Relative Tick Size and Low-latency Trading Activity

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Abstract

This study investigates the influence of relative tick size on low-latency trading (LLT) activity within the Australian equity market. Using an extensive dataset spanning 2008–2017, the analysis reveals a significant inverse relationship between relative tick size and LLT engagement. LLTs are shown to have a very low tolerance for adverse selection risk, and their risk-averse nature prioritise risk minimisation (order-undercutting) over profit maximisation (order-queuing). These results suggest that LLTs focus on generating marginal profits through repeated, low-risk trades, underscoring their fundamentally risk-averse nature. The evidence implies that policymakers may implement a dynamic tick size policy to direct LLT activity towards stocks where it enhances liquidity, while tempering LLT effects in stocks where it may compromise market quality.

JEL Classification Codes: G10, G14

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1. Introduction

Tick size, the smallest permissible price increment for stock movements on an exchange, forms a "pricing grid" that constrains the precision of bid and ask prices (Australian Securities and Investments Commission (ASIC), 2010).[1] Most global exchanges operate under a fixed tick size regime, whereby regulators assign specific nominal tick sizes to stocks within distinct price ranges. Although stock prices typically behave as continuous variables, tick size constraints impose a discrete structure, creating "tick size borders" that, when crossed, can significantly alter a stock's relative tick size – defined as the nominal tick size divided by stock price. This discrete pricing framework not only influences trading costs and liquidity dynamics but also impacts the strategic behaviours of market participants, particularly those engaged in low-latency trading (LLT).

The relationship between tick size and trading behaviour has garnered considerable interest, especially with respect to high-frequency traders (HFTs) who often serve as liquidity providers. Research suggests that larger tick sizes can enhance profitability for market makers by widening bid-ask spreads, which raises revenue margins and stabilises market depth (Yao & Ye, 2018; Bartlett & McCrary, 2020). Larger tick sizes create "liquidity provision rents" that encourage market-making HFTs to submit more limit orders, thereby extending order queues and reducing aggressive price competition (O'Hara et al., 2019). Conversely, in smaller-tick environments with narrower spreads, heightened adverse selection risk compels liquidity providers to prioritise reactive strategies, potentially reducing their market-making presence (Chordia et al., 2011; O'Hara et al., 2019).

Recent studies underscore the nuanced impacts of tick size on HFT-driven liquidity provision across different market structures. For instance, Barardehi et al. (2022) find that in the U.S. tick size pilot program, increasing tick size for certain stocks led to enhanced liquidity and deeper queues, but the benefits were most pronounced in tick-unconstrained stocks. In contrast, wider tick sizes imposed higher trading costs on tick-constrained stocks without proportionate liquidity gains, highlighting the importance of an optimal, stock-specific tick size policy (Bartlett & McCrary, 2020). Similarly, studies in alternative markets, such as cryptocurrency (Dyhrberg et al., 2023) and in exchanges employing speed bumps (Aït-Sahalia & Sağlam, 2024), suggest that larger tick sizes can promote stable liquidity by reducing order undercutting and extending the duration of displayed orders.

Given the diversity of rapid trading strategies impacted by tick size, this study adopts the term "low-latency trading" (LLT) to encompass not only traditional HFT firms but also other

[1] Angel (1997, 2012) emphasises the importance of tick size in market regulation, and explains why the optimal tick size is not zero: (1) a non-zero tick simplifies traders' information sets; (2) an economically significant (i.e. non-trivial) tick size preserves price and time priority in an order book, motivating traders to provide liquidity through limit orders; and, (3) tick size creates a floor for the quoted bid-ask spread, which serves as an incentive for dealers to make markets.

speed-driven, algorithmic traders such as hedge funds and proprietary trading desks. Using LLT as a proxy term for high-speed trading allows for a broader investigation of algorithmic trading activities without limiting the analysis to firms conventionally classified as HFT. The choice of this term also reflects dataset limitations, which preclude identification of individual HFT firms, thereby requiring a more inclusive lens to capture LLT behaviour within the Australian Securities Exchange (ASX).

