High Frequency Trading around Stock Splits and Consolidations

VITO MOLLICA

SHUNQUAN ZHANG

Macquarie Graduate School of Management

Macquarie University North Ryde, N.S.W.,2109, Australia

Abstract

Calls have been made by listed companies and institutional investors for market regulators to introduce mechanisms to curb the level of high frequency trading in financial markets. In this paper we suggest that companies may be able to affect the level of HFT in their stock without relying on rule changes being imposed by market regulators. We find that when a security undertakes a stock split (experiences a sudden increase in its relative tick size), it is associated with a lower order-to-trade ratio and longer order-resting time, indicative of a smaller proportion of high frequency trading.

1. INTRODUCTION

Technological advancement in recent decades has significantly reshaped financial markets around the globe. Since early 1990s, exchanges have gradually adopted electronic trading platforms and order books to facilitate trading, replacing conventional floor trading systems (Jain, 2005). Cheaper computation power, coupled with faster internet access provides traders with almost instantaneous access to movements in market order books. Market makers, in particular, benefit from such advances, enabling them to more closely track price movements and reduce their adverse selection costs (Glosten, 1987). Enhancements to exchange trading systems have also introduced a new breed of traders, high frequency traders (HFT).[2] Several empirical studies have reported the increased participation of HFT and demonstrated that they affect market quality: Hendershott et al., 2011 and Hasbrouck and Saar, 2012 report bid-ask spreads and volatility improve with the increased incidence of HFT, while Boehmer et al., (2012) suggest that HFTs increase short term volatility and exploit slower traders, leading to further negative externalities as modelled by Biais et al., 2012. More recently Chaboud, Chiquione, Hjalmarsson and Vega (2014) find HFT firms do not exacerbate volatility but demonstrate that algorithmic trading has led to a significant decline in triangular arbitrage opportunities and mispricing in markets. Recent calls have been made by market participants, including listed companies[3] and institutional investors[4], for market regulators to introduce mechanisms to curb the level of HFT in financial markets intensifying the debate surrounding the benefits and costs of HFT (see SEC, 2010 and ASIC, 2013). In this paper we suggest that companies may be able to affect the level of HFT in their stock without rule changes being imposed by market.

HFT profit from low-latency and repeated trading (Easely et al., 2012; Baron et al. 2012), however they are constrained by the market protocols of trade and characteristics of stocks listed on any exchange. This paper investigates whether one such characteristic, relative tick size, influences HFT behaviour. Relative tick size constrains the minimum value of bid-ask spread. Harris (1994) first documents the relationship between bid-ask spreads and tick size, and argues that the relative tick size, calculated as the minimum price variation divided by the stock price, is the measure of tick size which has an economic impact on both liquidity demanders and suppliers.

Stocks with smaller relative stick sizes are associated with smaller spreads and thinner depth (Bessembinder, 2003). The smaller the relative tick of a firm the greater the number of negotiation points. HFT with their fast market access and response time have the advantage of being able to offer small price improvement and get ahead in limit order book queues. Conversely, firms with larger relative ticks have wider bid-ask spreads (and greatest first level depth) and market makers can hence earn a higher profits for a given level of trade. Consequently, it remains an empirical question as to whether HFT prefer stocks with a low or high relative tick.

Existing studies examining tick size and its impact on markets have typically observed systematic tick regime reforms as their primary event (e.g. Aitken & Comerton-Forde, 2005;

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[2] ASIC (2013) states that in 2012, high frequency traders accounted for 27% of turnover in ASX200, just over 50% in USA, and 36% in Europe

[3] Peter Ker, "Mining boss raises alarm on high-frequency trading", *Sydney Morning Herald*, 25 January 2013, http://www.smh.com.au/business/mining-boss-raises-alarm-on-highfrequency-trading-20130124-2d9mh.html

[4] "ASIC dark pool, HFT consultation extended after feedback flood", *The Trade*, 25 January 2012, http://www.thetradenews.com/news/Regions/Asia/ASIC_dark_pool,_HFT_consultation_extended_after_feedback_flood.aspx

Bessembinder, 2003; Bacidore et al., 2002; Chung et al., 2004). Given the infrequency with which regulators modify tick sizes, undertaking a longitudinal study of trading behaviour around tick changes is limited. Consequently we adopt the ideology of Harris (1994) and focus on relative tick size changes. We identify two natural experiments to examine HFT around tick changes: stock splits and consolidations. These two corporate actions drastically influence a firms' stock price and its relative tick size, without any regulatory reform. The relative frequency of such events vis-à-vis the infrequency of tick reforms establishes an opportunity to monitor HFT over a considerable period of time.

Hagstromer and Norden (2013) using a proprietary database find HFT are mainly associated with market making activity. Hagstromer and Norden (2013) state that "tick size regulation may be an interesting solution for limiting quoting traffic … this is an interesting direction for future research." (p. 769). While not the focus of their study which examines the opportunistic versus market marker behaviour of HFT on market quality, they attempt to shed some light on this question by examining stocks which cross tick bands for at least one day. We argue that such an approach is limited as a firm may cross tick levels due to changes in the fundamental value of the firm, momentum or manipulation. This perhaps explains why Hagstromer and Norden (2013) are not able to clearly identify the impact of tick change on HFT involvement. In our study, the use of stock splits and consolidation is an exogenous event which can be considered 'cosmetic' in the short run in that it significantly impacts the prices of listed stocks (and tick), while market activity and the stock's fundamental value remain largely unchanged. Moreover our sample period extends 16 years, while Hagstromer and Norden (2013) examine a two year sample period.

