Abstract

Listed companies and institutional investors have called on market regulators to introduce mechanisms to curb high-frequency (HF) trading in financial markets. In this paper we suggest relative tick size is one such mechanism. We investigate for a non-fragmented market two HF trading proxies: order to trade ratio and order resting time, and how it changes around stock splits and reverse splits, exogenous events which significantly impact a firm’s relative tick size. We find that when a security undergoes a stock split and 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 lower levels of HF trading. The reverse is true of reverse splits, HF traders prefer to trade in firms with smaller relative ticks, as the marginal cost of getting ahead in the limit order book decreases. Such behaviour is not observed in our matched sample of control firms or in a pre HF trading environment.

Keywords

High frequency trading; Relative tick size; Stock splits; Order resting time

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G140; G180; D400

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1. INTRODUCTION

In recent decades, technological advancement has significantly reshaped financial markets around the globe and created a new breed of market participants, so-called High Frequency (HF) traders. Regulators, academics and the industry continue to debate the merits and toxicity of HF trading, whether it benefits or harms the existing market and other participants (see Chordia, Goyal, Lehmann & Saar, 2013 for a summary of recent studies). One question that remains to be explored is whether HF traders favour certain securities and markets over others (See ASIC Report 331, 2013). While high connection speeds and low trading latency are crucial to HF traders, within the same market with the same latencies, it is clear that HF traders are more active for some securities, which cannot be solely explained by conventional micro-structure facts, such as turnover, volatility and market capitalisation (Jones, 2013). In this paper, we investigate one security attribute, relative tick size, which is defined as the minimum price variation relative to the price level. A small relative tick could be preferred by an HF trading firm, as the cost of advancing in the queue is small. However, the wider the relative tick is, the larger the gain an HF trade can achieve by making markets. Hence, the following empirical question remains: do HF traders behave differently towards stocks with different relative tick sizes? Using stock recapitalisation (i.e., splits and reverse splits) events on the Australian Stock Exchange (ASX), we compare trading behaviours under different relative tick regimes in the HF trading environment of today’s markets relative to those of prior years.

Empirical studies have reported rapidly growing participation by HF traders over the past decade and have evaluated their effects on market quality. Jarnecic and Snape (2014) show that HF traders on the London Stock Exchange employ short duration orders that provide continuous liquidity but thin depth, increasing the transience of prices. Examining the NYSE and NASDAQ markets, Hendershott, Jones and Menkveld (2011) and Hasbrouck and Saar (2013) report that bid-ask spreads and volatility improved during times of increased HF trading. Carrion (2013) and Brogaard, Hendershot and Riordan (2013) extend these two studies by investigating the relation between HF trader involvement and information efficiency/price discovery. While these two studies reach different conclusions on HF traders’ profitability, they both find that sizeable trading by HF traders is associated with faster impounding of information into markets. However, Jain, Jain and McInish (2013) find HF trading increases tails risk in Japan while Boehmer, Fong and Wu (2012) in a global study find that HF traders increase short-term volatility, leading to further negative externalities in the market, as modelled by Biais, Foucault and Moinas (2012). In a more recent study, Chaboud, Chiquione, Hjalmarsson and Vega (2014) find that HF trading firms do not exacerbate volatility but that algorithmic trading leads to a significant decline in triangular arbitrage opportunities and mispricing in markets.

Hagstromer and Norden (2013), using a proprietary database, find that HF traders are mainly associated with market making activity and that such activity reduces intraday volatility, as stocks experience an increase in the minimum tick. Hagstromer and Norden (2013) unable to sufficiently identify the impact of tick change on HF trading involvement, state, “tick size...
regulation may be an interesting solution for limiting quoting traffic … this is an interesting
direction for future research” (p. 769).

Motivated by Hagströmer and Nordén (2013) and Menkveld (2013), who find that HF trader
profitability hinges on some of the very basic features of market design, such as trading
fees/rebates and clearing fees, our study aims to extend the existing HF trading literature by
examining another key component of market design: relative tick size. Our contributions are
listed as follows. First, we respond to the call by Hagströmer and Nordén (2013) and
demonstrate that HF traders are attracted to stocks with a smaller relative tick size. Using
exogenous shocks of stock split/reverse-split events, which result in significant changes in
stock prices and consequent changes in relative tick size, we find that HF trader participation
in the market decreases during higher relative tick periods. Second, we adopt a longitudinal
approach to conduct a difference-in-differences analysis across a sample of control-matched
firms’ stock splits/reverse-splits in both pre- and post-HF trading environments. Third, we
expand HF trading research to the Australian market. Unlike studies of the highly fragmented
US and European markets, the Australian market consisted of one central limit order book
until the introduction of Chi-X Australia in October 2011. We demonstrate that even highly
centralised lit markets such as Australia have experienced a rapid growth of HF trader
participation. Our results provide the first empirical evidence to support views by Weild, Kim
and Newport (2012), who suggest that small relative tick sizes are an important element to be
considered by exchanges and regulators in view of increased HF trader participation.

