liquidity portfolio (containing stocks with high LM12) and a high-liquidity portfolio (containing stocks with low LM12), and develops a liquidity-augmented CAPM (LCAPM). He shows that firms with greater liquidity risk earn higher returns, indicating that investors require a liquidity premium to compensate for the higher liquidity risk. Furthermore, he demonstrates that his LCAPM can explain the anomalies associated with firm size, book-to-market, cash-flow-to-price, earnings-to-price, dividend yield, and long-run price reversals. Because of its explanatory power on the cross-section of stock returns, we use Liu's model to measure liquidity risk and the cost of equity capital for each of our sample stocks.

Consistent with our hypothesis, we find that the incidence of no trading decreases (implying lower latent costs of trading), liquidity risk is mitigated, and the cost of equity capital is reduced following stock splits. Further, the split announcement returns are correlated with improvements in both liquidity levels and liquidity risk. While firms with more frequent trading discontinuities benefit more from stock splits, those with daily trades benefit as well.[3] On average, liquidity improvements reduce the cost of equity capital by 17.3%, or 2.42% points per annum, suggesting that the economic benefits of stock splits are nontrivial.

It is worth pointing out that the prior literature suggests two possible reasons for the positive effects of splits on prices. The first is liquidity improvement, given the positive value–liquidity relation (e.g., Amihud and Mendelson, 1986). Alternatively, the positive price reaction could be explained by Brennan and Copeland's (1988) signaling proposition, which is based on the premise that splits raise transaction costs and hence serve as a costly signal of managers' private information. Our findings are consistent with the first explanation, and do not support the basis of Brennan and Copeland's (1988) signaling model because latent trading costs decline rather than increase after stock splits.

The rest of our study is organized as follows. Section 2 formally proposes the trading continuity improvement hypothesis for firms' stock split decisions. Section 3 presents Liu's (2006) liquidity measure. Section 4 discusses our sample selection and the characteristics of the sample firms. Section 5 presents empirical results of the effect of stock splits on liquidity. Section 6 presents evidence that stock splits lead to liquidity risk reduction, resulting in a lower cost of equity capital. Section 7 investigates whether the split announcement returns are correlated with the liquidity improvements. Section 8 contains our conclusions.

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[1] We are indebted to the referee for directing us to this line of reasoning.

[2] Their finding is consistent with Admati and Pfleiderer (1988), who suggest that, to camouflage their trades, informed traders would follow as uninformed trades increase.

[3] For those firms with trades every day, the liquidity risk reduction following the split is significant. Although Liu's LM12 emphasizes trading discontinuity at the daily level and does not address intraday trading discontinuity (e.g., on an hourly basis), we conjecture that the liquidity risk reduction could be due to improvement in trading continuity at the intraday level.

2. The trading continuity improvement hypothesis

Uninformed traders play an important role in determining stock liquidity. As Stoll (1989) points out, there are three components of market-making costs—order processing costs, inventory holding costs, and adverse information costs. The last component represents market makers' losses from trading with informed investors, which can be covered by gains from trading with uninformed investors. Thus, more uninformed trading could reduce both market makers' inventory holding costs and adverse information costs. This implies that managers can reduce trading costs for shareholders and improve their stock's liquidity if there is a corporate policy that can be used to attract more uninformed traders to participate in trading.

Stock splits appear to be such a corporate policy in that they can attract more uninformed traders for the following reasons. As Fama, Fisher, Jensen, and Roll (1969) point out, a stock split is usually preceded by a significant increase in stock price. By engaging in a split to lower the price level, managers can effectively make buying shares easier for small investors. Lakonishok and Lev (1987) also argue that stock splits are executed by firms that have enjoyed unusual growth in both earnings and stock prices, and that the main objective of the split appears to be to return the stock price to a "normal" range in the wake of the unusual growth. Similarly, So and Tse (2000) address the sociological aspects of maintaining a stable target-price habit, and argue that one of the principal reasons for stock splits is to conform to the market norm. As Copeland (1979) suggests, there might be a certain clientele that prefers to buy stocks at a certain (lower) price range.[4] This clientele is usually thought to be uninformed or small investors (see also Easley, O'Hara, and Saar, 2001). Harris (1996) and Angel (1997) suggest that another clientele that could be attracted by a stock split might be traders, who find it profitable to supply liquidity via limit orders due to split-induced increases in (proportional) tick size. Using NYSE non-public data, Lipson (1999) indeed shows that the use of limit orders slightly increases following the splits and that the realized execution cost of limit orders declines substantially. However, he finds that the realized execution cost for market orders increases.

Furthermore, managers could use stock splits to attract more analysts to follow their stocks. According to Brennan and Hughes (1991), splits could create incentives for brokerage houses to produce more information on split firms. Similarly, Schultz (2000) argues that splits give stockbrokers greater incentives to promote the stocks (see also Kadapakkam, Krishnamurthy, and Tse, 2005). Improved information production and promotion of the split firms could attract more investors to participate in stock trading.

In view of these reasons, we propose the trading continuity improvement hypothesis to explain firms' stock split decisions. It posits that firms facing some possibility of trading discontinuity can use stock splits to attract more uninformed trading. This enables market makers to provide liquidity services at lower cost following the splits. With lower trading costs, investors' propensity to trade increases. Thus, while the split-induced increase in uninformed trading contributes to trading continuity, the resulting lower trading costs further improve trading continuity after the splits.

Furthermore, as the liquidity environment improves, stock prices should become more resilient and less vulnerable to shocks to market liquidity. Consequently, investors face reduced liquidity risk and require a lower liquidity premium which, in turn, lowers the cost of equity capital for the firm, and the value of the firm should increase. Indeed, as many studies have documented, the market reacts positively to stock splits; see, e.g., Grinblatt, Masulis, and Titman (1984), Lamoureux and Poon (1987), and Ikenberry, Rankine, and Stice (1996).

To test our hypothesis, we focus on the following issues. First, do stock splits improve liquidity in terms of greater trading continuity? Second, do stock splits reduce the liquidity risk that investors face and lower firms' cost of equity capital? Third, given the importance of liquidity in asset pricing (see Amihud, Mendelson, and Pedersen, 2005), are split announcement returns related to improvements in both liquidity levels and liquidity risk?

In the following sections, we describe how we measure liquidity before and after the splits, collect our split sample, and conduct our analyses to address the above issues.

3. Measuring stock liquidity

Based on the premise that a greater incidence of no trading implies higher latent costs of trading and that non-trading reflects illiquidity, we measure stock liquidity using Liu's (2006) LMx, the standardized turnover-adjusted number of days with zero trading volume over the prior x months. Specifically, Liu formulates his LMx as

$$LMx = \left[\text{Number of zero daily volumes in prior } x \text{ months} + \frac{1/(x\text{-month turnover})}{\text{Deflator}} \right] \times \frac{21x}{\text{NoTD}},$$

where "x-month turnover" is the stock's turnover in the prior x months calculated as the sum of daily turnover over the prior x months (daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day), NoTD is the total number of trading days in the market over the prior x months, and Deflator is chosen such that

$$0 < \frac{1/(x\text{-month turnover})}{\text{Deflator}} < 1$$

for all sample stocks (for example, Liu chooses a deflator of 11,000 in constructing his LM12).

Liu (2006) shows that LMx reflects multiple dimensions of liquidity, is highly correlated with conventional liquidity measures such as bid-ask spread, turnover, and price impact measures, and places particular emphasis on

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[4] Interestingly, analyzing mutual fund share splits, Fernando, Krishnamurthy, and Spindt (1999) show that, relative to non-splitting matched funds, split funds experience significant increases in shareholders.

trading discontinuity. The measure uses the number of zero daily trading volumes over the prior x months to capture the intuition that the absence of trading in a security indicates its degree of illiquidity. As expected, Liu shows that smaller firms and firms with high book-to-market equity ratios, which tend to be less liquid, have high LM12. Also, compared to firms with low LM12, there is a significant liquidity premium associated with firms with high LM12.

While LMx emphasizes trading discontinuity at the daily level, trading discontinuity could also occur at the intraday level (e.g., on an hourly basis). Unfortunately, the measure does not explicitly take into account intraday trading discontinuity. As Liu (2006, p. 636) points out, "LMx uses the pure number of zero daily trading volumes over the prior x months to identify the least liquid stocks, but it relies on turnover to distinguish the most liquid among frequently traded stocks as classified by the pure number of zero trading volumes." Thus, for stocks that trade every day, it is possible that stock splits attract more trades (Schultz, 2000; Easley, O'Hara, and Saar, 2001), but that turnover decreases (Copeland, 1979; Lamoureux and Poon, 1987). That is, following the splits, there could be more trades, but the average trade size might not increase proportionally with the split factor, resulting in a lower turnover. In this case (for the more liquid firms with $LMx < 1$), since LMx is essentially determined by 1/turnover, it might not show a split-induced improvement in intraday trading continuity, indicating that the measure has its limitations. Nevertheless, with zero-volume days as its main component, LMx would sufficiently capture severe illiquidity, as manifested in non-trading.

4. Data

To test the trading continuity improvement hypothesis, we use a sample of 3,721 stock splits that occur during the 30-year period from 1975 to 2004. We identify this sample by searching through the Center for Research in Security Prices (CRSP) files for ordinary single-class common stocks with a split factor of one or higher, a pre-split price of $10 or above, and the availability of both firm size (i.e., pre-split market value of equity) and the book value of equity on the Compustat files over the 1975–2004 period. Furthermore, we require each sample firm to have at least one year of daily trading volume data, both before and after its stock split, available on the CRSP files for computing our liquidity measure, LM12. The split factor is the number of additional shares issued per existing share. For example, a split factor of one means a two-for-one split, i.e., investors receive one additional share for every old share they hold. To be included in our sample, a stock must have a share code of 10 or 11 and be a single-class stock, with the CRSP Factor to Adjust Price (FACPR) equal to or greater than one and equal to the CRSP Factor to Adjust Shares Outstanding (FACSHR). We require firm size and book equity so that we can determine in which firm size quartile and B/M (book-to-market equity ratio) quartile each split firm is. As we show in the next section, for each split firm, we choose a comparable (benchmark) firm, which is a non-split firm whose price at the end of month -1 (relative to the declaration month) is closest to that of the split firm among all non-split firms in the same size quartile and B/M quartile as the split firm.