We investigate two proxies of the level of HFT: a modified version of the proxy used in Hendershott et al. (2011), and a new measure order resting time, which reflects the pace of the order book. We find a significant increase in HFT participation and a significant decrease in order resting time when stocks move to a lower relative tick size. We conclude that, other things equal, stocks with a lower tick size attract greater proportion of HFT.

2. Literature Review

Tick size is one of the fundamental elements in market design. In his seminal paper Harris (1994) develops and tests the impact of a reduction in minimum price variation in a quote driven market. He argues that tick size in setting the minimum value of bid ask spread, has implications for attracting market makers to supply liquidity and hence increase displayed depth and bid-ask spreads. Bessembinder (2003) uses the advent of decimalization on the NYSE in 2001 and finds the reduction in tick-levels leads to a decrease in bid-ask spreads (most evident in large market cap stocks), quotation size (depth) and intraday return volatility. Bessembinder (2003) also reports that smaller traders who use market orders benefited the most from decimalization. Similar results are also illustrated by Bacidore et al. (2002), who examine hidden depth.

In terms of stocks splits similar conclusions have been drawn surrounding the price behaviour of such events in the microstructure literature. Stock splits are corporate events initiated by listed companies which have the effect of increasing the number of shares on issue without changing a firm's market capitalisation, but reducing its price level. Angel (1997) points out that such an action increases the relative tick size, which inflates the floor value of the bid-ask spread. Higher spreads give liquidity providers an incentive to make markets and leads to higher depth for the stock, these findings are corroborated by Schultz (2000) and

Kadapakkam et al. (2005) who also observes an increase in small buy orders after stock splits and an increase in transaction costs following stock splits, consistent with the hypothesis that brokers more actively promote stocks after split event. Desai et al. (1998) also finds a significant increase in volatility and number of trades following stock splits.

Hendershott et al. (2011) is the seminal study on the impact of algorithmic traders on market quality. Hendershott et al. (2011) reports that algorithmic trading has been increasing over the past years, and associates their increased prominence with an improvement in market quality as determined by a decreasing spread, increasing depth and reduced price impact. Hasbrouck and Saar (2011) examine the dynamic trading strategy of algorithmic trading in calendar and trade time. Hasbrouck and Saar (2011) show that conventional market quality measures improve with higher HFT involvement, but also indicate that this may be limited to the conventional market measures, which are unable to capture HFT's negative impact on the market. Kirilenko and Lo (2013) conversely argues that HFT can potentially destabilise the market. Using five existing market incidents, Kirilenko and Lo (2013) show that HFT can lead to inaccurate pricing and amplify market misbehavior, such as price manipulation and trading errors. Zhang (2010) empirically showed that HFT are in fact positively associated with volatility, after controlling fundamental volatility, and delay market price convergence to fundamental value.

In this study, rather than focusing on whether HFT influence market conditions, we attempt to bring the three aspects of microstructure research to determine whether the relative tick size, as a basic attribute of markets and securities affects HFT participation.

3. Methodology

3.1. Experiment Design and Data

We identify the occurrence of stock splits and consolidations for firms listed on the Australia Securities Exchanges (ASX) for the period 1996 to 2012[5] using data from IRESS Australia. We obtain a time series of price adjustment factors (flagged by event description) to identify all corporate events dates that result in significant price changes. A price adjustment factor less (larger) than one suggests the stock underwent a stock split (consolidation), hence a reduced (increased) stock price and higher (lower) relative tick size.[6] We filter through event descriptions provided by IRESS Australia, and retain those associated with "splits", "bonus issues", and "consolidations". To ensure that relative tick changes significantly around each event, we only sample events with adjustment factors larger than 1.50 (consolidations that increase price by more than half) or less than 0.67 (splits that reduce price by more than a third)[7]. A total of 229 events are identified.

[5] We select 1996 as our starting point to avoid the 1995 major tick size regime change On 04/12/1995, the tick size for stocks with a price below $0.1 was changed from 0.5c to 0.1c; stocks with a price between $0.1 to $0.5 had their tick size decreased from 1c to 0.5c. The tick size for all stocks above $2 was lowered from 2c ($10 ~ $50 stocks), 5c ($50 ~ $100 stocks), 10c ($100 ~ $999 stocks) and $1 (above $999 stocks) to a unified 1c tick. Another minor tick regime change occurred on 12/02/2005, which lowered the tick size of $0.5 ~ $2 stocks from 1c to 0.5c.

[6] An adjustment factor is created on the day of the of the split and consolidation event to reflect the stock price change due to the change of stock pool, so that the pre-event change is at the same level as the post event price. E.g. a 2:1 consolidation half the stock pool, double the price and hence the adjustment factor (for pre-event price) is 2.