This study examines how relative tick size affects LLT activity by focusing on stocks across two nominal tick size categories, with a particular emphasis on dynamics near the A$2.00 tick size threshold. Specifically, we investigate LLT responses in two scenarios: (i) stocks within similar nominal tick sizes, and (ii) stocks that cross the A$2.00 threshold, moving either upward or downward. Using ASX data from January 2008 to December 2017, we measure LLT activity through proxies such as quoting intensity (MTR), algorithmic liquidity provision (ALGO), high-frequency OrderIDs (HFO), and HFO-contributed messages (HFOR), capturing how LLTs adapt their strategies to changes in tick size.

The results reveal that LLTs on the ASX display a strong preference for undercutting existing limit orders rather than joining long order queues, with this preference intensifying for stocks with very small relative tick sizes. This behaviour challenges the conventional view that larger tick sizes are essential for sustaining LLT-driven liquidity. Instead, the findings suggest that finer pricing grids facilitate LLT strategies by allowing rapid position adjustments with minimal risk. Through a difference-in-differences (DID) approach, the study demonstrates that LLT activity declines sharply when a stock's tick size crosses the A$2.00 border upwards and increases when crossing downwards, indicating a preference for smaller tick sizes that support speed-driven trading. Our findings also contrast with research from U.S. markets, where larger tick sizes often attract market-making HFTs. The observed divergence in the ASX environment, likely due to reduced market fragmentation and the absence of designated market makers, suggests that ASX-based LLTs prioritise undercutting for risk minimisation. This behaviour aligns with theories that view LLTs as profit-seeking yet risk-averse, generating returns through repeated low-risk trades (Zhang, 2010).

The study's findings support the potential benefits of a dynamic tick size regime that could strategically guide LLT activity. By assigning smaller tick sizes to less liquid stocks, regulators may foster liquidity provision by LLTs, while larger tick sizes could mitigate LLT-driven adverse effects in highly liquid stocks. This approach aligns with calls for policies that balance LLT impact on market welfare (Chordia et al., 2013), offering a practical pathway to optimise liquidity and enhance market stability on the ASX.

1.1. Tick Size Borders and Trading Dynamics in Australia

In the Australian equity market, tick sizes vary based on stock price levels, creating distinct "tick size borders." Specifically, stocks are assigned one of three nominal tick sizes: (i) A$0.001 (one-tenth of a cent) for stocks priced below A$0.10, (ii) A$0.005 (half a cent) for stocks priced between A$0.10 and A$1.995, and (iii) A$0.01 (one cent) for stocks priced at or above A$2.00. These thresholds introduce two critical borders at A$0.10 and A$2.00. Consequently, stocks positioned on either side of these borders exhibit substantial differences in relative tick size. This disparity has notable implications for trading dynamics, particularly for LLTs. O'Hara et al. (2019) highlight that "a larger relative tick size benefits HFT firms that make markets on the NYSE: they leave orders in the book longer, trade more aggressively, and have higher profit margins." Thus, larger relative tick sizes may serve as an incentive for liquidity-providing LLTs, as they can potentially capture higher profits from each tick of price movement in a transaction.

The tick size borders in Australia create distinct shifts in relative tick size. For example, stocks priced at A$0.099 and A$0.10 exhibit relative tick sizes of 1.01% and 5.00%, respectively, while those priced at A$1.995 and A$2.00 display relative tick sizes of 0.25% and 0.50%. These discontinuities in relative tick size at the A$0.10 and A$2.00 borders, as illustrated in Figure 1, signify a meaningful difference in potential profit for LLTs' limit orders placed near these price points. This could, in turn, shape their strategies, particularly in relation to order placement and timing around these borders. Figures 2 and 3 provide a closer look at the dynamics between relative tick size and stock price around the respective borders.[2]

[Insert Figure 1 here]
[Insert Figure 2 here]
[Insert Figure 3 here]