Of the 3,721 splits, 2,109 are for NYSE/AMEX stocks over the 1975–2004 sample period, and the remaining 1,612 are for Nasdaq stocks over the 1985–2004 sample period. A total of 3,399, or 91.3%, have a split factor equal to one; 269, or 7.2%, have a split factor greater than one and less than or equal to two; and the remaining 53, or 1.5%, have a split factor above two. The highest split factor in our sample is 9.

In terms of pre-split liquidity, denoted as $preLM$12, about 28.7%, or 1,069 firms, have $preLM$12 $\geq$ 1, and the remaining 71.3%, or 2,652 firms, have $preLM$12 < 1. While the firms in the former subsample have at least one zero-volume day in the year prior to the splits, the firms in the latter subsample have trades every day. Our trading continuity improvement hypothesis postulates that, for firms with some possibility of trading discontinuity, managers could use stock splits to improve their stock's illiquidity. This suggests that the effects of stock splits on liquidity improvements would be greater for less liquid firms. For this reason, we carry out our analyses for the full sample as well as for the $preLM$12 subsamples.

Table 1 reports the mean and the median of pre-split firm characteristics for the full sample and for each subsample by stock exchange and by $preLM$12. For the full sample, the average pre-split price, measured at day -5 relative to the declaration date, is $58.23, and the average split factor is 1.11, i.e., shareholders receive 1.11 additional shares on average for every pre-split share they have. The average firm size prior to the splits is $4.55 billion. The average book-to-market equity ratio is 0.373, suggesting that the sample firms tend to have relatively high growth opportunities.

While the pre-split average prices and split factors are similar between the NYSE/AMEX and the Nasdaq subsamples, the Nasdaq stocks are generally smaller in terms of firm size. Further, the Nasdaq stocks also have an average book-to-market equity ratio of 0.287, versus 0.438 for the NYSE/AMEX stocks. Due to the distinctions in firm characteristics and the differences in how trading volumes are reported, we control for the effect of the listing exchange while examining the effects of stock splits on liquidity.

Relative to firms with $preLM$12 < 1, firms with $preLM$12 $\geq$ 1 are, on average, smaller ($0.43 billion vs. $6.21 billion) and have a higher B/M (0.502 vs. 0.321). Furthermore, the pre-split number of shareholders is smaller as well (2,645 vs. 26,792). While the average firm in the $preLM$12 < 1 subsample splits their shares at a price of $65.57, the less liquid firms with $preLM$12 $\geq$ 1 tend to split their shares at $40.03.

Table 2 reports changes in firm characteristics from before to after stock splits. For the full sample, the split lowers the average post-split share price, measured at day +5 relative to the ex-distribution date, to $29.94 from $58.23 prior to the splits. Consistent with the hypothesis that stock splits attract new investors (Lamoureux and

Table 1
Pre-split sample characteristics.

This table reports the mean (median) values of firm characteristics prior to the split. Split factor (*splitfactor*) is the number of additional shares per old share issued. Pre-split share price (*preprc*) is the closing price or bid/ask average from CRSP at day −5 relative to the stock split declaration date. Pre-split market capitalization (*presz*) is market value in millions, and the pre-split book-to-market ratio (*prebm*) is the ratio of book equity value (Compustat item 60+item 74) to market value of equity at day −5 relative to the declaration date. Pre-split investor base (*preinvestor*) is the number of shareholders (in 1,000 s, Compustat item 100) before the declaration month. Pre-split institutions (*preinstitution*) is the number of 13f institutions that hold stocks, and pre-split institutional ownership (*preinslown*) is 13f institutions' stock ownership from Thomson Financial in the calendar quarter before the split declaration. Pre-split turnover (*preturn*) is the average daily turnover from month −12 to month −1 relative to the declaration month. The daily turnover is the ratio of the number of shares traded to the number of shares outstanding at the end of the day from CRSP. The pre-split number of zero daily volumes (*prezerovol*) is the number of days with zero trading volume from CRSP from month −12 to month −1 relative to the declaration month. The pre-split price run-up (*prerunup*) is the price run-up from day −120 to day −2 relative to the declaration date. We report the mean (median) values for the whole sample, the subsamples by exchange, and the subsamples by pre-split trading discontinuity (*preLM*12).

	Whole sample ($N = 3{,}721$)	NYSE/AMEX ($N = 2{,}109$)	Nasdaq ($N = 1{,}612$)	$preLM12 \geq 1$ ($N = 1{,}069$)	$preLM12 < 1$ ($N = 2{,}652$)
splitfactor	1.112	1.119	1.104	1.160	1.093
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
preprc	58.232	61.101	54.479	40.027	65.570
	(50.250)	(54.250)	(45.395)	(36.000)	(57.400)
presz (10^6)	4550.009	5604.959	3169.804	431.226	6210.257
	(640.845)	(959.495)	(415.216)	(107.712)	(1259.089)
prebm	0.373	0.438	0.287	0.502	0.321
	(0.291)	(0.362)	(0.194)	(0.428)	(0.243)
preinvestor (10^3)	20.646	32.018	4.046	2.645	26.792
	(2.766)	(5.048)	(1.051)	(1.247)	(4.148)
preinstitution	119.614	156.986	76.783	20.126	156.622
	(72.000)	(105.000)	(47.000)	(13.000)	(107.000)
preinslown	0.463	0.479	0.444	0.228	0.550
	(0.467)	(0.497)	(0.411)	(0.180)	(0.557)
preturn (10^{-3})	6.332	3.356	10.227	2.448	7.898
	(3.007)	(2.312)	(6.082)	(1.398)	(3.883)
prezerovol	9.956	4.731	16.792	34.557	0.039
	(0.000)	(0.000)	(0.000)	(12.000)	(0.000)
prerunup (%)	40.262	23.760	61.853	42.950	39.179
	(20.698)	(15.558)	(30.129)	(21.382)	(20.294)

Poon, 1987; Maloney and Mulherin, 1992; Mukherji, Kim, and Walker, 1997), the average number of shareholders significantly increases from 20,646 before the split to 24,982 after the split. The average number of institutional investors increases as well, from 119 to 131. However, there is a slight decrease in average institutional share ownership, from 46.3% to 45.3%. These results suggest that while stock splits attract new investors, existing shareholders appear to sell a portion of the shares they receive pursuant to the stock splits. Consequently, there are more investors holding the shares, on average, but the proportionate holding per investor seems to decline following the splits.

The average increase in investor base is particularly notable for the subsample of firms with *preLM*12 ≥ 1, which changes from 2,645 pre-split shareholders to 6,893 post-split shareholders, a 160% increase! The *preLM*12 < 1 subsample increases from 26,792 pre-split shareholders to 31,150 post-split shareholders, a 16% increase. In the sections that follow, we will address the extent to which the increase in investor base following the splits contributes to the trading continuity improvement and to liquidity risk reduction. Also, consistent with Merton (1987), Mukherji, Kim, and Walker (1997) find that split announcement returns are positively related to the increase in the investor base. We will control for the increase in the investor base as well in testing our

hypothesis that split announcement returns are correlated with liquidity improvements.

Table 2 also reports changes in liquidity based on Roll's (1984) spread, the Gibbs estimate of Roll's spread as suggested by Hasbrouck (2005), Amihud's (2002) price impact measure, and average daily turnover.[5] For Roll's spread, Amihud's impact measure, and turnover, the pre-split estimates are obtained from month −12 to month −1 relative to the declaration month, and the post-split estimates are from month 1 to month 12 relative to the ex-distribution month. Hasbrouck (2005) suggests that Gibbs estimate might not be reliable if the observation number of daily returns used in estimation is less than 50. Hence, if the number of pre-split (post-split) return observations is less than 50, we use the Gibbs estimate from one year before (after) the split year.

On average, both Roll's spread and the Gibbs estimate of Roll's spread increase significantly following the splits, which is consistent with Copeland (1979), Conroy, Harris, and Benet (1990), Easley, O'Hara, and Saar (2001), and Gray, Smith, and Whaley (2003). However, we find that average daily turnover is higher following the splits,

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[5] For Gibbs estimate of Roll's spread, we obtain the pre- and post-split estimates from Professor Hasbrouck's website: http://pages.stern.nyu.edu/~jhasbrou/.

Table 2
Changes in sample characteristics after stock splits.

This table reports mean (median) changes in sample characteristics following the splits. Pre-split *prc* is the closing price or bid/ask average from CRSP at day −5 relative to the stock split declaration date, and post-split *prc* is at day 5 relative to the ex-distribution date. *investor* is the number of shareholders (in 1,000 s, Compustat item 100); the pre-split estimate is obtained before the declaration month and the post-split estimate after the ex-distribution month. *institution* is the number of 13f institutions, and *inslown* is 13f institutions' stock ownership from Thomson Financial; the pre-split estimate is obtained in the calendar quarter before the declaration and the post-split estimate after the ex-distribution. *turnover* is the average ratio of daily trading volume to the number of shares outstanding. For 1/(12-*month turnover*), the 12-*month turnover* is the sum of daily turnover over 12 months. *Roll's Spread* is measured as $\sqrt{-\text{cov}(r_{i,t}, r_{i,t-1})}$. Following Harris (1990), we set *Roll's spread* = 0 if $\text{cov}(r_{i,t}, r_{i,t-1}) > 0$. Following Hasbrouck (2005), we also provide *Gibbs* estimates of Roll's spread. *Amihud's IM* is $|r_{i,t}|/(p_{i,t} \times vol_{i,t})$, where $r_{i,t}$ is the daily return, $p_{i,t}$ is the closing price or bid/ask average, and $vol_{i,t}$ is daily volume. For *turnover*, 1/(12-*month turnover*), *Roll's spread*, and *Amihud's IM*, the pre-split estimates are obtained from month −12 to month −1 relative to the declaration month and the post-split estimates are from month 1 to month 12 relative to the ex-distribution month. 12-*month turnover* is the sum of daily turnover over the 12 months. *Stat. test* reports the *t*-value (*p*-value of the signed rank tests) for testing whether the mean (median) difference between post- and pre-split values is equal to zero.