[7] We carried out our analysis using adjustment factors of 2.0 and 0.5; and find similar results, despite the reduced sample size; there are only 55 events satisfying the criteria.

For each event we construct a 180-day window centred on the stock split or consolidation dates. Each stock split or consolidation event in our experiment can be categorised by its impact on the relative tick. A stock consolidation causes a sharp increase in the price, corresponding to a reduction in the relative tick size. Thus pre-consolidation trading days are considered as a *large-tick period* and post-consolidation trading days as a *small-tick period*. Vice versa, pre-split is regarded as a *small-tick period* and post-split is regarded as a *large-tick period*. Since this paper focuses on the change in tick size, not the direction of tick change, all the sample events are categorised into *large-* or *small-tick* events. Using the event date as time zero (t = 0), the *small-tick* group, after consolidations or before splits, is labelled with positive time indices (t = 1, 2,…, n), while *large-tick* period (before consolidations or after splits) is labelled with negative time indices (t = -1, -2,…, n). To ensure the change in HFT levels is due to the change in relative tick size, we associate each sample stock with a controlled stock during the same period. The benchmark firm stock is conditioned on daily turnover but does not experience any corporate actions during the 180-day sample period.

To capture the impact of HFT rather than some unobserved market reaction towards tick change that pre-exist before market wide adoption of algorithmic trading, we further categorise our sample into two periods based on the general level of HFT activity in markets.

< Insert Figure One >

Figure 1 charts the evolution of the order-to-trade ratio for ASX listed firms since 1996. A larger order-to-trade ratio indicates a greater proportion of HFT in the market. Figure 1 depicts that the order-to-trade ratio remains flat until 2007 and then starts to increase rapidly. This coincides with market general view that HFT is a recent phenomena in the Australian market and our sample period contains a pre- and post-HFT trading environment., We remove from the 229 events those which occurred during the transition period (i.e 88 events) and separate our sample into a *Pre-HFT* period (1996-2004, 76 events) and a *Post-HFT* period (2009-2012, 55 events).

Data used in this paper are obtained from the Thomson Reuters Tick History (TRTH) database, managed and distributed by the Securities Industry Research Centre of Asia Pacific. TRTH is a financial data network which receives real-time bid and ask quotes and transaction data directly from exchanges.[8] We limit our order-book to observations between 10:10 am to 3:55 pm to avoid any interference resulting from opening (9:59 to 10:09 am) and closing (after 4:00 pm) auctions. The data contains all message traffic on the market, including: “Order Entering”, “Order Amendment”, “Order Deletion”, “Trade”, “Off Market Trades”, and “Trade Cancellation”; along with unique order identification numbers and time stamps, accurate to the millisecond. This information enables the tracking of each individual order submitted to the limit order book.[9] Unlike data analysed by Hagstromer and Norden (2013) or Borgaard (2013), ours does not flag messages originated specifically by HFT. We thus employ two measures to proxy the level of HFT in the market: order-to-trade ratio (*OTR*) and order-rest time (*ORT*).

As stated previously four message types are identified in the data: “Order Entering”, “Order Amendment”, “Order Deletion”, and “Trade”. Intuitively, “Order Entering” marks the start of an order; if an order was not fully traded upon entry, it would join the end of the exiting order

[8] For more information on this database, please see Thomson and Reuters homepage: http://thomsonreuters.com/

[9] “Off Market Trades” and “Trade Cancellation” messages are associated with off-market trade reporting. Since our main focus here is to investigate on-market orders and trades, these two types of messages are removed from the analysis.

queue at the same price level. This procedure reflects both price and time priority: orders with the best price are always traded first and orders with the same price are traded on a first in, first out basis. If orders are deleted or fully traded, they would be removed from the order book. “Order Deletion” and “Trade” are naturally recognised as the end of an order.

On the other hand, “Order Amendment” messages affect existing orders in two different ways on the ASX. When the only amendment is a decrease in quoted volume, the amended order still enjoys the same time priority as the original order. If the amendment alters the price per share or increases the quoted volume, the order loses its time priority and is placed at the end of the order queue. The latter amendment is therefore equivalent to deleting the current order and submitting a new order with a new price and/or increased volume. If all order messages are assessed purely on their impact on the order book, then the second type of order amendment would mark both the end of the original order (order deletion) and the beginning of a new order (order entering). The first type of amendment does not however influence the order’s ranking on the order book and is discarded from the dataset. Based on this criterion, we consider an order to begin with an “Order Enter” or “Order Amendment” message and terminated with an “Order Deletion”, “Order Amendment” or “Trade” message. The time that lapses between the start and end of an order is regarded as individual order survival or resting time (*ORT*). This is the time that it takes for a newly created order to lose its time priority (due to deletion or amendment) or is partially traded. The order time related to subsequent trades is not considered. If an order is not terminated by the end of the trading day (3:55 pm), it is excluded from the analysis.[10]

Based on the new definition of individual orders and filtered market messages, we evaluate order-to-trade ratio (*OTR*) as ratio of total order counts and on-market dollar turnover. We replace ‘message counts’ used by Hendershott et al. (2011) with the total number of orders during the day. This separates the number of trades from the message counts and equates the effect of the amendments (changing time priority) and the deletion-resubmission algorithm (As shown in Appendix 1), which improves the robustness of the measure. For event i, on date t, we record the total number of orders ($TotalOrder_{i,t}$) that enter and leave the market on the same trading day (using the order definition presented earlier), the total on-market dollar turnover ($Turnover_{i,t}$) during the time interval and calculate our adjusted order to trade ratio ($OTR_{i,t}$),

$$OTR_{i,t} = \frac{TotalOrder_{i,t}}{Turnover_{i,t}} \times 1000 \ldots (1)$$

Let l be the l_{th} order recorded with non-zero order resting time. For event i, on date t, the individual order survival time is recorded as $OrderTime\_Ind_{i,t,l}$.