Table 1 highlights the distinct tick size structures and relative tick size values in the Australian and U.S. equity markets. In the U.S. market, there are only two nominal tick sizes for all stocks: US$0.0001 (one-hundredth of a cent) for stocks priced below US$1.00, and US$0.01 (one cent) for stocks priced at or above US$1.00. This structure results in a pronounced disparity in relative tick sizes near the US$1.00 threshold. For example, a stock priced at US$0.9999 has a relative tick size of 0.01%, whereas a stock priced at US$1.00 has a relative tick size of 1.00% – a nearly 100-fold increase due to the crossing of a single tick. In contrast, the largest relative tick size increase observed in the Australian market is fivefold, which is only one-twentieth of the relative increase seen in the U.S. market. Consequently, these structural differences may drive LLTs to adopt distinct trading strategies in each market, which could, in turn, influence their overall role and impact.

[2] The scale used for the Y-axis in Figure 2 is ten times larger than the scale used in Figure 3.

Furthermore, the Australian market lacks designated market-makers, presenting an opportunity for willing LLTs to assume this role voluntarily by capitalizing on their speed advantage. This environment may be more conducive for LLTs to function as liquidity providers in Australia than in the U.S., where designated market-makers and specialists increase the competition for liquidity provision. In this context, LLTs in Australia might be less inclined to pursue aggressive, liquidity-taking strategies that could disrupt other market participants. Instead, they may prioritize market-making activities, contributing to market stability.

Additionally, the minimum trading unit policy further differentiates the Australian and U.S. markets. In the U.S., all equities are typically traded in board lots of at least 100 shares, with odd-lot trades often incurring higher transaction costs. By contrast, Australia mandates a minimum trading unit of just one share, allowing all traders, including LLTs, to execute trades in any volume without incurring additional odd-lot fees. This flexibility in the Australian market enables LLTs to develop various trading strategies unconstrained by larger minimum trading units. It also allows large institutional traders to "repackage" large orders into multiple smaller ones, making it easier to disguise their trades among retail orders. As a result, this trait may impair LLTs' ability to detect approaching large orders, making it more difficult for them to "ride the wind".

Empirical research on tick size has primarily focused on the U.S. markets (see, e.g., Aït-Sahalia & Sağlam, 2024; Angel, 1997; Barardehi et al., 2022; Bartlett & McCrary, 2020; Bessembinder, 2003; Gibson et al., 2003; Goldstein & Kavajecz, 2000; Jones & Lipson, 2001; Lipson & Mortal, 2006; O'Hara et al., 2019; Schultz, 2000; Yao & Ye, 2018). However, the distinctions in market structures between Australia and the U.S. suggest that LLTs may adapt their strategies, activities, and behaviours differently in each market. In summary, the unique combination of a differentiated tick size structure, the absence of designated market-makers, and a more flexible minimum trading unit in Australia creates a unique trading environment for LLTs. Therefore, this research, utilizing an Australian dataset, offers valuable insights into the behaviour of LLTs, especially concerning the influence of tick size on their strategies in a purely order-driven market.

1.2. Low-latency trading in Australia

Figures 4, 5, 6, and 7 illustrate the trends in low-latency trading (LLT) activity in Australia on the ASX from 2008 to 2017, using four primary LLT proxies: the message-to-trade ratio (MTR), algorithmic trading ratio (ALGO), high-frequency order identifiers (HFO), and HFO's message ratio (HFOR).[3] Overall, the data in these figures depict an initial period of rapid growth in LLT activity on the ASX, particularly pronounced between 2010 and 2011, which likely corresponds to both technological advancements and regulatory changes encouraging LLT adoption. However, the period after 2012 shows a more stabilized or even slightly declining trend across some metrics,

[3] In the latter section of this article, the method used to derive these measures is described in detail.

suggesting that the LLT landscape in Australia had matured, with the regulatory environment and market dynamics shaping a more controlled growth path. These patterns reflect the global evolution of LLT, where early growth phases eventually lead to stabilization as markets and regulators adjust to the new trading paradigm.