	Whole sample			Subsample of *preLM*12 ≥ 1			Subsample of *preLM*12 < 1		
	Pre-Split	Post-Split	Stat. test	Pre-Split	Post-Split	Stat. test	Pre-Split	Post-Split	Stat. test
prc	58.232	29.940	−170.352[a] ***	40.027	20.739	−81.460[a] ***	65.570	33.648	−151.515[a] ***
	(50.250)	(26.250)	(<.0001)[b]	(36.000)	(19.000)	(<.0001)[b]	(57.400)	(29.750)	(<.0001)[b]
investor (10³)	20.646	24.982	19.359[a] ***	2.645	6.893	9.096[a] ***	26.792	31.150	17.093[a] ***
	(2.766)	(3.500)	(<.0001)[b]	(1.247)	(1.500)	(<.0001)[b]	(4.148)	(5.357)	(<.0001)[b]
institution	119.614	131.424	41.343[a] ***	20.126	24.501	23.090[a] ***	156.622	172.120	37.925[a] ***
	(72.000)	(83.000)	(<.0001)[b]	(13.000)	(16.000)	(<.0001)[b]	(107.000)	(123.000)	(<.0001)[b]
inslown	0.463	0.453	−2.838***	0.228	0.234	5.451***	0.550	0.536	−5.549***
	(0.467)	(0.464)	(0.9810)	(0.180)	(0.188)	(<.0001)	(0.557)	(0.548)	(<.0001)
turnover (10⁻³)	6.332	6.859	3.506***	2.448	3.361	5.431***	7.898	8.269	1.859*
	(3.007)	(3.072)	(<.0001)	(1.398)	(1.506)	(<.0001)	(3.883)	(3.928)	(0.0474)
1/(12-*month turnover*)	2.230	2.147	−2.546**	4.311	3.964	−3.211***	1.391	1.414	1.721*
	(1.316)	(1.286)	(0.0330)	(2.827)	(2.634)	(0.0010)	(1.020)	(1.007)	(0.6985)
Roll's Spread (%)	0.319	0.421	9.963***	0.656	0.682	1.054	0.183	0.316	12.707***
	(0.000)	(0.000)	(<.0001)	(0.236)	(0.342)	(0.0168)	(0.000)	(0.000)	(<.0001)
Gibbs (%)	0.531	0.706	21.832***	0.815	0.978	7.371***	0.414	0.594	26.774***
	(0.356)	(0.529)	(<.0001)	(0.494)	(0.707)	(<.0001)	(0.324)	(0.487)	(<.0001)
Amihud's IM (10⁻⁷)	4.954	3.159	−1.998*	16.469	10.372	−1.951*	0.313	0.251	−2.998***
	(0.206)	(0.111)	(<.0001)	(4.876)	(2.730)	(<.0001)	(0.064)	(0.038)	(<.0001)

***, **, * Significant at the 1%, 5%, and 10% level, respectively, for the *t*-tests.

[a] The *t*-value is based on the difference in the log post-split versus log pre-split values.

[b] The *p*-value of the signed rank test is based on the difference in the log post-split versus log pre-split values.

especially for the less liquid subsample of firms with *preLM*12 ≥ 1. For the subsample of firms with *preLM*12 < 1, the evidence of turnover increase is weak. Consistent with Copeland (1979) and Lamoureux and Poon (1987), we find that the average turnover decreases after the splits for our NYSE/AMEX subsample, although it increases for our Nasdaq subsample. Similarly, Amihud's (2002) illiquidity measure shows a slight decrease in the price impact of trades following the splits. Thus, based on turnover and Amihud's illiquidity measure, there is weak evidence that stock splits improve liquidity.

In the next section, we present the results based on *LM*12. As Liu (2006) argues, it can capture multiple dimensions of liquidity and should thus be able to better reflect split-induced liquidity changes.

5. Liquidity and the split factor

5.1. Evidence of liquidity improvement

We use Liu's (2006) *LM*12, the standardized turnover−adjusted number of days with zero trading volume over 12 months, to measure liquidity. To show the effects of stock splits on liquidity, we use two approaches. The

first is to compare each sample firm's pre-split *LM*12, measured over month −12 through month −1 relative to the split declaration month, and the post-split *LM*12, measured over month +1 through month +12 relative to the ex-distribution month. The second approach compares each sample firm to a benchmark firm, which is a non-split firm whose price at the end of month −1 (relative to the declaration month) is closest to that of the split firm among all non-split firms (ordinary common stocks) in the same size quartile and B/M quartile as the split firm. For each split firm, we define non-split firms as those firms that have no stock split in the window of two years before the split firm's split declaration date through two years following the split firm's split distribution. Following Fama and French (1993), we obtain the quartile cutoff points of firm size and of book-to-market equity ratio based on NYSE stocks. This second approach allows us to control for marketwide liquidity changes. Since the two approaches produce very similar results, we report in Table 3 only the results of the benchmark-adjusted approach, and give a brief summary of the results of the first approach below.

The pre-split average *LM*12 is 9.94, indicating that the average split firm has 9.94 turnover-adjusted no-trade days in the year prior to the split. The post-split average

Table 3
The effect of stock splits on trading continuity.

This table reports the effects of stock splits on trading discontinuity, measured by Liu's (2006) $LM12$, the standardized turnover-adjusted number of zero daily trading volumes over 12 months, which is defined as

$$LM12 = \left[\text{Number of zero daily volumes in 12 months} + \frac{1/(12\text{-month turnover})}{\text{Deflator}} \right] \times \frac{21 \times 12}{\text{NoTD}}.$$

Number of zero daily volumes in 12 *months* is the number of days with zero trading volume over the 12 months. 12-*month turnover* is the sum of daily turnover over the 12 months. *Deflator* is set at 11,000 such that $0 < \frac{1/(12\text{-month turnover})}{\text{Deflator}} < 1$ for each stock (Liu, 2006). *NoTD* is the number of trading days in the market over the 12 months. Pre-split measure (*preLM12*), post-split measure (*postLM12*), and change in LM12 (*chgLM12*) are the benchmark-adjusted measures (the difference between a split firm's $LM12$ and that of its benchmark firm). Pre-split $LM12$ is from month -12 to month -1 relative to the stock split declaration month, and post-split $LM12$ is from month 1 to month 12 relative to the stock split ex-distribution month. The excess change in trading continuity (*chgLM12*) is the difference between the benchmark-adjusted *postLM12* and *preLM12*. For each split firm, we choose a benchmark firm that is a non-split firm whose price at the end of month -1 (relative to the declaration month) is closest to that of the split firm among all non-split firms in the same size quartile and B/M quartile as the split firm. The *t*-values in parentheses assume independence across firms; and in the brackets are the *t*-values with autoregressive error correction standard error, assuming that the errors (i.e., the deviations from the mean) of the variable estimates follow an AR(1) process.

	Whole sample	Subsample of *preLM12* ≥ 1	Subsample of *preLM12* < 1	Subsample of *splitfactor* = 1	Subsample of *splitfactor* = (1,2)	Subsample of *splitfactor* > 2
preLM12	0.109	8.396***	−2.898***	−0.248	3.210	8.245*
	(0.21)	(4.73)	(−9.82)	(−0.46)	(1.36)	(1.95)
	[0.19]	[4.47]	[−9.82]	[−0.45]	[1.33]	[1.41]
postLM12	−4.765***	−9.219***	−3.149***	−4.529***	−7.083***	−8.602*
	(−10.11)	(−5.99)	(−10.14)	(−9.41)	(−3.25)	(−2.00)
	[−9.63]	[−5.77]	[−10.09]	[−8.81]	[−3.34]	[−1.95]
chgLM12	−4.874***	−17.615***	−0.251**	−4.281***	−10.294***	−16.848***
	(−15.39)	(−16.94)	(−2.26)	(−13.83)	(−6.07)	(−3.36)
	[−13.92]	[−15.95]	[−2.34]	[−12.65]	[−6.58]	[−2.82]
Proportion of stocks with *chgLM12* < 0	0.513	0.812	0.404	0.506	0.567	0.705
(*p*-value)[a]	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

***, **, * Significant at the 1%, 5%, and 10% level, respectively, for the *t*-tests.

[a] The *p*-value is based on the signed rank test for the null hypothesis that *chgLM12* = 0.

$LM12$ is 4.94, suggesting that the split firms, on average, experience a decrease of five no-trade days following the splits. The average change in $LM12$ (*chgLM12*) is significantly different from zero and about 62.9% of the sample firms experience a decrease in turnover-adjusted no-trade days. The correlations between *chgLM12* and the changes in Roll's spread and between *chgLM12* and the changes in the Gibbs estimate of Roll's spread are 0.13 and 0.15, respectively. Both correlations are significant at the 1% level. The correlation between *chgLM12* and the changes in Amihud's illiquidity measure is stronger at 0.20. These correlations suggest that firms with greater reduction in no-trade days tend to experience a larger decline in Roll's spread and in the price impact of trades as well.

Table 3 shows that the pre-split $LM12$ of the sample firms is, on average, insignificantly different from that of the benchmark firms, indicating that prior to stock splits, the degree of trading discontinuity of split firms is similar to that of comparable non-split firms. Following the splits, the average $LM12$ of the sample firms is lower than that of the benchmark firms by 4.76 turnover-adjusted zero-volume days, which is significantly different from zero. This suggests that the split firms have a lower incidence of no trading than the benchmark firms in the post-split period. Furthermore, the sample firms' excess change in $LM12$ from the pre- to post-split period (i.e., the difference between the post-split benchmark–adjusted $LM12$ and the pre-split benchmark–adjusted $LM12$) shows a sig-

nificant decrease of 4.87 turnover-adjusted no-trade days. The results suggest that liquidity improves following stock splits, which is consistent with our trading continuity improvement hypothesis.

We next use $LM1$ (the standardized turnover-adjusted number of zero daily trading volumes over one month) to illustrate and compare the pattern of trading discontinuity for the split firms and their benchmark firms. Specifically, Fig. 1 contrasts the pre-split average $LM1$ of both samples (from month -24 through month -1 relative to the split declaration month) and the post-split average $LM1$ (from month $+1$ through month $+24$ relative to the ex-distribution month). It illustrates that the post-split average $LM1$ of the split firms is lower than their pre-split average $LM1$. It also shows that the post-split average $LM1$ of the split firms is lower than that of their benchmark firms. Furthermore, the picture reveals that the effects of stock splits on reducing trading discontinuity are long term, lasting at least 24 months after the splits. Therefore, the liquidity improvement following stock splits is not a short-term or a transitory phenomenon.