In a market where HFT are dominant their direct market access and increased response time hasten the pace of trading. Algorithms quickly delete the order if the risk of adverse selection increases and/or submit new orders to capture trading opportunities. Thus each order would rest for a shorter time than they would be in a market with less HFT. Our second HFT proxy is order resting time ($OTR_{i,t}$):

[10] An illustrative example is included in the Appendix 1.

$$ORT_{i,t} = \frac{\sum_l \log\left(OrderTime\_Ind_{i,t,l}\right)}{\sum_l 1} = \log\left[\left(\prod_l OrderTime_{Ind_{l,i,t}}\right)^{\sum_l 1}\right], \dots (2)$$

where the latter expression represents the end of day $ORT_{i,t}$ as the log of the geometric mean of the order time for stock *i*, on date *t*. Unlike $TotalOrder_{i,t}$ (numerator in $AT_{i,t}$), $\sum_l 1$ does not include orders that are executed or deleted upon entry.

Order rest time (*ORT*) is calculated as the average of log individual order survival time. Figure 2 justifies for aggregating the order time with a log transformation over directly averaging order time.

< Insert Figure 2 >

The distribution under original scale (Figure 2, panel A) indicates that individual order time is strongly skewed to the right. Direct arithmetic averaging is hence biased toward long-survived orders. Conversely, log-transformed order times (Figure 2, panel B) are more symmetrical and condensed. The average of the log order time hence is a better representation of the general speed of trading in the market and used in the subsequent analysis.

3.1.2 Model

Our HFT proxies, being calculated from the data, are naturally influenced by the corporate events during both periods. Thus, it is not the change in HFT proxies around the tick changing events that are of interest. Rather, it is how the change differs between the low HFT (1996-2004) and high HFT (2005-2012) environment. This leads to two tick-change related variables in the model: $SmallTick$ acts as a control for the natural change of HFT proxies around the corporate events and the interaction term, $HighAT * SmallTick$, capture the difference of proxies changes in low and high HFT period and is the variable of interest in the study. The basic form of the model tested is,

$$H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot \left(HighAT_i * SmallTick_{i,t}\right) + \varepsilon_{i,t}, \dots (3)$$

$H_{i,t}$ is the sample HFT proxy (*OTR* or *ORT*); $Firm_i$ is a fix effect; $SmallTick_{i,t}$ is an indicator variable, equal to 1 when tick size is relatively small $(t > 0)$ and 0 otherwise. $HighAT_i * SmallTick_{i,t}$ is the interaction term, equal to 1 when tick size is relatively small ($t > 0$) for events during the post-HFT period (2009-2012). Each observation in our sample is recorded with different measurement error based on the underlying stock liquidity. Liquid stocks with large daily turnover provide more accurate measures for our HFT proxies. For example, an extremely illiquid stock with infrequent trades during the day and a still order book would naturally result in large *OTR* and *ORT*. Such observations should be weighted less than observations in liquid stocks with frequent trades. Thus we uses the denominator of *ORT* proxy, $n = \sum_l 1$, counts of orders which do not exit order book (e.g. cancelled or traded) upon entry, as weights for observations.

We also control for known determinants of HFT participation including trading volume and volatility to estimate Equation 4,

$$H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot \left(HighAT_i * SmallTick_{i,t}\right) + \sum_k a_k \cdot Control_{i,t,k} + \varepsilon_{i,t}, \ldots (4)$$

We choose log of daily dollar turnover ($\log[Turnover_{i,t}]$) and 15-minute return volatility ($Volatility_{i,t}$) as control variables and fit Equation 4 to the two HFT proxies in the sample observations.

3.1.3 Robustness

Although Equation 4 has taken into consideration other aspects of the market and the stocks there are other potential factors which could influence our results. To evaluate the robustness of our analysis, we further incorporate a sample of control firms. We use $\Delta H_{i,t} = H\_sample_{i,t} - H\_control_{i,t}$, as response variables, where H_sample ($H\_control$) is the corresponding HFT proxy calculated from sample (control) stocks. Since the sample and corresponding control stock share similar attributes (other than the corporate event), any market interference of HFT proxies are presented in both our sample and control observations. By differencing the proxies of the two groups, we eliminate such interferences.