[Insert Figure 4 here]
[Insert Figure 5 here]
[Insert Figure 6 here]
[Insert Figure 7 here]

2. Literature review and hypotheses development

2.1. Tick size trade-off

Tick size, both nominal and relative, fundamentally shapes the profitability and strategies of liquidity providers and takers (e.g., Angel, 1997; Foley et al., 2019; Li et al., 2021; O'Hara et al., 2019; Yao & Ye, 2018). Liquidity providers, or market makers, post limit orders and await execution, typically operating as passive participants, while liquidity takers submit market orders to trade immediately, acting as aggressive market participants (Li et al., 2021; Yao & Ye, 2018). Markets generally use a price-time priority system where orders are executed based on price, and among equally priced orders, by the time of submission (O'Hara, 2015; Parlour & Seppi, 2008). To secure execution priority, a liquidity provider must improve the best existing price by at least one tick increment.

The bid-ask spread, formed when a liquidity taker's order matches with a liquidity provider's, is central to balancing the incentives of both parties. Liquidity providers profit from the spread by buying at the bid and selling at the ask, while liquidity takers bear the spread as a transaction cost. Thus, larger tick sizes, which widen the spread, may enhance the profitability of liquidity providers but also increase transaction costs, potentially deterring trade from liquidity takers. Optimising tick size, therefore, involves a trade-off between incentivising liquidity providers and minimising costs for takers (Bacidore, 1997; Bourghelle & Declerck, 2004; Cordella & Foucault, 1999; Goldstein & Kavajecz, 2000; Werner et al., 2023).

Tick size influences liquidity providers' profitability by establishing the minimum price increment for which profit can be earned. Larger relative tick sizes typically expand profit margins, encouraging more assertive market-making (Angel, 1997). Research shows that tick size effects depend on whether stocks are "tick-constrained" (with spreads of one tick) or "tick-unconstrained" (spreads over one tick). O'Hara et al. (2019) find that in tick-constrained stocks, larger tick sizes promote deeper order book queues, while in tick-unconstrained stocks, HFTs often opt to undercut rather than queue, thereby reducing depth.

Studies of regulatory interventions further illustrate these dynamics. Barardehi et al. (2022) examine a tick size pilot programme in the U.S. that increased tick sizes to 5 cents for selected stocks. They find that for tick-unconstrained stocks, the larger tick size improved liquidity, increased quoted depth, and reduced HFT-driven undercutting. Conversely, Bartlett and McCrary (2022) report that the same policy imposed higher costs on tick-constrained stocks without substantial liquidity benefits, highlighting the need for tailored tick size policies based on stock characteristics. Additionally, Aït-Sahalia and Sağlam (2024) show that speed bumps in the NYSE American moderated HFT behaviour, reducing quote aggressiveness. The larger tick size in such contexts curbed order undercutting, enhancing market depth and order queuing stability.

In cryptocurrency markets, Dyhrberg et al. (2023) find that larger tick sizes also reduce undercutting, encourage durable order posting, and increase quoted depth. This longer average exposure time for limit orders reflects a less volatile and more stable order book. Their findings suggest that optimal tick sizes balance liquidity costs while discouraging excessive undercutting, thereby improving market quality.

Larger tick sizes also generate liquidity provision "rents," incentivising HFTs to increase their order volume and lengthen queues at the best bid and ask prices (Yao & Ye, 2018). This structure discourages HFTs from cancelling their orders once they reach the front of the queue, as re-queuing is costly, especially for slower traders who lack a speed advantage. Hasbrouck and Saar (2013) observe that non-HFTs place limit orders mainly to minimise transaction costs rather than to profit, which allows them to quote tighter spreads. This results in lower opportunity costs for non-HFTs when placing limit orders, though they may face adverse selection risk from HFTs' strategic undercutting.