Previous studies examining tick size predate the introduction of HF trading and conclude that
a smaller tick size promotes competition, improves liquidity and reduces transaction costs.
Harris (1994) is the first to document the relationship between bid-ask spreads and tick size,
and he argues that the relative tick size is the relevant economic measure of tick size, which
impacts both liquidity demanders and suppliers. Ahn, Cao and Choe (1996) confirm Harris’
conclusion with AMEX data and further establish the importance of trading volume for tick
reduction’s ability to effectively reduce the bid-ask spread. Subsequent studies expand tick
size related research to other countries such as Singapore (Lau and McInish, 1995) and
Taiwan (Ke, Jiang and Huang, 2004). Aitken and Comerton-Forde (2005) examine the
Australian tick regime change in 1996 and show that tick reduction improves liquidity most
for stocks with large relative ticks. Bessembinder (2003) uses the decimalisation of the NYSE
in 2001 and finds that the reduction in tick levels leads to a decrease in bid-ask spreads (most
evidently in large market cap stocks), quotation size and intraday return volatility. Bessembinder (2003) also reports that smaller traders who use market orders benefit most
from decimalisation. Similar results are also reported by Bacidor, Battalio and Jennings
(2002), who examine the hidden impacts of tick reduction.

Research examining regulatory tick regime changes provide powerful market-wide natural
experiments, however, the occurrence of these changes is infrequent. A selection of
researchers have proxied these events by examining firms as they shift trading across
minimum tick increments. Unlike in the US, where stocks above a penny have a fixed tick of
1 cent, European and Asian markets stipulate variable minimum tick increments conditioned
on price level. Consequently, significant tick change can be observed by monitoring stocks
that frequently fluctuate around price bands, this approach however severely limits the number of observable experiments which are far from representative of the entire market. Furthermore, it is difficult to disentangle the effect of tick change from a stocks’ fundamental information shift because such events are naturally endogenous to securities.

Relative tick size is economically more significant and relevant than the minimum tick size because investors and traders are subject to capital constraints (Harris, 1994). A firm’s relative tick size however can be significantly altered by modifying stock prices through events such as splits and reverseplits, which are at the discretion of management. Stock splits (reverse-splits) are corporate events that are initiated by listed companies and that have the effect of increasing (reducing) the number of shares issued without changing a firm’s market capitalisation but with reducing (increasing) its price level. Because the announcements of such events are months in advance of their completion, any potential information content of these corporate actions is priced beforehand. This results in exogenous tick-changing experiments, exclusive of change in stock fundamentals. Consequently, any results we observe can be attributed to the nature of the changing relative tick around these event dates.

Angel (1997) is the first to conduct an empirical examination of stock splits. Angel (1997) notes that such an action increases the relative tick size, which inflates the floor value of the bid-ask spread. Higher spreads incentivise liquidity providers to make markets, which leads to greater depth. These findings are corroborated by Schultz (2000) and Kadapakkam, Krishnamurthy and Tse (2005), who observe an increase in small-sized buy orders after stock splits and an increase in transaction costs following stock splits, consistent with the hypothesis that brokers promote stocks more actively following splits. Desai, Nimalendran and Venkataraman (1998) also find a significant increase in volatility and the number of trades following stock splits.

More recently, a focus on ticks emerged after the introduction of the Tick-Size Pilot Program in the US2 (see Buti, Rindi and Wen and Werner, 2013, Yao and Ye, 2013, O’Hara, Saar and Zhong, 2014). Our work also contributes to the tick size debate and provides supportive evidence related the significant impact of tick change legislation on equity markets. We add to this growing body of research and provide a unique contribution by showing that HF trader involvement can be influenced by corporate events, such as stock splits or reverse-splits, which directly impact a stock’s relative tick size. We investigate two proxies for the level of HF trading: 1) a modified version of the proxy developed by Hendershott, Jones and Menkveld (2011) and 2) a new measure, order resting time, which reflects the time an order stays on the market and the general pace of the order book. We find a significant increase in HF trading and a significant decrease in order resting time when stocks move to a lower relative tick size. We conclude that, all else equal, stocks with a lower tick size attract a greater proportion of HF trading.