Since the new responses, $\Delta H_{i,t}$, are the difference of two sample variables, weights in the new regression need to be adjusted to $\frac{1}{1/n\_sample + 1/n\_control}$, which reflect the difference of variance (accuracy) between sampled and controlled stocks. Further, to refit Equation 4, control factors are not just limited to turnover and volatility of the sample stocks, but also microstructures factors in controlled stocks. Turnover and volatility of both stock groups ($\log[Turnover\_Sample_{i,t}]$, $\log[Turnover\_Control_{i,t}]$, $Volatility\_sample_{i,t}$ and $Volatility\_Control_{i,t,k}$) are included as control variables.

4. Results

Table 1 contains summary statistics for all variables in our analysis. We examine 131 stock splits or consolidations: 76 in the low AT period (1996-2004) and 55 in high AT (2009-2012). Each treatment event is also paired with a control stock based on average daily turnover over the 180-day period and industry. Turnover and daily order counts for treatment and control firms are similar in both mean and standard deviation. Both treatment and control firms have shorter average order resting times and larger order-to-trade ratios during high AT period as expected given our categorisation into low and high AT trading environments.

< Insert Table 1 >

< Insert Figure 3 >

Figure 3 depicts average weekly OTR for all treatment firms undertaking stock splits/consolidations across the two AT trading environments. Figure 3 provides preliminary evidence that HFT are more active in the stocks where relative ticks are smaller. This is evident by the sudden jump in the order to trade ratio as a firm shifts from a high relative tick to a low relative tick between 2009 and 2012 (i.e. our high AT period). Such behaviour is not evident in the 1996-2004 low AT period.

Table 2 reports regression results for Equations 3 and 4. Table 2 confirms the HFT behaviour documented in Figure 3. Turning first to results on the order to trade ratio proxy for HFT our variable of interest $HighAT * SmallTick$ is significantly positive suggesting that an increase in the order to trade ratio when treatment firms move to a lower relative tick is significantly larger during the high AT period (2009-2012) vis-à-vis the low AT period (1996-2004). Further, insignificant coefficients of $SmallTick$ variable demonstrate that the sharp increase in order to trade ratio is only observed after HFT are active in markets, supporting the appropriateness of order-to-trade ratios as a proxy for HFT. Overall, the order to trade ratio, as one of the HFT proxies in this paper, indicates that HFT participate more in low tick stocks, in comparison with the same stock with higher relative ticks.

< Insert Table 2 >

Similar conclusions can be drawn from our second proxy, order resting time, as our variable of interest is significantly negative. Table 2 reports that during the high AT period, reductions in order resting time are significant shorter when firms shift to a lower tick trading environment vis-à-vis firms which undertake corporate actions to reduce ticks sizes during the low AT period. Results in Table 2 show HFT more actively participate in stocks with smaller relative ticks, leading to a significantly shortened order resting time in more recent times. Contrary to results for our order-to-trade proxy, order resting times generally decrease over our sample period and indicating that the pace of trading increases following a tick reduction initiative, however results in Table 2 confirm any reduction is significantly larger in the post AT sample period. Together these results yield similar conclusions, that during a period defined as an active HFT trading environment, firms which are associated with smaller relative ticks are associated with higher *OTR* and shorter *ORT*. A higher *OTR* suggests that more orders are submitted into the market to facilitate the same amount of turnover, while a shorter *ORT* means that orders spend much less time in limit order books and the pace of trading is accelerated.

As a robustness test we also include a one-to-one matched control firm-event based on daily turnover and industry, which have not undertaken any corporate action. This further eliminates market condition changes on AT proxies and make the AT proxies here to truly reflect the AT participation level in trading. [11] We use ΔH, the differences of AT proxies between treatment and control firms as the response variable in Equations 3 and 4.

< Insert Table 3 >

Results in Table 3 report coefficient estimates for interaction term, $HighAT * SmallTick$ are insignificantly positive when we exclude controls for firm volatility and turnover. However following the inclusion of these control variables coefficient estimates are significantly positive and adjusted R^2 increase from 0.029 to 0.242. In terms of order resting times, results reported in Table 3 confirm aforementioned results of a significant decline and consequently increased HFT participation in stocks which move from a large relative tick to smaller relative tick.[12]

5. Conclusion

[11] One may argue that the use of proxies of HFT may be a result due to the other market condition changes, not directly related to the true HFT involvement. However, we argue that our experiment reduces such interferences by including treatment firms not only in the more recent high AT environment (2009-2012), but also a respective from low AT period (1996~2004). Coefficient estimates on the interaction term incorporated firms from both periods and the significant change in HFT proxies is not observed prior to AT market-wide introduction.

[12] We replicate our analysis without weights variables and find similar results.

We analyse trading around stock splits and consolidations to ascertain whether the resulting reduction in tick size reduces HFT.

Our results show that HFT are attracted to low-tick stocks. This result supports the hypothesis that stocks with small relative tick size, in having a larger price grid create more short-lived trading opportunities in the market. For stocks with large relative tick sizes, the opposite is true. Since there are few price grids for the same percentage return, and depth is more so consolidated per price level, price moves with less frequency, and short-lived trading opportunities are less likely to occur. In this scenario, the time (queue) priority is extremely valuable.