Table 3 also provides the subsample results by pre-split liquidity. The 1,069 sample firms with *preLM12* ≥ 1 have 8.39 more turnover-adjusted no-trade days, on average, than their benchmark firms before the splits; after the splits, they have 9.21 fewer turnover-adjusted no-trade days than their benchmark firms. Thus, on average, the subsample firms experience a significant excess reduction
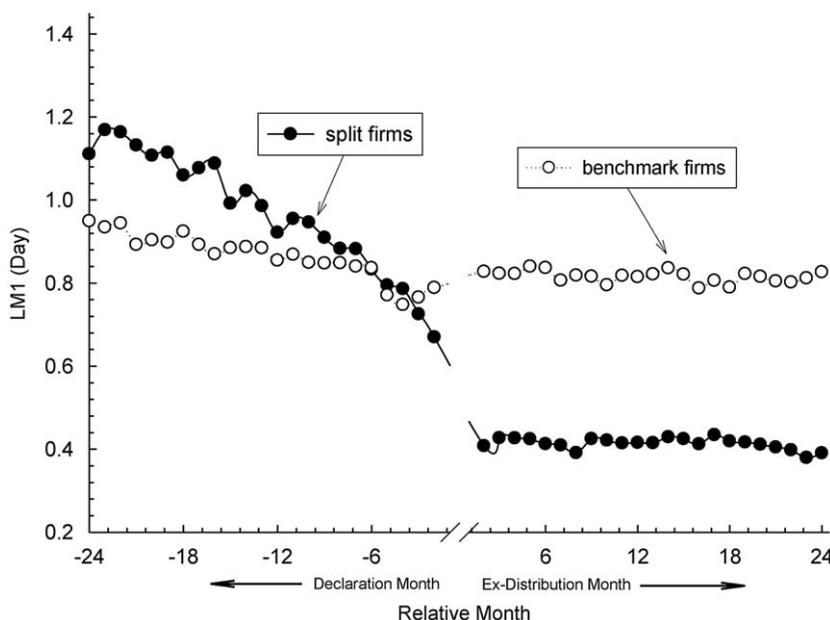
Fig. 1. Pre-split and post-split *LM*1 of the split firms vs. their benchmark firms.
This figure plots the pre-split average *LM*1 from month −24 to −1 relative to the stock split declaration month and the post-split average *LM*1 from month 1 to 24 relative to the ex-distribution month for the split firms and their benchmark firms. For each split firm, we choose a benchmark firm that is a non-split firm whose price at the end of month −1 (relative to the declaration month) is closest to that of the split firm among all non-split firms in the same size quartile and B/M quartile as the split firm. *LM*1 is the standardized turnover-adjusted number of zero daily trading volumes over one month (Liu, 2006). The estimate is

$$LM1 = \left[Number\ of\ zero\ daily\ volumes\ in\ one\ month \right.$$
$$\left. + \frac{1/(one\text{-}month\ turnover)}{Deflator} \right] \times \frac{21 \times 1}{NoTD}.$$

Number of zero daily volumes in one month is the number of days with zero trading volume over one month. *One-month turnover* is the sum of daily turnover over the month. Daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day. *Deflator* is set at 480,000 such that

$$0 < \frac{1/(one\text{-}month\ turnover)}{Deflator} < 1$$

for each stock (Liu, 2006). *NoTD* is the number of trading days in the market over the month.

of 17.61 (t-value $= -16.94$) turnover-adjusted no-trade days, compared to their counterparts.

Similarly, the average firm in the $preLM12 < 1$ subsample experiences a significant excess reduction of 0.25 (t-value $= -2.26$) in *LM*12 following the splits, relative to their benchmark firms. Thus, the more actively traded subsample also shows a significant reduction in trading discontinuity following the splits.

We also examine the subsample results by split factor. As the split factor increases from one to between one and two, and then to higher than two, the average number of turnover−adjusted no-trade days prior to the splits rises from 8.92 to 17.99, and then to 34.60, respectively. The numbers imply that firms appear to choose a higher split factor when their stocks face more frequent trading discontinuities.

On average, following the splits, the sample firms with a split factor equal to one experience an excess reduction of 4.28 days of turnover-adjusted no-trade days (excess with respect to their benchmark firms). The excess reduction is more pronounced—an average decrease of 10.29 days—for the sample stocks with a split factor

between one and two, and the excess reduction further increases to 16.84 days for the sample stocks with a split factor greater than two. The excess reductions in *LM*12 for the three groups are all statistically significant. The results suggest that firms choosing a higher split factor seem to experience more trading continuity improvement following the splits.

Thus, our results from the subsample analyses are consistent with the trading continuity improvement hypothesis. We next use cross-sectional regression analyses to further investigate whether pre-split trading discontinuity is one of the determinants of the split factor, and also to check the robustness of our finding that choosing a higher split factor leads to a greater trading continuity improvement.

5.2. Is pre-split liquidity a determinant of the split factor?

Our trading continuity improvement hypothesis argues that firms whose stocks have higher *LM*12, i.e., a greater incidence of no trading, could use a higher split factor to

attract more trading from uninformed investors. The hypothesis thus predicts that, ceteris paribus, the split factor is positively related to pre-split $LM12$.

Lakonishok and Lev (1987) and So and Tse (2000) argue that managers choose a split factor to return the price level to a "preferred" range. This implies that the higher the pre-split price, the higher the split factor must be to return the price level to a certain range. Furthermore, Dyl and Elliott (2006) argue that lower share prices are a characteristic of firms owned by so-called small investors, and that higher share prices are a characteristic of large firms. Their argument suggests that, holding other things constant, large firms would choose a smaller split factor.

To test our hypothesis that pre-split liquidity is a determinant of the split factor, we use the following regression model:

$$splitfactor_i = \alpha_0 + \alpha_1 preLM12_i + \alpha_2 lnpreprc_i + \alpha_3 lnpresz_i$$
$$+ \alpha_4 lnprebm_i + \alpha_5 prerunup_i + \alpha_6 lnpreinvestor_i$$
$$+ \alpha_7 lnpreinslown_i + \alpha_8 exchdummy_i + e_i \quad (1)$$

The dependent variable, $splitfactor$, is the number of additional shares issued per old shares. The model allows us to test the relation between $splitfactor$ and $preLM12$, which is the pre-split $LM12$ from month -12 to month -1 relative to the declaration month, while controlling for the following variables: $lnpreprc$, the log value of pre-split stock price; $lnpresz$, the log value of pre-split market capitalization; $lnprebm$, the log value of pre-split book-to-market equity ratio at day -5 relative to the stock split declaration date; $prerunup$, the pre-split stock price run-up from days -120 to -2 before the split declaration day (see Grinblatt, Masulis, and Titman, 1984); $lnpreinvestor$, the log value of the pre-split number of shareholders before the declaration month; $lnpreinslown$, the log value of the pre-split institutional share ownership in the calendar quarter before the split declaration; and $exchdummy$, an indicator variable for the exchange listing, which is equal to one if the sample stock is listed on Nasdaq and zero otherwise. We have also considered $lnpreinsl$, the log value of the number of institutional investors, and found that it has no significant effect. Furthermore, it has a correlation of 0.91 with log firm size, $lnpresz$. To avoid multicollinearity, we do not include it in our set of control variables. Of the 3,721 sample firms, 3,164 have all these control variables available for the regression analysis. Table 4 reports the regression results.

According to model 1 in the table, the split factor is significantly and positively related to $preLM12$. Thus, the regression results are consistent with our hypothesis that, ceteris paribus, firms choose a higher split factor when their stocks face more frequent trading discontinuities.

Model 1 also shows that the split factor is significantly and positively related to the pre-split price level and the book-to-market equity ratio, but negatively related to firm size, the pre-split price run-up, and institutional share ownership. Thus, holding other things constant, larger firms and firms with higher institutional ownership tend

Table 4
Cross-sectional analysis of the split factor.

This table reports the cross-sectional relation between the split factor ($splitfactor$, the number of additional shares per old share issued) and pre-split liquidity ($preLM12$, the pre-split $LM12$ from month -12 to month -1 relative to the declaration month). For the subsample relations, we set $preLM12\_D1 = preLM12$ if $preLM12 \geq 1$, otherwise $preLM12\_D1 = 0$; and $preLM12\_D0 = preLM12$ if $preLM12 < 1$, otherwise $preLM12\_D0 = 0$. We control for firm characteristics, including $lnpreprc$, the log pre-split stock price; $lnpresz$, the log pre-split market capitalization; $lnprebm$, the log pre-split book-to-market equity ratio at day -5 relative to the declaration date; $prerunup$, the pre-split price run-up from day -120 to day -2 relative to the declaration date; $lnpreinvestor$, the log pre-split investor base before the declaration month; $lnpreinslown$, the log pre-split institutional share ownership in the calendar share quarter before the split declaration; and $exchdummy$, an indicator variable equal to one if the sample stock is listed on the Nasdaq, and zero otherwise. The t-values are given below the coefficient estimates.

Model	Dependent variable: $splitfactor$	
	1	2
$preLM12$	**0.0016*****	
	(3.71)	
$preLM12\_D1$		**0.0017*****
		(3.82)
$preLM12\_D0$		**0.0687**
		(1.39)
$lnpreprc$	0.6292***	0.6292***
	(25.21)	(25.22)
$lnpresz$	−0.0890***	−0.0879***
	(−9.44)	(−9.30)
$lnprebm$	0.0274**	0.0274**
	(2.48)	(2.47)
$prerunup$	−0.0354***	−0.0354***
	(−3.33)	(−3.33)
$lnpreinvestor$	0.0022	0.0020
	(0.32)	(0.30)
$lnpreinslown$	−0.1109***	−0.1108***
	(−9.20)	(−9.19)
$exchdummy$	0.0275	0.0281
	(1.41)	(1.45)
$intercept$	−0.8601***	−0.8699***
	(−10.23)	(−10.31)
Adj. R^2	0.1907	0.1910
N	3,164	3,164

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

to choose a lower split factor to maintain a higher target price level, which is consistent with Dyl and Elliott's (2006) observation noted above.