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The paper is structured as follows. Section 2 introduces the experiment and data used in the study. Section 3 defines the HF trading proxies and details the analysis. Section 4 presents and discusses the results, along with the robustness tests. Section 5 outlines the conclusion.

2. Experimental Design and Data

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

For each event, we construct a 180-day window centred on the stock split/reverse-split dates. Each stock split/reverse-split event in our experiment is categorised by its impact on the relative tick. A stock reverse-split causes a sharp increase in the price, corresponding to a reduction in the relative tick size. Thus, pre-reverse-split trading days are considered a large-tick period and post-reverse-split trading days, a small-tick period. Conversely, the pre-split period is regarded as a small-tick period, and the post-split period is regarded as a large-tick period. Because this paper focuses on the change in tick size and not on the direction of tick change, both splits and reverse-splits are then categorised into large- or small-tick events. Using the event date as time zero \((t = 0)\), the small-tick observations after reverse-splits or before splits are labelled with positive time indices \((t = 1, 2, \ldots, n)\), while the large-tick observations before reverse-splits or after splits are labelled with negative time indices \((t = -1, -2, \ldots, -n)\).

To ensure that the change in HF trading levels is due to the change in relative tick size, we pair each sample stock with a control stock traded during the same period. The benchmark firm stock is selected based on similar daily turnover and industry as the sample stock. Benchmark firms do not experience any corporate actions during the same observation period. To capture the impact of HF trading rather than some unobserved market reaction towards tick change that precedes the market-wide adoption of algorithmic trading, we further

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3 We select 1996 as our starting point to avoid the major market wide tick size regime change on December 4, 1995.

4 An adjustment factor is created on the day of the of the split or reverse-split event to reflect the stock price change due to the change in the stock pool, so the pre-event change is at the same level as the post-event price, e.g., a 2:1 reverse-split halves the stock pool and doubles the price. Hence, the adjustment factor (for the pre-event price) is 2.

5 We carry out our analysis using adjustment factors of 2.0 and 0.5 and find similar results despite the reduced sample size.
categorise our sample into two periods based on the general level of HF trading activity in the market.

< Insert Figure One >

Figure 1 charts the evolution of the order-to-trade ratio for ASX listed firms since 1996. As per Hendershott, Jones and Menkveld (2011), a larger order-to-trade ratio indicates a greater proportion of HF trading in the market. Figure 1 depicts that the order-to-trade ratio remains uniform until 2007 and then increases rapidly. This finding coincides with the general market view that HF trading is a recent phenomenon in the Australian market. In view of this change, we split the sample period into a pre- and post-HF trading environment: the pre-HF period contains 76 events from 1996 to 2004, and the post-HF period contains 55 events from 2009 to 2012. Events during the transition period (2005-2008) are removed from the experiment.

The order book data used in this paper are sourced from the Australian Equities Tick History (AusEquities) database, which is managed and distributed by the Securities Industry Research Centre of Asia Pacific (SIRCA). AusEquities provides order book messages and transaction data directly from the ASX. We limit our order book to observations between 10:10 am and 3:55 pm to avoid any confounding factors associated with the opening (9:59 to 10:09 am) and closing (after 4:00 pm) auctions. The data contain all message traffic on the market, including: “Order Entering”, “Order Amendment”, “Order Deletion”, “Trade”, “Off-Market Trades”, and “Trade Cancellation”. In addition the data include order identification sequence numbers and time stamps, accurate to the nearest millisecond. This information enables the tracking of each individual order submitted to the limit order book. 6 Unlike the data analysed by Hagstromer and Norden (2013) or Borgaard (2013), our data do not flag messages originated specifically by HF traders. We thus employ two measures to proxy the general level of HF activities in the market: the order-to-trade ratio (\(OTR\)) and order rest time (\(ORT\)).