While most market protocols are fixed by trading rules which are set by the regulators and/or exchanges, relative tick size is a feature not purely controlled by the market regulator. Firms can actively alter their relative tick sizes in order to either attract or detract the extent of HFT. Our results show that if a listed stock aims to attract more institutional investors in their share trading, undertaking a sock split and increasing tick size can actually help to limit HFT activity. This hence provides market participants a more convenient and active approach in regulating their own securities, rather than purely relying on the regulatory action.

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Table 1: Summary Statistics

This table reports summary statistics for our treatment firms which undertake stock splits or consolidations and their matched pair control firm. For each treatment firms, a corresponding control firm is selected at based on daily turnover and industry. A total 131 ASX firms are identified as having undertaken a corporate action which significantly modify its relative tick during the period 1996 to 2012. A six month event window is identified centred around each of the 131 events. The sample is split between a low HFT (1996-2004) and high HFT (2009-2012) trading environment. Turnover is calculated as the mean of dollar turnover at the end of trading day per stock; Volatility is evaluated as mean of all 15-minute return standard deviations; No of orders is the average count of orders not traded or deleted upon entry; Order Rest Time (*ORT*) is calculated based on average log orders resting time (recorded in seconds) of orders not traded or deleted upon entry; Order-to-Trade ratio (*OTR*) is the number of total order counts standardised by dollar turnover and scaled by 1000. Both measures are valued on daily basis for each stock dilution event. Standard deviations of variables are included in parentheses.

	No. of Firms	**Turnover $000**	**Volatility**	**No of orders**	**LnORT**	**OTR**
Panel A: Low HFT Trading Environment						
Treatment (1996-2004)	76	2,787 (10,991)	0.0436 (0.226)	166.82 (327.5)	6.334 (1.099)	1.548 (157.44)
Control (1996-2004)	76	2,588 (12,659)	0.0071 (0.0066)	154.02 (453.71)	6.481 (1.128)	0.848 (52.67)
Panel B: High HFT Trading Environment						
Treatment (2009-2012)	55	2,559 (4,630)	0.0123 (0.0186)	2523.9 (5116.7)	4.847 (1.885)	1.744 (21.33)
Control (2009-2012)	55	2,378 (5,496)	0.0094 (0.0106)	2459.8 (4691.5)	4.862 (1.920)	3.002 (51.34)

Table 2: Regression Analysis with Sample Observations

This table reports regression coefficients for the model: $H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot \left(HighAT_i * SmallTick_{i,t}\right) + \sum_k a_k \cdot Control_{i,t,k} + \varepsilon_{i,t}$, fitted across the 131 stock dilution events. i is the event index and ranked by event dates; t is the date index for each event: $t > 0$ represents the small tick period (before consolidations or after splits) and $t < 0$ the large tick period. $Firm_i$ is a firm fixed effect; $SmallTick_{i,t}$ is an event dummy which equals 1 when relative tick size is low ($t > 0$) and 0 otherwise. $HighAT_i * SmallTick_{i,t}$ is an interaction dummy term equal to 1 when tick size is relatively low for events in High AT period (2009-2012). The regressions are fitted with the two AT proxies as responses ($H_{i,t}$): Order-to-Trade ratio (*OTR*) and log Order Rest Time (*ORT*). $Control_{i,t,k}$. Represent control variables: Log of daily dollar turnover ($log\left[Turnover_{i,t}\right]$) and 15-minute return volatility ($Volatility_{i,t}$). All regressions are weighted using an adjusted weighted, $\frac{1}{1/\text{n\_sample}_{i,t} + 1/\text{n\_control}_{i,t}}$, where $n\_sample_{i,t}$ and $n\_control_{i,t}$ are counts of orders which do not exit order book (e.g. cancelled or traded) upon entry for sampled and controlled observations respectively, on day t, event i. *t-stats* included in the parentheses and adjusted-R^2 are also reported.

	Order-to-Trade Ratio		Order Rest Time	
SmallTick	-0.016	0.074	-0.322**	-0.263**
	(-0.19)	(0.93)	(-10.99)	(-9.70)
*HighAT*SmallTick*	0.770**	0.767**	-0.514**	-0.515**
	(8.67)	(8.85)	(-15.96)	(-17.33)
Ln Turnover		-0.622**		-0.417**
		(-23.75)		(-46.41)
Volatility		-0.034		-0.007
		(-0.07)		(-0.04)
R^2	0.307	0.342	0.824	0.852

* significant at 5% level
** significant at 1% level

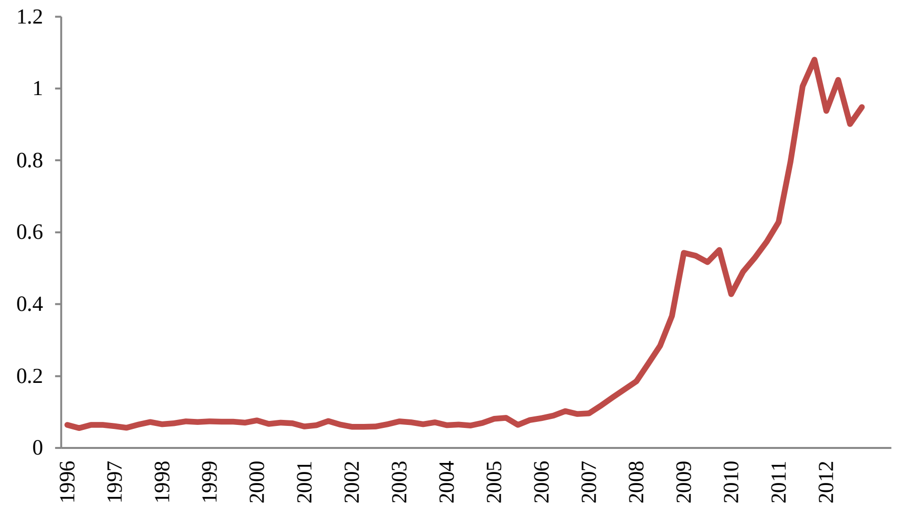
Table 3: Regression Analysis with Sample And Controlled Observations