Model 2 in Table 4 examines the subsample relation between the split factor and pre-split liquidity. We set $preLM12\_D1 = preLM12$ if $preLM12 \geq 1$, otherwise $preLM12\_D1 = 0$; and $preLM12\_D0 = preLM12$ if $preLM12 < 1$, otherwise $preLM12\_D0 = 0$.

It follows that $preLM12 = preLM12\_D1 + preLM12\_D0$. The results indicate that the pre-split liquidity level is a determinant of the split factor only for the less liquid firms. The finding is reasonable because, for the firms that have trades every day, illiquidity is not an imminent problem. Consequently, for the $preLM12 < 1$ subsample, the pre-split liquidity level is not important in setting the split factor. Conversely, the less liquid firms, which face greater illiquidity, choose a higher split factor.

5.3. The relation between changes in liquidity and the split factor

If firms facing more frequent trading discontinuities tend to choose a higher split factor, does doing so lead to greater post-split liquidity improvement? To answer this question, we use the following cross-sectional regression analysis:

$$chgLM12_i = \beta_0 + \beta_1 splitfactor_i + \beta_2 preLM12_i + \beta_3 lnpreprc_i$$
$$+ \beta_4 lnpresz_i + \beta_5 lnprebm_i + \beta_6 prerunup_i$$
$$+ \beta_7 lnpreinvestor_i + \beta_8 lnchginvestor_i$$
$$+ \beta_9 lnpreinslown_i + \beta_{10} exchdummy_i + \delta_i \quad (2)$$

The dependent variable, $chgLM12$, is the difference between post- and pre-split $LM12$. While our focus is on the relation between $chgLM12$ and $splitfactor$, we are also interested in exploring which types of firms have more liquidity improvement from stock splits. In addition to the seven firm characteristic variables in Eq. (1), Eq. (2) includes $lnchginvestor$, the difference between the log post-split number of shareholders and the log pre-split number of investors, which allows us to check the extent to which the increase in investor base contributes to liquidity improvement. The equation also includes $preLM12$, with which we expect to measure the extent to which less liquid firms experience greater liquidity improvement.

Table 5 reports the regression results. Model 1 shows that $chgLM12$ is significantly and negatively related to $splitfactor$, indicating that a greater reduction in turnover-adjusted no-trade days is associated with a higher split factor. Model 2 shows that the relation holds for both subsamples by $preLM12$. Thus, consistent with the trading continuity improvement hypothesis, firms choosing a higher split factor experience greater liquidity improvement.

The regression results also reveal that $chgLM12$ is significantly and positively related to $lnpreprc$, but negatively related to $preLM12$, $lnpresz$, and $prerunup$. This suggests that larger firms, firms with a lower pre-split price level, and firms with a higher pre-split price run-up—and especially higher pre-split trading discontinuity—experience greater liquidity improvement following the splits.

However, contrary to our expectation, $lnchginvestor$ is insignificant, suggesting that, ceteris paribus, the extent of liquidity improvement is not related to the increase in investor base. Notice that the way we measure $chgLM12$ focuses on the long-term effects of trading—from one year before to one year after the splits—which excludes the effects of short-term trading from the split announcement month to the ex-distribution month. This focus allows us to minimize the short-term effects of information contained in the split announcement and any ex-distribution effects on trading. It is possible that the trading contributed by the increase in investor base occurs largely during this short period, and thus is not picked up by $chgLM12$.

6. Changes in liquidity risk

The trading continuity improvement hypothesis asserts that as stock splits attract more uninformed investors to participate in trading, market makers could

Table 5

Cross-sectional analysis of changes in liquidity.

This table reports the cross-sectional relation between $chgLM12$, the difference between log post-split $LM12$ and log pre-split $LM12$, and $splitfactor$. For the subsample relations, we set $splitfactor\_D1 = splitfactor$ if $preLM12 \geq 1$, otherwise $splitfactor\_D1 = 0$; and $splitfactor\_D0 = splitfactor$ if $preLM12 < 1$, otherwise $splitfactor\_D0 = 0$. We include a set of control variables, including $preLM12$, the log pre-split $LM12$ from month -12 to month -1 relative to the declaration month; $lnpreprc$, the log pre-split stock price; $lnpresz$, the log pre-split market capitalization; $lnprebm$, the log pre-split book-to-market equity ratio at day -5 relative to the declaration date; $prerunup$, the pre-split price run-up from day -120 to day -2 relative to the declaration date; $lnpreinvestor$, the log pre-split investor base before the declaration month; $lnpreinslown$, the log pre-split institutional share ownership in the calendar quarter before the split declaration; and $exchdummy$, an indicator variable equal to one if the sample stock is listed on the Nasdaq and zero otherwise. Also included is $lnchginvestor$, the difference between the log post-split number of shareholders and the log pre-split number of investors. The t-values are given below the coefficient estimates.

Model	Dependent variable: $chgLM12$	
	1	2
splitfactor	−**2.0948*****	
	(−**6.60**)	
splitfactor_D1		−**3.4978*****
		(−**9.57**)
splitfactor_D0		−**0.9010****
		(−**2.56**)
preLM12	−0.4906***	−0.4737***
	(−63.82)	(−59.65)
lnpreprc	2.5430***	2.7112***
	(5.20)	(5.58)
lnpresz	−0.3471**	−0.6020***
	(−2.02)	(−3.47)
lnprebm	0.0290	0.0777
	(0.15)	(0.40)
prerunup	−0.9428***	−0.9738***
	(−4.92)	(−5.13)
lnpreinvestor	−0.0330	−0.0598
	(−0.27)	(−0.49)
lnchginvestor	0.0297	0.0111
	(0.13)	(0.05)
lnpreinslown	0.3895*	0.0552
	(1.77)	(0.25)
exchdummy	−0.4640	−0.3023
	(−1.34)	(−0.88)
intercept	−4.9345***	−4.8679***
	(−3.22)	(−3.21)
Adj. R^2	0.6681	0.6739
N	3,130	3,130

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

provide liquidity services at lower costs, which increases investors' propensity to trade. This improvement in the liquidity environment would make stock prices more resilient and less subject to impact from shocks to market liquidity. Consequently, investors would face lower liquidity risk and require a lower liquidity premium, which in turn leads to a lower cost of equity capital for the split firms. In this section, we test this prediction on changes in liquidity risk.

6.1. Evidence of a reduction in liquidity risk

Liu (2006) proposes a two-factor liquidity-augmented CAPM (LCAPM) in which, in addition to the market

portfolio, stock returns are also related to a mimicking liquidity factor, *LIQ*. Similar to Fama and French's (1996) size factor, *SMB*, and B/M factor, *HML*, *LIQ* is the return difference between a low-liquidity portfolio (containing stocks with high *LM*12) and a high-liquidity portfolio (containing stocks with low *LM*12).[6] Specifically, the LCAPM posits that the expected excess return on stock *i* can be expressed as

$$E(r_i) - r_f = \beta_{im}[E(r_m) - r_f] + \beta_{il}E(LIQ), \tag{3}$$

where $E(r_m)$ is the expected return on the market portfolio, $E(LIQ)$ is the expected value of the mimicking liquidity factor, and β_{im} and β_{il} are firm *i*'s factor loadings. As Liu (2006) demonstrates, this two-factor LCAPM performs better than Fama and French's (1996) three-factor model and Pastor and Stambaugh's (2003) asset pricing model in explaining the cross-section of stock returns.[7] In particular, while the LCAPM can explain the size and the B/M effects, both the Fama-French and the Pastor-Stambaugh models cannot explain the liquidity premium associated with firms with high *LM*12. The LCAPM can also explain anomalies associated with the cash-flow-to-price ratio, dividend yield, earnings-to-price ratio, and long-term contrarian investment strategies, as shown by Liu (2006).

Thus, given its usefulness in explaining the cross-section of stock returns, we use Liu's LCAPM to measure the liquidity risk of each split firm and also to examine how it changes from before to after a stock split. First, we run the following time-series regression for each split firm:

$$r_{it} - r_{ft} = \alpha_{i,0} + \alpha_{i,1}D_t + (\beta_{im,0} + \beta_{im,1}D_t)(r_{mt,i} - r_{ft,i})$$
$$+ (\beta_{il,0} + \beta_{il,1}D_t)LIQ_{t,i} + \varepsilon_{it}, \tag{4}$$

where r_{it} is the monthly return of split firm *i* at time *t*; r_{ft} is the risk-free rate at time *t*; $D_t = 1$ if *t* is in the post-split period and $D_t = 0$ otherwise; $\beta_{im,0}$ and $\beta_{il,0}$ are the pre-split factor loadings on the market portfolio and the liquidity factor, respectively; $\beta_{im,1}$ and $\beta_{il,1}$ are the differences between the post- and pre-split factor loadings on the market portfolio and the liquidity factor, respectively; $\alpha_{i,0}$ is the pre-split abnormal return; and $\alpha_{i,1}$ is the difference between the post- and pre-split abnormal return. To avoid the announcement effect, the ex-date effect, and potential information leakage prior to the split, we run the regression in Eq. (4) for each firm for *t* from month −24 to month −2 prior to the split declaration month and from month +2 to month +24 after the ex-distribution month.

Next, we use the benchmark-adjusted return as the dependent variable and re-run the regression for each split firm, i.e.,

$$r_{it} - r_{bit} = \alpha_{i,0} + \alpha_{i,1}D_t + (\beta_{im,0} + \beta_{im,1}D_t)(r_{mt,i} - r_{ft,i})$$
$$+ (\beta_{il,0} + \beta_{il,1}D_t)LIQ_{t,i} + \varepsilon_{it}, \tag{5}$$

where r_{bit} is the monthly return of split firm *i*'s benchmark firm, $\alpha_{i,0}$ and $\alpha_{i,1}$ are firm *i*'s excess alphas (excess with respect to the benchmark firm), and $\beta_{im,0}$, $\beta_{il,0}$, $\beta_{im,1}$, and $\beta_{il,1}$ are its excess betas. For each split firm, we again choose a benchmark firm that is a non-split firm whose price at the end of month −1 (relative to the declaration month) is closest to that of the split firm among all non-split firms in the same size quartile and B/M quartile as the split firm. This benchmark-adjusted approach allows us to mitigate the effects of possible marketwide movements in liquidity risk.