Further, Foley et al. (2019) demonstrate that larger tick sizes deepen queues in tick-constrained stocks. This discourages HFT cancellations, increasing their exposure to adverse selection risk as they maintain order priority, while providing slower traders the advantage of reduced competition. Consequently, a coarser pricing grid or larger relative tick size can create a favourable environment for market-making HFTs by lowering adverse selection risks, thus enabling consistent liquidity provision (Chordia et al., 2013).

On the contrary, smaller tick sizes compress bid-ask spreads, creating a finer pricing grid that reduces the cost of undercutting standing limit orders. This can enable HFTs to crowd out slower liquidity providers (Chordia et al., 2013). While tighter spreads lower transaction costs for non-HFTs, lower execution probability often forces them to take liquidity at greater expense. Smaller tick sizes also elevate adverse selection risk, as HFTs are more inclined to undercut based on anticipated price shifts, disadvantaging slower participants (O'Hara et al., 2019).

However, smaller tick sizes can also attract non-HFTs by enabling them to establish price priority over HFTs, increasing competition and forcing HFTs to assume greater adverse selection risk. O'Hara et al. (2019) suggest that this environment results in "fleeting" liquidity, as HFTs frequently cancel orders. Dyhrberg et al. (2023) caution that non-HFT undercutting could undermine market makers' execution priority, potentially discouraging participation and reducing liquidity.

Research by Werner et al. (2023) indicates that reducing tick sizes disperses order queues across more price levels, particularly for highly liquid stocks. For these stocks, shorter queues may increase execution chances and promote liquidity provision. However, for less liquid stocks, smaller ticks may lead to aggressive undercutting with economically insignificant price improvements, thereby discouraging liquidity provision. Angel et al. (2011) also argue that smaller tick sizes can reduce visible liquidity by discouraging traders from displaying large orders, increasing the risk of disruptive trading strategies.

Tick size adjustments reflect a trade-off for liquidity providers between profit maximisation and risk minimisation. Larger tick sizes can provide higher profit margins but elevate adverse selection risk, while smaller tick sizes lower risk but also limit profit potential (Angel, 1997; Sandås, 2001). For low-latency traders (LLTs), this trade-off often guides their strategy choice. LLTs that queue at current price levels may prioritise profit, while those that undercut may adopt a risk-averse stance, minimising exposure to adverse price movements. In summary, the literature suggests that optimal tick size policies should balance the needs of liquidity providers and takers while considering the trade-offs between stability and transaction costs in different market conditions.

2.2. Hypotheses development

The calculation of relative tick size depends on two key parameters: the stock price and the nominal tick size. When the nominal tick size is fixed, relative tick size varies inversely with stock price. For example, in Australia, all stocks priced between A$0.100 and A$1.995 share a nominal tick size of A$0.005 (half-cent). This results in a substantial difference in relative tick sizes: a stock priced at the low end (A$0.100) has a relative tick size of 5.000%, whereas a stock priced near the upper limit (A$1.995) has a relative tick size of 0.251%. This disparity in relative tick size influences LLTs behaviour. The literature suggests that larger relative tick sizes encourage LLTs to engage in order-queuing activities, as the economic incentives to secure execution priority increase when price competition is limited. Conversely, smaller relative tick sizes enable order-undercutting, where LLTs can leverage their speed to make marginal price improvements.

This study aims to investigate whether the difference in relative tick size within a price band leads to significant variation in LLT activity. Accordingly, we propose the following hypothesis:

H1: *Stocks with larger relative tick sizes will exhibit significantly higher levels of LLT activity, driven primarily by order-queuing behaviour, compared to stocks with smaller relative tick sizes.*

In financial markets, stock prices are often perceived as continuous; however, they are, in fact, constrained by discrete tick sizes that create a pricing grid. When a stock's price crosses a tick size border, its nominal tick size – and consequently its relative tick size – changes abruptly. For example, stocks priced at A$2.00 or higher in the Australian market move to a pricing grid of A$0.01 (one cent), while stocks below A$2.00 remain on a grid of A$0.005 (half-cent). This crossing of tick size borders is driven by supply and demand forces that cause price fluctuations. When a stock crosses a tick size border in an upward direction, the increase in its nominal tick size causes a sharp rise in relative tick size. Conversely, a downward crossing reduces both the nominal and relative tick sizes significantly. These shifts in relative tick size, triggered by crossing tick size borders, may impact LLT behaviour by altering the balance between order-queuing and order-undercutting incentives.