3. Methodology

The commencement of an order in the data is labelled “Order Entering”; if an order is not fully traded upon entry, it will join the end of the existing order queue at the same price level consistent with price and time priority rules. If orders are deleted or fully traded, they are removed from the order book. “Order Deletion” and “Trade” are naturally recognised as the end of an order. The effect of “Order Amendment” messages on the ASX time rules is contingent however on what elements of the order are amended. When the only amendment is a decrease in quoted volume, the amended order still enjoys the same time priority as original order entry. If the amendment however alters the price or increases the quoted volume, the order loses its time priority, and it 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 by their impact on the order book, then the second type of order amendment is equivalent to the

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6 “Off-Market Trades” and “Trade Cancellation” messages are associated with off-market trade reporting. Because our main focus here is to investigate on-market orders and trades, these two types of messages are removed from the analysis.
end of the original order (order deletion) and the beginning of a new order (order entering). The first type of amendment, however, does not influence the order’s ranking in the order book, and hence is excluded from the analysis. Based on this criterion, we consider an order to begin with an “Order Enter” or “Order Amendment” message and to terminate with an “Order Deletion”, “Order Amendment” or “Trade” message. The time that lapses between the start and end of an order is recorded as the individual order resting time. This is the time that it takes for a newly created order to lose its time priority (due to either deletion or amendment) or to be partially traded. \(^7\)

Based on these definitions of individual orders and filtered market messages, we measure the order-to-trade ratio (\(OTR\)) as the ratio of total order counts and on-market dollar turnover. We replace the message counts used by Hendershott, Jones and Menkveld (2011) with the total number of orders during the day. This approach 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), improving the accuracy 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 the order-to-trade ratio (\(OTR_{i,t}\)).

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

In a market in which HF traders are dominant, their direct market access and increased response time hasten the pace of trading. Algorithms delete orders if the risk of adverse selection increases and/or submit new orders to capture trading opportunities. Thus, each order will rest for a shorter time than it would in a market with fewer HF activities. Our second HF trading proxy is the order resting time (\(ORT_{i,t}\)):

\[
ORT_{i,t} = \frac{\sum_l \log(OrderTime_{\text{Ind},i,t,l})}{\sum_l 1} = \log \left( \prod_l \frac{\text{OrderTime}_{\text{Ind},i,t,l}}{\Sigma_l 1} \right)^{\Sigma_l 1}, \ldots (2)
\]

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 \(OrderTime_{\text{Ind},i,t,l}\). 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 \(AT_{i,t}\)), \(\Sigma_l 1\) does not include orders that are executed or deleted upon entry. Figure 2 Panel A depicts the distribution of \(ORT\), Panel B reports the log-scale transformation. Figure 2 justifies aggregating the order time with a log transformation over directly averaging the order time. Figure 2 depicts the histogram of \(ORT\) from a randomly selected stock.

\(^7\) 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. An illustrative example is included in Appendix 1.
The distribution of the original scale (Figure 2, panel A) indicates that individual order time is strongly skewed to the right. Direct arithmetic averaging is hence biased towards long-lasting orders. Conversely, the log-transformed order times (Figure 2, panel B) are more symmetrical and condensed. The average of the log order time is therefore a better representation of the general speed of trading in the market, and it is used in the subsequent analysis.

3.1 Model

Our HF trading proxies, which are calculated from the data, are naturally influenced by corporate events during both periods. Thus, we are not interested in the change in HF trading proxies around tick change events but rather in how the change differs between the pre-HF (1996-2004) and post-HF (2009-2012) environments. We examine 131 stock splits or reverse-splits: 76 in the pre-HF period (1996-2004) and 55 in the post-HF period (2009-2012). This focus leads us to include two tick-change-related variables in the model: SmallTick acts as a control for the natural change of HF proxies around corporate events and the interaction term HighAT * SmallTick, which captures the difference in proxies’ changes in the pre- and post-HF periods and constitutes the variable of interest in the study.

The basic form of the model tested is

$$H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot (HighAT_i \ast SmallTick_{i,t}) + \varepsilon_{i,t}, \ldots \quad (3)$$

where $H_{i,t}$ is the sample HF trading proxy (OTR or ORT); $Firm_i$ is a fixed effect term; and $SmallTick_{i,t}$ is an indicator variable equal to 1 when tick size is relatively small ($t > 0$) and 0 otherwise. The interaction $HighAT_i \ast SmallTick_{i,t}$ is equal to 1 when tick size is relatively small ($t > 0$) for events during the post-HF 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 of our HF proxies. For example, an extremely illiquid stock with infrequent trades during the day and a still order book naturally results in large OTR and ORT. Such observations should be weighted less than observations for liquid stocks with frequent trades. Thus, we use the denominator of the ORT proxy, counts of orders that do not exit the order book (e.g., cancelled or traded) upon entry, as weights for observations.

We also control for some known determinants of HF participation, including trading volume and volatility, to estimate Equation 4 as follows:

$$H_{i,t} = Firm_i + \gamma \cdot SmallTick_{i,t} + \delta \cdot (HighAT_i \ast SmallTick_{i,t}) + \sum_k a_k \cdot Control_{i,t,k} + \varepsilon_{i,t}, \ldots \quad (4)$$
We choose the log of daily dollar turnover ($\log[\text{Turnover}_{i,t}]$) and 15-minute return volatility ($\text{Volatility}_{i,t}$) as control variables and estimate Equation 4 using the two HF proxies in the sample observations.