Table 6 reports both estimation results. To ensure that our factor loadings are estimated with sufficient observations, we exclude firms that have fewer than 12 (non-missing) monthly returns available in either the pre-split or the post-split period. For the whole sample, the average of the $\alpha_{i,0}$ estimates is 3.12%, which is consistent with earlier findings of price run-ups prior to the splits. While the average of the pre-split market beta $\beta_{im,0}$ is 1.0417, the mean of the pre-split liquidity beta is −0.1302. On average, the split firms have higher pre-split market betas than the benchmark firms by 0.1258. The average excess $\beta_{il,0}$ is insignificantly different from zero, suggesting that, on average, the split firms and their benchmark firms have similar pre-split liquidity betas. After the splits, however, the split firms experience a significant reduction in liquidity risk—the average $\beta_{il,1}$ is −0.2624 (*t*-value = −7.05) and the average excess $\beta_{il,1}$ is −0.3343 (*t*-value = −7.22). For the whole sample, 56.0% of the split firms show excess $\beta_{il,1} < 0$. For the *preLM*12 ≥ 1 subsample, 59.4% of the firms have excess $\beta_{il,1} < 0$ and for the *preLM*12 < 1 subsample, 54.8% of the firms exhibit excess $\beta_{il,1} < 0$. The results indicate that the majority of the sample firms, relative to their benchmark firms, experience a reduction in liquidity beta. The results are thus consistent with our trading continuity improvement hypothesis, which posits that as stock splits improve the liquidity environment, investors face lower liquidity risk.

Note that, to adjust for possible dependence in the $\beta_{il,1}$ estimates across firms, we sort and average the estimates by ex-date in calendar time (e.g., if two firms have the same ex-date, we average their $\beta_{il,1}$) to obtain a time series of $\beta_{il,1}$ estimates. Then, following Fama and French (2002), we obtain the autoregressive error correction standard error of the mean, assuming that the errors (i.e., the deviations from the mean) of the $\beta_{il,1}$ estimates follow an AR(1) process. We do the same autoregressive error correction for the other regression coefficients. In most cases, the AR(1) parameters are indeed significantly negative and, after the correction, the Durbin-Watson statistics are equal to 2.0, suggesting no more first-order correlation. For comparison, Table 6 also includes *t*-values under the assumption that the coefficient estimates are independent across firms.

The effects of stock splits on market betas are marginal. The average $\beta_{im,1}$ is −0.0637 (*t*-value = −1.86), and the average excess $\beta_{im,1}$ is −0.0793 (*t*-value = −1.73). The results suggest that liquidity improvement also leads to a slight reduction in market betas, which implies that the reduction in liquidity risk following the splits is not offset by the change in market betas. Scholes and Williams

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[6] We thank Liu for providing us his liquidity factor, *LIQ*. For the detailed construction of *LIQ*, see Liu (2006, pp. 650–651).

[7] Pastor and Stambaugh (2003) suggest that liquidity risk can be measured by return sensitivity to market liquidity. However, their measure does not capture the liquidity risk stemming from trading discontinuity; instead, it captures the illiquidity related to price impacts of trades.

Table 6

Changes in liquidity risk.

This table reports the results of the following time-series regression, which is run for each split firm for t from month -24 to month -2 prior to the split declaration month and from month $+2$ to month $+24$ after the ex-distribution month:

$$r_{it} - r_{ft} = \alpha_{i,0} + \alpha_{i,1}D_t + (\beta_{im,0} + \beta_{im,1}D_t)(r_{mt,i} - r_{ft,i})$$
$$+ (\beta_{il,0} + \beta_{il,1}D_t)LIQ_{t,i} + \varepsilon_{it}, \qquad (4)$$

where $D_t = 1$ if t is in the post-split period, and $D_t = 0$ otherwise; $\beta_{im,0}$ and $\beta_{il,0}$ are the pre-split betas on the market portfolio and the liquidity factor, respectively; $\beta_{im,1}$ and $\beta_{il,1}$ are the differences between the post- and pre-split betas on the market portfolio and the liquidity factor, respectively; $\alpha_{i,0}$ is the pre-split abnormal return; and $\alpha_{i,1}$ is the difference between the post- and pre-split abnormal return. We also report the results of the regression that replaces dependent variable $r_{it} - r_{ft}$ by $r_{it} - r_{bit}$, the benchmark-adjusted return. In this case, the results show firm i's excess α's and β's over its benchmark firm. To ensure that our factor loadings are estimated with sufficient observations, we exclude from the report firms that have fewer than 12 (non-missing) monthly returns available in either the pre-split or the post-split period. The t-values in parentheses assume independence across firms; and in the brackets are the t-values with autoregressive error correction standard error, assuming that the errors (i.e., the deviations from the mean) of the coefficient estimates follow an AR(1) process.

Panel A: The whole sample ($N = 3,706$)						
Dependent variable	$\alpha_{i,0}$	$\alpha_{i,1}$	$\beta_{im,0}$	$\beta_{im,1}$	$\beta_{il,0}$	$\beta_{il,1}$
$r_{it} - r_{ft}$	0.0312	−0.0252	1.0417	−0.0637	−0.1302	**−0.2624**
	(51.20)	(−32.93)	(49.03)	(−2.32)	(−5.06)	(**−8.19**)
	[40.98]	[−29.46]	[40.38]	[−1.86]	[−3.73]	[**−7.05**]
$r_{it} - r_{bit}$	0.0165	−0.0091	0.1258	−0.0793	−0.0093	**−0.3343**
	(22.05)	(−9.13)	(4.85)	(−2.21)	(−0.29)	(**−8.16**)
	[20.39]	[−8.63]	[4.38]	[−1.73]	[−0.63]	[**−7.22**]
Panel B: Subsample results by pre-split trading discontinuity						
$preLM12 \geq 1$ ($N = 1,063$)						
$r_{it} - r_{ft}$	0.0246	−0.0217	1.0975	−0.1191	0.4058	**−0.4696**
	(24.16)	(−15.68)	(24.39)	(−2.18)	(7.64)	(**−6.72**)
	[21.96]	[−14.88]	[24.23]	[−2.09]	[7.51]	[**−6.51**]
$r_{it} - r_{bit}$	0.0095	−0.0041	0.1889	−0.0252	0.4009	**−0.4913**
	(6.99)	(−2.12)	(3.31)	(−0.34)	(6.00)	(**−5.75**)
	[6.77]	[−1.97]	[3.32]	[−0.39]	[5.47]	[**−6.04**]
$preLM12 < 1$ ($N = 2,643$)						
$r_{it} - r_{ft}$	0.0339	−0.0267	1.0192	−0.0414	−0.3459	**−0.1790**
	(45.51)	(−29.03)	(43.09)	(−1.31)	(−12.36)	(**−5.12**)
	[36.67]	[−25.49]	[34.86]	[−1.28]	[−9.54]	[**−4.71**]
$r_{it} - r_{bit}$	0.0189	−0.0109	0.1032	−0.0986	−0.1560	**−0.2781**
	(21.44)	(−9.38)	(3.59)	(−2.40)	(−4.40)	(**−5.99**)
	[19.75]	[−8.90]	[3.36]	[−2.23]	[−3.98]	[**−5.24**]

(1977) show that CAPM beta estimates are biased downward for infrequently traded stocks and biased upward for stocks traded very frequently. Our results show that trading continuity improves following the splits, suggesting that the market beta estimates should increase following the splits if the "true" market betas do not change. Instead, we find that the market beta estimates slightly decrease. It is possible that the slight decrease in the average market beta is simply due to a mean-reverting tendency (see, e.g., Blume, 1975).

How much would the cost of equity capital be reduced for the split firms because investors face lower liquidity risk and require a lower liquidity premium? Since we use monthly data, we estimate the cost of equity capital

reduction per annum by compounding $\beta_{il,1}E(LIQ)$ for 12 months. During the sample period from 1975 through 2004, $E(LIQ)$ is about 0.76% per month, which is very similar to Liu's estimate (2006, Table 5) of a monthly mean of LIQ over 1964–2003 of 0.749%. Thus, an average split-induced reduction in liquidity risk by 0.2624 translates into an average reduction of 2.42 percentage points per annum in the cost of equity capital for the split firms. This is a sizable reduction—a 17.3% reduction in the cost of equity capital—because the average pre-split cost of equity capital of the split firms is about 13.99% per annum (by Eq. (3), we have $r_f = 0.49\%$, $E(r_m) - r_f = 0.678\%$, and $E(LIQ) = 0.76\%$).

Fig. 2 illustrates the month-by-month liquidity risk estimates from month -24 prior to the stock split declaration month to month $+24$ after the ex-distribution month for the split firms and for their benchmark firms. Following Ball and Kothari (1989), we obtain the month-by-month liquidity risk estimates by running a cross-sectional regression,

$$r_{it} - r_{ft} = \alpha_t + \beta_{m,t}(r_{mt,i} - r_{ft,i}) + \beta_{l,t}LIQ_{t,i} + \varepsilon_{it}, \qquad (6)$$

for each event month. The process allows us to obtain an aggregate measure of liquidity risk $\beta_{l,t}$ in each event month t for the sample firms and for their benchmark firms. As Ball and Kothari (1989) point out, the advantage of the technique is to measure risks, which can shift during the event period. Fig. 2 shows that (1) the post-split liquidity risk estimates of the split firms are lower than their pre-split estimates, and (2) while the pre-split liquidity risk estimates of the split firms are not much different from those of the benchmark firms, the split firms' post-split liquidity risk estimates are lower than their counterparts' estimates. Thus, the cross-sectional, month-by-month liquidity estimates confirm our time-series, firm-by-firm liquidity risk estimates.

6.2. Would firms with no zero-volume days benefit from stock splits?

One might still be concerned about the following question: Would more liquid firms (e.g., those with no zero-volume days) benefit from stock splits? To address this question, we examine the changes in liquidity risk in the $preLM12$ subsamples.