This table reports regression coefficients for the model:
$\Delta H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot \left(HighAT_i * SmallTick_{i,t}\right) + \sum_k a_k \cdot Control_{i,t,k} + \sum_k a_k \cdot Control_{j,t,k} + \varepsilon_{i,t}$, fitted across the 131 stock dilution events. i is the event index and ranked by event dates; t is the date index for each event: $\mathrm{t} > 0$ represents the small tick period (before consolidations or after splits) and $\mathrm{t} < 0$ the large tick period. Response, $\Delta H_{i,t}$, is the difference in AT proxies between treatment and control firms: $\Delta H_{i,t} = H\_sample_{i,t} - H\_control_{i,t}$; $Firm_i$ is a firm fixed effect; $SmallTick_{i,t}$ is an event dummy which equals 1 when relative tick size is low ($\mathrm{t} > 0$) and 0 otherwise. $HighAT_i * SmallTick_{i,t}$ is an interaction dummy term equal to 1 when tick size is relatively low for events in High AT period (2009-2012). The regressions are fitted with the two AT proxies as responses ($H_{i,t}$): Order-to-Trade ratio (*OTR*) and log Order Rest Time (*ORT*); $Control_{i,t,k}$represents control variables for treatment firms i;$Control_{j,t,k}$represents control variables for control firms j. Control variable include: Log of daily dollar turnover ($log[Turnover\quad]$) and 15-minute return volatility ($Volatility_{i,t}$). All regressions are weighted using an adjusted weighted, $\frac{1}{1/\mathrm{n\_sample}_{i,t} + 1/\mathrm{n\_control}_{i,t}}$, where $n\_sample_{i,t}$ and $n\_control_{i,t}$ are counts of orders which do not exit order book (e.g. cancelled or traded) upon entry for sampled and controlled observations respectively, on day t, event i. *t-stats* included in the parentheses and adjusted-R^2 are also reported.

	ΔOrder-to-Trade Ratios		ΔOrder Rest Time	
SmallTick	-0.23	0.067	-0.390**	-0.342**
	(-0.27)	(0.46)	(-9.19)	(-8.17)
HighAT*SmallTick	1.211	0.701**	-0.271**	-0.310**
	(1.32)	(4.53)	(-5.94)	(-6.90)
LnTurnover (Treatment Firms)		-0.729**		-0.356**
		(-16.31)		(-27.43)
LnTurnover (Control Firms)		0.923**		0.156**
		(18.19)		(10.6)
Volatility (Treatment Firms)		-0.344		0.133
		(-0.42)		(0.56)
Volatility (Control Firms)		-9.087		-8.667*
		(0.64)		(-2.10)
R	0.029	0.242	0.743	0.761

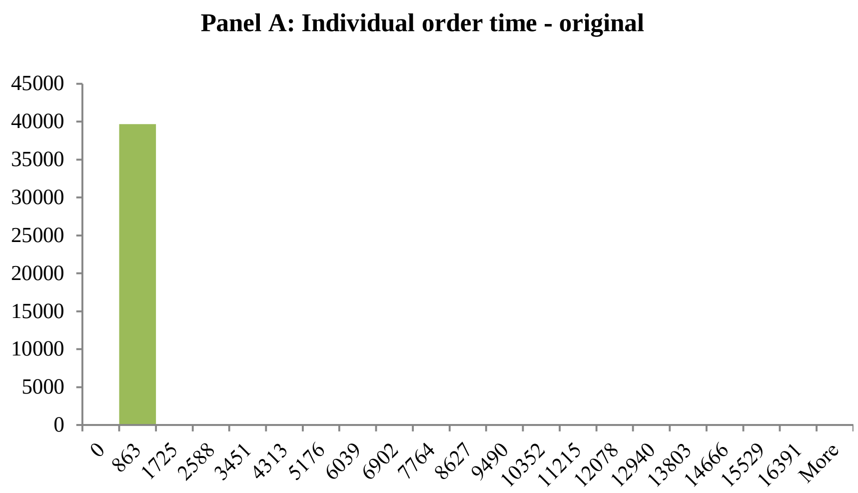
* significant at 5% level
** significant at 1% level