### 3.2 Robustness

To evaluate the robustness of our analysis, we further incorporate a sample of control firms and use $\Delta H_{i,t} = H_{\text{sample}_{i,t}} - H_{\text{control}_{i,t}}$ as our response variable, where $H_{\text{sample}}$ is the HF trading proxy calculated for treatment sample firms, and $H_{\text{control}}$ is the corresponding HF trading proxy measured for control stocks. Because the sample and corresponding control stocks share similar attributes (other than the corporate event), any market interference in the HF proxies is present in both our sample and the control observations. By differencing the proxies of the two groups, we eliminate such interference.

Because the new responses, $\Delta H_{i,t}$, reflect the difference of two sample variables, the weights in the new regression are thus adjusted to $\frac{1}{1/n_{\text{sample}} + 1/n_{\text{control}}}$, which reflects the difference in variance (accuracy) between the sample and control stocks. Further, to re-estimate Equation 4, control factors are not only limited to the turnover and volatility of the sample stocks but also to microstructure factors in the control stocks. The turnover and volatility for both stock groups ($\log[\text{Turnover}_{\text{Sample}_{i,t}}]$, $\log[\text{Turnover}_{\text{Control}_{i,t}}]$, $\text{Volatility}_{\text{Sample}_{i,t}}$ and $\text{Volatility}_{\text{Control}_{i,t,k}}$) are included as control variables.

### 4. Results

Table 1 contains the summary statistics for all variables in the subsequent analysis. Each treatment event is paired with a control stock based on the average daily turnover in the 180-day period and the industry. Turnover and daily order counts for treatment and control firms are similar in both mean and standard deviation. Panel A of Table 1 reports in the pre-HF trading environment, treatment firms turnover approximately $2.8$ million while the control firms turnover approximately $2.6$ million, reflecting the appropriateness of our matching procedure. Similar results are reported in Panel B of Table 2 in the post-HF trading environment. Both treatment and control firms have shorter average order resting times and larger order-to-trade ratios during the post-HF period, which is expected given our categorisation of trading environments between low and high HF trading.

< Insert Table 1 >

< Insert Figure 3 >

Figure 3 depicts the average weekly OTR for all treatment firms undertaking stock splits/reverse-splits in the two HF trading environments. Figure 3 provides preliminary evidence that HF traders prefer stocks with smaller relative ticks. This is evident by the increase in the order-to-trade ratio as a firm shifts from a high relative tick to a low relative tick between 2009 and 2012. Such behaviour is not evident in the pre-HF period.
Table 2 reports the coefficient estimates for Equations 3 and 4. Table 2 confirms the HF trading behaviour documented in Figure 3. Turning first to the results for the order-to-trade ratio proxy for HF activities, our variable of interest $\text{HighAT} \times \text{SmallTick}$ 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 post-HF period (2009-2012) vis-à-vis the pre-HF period (1996-2004). Furthermore, the insignificant coefficients of the $\text{SmallTick}$ variable demonstrate that the sharp increase in the order-to-trade ratio is only observed in trading periods after HF traders are active in markets, supporting the appropriateness of order-to-trade ratios as a proxy for HF trading. Overall, the order-to-trade ratio, as one of the HF trading proxies in this paper, indicates that HF traders trade more low-tick stocks than similar stocks with higher relative ticks.

Similar conclusions can be drawn from our second proxy, order resting time, again our variable of interest is significantly negative at the 1 percent level. Table 2 reports that during the post-HF period, reductions in order resting time are significantly shorter when firms shift to a lower tick trading environment vis-à-vis firms that undertake corporate actions to reduce tick sizes during the pre-HF period. The results in Table 2 show that HF traders more actively participate in stocks with smaller relative ticks, leading to a significantly shortened order resting time in recent times. Unlike results for our order-to-trade proxy, order resting times generally decrease over our sample period, indicating that the pace of trading increases following a tick-reduction initiative. However, the results in Table 2 confirm that any reduction is significantly larger in the post-HF sample period. Together, these results yield similar conclusions: during a period defined as an active HF trading environment, firms that are associated with smaller relative ticks are associated with a higher $\text{OTR}$ and a shorter $\text{ORT}$. A higher $\text{OTR}$ suggests that more orders are submitted to the market to facilitate the same amount of turnover, while a shorter $\text{ORT}$ means that orders spend much less time in limit order books and that the pace of trading is accelerated.