As shown in Panel B of Table 6, the average pre-split market beta of the high- trading-discontinuity firms is 1.0975, which is slightly higher than 1.0192 for the low-trading-discontinuity subsample. As expected, the two subsamples have very different pre-split liquidity betas: 0.4058 (t-value = 7.64) for the firms with high pre-split trading discontinuity versus −0.3459 (t-value = −12.36) for those with low pre-split trading discontinuity. This is consistent with the notion that investors face high (low) liquidity risk in firms with high (low) trading discontinuity.

Interestingly, both subsamples experience significant reductions in liquidity risk following the splits. The reduction is greater for the high-trading-discontinuity subsample—the average $\beta_{il,1}$ is −0.4696 (t-value = −6.72)
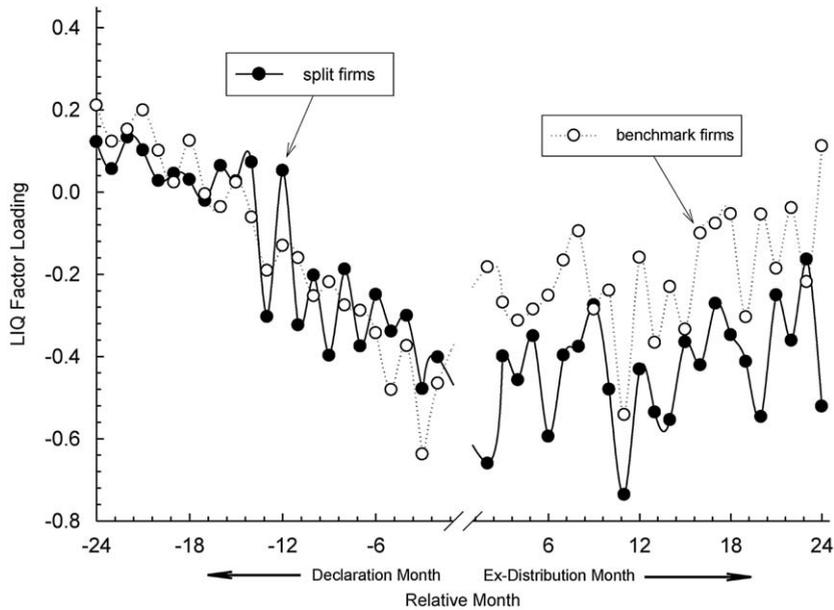
Fig. 2. Pre-Split and post-split liquidity risk of the split firms vs. their benchmark firms.

This figure plots the pre-split liquidity risk estimates from month −24 to −1 relative to the stock split declaration month and the post-split liquidity risk estimates from month 1 to 24 relative to the ex-distribution month for the split firms and their benchmark firms. For each split firm, we choose a benchmark firm that is a non-split firm whose price at the end of month −1 (relative to the declaration month) is closest to that of the split firm among all non-split firms in the same size quartile and B/M quartile as the split firm.

Following Ball and Kothari (1989), we obtain the month-by-month liquidity risk estimates by running a cross-sectional regression,

$$r_{it} - r_{ft} = \alpha_t + \beta_{m,t}(r_{mt,i} - r_{ft,i}) + \beta_{l,t}LIQ_{t,i} + \varepsilon_{it} \qquad (6)$$

for each event month in the pre-split period and in the post-split period. The process allows us to obtain an aggregate measure of liquidity risk, $\beta_{l,t}$, in each event month t for the sample firms and their benchmark firms. As Ball and Kothari (1989) point out, the advantage of the technique is to measure risks, which can shift during the event period.

and the average excess $\beta_{il,1}$ is −0.4913 (t-value = −5.75). For the low-trading-discontinuity subsample, the average $\beta_{il,1}$ is −0.1790 (t-value = −5.12) and the average excess $\beta_{il,1}$ is −0.2781 (t-value = −5.99). Thus, while less liquid firms exhibit greater reduction in liquidity risk, stock splits also lower liquidity risk for the relatively more liquid firms that have trades every day prior to the splits. For the latter group, the liquidity risk reduction could be due to the fact that stock splits bring in more small, uninformed trades, as Schultz (2000) and Easley, O'Hara, and Saar (2001) show, and reduce the possibility of intraday trading discontinuity.

For the high-trading-discontinuity subsample, the average reduction of 0.4696 in liquidity beta translates into an average reduction of 4.37% points per annum in the cost of equity, which is about 21.7% of the group's pre-split average cost of equity capital of 20.16% per annum. Similarly, for the low-trading-discontinuity subsample, the reduction of 0.1790 in liquidity risk translates into a reduction of 1.6 percentage points per annum, or about 13.8% of the group's pre-split average cost of equity capital of 11.59% per annum. Thus, by reducing the liquidity risk that investors face, stock splits generate substantial benefits for the firms. While less liquid firms benefit more from stock splits, firms that have trades every day benefit as well.

6.3. Liquidity improvement and liquidity risk reduction

What contributes to the liquidity risk reduction? According to our trading continuity improvement hypothesis, liquidity risk reduction should be related to liquidity improvement, as measured by $chgLM12$. We are also interested in knowing whether a larger investor base could provide better protection against shocks to market liquidity, thus reducing liquidity risk. To explore these relations, we use the following regression:

$$\begin{aligned} \beta_{il,1} = {}& \gamma_0 + \gamma_1 lnchgLM12_i + \gamma_2 lnchginvestor_i + \gamma_3 splitfactor_i \\ & + \gamma_4 lnpreprc_i + \gamma_5 lnpresz_i + \gamma_6 lnprebm_i + \gamma_7 prerunup_i \\ & + \gamma_8 exchdummy_i + \xi_i \end{aligned} \qquad (7)$$

where $\beta_{il,1}$ is firm i's excess change in liquidity risk (excess with respect to its benchmark firm) and $lnchgLM12_i$ is its excess change in $LM12$. Note that $lnchgLM12 = \log(1+postLM12) - \log(1+preLM12)$. We also use the split firm's change in $LM12$ and change in liquidity beta in the regression (7), and obtain similar results. Our experiments show that $lnchgLM12$ performs slightly better than $chgLM12 = postLM12 - preLM12$ in the regression. Also, we have experimented to include $lnpreinvestor$ and $lnpreinslown$ into the regression, and found that they are insignificant. Furthermore, with them in the model, the

Table 7
Cross-sectional analysis of changes in liquidity risk.

This table reports the results of regressing $\beta_{il,1}$, the excess change in liquidity risk, from Eq. (5), on $lnchgLM12$, the excess change in $LM12$ (the difference between benchmark-adjusted log (1+$postLM12$) and benchmark-adjusted log (1+$preLM12$)), and $lnchginvestor$, the change in the log (number of shareholders) following the splits, controlling for firm characteristics. For the subsample relations, we set $lnchgLM12\_D1 = lnchgLM12$ if $preLM12 \geq 1$, otherwise $lnchgLM12\_D1 = 0$; and $lnchgLM12\_D0 = lnchgLM12$ if $preLM12 < 1$, otherwise $lnchgLM12\_D0 = 0$. Similarly, $lnchginvestor\_D1 = lnchginvestor$ if $preLM12 \geq 1$, otherwise $lnchginvestor\_D1 = 0$; and $lnchginvestor\_D0 = lnchginvestor$ if $preLM12 < 1$, otherwise $lnchginvestor\_D0 = 0$. The t-values are given below the coefficient estimates.

	Dependent variable: $\beta_{il,1}$	
Model	1	2
$lnchgLM12$	**0.1981*****	
	(3.70)	
$lnchgLM12\_D1$		**0.1351****
		(2.16)
$lnchgLM12\_D0$		**0.3527*****
		(3.18)
$lnchginvestor$	−**0.0410**	
	(−**0.58**)	
$lnchginvestor\_D1$		−**0.2067**
		(−**1.35**)
$lnchginvestor\_D0$		−**0.0033**
		(−**0.04**)
$splitfactor$	−0.0818	−0.0886
	(−0.87)	(−0.94)
$lnpreprc$	−0.1653	−0.1554
	(−1.17)	(−1.10)
$lnpresz$	0.0928**	0.0960**
	(2.32)	(2.39)
$lnprebm$	0.2002***	0.1990***
	(3.57)	(3.55)
$prerunup$	−0.1359**	−0.1423**
	(−2.19)	(−2.29)
$exchdummy$	0.1321	0.1218
	(1.29)	(1.19)
$intercept$	0.1186	0.0522
	(0.30)	(0.13)
Adj. R^2	0.0166	0.0172
N	3,017	3,017

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

overall fit of the regression, in terms of adjusted R^2, declines and $lnchgLM12$ becomes less significant. For these reasons, we do not include them in Eq. (7).

Table 7 reports the regression results. Model 1 shows that $\beta_{il,1}$ is positively and significantly related to $lnchgLM12$, suggesting that the splits that induce more liquidity improvement have more liquidity risk reduction. However, $\beta_{il,1}$ is insignificantly related to $lnchginvestor$, which implies that the reduction in liquidity risk following the splits is not related to changes in the investor base.

In model 2, we decompose $lnchgLM12$ into $lnchgLM12\_D1$ and $lnchgLM12\_D0$, and similarly $lnchginvestor$ into $lnchginvestor\_D1$ and $lnchginvestor\_D0$, for examining the subsample relations.[8] The results show

that the liquidity risk reduction is significantly related to the liquidity improvement in both the $preLM12 \geq 1$ and $preLM12 < 1$ subsamples. Again, changes in liquidity risk are not related to changes in the investor base in either subsample.

We next turn to the split announcement effect on stock returns and test whether the announcement returns are correlated with changes in liquidity levels and changes in liquidity risk.

7. Split announcement returns and liquidity improvements

We measure stock price reactions, adjusted for market-wide movements, over the three days surrounding the split declaration date (day 0) as the split announcement effect on stock returns. Specifically, we use both the compounded benchmark-adjusted return,

$$annBAR_i = \prod_{t=-1}^{1}(1+RET_{i,t}) - \prod_{t=-1}^{1}(1+RET_{bi,t})$$

and the compounded market-adjusted return,

$$annMAR_i = \prod_{t=-1}^{1}(1+RET_{i,t}) - \prod_{t=-1}^{1}(1+MKTRET_t)$$

where $RET_{i,t}$ is the return on firm i on day t, $RET_{bi,t}$ is its benchmark firm's return on day t, and $MKTRET_t$ is the return on day t on the CRSP value-weighted market portfolio, including NYSE/AMEX/Nasdaq stocks. Since the results are virtually the same, our discussion focuses on the benchmark-adjusted returns.