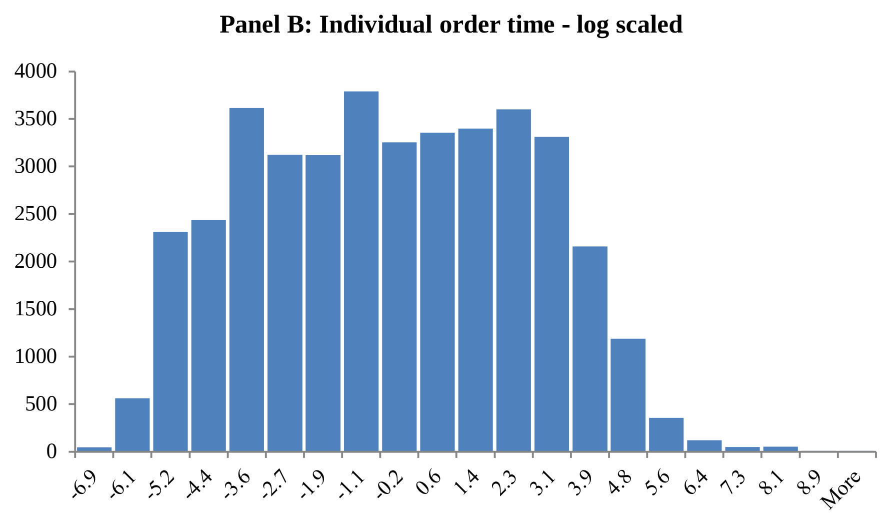
Figure 1: Order to Trade Ratio



This figure depicts the Order-to-Trade ratio for ASX 50 stocks, as defined by Hendershott et al. (2011). We utilised full order book data during normal trading hours.

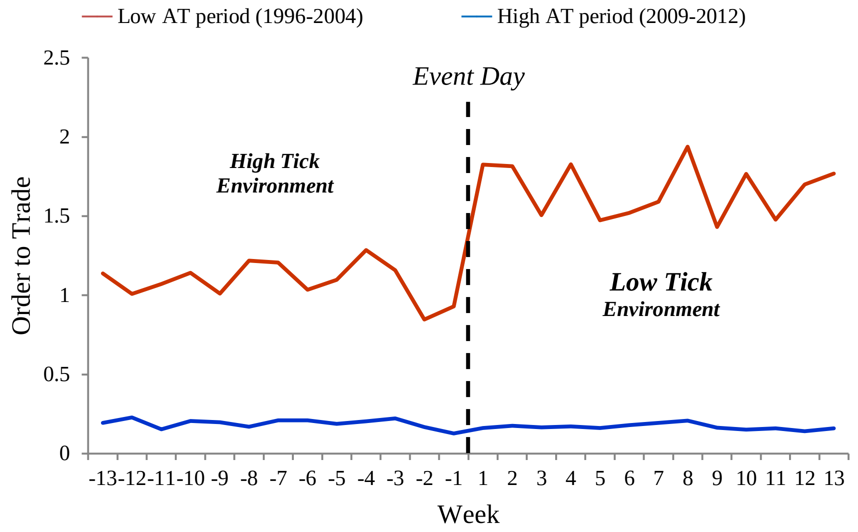
Figure 2: Log transform of order time





As an example Figure 2 depicts order rest times histograms in non-scale and log-scale for one stock in 2012. No scaling data reported in Panel A show an extreme right skewed shape; while log transformed data appear to ore symmetrical and centred.

Figure 3: HFT participation around Stock Splits and Consolidations



We take weekly average of order to trade ratio (*OTR*), during high and low AT period respectively. Samples with lower relative tick sizes (pre splits and post consolidations) are labelled with negative time index, while higher relative tick sizes (post splits and pre consolidations) are labelled with positive time index.

APPENDIX: Order Definition Illustration

In this section, we include an illustration of how the order time and number of orders are calculated from the data. Order amendments can have two effects if not deleted: (1) if order volume is decreased said orders retain time priority; (2) amendment which include a price change or volume increase are re-queued. This is equivalent to deleting an order and resubmission. Hence, an order is started when an “Order Enter” message or “Order Amendment” message and ended with “Order Deletion” or “Order Amendment” or “Trade” message. Order book message associated with “Off Market Trades”, and “Trade Cancellation” messages are removed from the sample since they have no direct interaction with the central limit order book.

The following table samples order level data utilised in the study,.

	Time	Type	Price	Volume
1	11:00	Enter	10	1000
2	11:01	Amendment	10	900
3	11:02	Amendment	11	900
4	11:03	Trade	11	400
5	11:04	Amendment	11	600
6	11:05	Delete	-	-

An exchange order is firstly entered into the limit order book at 11:00 (starting point of first order). It is first amended at 11:01 with a decrease in volume to 900 (no impact to queue) and amended again at 11:02 with price increase to $11 (ending first order and starting second order). The order is then partially traded at 11:03, 400 shares (ending second order). The order has outstanding 500 shares, is then increased to 600 (starting the third order). The order is then deleted at 11:05 (end of the third order). This one single exchange order would be considered as 6 messages, while three order counts under our definition. The first order lasts for 1 second and the latter two last for 1 second.

Our philosophy here is to define orders not based on how these messages are propagated or recorded. Rather it focuses on how the messages impact the order’s time priority. In other words, we look at the outcome of messages making it more robust. For example, order amendment (impact time priority) and order deletion-resubmission leads to different number messages counts, while order counts stay the same.