As a robustness test, we re-estimate Equation 4 with response variable $\Delta H_{it}$, which measures the $\text{OTR}$ and $\text{ORT}$ for treatment and a matched control firms. Results reported in Table 3 confirm the aforementioned results for $\text{OTR}$, the coefficient estimate for our variable of interest is significantly positive. In terms of order resting times, the results reported in Table 3 confirm a significant decline, consistent with an increase in HF participation for stocks that move from a larger relative tick to smaller relative tick.8

5. Conclusion

In this study we analyse HF trading around stock splits and reverse-splits to ascertain whether the resulting change in tick size exhibits any preference of HF trader. Our results show that

8 We replicate our analysis without weighted variables and find similar results.
HF traders are attracted to low-tick stocks, providing supporting for Hagströmer and Nordén’s (2013) assumption that the tick influences HF trading and Weild, Kim and Newport’s (2012) hypothesis that stocks with small relative tick sizes create more short-lived trading opportunities in the market by having a larger price grid. A direct consequence of a small relative tick is that it is less expensive for HF traders to undercut other traders to move ahead of the trading queue. For stocks with large relative tick sizes, the opposite is true. Because there are few price grids for the same percentage return and because depth is more consolidated near the best bid/ask prices, prices move less frequently, and short-lived trading opportunities are less likely to occur. In this scenario, the time (queue) priority is extremely valuable, and HF traders must wait in the queue, as do other, slower participants.

While most market protocols are fixed by trading rules set by regulators and/or exchanges, relative tick size is a feature that is not necessarily controlled by market regulators. We utilise this feature and demonstrate the surge of HF activities during recent years in the Australian equity market. Firms can actively alter their relative tick sizes to either attract or detract the extent of HF trading activity. Our results show that if a listed stock aims to attract more institutional and retail investors to their share trading, undertaking a stock split and increasing tick size can assist to limit HF activity. This result hence provides market participants with an approach to regulating their own securities in lieu of mandated actions.
References


This table reports the summary statistics for our treatment firms, which undertake a stock split or reverse-split, and their matched-pair control firms which did not undertake any corporate action. Control firms are selected based on closest daily turnover and industry. A total of 131 ASX firms are identified as having undertaken a corporate action that significantly modifies its relative tick during the period from 1996 to 2012. A six-month event window is centred on each of the 131 events. The sample is split between a pre-HF (1996-2004) and post-HF (2009-2012) trading environment. Turnover is calculated as the mean of dollar turnover at the end of the trading day per stock. Volatility is evaluated as the mean of all 15-minute return standard deviations. The number of orders is the average count of orders deleted or not traded upon entry. Order resting time ($\text{ORT}$) is calculated based on the average log of the resting time (recorded in seconds) of orders not traded or deleted upon entry. The order-to-trade ratio ($\text{OTR}$) is the number of total order counts standardised by dollar turnover and scaled by 1000. Both measures are valued on a daily basis for each stock dilution event. The standard deviations of the variables are included in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>No. of Firms</th>
<th>Turnover $\text{000}$</th>
<th>Volatility</th>
<th>No. of orders</th>
<th>LnORT</th>
<th>$\text{OTR}$</th>
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</thead>
<tbody>
<tr>
<td><strong>Panel A: Pre-HF Trading Environment</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Treatment (1996-2004)</td>
<td>76</td>
<td>2,787 (10,991)</td>
<td>0.0436 (0.226)</td>
<td>166.82 (327.5)</td>
<td>6.334 (1.099)</td>
<td>1.548 (157.44)</td>
</tr>
<tr>
<td>Control (1996-2004)</td>
<td>76</td>
<td>2,588 (12,659)</td>
<td>0.0071 (0.0066)</td>
<td>154.02 (453.71)</td>
<td>6.481 (1.128)</td>
<td>0.848 (52.67)</td>
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<tr>
<td><strong>Panel B: Post-HF Trading Environment</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Treatment (2009-2012)</td>
<td>55</td>
<td>2,559 (4,630)</td>
<td>0.0123 (0.0186)</td>
<td>2523.9 (5116.7)</td>
<td>4.847 (1.885)</td>
<td>1.744 (21.33)</td>
</tr>
<tr>
<td>Control (2009-2012)</td>
<td>55</td>
<td>2,378 (5,496)</td>
<td>0.0094 (0.0106)</td>
<td>2459.8 (4691.5)</td>
<td>4.862 (1.920)</td>
<td>3.002 (51.34)</td>
</tr>
</tbody>
</table>
Table 2: Regression Analysis with Sample Observations