Consistent with previous studies, we find that the market responds positively to the split announcement—the average three-day benchmark-adjusted return for our sample of 3,721 stock splits over days −1 to +1 is a significant 3.30%. The average three-day market-adjusted return is 3.28%, which is also significantly different from zero. This split announcement return is similar to those found in previous studies (see, e.g., Grinblatt, Masulis, and Titman, 1984; Ikenberry, Rankine, and Stice, 1996).

For the firms with $preLM12 \geq 1$, the average excess return is 4.88%, which is significantly larger than the average excess return of 2.73% for the firms with $preLM12 < 1$. The results suggest that the market response to the split announcement is much stronger for less liquid firms.

Next, we examine whether the benchmark-adjusted announcement return is related to the excess change in the liquidity level, as measured by $lnchgLM12$, and to the excess change in liquidity risk, as estimated by $\beta_{il,1}$ from Eq. (5), using the following regression:

$$
\begin{aligned}
annBAR_i = {}& a_0 + a_1 lnchgLM12_i + a_2\beta_{il,1} + a_3 splitfactor_i + a_4 lnpreprc_i \\
& + a_5 lnpresz_i + a_6 lnprebm_i + a_7 prerunup_i + a_8 lnpreLM12_i \\
& + a_8\beta_{il,0} + a_9 lnchginvestor_i + a_{10} lnpreinslown_i + u_i \quad (8)
\end{aligned}
$$

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[8] $lnchgLM12\_D1 = lnchgLM12$ if $preLM12 \geq 1$, otherwise $lnchgLM12\_D1 = 0$; and $lnchgLM12\_D0 = lnchgLM12$ if $preLM12 < 1$, otherwise $lnchgLM12\_D0 = 0$. Similarly, $lnchginvestor\_D1 = lnchginvestor$ if

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(*footnote continued*)
$preLM12 \geq 1$, otherwise $lnchginvestor\_D1 = 0$; and $lnchginvestor\_D0 = lnchginvestor$ if $preLM12 < 1$, otherwise $lnchginvestor\_D0 = 0$.

Note that many of the explanatory variables on the right-hand side of Eq. (8) have been shown in prior research to affect split announcement returns. For example, the split factor (*splitfactor*) has been examined as a proxy for the strength of the signal by Brennan and Copeland (1988), Grinblatt, Masulis, and Titman (1984), and McNichols and Dravid (1990). The book-to-market equity ratio (*lnprebm*) and firm size (*lnpresz*) have been examined by Ikenberry, Rankine, and Stice (1996) as cross-sectional determinants of split announcement returns. The pre-split price run-up (*prerunup*) is used by Grinblatt, Masulis, and Titman (1984) as a proxy for the extent to which the stock price is away from its normal trading range. The change in investor base (*lnchginvestor*) has been examined by Mukherji, Kim, and Walker (1997) and Amihud, Mendelson, and Uno (1999). And institutional share ownership (*lnpreinslown*) has been studied by Dennis and Strickland (2003). We control for these variables in testing the relations between *annBAR* and *lnchgLM*12 and $\beta_{il,1}$.

Table 8 reports the regression results. Model 1 shows that *annBAR* is significantly and negatively related to both *lnchgLM*12 and $\beta_{il,1}$, indicating that the split announcement return is indeed more positive for the firms with a greater decrease in no-trade days and a greater reduction in the liquidity beta following their stock splits. The evidence is consistent with our trading continuity improvement hypothesis, and implies that investors are concerned with stock illiquidity and liquidity risk and reward firms that split their stocks to improve liquidity and to reduce liquidity risk.

For the subsample relations, model 2 reveals that the negative relation between *annBAR* and *lnchgLM*12 holds only in the *preLM*12 $\geq$ 1 subsample, but the negative relation between *annBAR* and $\beta_{il,1}$ holds only in the *preLM*12 < 1 subsample. Thus, *lnchgLM*12 has a significant valuation effect for the less liquid subsample in which there is a significant reduction in no-trade days. But it has an insignificant valuation effect for the relatively liquid subsample in which illiquidity is not an imminent problem. Conversely, the liquidity risk reduction has a significant valuation effect only for the *preLM*12 < 1 subsample.

For a robustness check, Table 8 also includes the results of using the market-adjusted announcement return, *annMAR*$_i$, as the dependent variable in Eq. (8) with *lnchgLM*12 as the change in liquidity level and $\beta_{il,1}$ as the change in liquidity risk from Eq. (4). The inferences are essentially the same. Nevertheless, the results show that the split announcement returns are more strongly related to the improvements in both the liquidity level and liquidity risk.

Inconsistent with Mukherji, Kim, and Walker (1997), neither the benchmark-adjusted nor market-adjusted split announcement return is related to the expansion of the investor base. We also experiment with *lnchginvestor_D*1 and *lnchginvestor_D*0 and find no subsample relations. Thus, our findings suggest that it is not the expanded investor base per se that is material in explaining the split announcement returns; instead, what matters is the extent of liquidity improvement and the degree of liquidity risk reduction brought about by expanded investor trading.

Table 8
Cross-sectional analysis of split announcement returns.

In models 1 and 2, the dependent variable is *annBAR*, the three-day benchmark-adjusted split announcement returns, and the explanatory variables *lnchgLM*12, $\beta_{il,1}$, *lnpreLM*12, and $\beta_{il,0}$ are also benchmark-adjusted. In Models 3 and 4, the dependent variable is *annMAR*, the market-adjusted split announcement returns, and the explanatory variables *lnchgLM*12, $\beta_{il,1}$, *lnpreLM*12, and $\beta_{il,0}$ are not benchmark-adjusted. For the subsample relations, we set *lnchgLM*12_*D*1 = *lnchgLM*12 if *preLM*12 $\geq$ 1, otherwise *lnchgLM*12_*D*1 = 0; and *lnchgLM*12_*D*0 = *lnchgLM*12 if *preLM*12 < 1, otherwise *lnchgLM*12_*D*0 = 0. Similarly, $\beta_{il,1}$_*D*1 = $\beta_{il,1}$ if *preLM*12 $\geq$ 1, otherwise $\beta_{il,1}$_*D*1 = 0; and $\beta_{il,1}$_*D*0 = $\beta_{il,1}$ if *preLM*12 < 1, otherwise $\beta_{il,1}$_*D*0 = 0. The *t*-values are given below the coefficient estimates.

Model	Dependent variable: annBAR		Dependent variable: annMAR	
	1	2	3	4
*lnchgLM*12	−0.5802***		−0.8154***	
	(−2.97)		(−4.25)	
*lnchgLM*12_*D*1		−0.7126***		−0.8741***
		(−3.20)		(−4.44)
*lnchgLM*12_*D*0		−0.1814		−0.2204
		(−0.48)		(−0.26)
$\beta_{il,1}$	−0.1392*		−0.2227**	
	(−1.77)		(−2.52)	
$\beta_{il,1}$_*D*1		−0.1176		−0.0924
		(−0.94)		(−0.71)
$\beta_{il,1}$_*D*0		−0.1558*		−0.2722***
		(−1.80)		(−2.84)
splitfactor	1.2451***	1.2308***	1.2446***	1.2453***
	(4.01)	(3.96)	(4.65)	(4.66)
lnpreprc	−2.8931***	−2.8647 ***	−2.8439***	−2.8486***
	(−6.04)	(−5.98)	(−6.95)	(−6.96)
lnpresz	−0.0205	−0.0152	0.0350	0.0365
	(−0.12)	(−0.09)	(0.29)	(0.31)
lnprebm	−1.2164***	−1.2139***	−0.9737***	−0.9813***
	(−6.31)	(−6.30)	(−6.59)	(−6.64)
prerunup	0.5359***	0.5268***	0.2378	0.2474
	(2.66)	(2.61)	(1.47)	(1.53)
*lnpreLM*12	0.3380***	0.3324***	0.0048	0.0043
	(2.64)	(2.59)	(0.74)	(0.66)
$\beta_{il,0}$	−0.2257**	−0.2297**	−0.4454***	−0.4211***
	(−2.20)	(−2.23)	(−3.91)	(−3.66)
lnchginvestor	0.0478	0.0548	−0.2161	−0.2078
	(0.40)	(0.46)	(−1.13)	(−1.09)
lnpreinslown	−0.7510***	−0.7349***	−0.9435***	−0.9479***
	(−3.48)	(−3.40)	(−5.20)	(−5.21)
intercept	10.5074***	10.3491***	9.9959***	9.9838***
	(7.14)	(7.00)	(8.03)	(8.02)
Adj. R^2	0.0856	0.0855	0.1061	0.1062

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

8. Conclusions

Despite extensive research on stock splits, Easley, O'Hara, and Saar (2001) note that "it remains a puzzle why companies ever split their shares." To resolve the puzzle, we propose and test the trading continuity improvement hypothesis, which asserts that managers of firms facing some possibility of trading discontinuity can use stock splits to attract more uninformed trading, which allows market makers to provide liquidity services at lower costs. With lower trading costs, investors' propensity to trade increases, and investors face reduced liquidity risk. We examine a large sample of stock splits and find, consistent with our hypothesis, that the incidence of no

trading decreases, implying lower latent costs of trading, and that liquidity risk is mitigated following the splits.

Because stock splits improve trading continuity and alleviate liquidity risk, investors require a lower liquidity premium, resulting in a lower cost of equity capital. Our analysis suggests that, on average, liquidity improvements reduce the cost of equity capital by 17.3%, or 2.42 percentage points per annum. Thus, the economic benefits of stock splits are nontrivial. While less liquid firms benefit more from stock splits, firms that trade every day benefit as well.

Furthermore, we find that firms facing more frequent trading discontinuities choose a higher split factor and experience greater liquidity improvements. And the split announcement returns tend to be higher for firms with a larger decline in no-trade days and for firms with a greater reduction in liquidity risk.

Overall, our study provides an explanation with economic benefits for why companies split their shares. Our findings support managers' view and Muscarella and Vetsuypens' (1996) findings that stock splits are intended to improve liquidity. Also, in line with Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), Liu (2006), and Bekaert, Harvey, and Lundblad (2007), our study highlights the importance of using trading discontinuity to measure liquidity.

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