This table reports regression coefficients for the model:

\[ H_{it} = \text{Firm}_i + \gamma \cdot \text{SmallTick}_{it} + \delta \cdot (\text{HighAT}_i \cdot \text{SmallTick}_{it}) + \sum_k a_k \cdot \text{Control}_{it,k} + \epsilon_{it}, \]

which is fitted across the 131 stock events. \( i \) is the event index ranked by event dates, and \( t \) is the date index for each event, where \( t > 0 \) represents the small tick period (before reverse-splits or after splits) and \( t < 0 \) the large tick period. \( \text{Firm}_i \) is a firm fixed effect, and \( \text{SmallTick}_{it} \) is an event dummy that equals 1 when the relative tick size is low (\( t > 0 \)) and 0 otherwise. \( \text{HighAT}_i \cdot \text{SmallTick}_{it} \) is an interaction dummy variable equal to 1 when tick size is relatively low for events in the pre-HF period (2009-2012). The regressions are fitted with the two HF proxies as responses (\( H_{it} \)): the order-to-trade ratio (\( \text{OTR} \)) and log order resting time (\( \text{ORT} \)). \( \text{Control}_{it,k} \) represents the control variables: the log of daily dollar turnover (\( \text{LnTurnover} \)) and the 15-minute return volatility (\( \text{Volatility} \)). All regressions are weighted using an adjusted weighted \( \frac{1}{n_{\text{sample},t}} \cdot \frac{1}{n_{\text{control},t}} \), where \( n_{\text{sample},t} \) and \( n_{\text{control},t} \) are the counts of orders that do not exit the order book (e.g., cancelled or traded) upon entry for sampled and controlled observations, respectively, on day \( t \), event \( i \). The \( t\)-stats are included in parentheses, and adjusted-\( R^2 \) values are also reported.

<table>
<thead>
<tr>
<th></th>
<th>Order-to-Trade Ratio</th>
<th>Order Resting Time</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SmallTick</strong></td>
<td>-0.016</td>
<td>-0.322**</td>
</tr>
<tr>
<td></td>
<td>( 0.19)</td>
<td>(-10.99)</td>
</tr>
<tr>
<td><strong>HighAT*SmallTick</strong></td>
<td>0.770**</td>
<td>-0.514**</td>
</tr>
<tr>
<td></td>
<td>( 8.67)</td>
<td>(-15.96)</td>
</tr>
<tr>
<td><strong>Ln Turnover</strong></td>
<td>-0.622**</td>
<td>-0.417**</td>
</tr>
<tr>
<td></td>
<td>(-23.75)</td>
<td>(-46.41)</td>
</tr>
<tr>
<td><strong>Volatility</strong></td>
<td>-0.034</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(-0.07)</td>
<td>(-0.04)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.307</td>
<td>0.342</td>
</tr>
</tbody>
</table>

* significant at the 5% level
** significant at the 1% level
Table 3: Regression Analysis with Sample and Control Observations

This table reports regression coefficients for the model:

\[ \Delta H_{it} = \beta_0 + \beta_1 \cdot \text{SmallTick}_{it} + \beta_2 \cdot \left( \text{HighAT}_{i} \cdot \text{SmallTick}_{it} \right) + \sum \alpha_k \cdot \text{Control}_{i,k} + \sum \gamma_k \cdot \text{Control}_{i,k} + \epsilon_{it}, \]

which is fitted across the 131 stock events. \( i \) is the event index ranked by event dates, and \( t \) is the date index for each event, where \( t > 0 \) represents the small tick period (before reverse-splits or after splits) and \( t < 0 \) the large tick period. Response \( \Delta H_{it} \) is the difference in HF proxies between the treatment and control firms, \( \Delta H_{it} = H_{\text{sample}_{it}} - H_{\text{control}_{it}} \); \( \beta_0 \) is a firm fixed effect; and \( \text{SmallTick}_{it} \) is an event dummy that equals 1 when relative tick size is low \((t > 0)\) and 0 otherwise. \( \text{HighAT}_{i} \cdot \text{SmallTick}_{it} \) is an interaction dummy term equal to 1 when tick size is relatively low for events in the post-HF period (2009-2012). The regressions are fitted with the two HF proxies as responses \((H_{it})\). The order-to-trade ratio \((\text{OTR})\) and the log order resting time \((\text{ORT})\). \( \text{Control}_{i,k} \) represents control variables for treatment firms \(i\); \( \text{Control}_{j,k} \) represents control variables for control firms \(j\), including the log of the daily dollar turnover \(\log(\text{Turnover}_{it})\) and 15-minute return volatility \(\text{Volatility}_{it}\). All regressions are weighted using an adjusted weighted, \( \frac{1}{n_{\text{sample}_{it}} + 1/n_{\text{control}_{it}}} \), where \( n_{\text{sample}_{it}} \) and \( n_{\text{control}_{it}} \) are counts of orders that do not exit the order book (e.g., cancelled or traded) upon entry for the sample and control observations, respectively, on day \( t \) for event \( i \). The t-stats are included in parentheses, and adjusted-\(R^2\) values are also reported.

<table>
<thead>
<tr>
<th></th>
<th>( \Delta \text{Order-to-Trade Ratios} )</th>
<th>( \Delta \text{Order Resting Time} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>SmallTick</td>
<td>0.067</td>
<td>-0.342**</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(-8.17)</td>
</tr>
<tr>
<td>HighAT*SmallTick</td>
<td>0.701**</td>
<td>-0.310**</td>
</tr>
<tr>
<td></td>
<td>(4.53)</td>
<td>(-6.90)</td>
</tr>
<tr>
<td>LnTurnover (Treatment Firms)</td>
<td>-0.729**</td>
<td>-0.356**</td>
</tr>
<tr>
<td></td>
<td>(-16.31)</td>
<td>(-27.43)</td>
</tr>
<tr>
<td>LnTurnover (Control Firms)</td>
<td>0.923**</td>
<td>0.156**</td>
</tr>
<tr>
<td></td>
<td>(18.19)</td>
<td>(10.6)</td>
</tr>
<tr>
<td>Volatility (Treatment Firms)</td>
<td>-0.344</td>
<td>0.133</td>
</tr>
<tr>
<td></td>
<td>(-0.42)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Volatility (Control Firms)</td>
<td>-0.087</td>
<td>-8.667*</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
<td>(-2.10)</td>
</tr>
<tr>
<td>R</td>
<td>0.242</td>
<td>0.761</td>
</tr>
</tbody>
</table>

* significant at the 5% level  
** significant at the 1% level
This figure depicts the Order-to-Trade ratio for the ASX 50 stocks as defined by Hendershott, Jones and Menkveld (2011). We utilised full order book data during normal trading hours.
Figure 2 depicts histograms of the non-scaled and log-scaled order resting times for a random stock in 2012. Note that the data reported in Panel A show an extremely right-skewed shape, while the log-transformed data appear more symmetrical and centred.
Figure 3: HF Participation Around Stock Splits and Reverse-splits

Figure 3 depicts the average weekly OTR for all treatment firms undertaking stock splits/reverse-splits in the two HF trading environments. Split events with lower relative tick sizes (pre-splits and post-reverse-splits) are labelled with a negative time index, while higher relative tick sizes (post-splits and pre-reverse-splits) are labelled with a positive time index.
APPENDIX 1: Order Definition Illustration

In this section, we include an illustration of how order times and the number of orders are calculated from the data. Order amendments can have two effects if not deleted: (1) if the order volume is decreased, these orders retain time priority or (2) amendments that include a price change or volume increase are re-queued. These actions are equivalent to deleting and resubmitting an order. Hence, an order starts with “Order Enter” or “Order Amendment” messages and ends with “Order Deletion”, “Order Amendment” or “Trade” messages. Order book messages associated with “Off-Market Trades” and “Trade Cancellation” are removed from the sample because they have no direct interaction with the central limit order book.

The following table illustrates the order-level data utilised in this study.

<table>
<thead>
<tr>
<th>Time</th>
<th>Type</th>
<th>Price</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Enter</td>
<td>10</td>
<td>1000</td>
</tr>
<tr>
<td>2</td>
<td>Amendment</td>
<td>10</td>
<td>900</td>
</tr>
<tr>
<td>3</td>
<td>Amendment</td>
<td>11</td>
<td>900</td>
</tr>
<tr>
<td>4</td>
<td>Trade</td>
<td>11</td>
<td>400</td>
</tr>
<tr>
<td>5</td>
<td>Amendment</td>
<td>11</td>
<td>600</td>
</tr>
<tr>
<td>6</td>
<td>Delete</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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

In this study we define orders not based on how these messages are propagated or recorded. Rather, the focus is on how the messages impact the order’s time priority. In other words, we look at the outcome of messages, making the analysis more robust. For example, order amendment (impact time priority) and order deletion-resubmission leads to different message counts, but the order count stays the same.