This study examines whether LLT activity changes significantly before and after a stock crosses a tick size border, hypothesizing that such border crossings lead to measurable differences in trading patterns. Thus, we propose the following hypothesis:

H2: *Crossing a tick size border in an upward (downward) direction results in a statistically significant increase (decrease) in LLT activity for the affected stock.*

3. Methodology

3.1. Data description

This study analyses order book data spanning from January 2008 to December 2017, sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA). The order book data was derived from the Australian Equities Tick History (AETH) database prior to May 31, 2016. From June 1, 2016, onward, it transitioned to the ASX ITCH dataset. By focusing on stocks within the S&P/ASX 100 (ASX: XTO) index – which encompasses both large and medium-cap firms – this study ensures a sample of sufficiently liquid stocks.[4] In total, this dataset comprises approximately 9.5 billion rows of order book data across the study period. Due to the sheer volume of data, RStudio was employed to filter and aggregate the raw data into a daily-level dataset. Order book data from both sources includes various types of messages and price details that capture the dynamics of order flow in the market. Table 2 provides a summary of the key characteristics of the AETH and ITCH datasets, highlighting the volume, time granularity, and data specifications used in this study.

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[4] The list of constituent stocks is based on the information provided by Thomson Reuters Datastream and updated on a monthly basis.

[Insert Table 2]

3.2. Sample selection

The test the first hypothesis, samples are categorised according to their nominal tick sizes, which are either A$0.005 (half-cent) or A$0.01 (one-cent).[5] Observations are grouped based on whether stock prices fall between A$0.10 and A$1.995 for the half-cent category or at A$2.00 or above for the one-cent category, ensuring each stock's daily low and high prices remain within these ranges. The closing prices of stocks in each category are further divided into quintiles, enabling a distinction between stocks with the largest relative tick size (RTS_{LARGE}) in the first quintile and those with the smallest relative tick size (RTS_{SMALL}) in the fifth quintile. This approach results in four relative tick size (RTS) groups and two pairs for analysis: (i) $RTS_{SMALL\_0.005}$ and $RTS_{LARGE\_0.005}$, and (ii) $RTS_{SMALL\_0.01}$ and $RTS_{LARGE\_0.01}$. Table 3 outlines the data distribution across these tick size categories for testing the first hypothesis.

[Insert Table 3]

To test the second hypothesis, samples are classified based on whether their daily high and low prices cross the A$2.00 tick size border. Observations are categorized as follows: (i) RTS_{SMALL} if both high and low prices are below A$2.00; (ii) RTS_{LARGE} if both high and low prices are above A$2.00; and CROSS if the low price is below A$2.00 while the high price is above it. Events labelled as CROSS are further filtered to determine their classification as either an UPWARDS or DOWNWARDS crossing based on relative tick size shifts before and after the crossing. Table 4 details the classification criteria for tick size crossing events, while Table 5 provides a summary of the final sample for testing the second hypothesis.

[Insert Table 4]
[Insert Table 5]

3.3. Measurement of variables

3.3.1. LLT activity measures

Trade-level datasets like NASDAQ HFT, NASDAQ OMX-St, and TSX provide order-specific identifiers, allowing for precise tracking and isolation of high-frequency trading (HFT) activity within order books. However, the datasets utilised in this study lack these identifying features. To address this limitation, the study applies a set of broadly recognized HFT characteristics, as established by regulatory authorities and academic research, to construct reliable proxies.

To prevent any misconception that this study exclusively targets traditional HFT firms such as Akuna Capital, Citadel Securities, DRW, Jump Trading, Quantlab, Susquehanna International

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[5] Due to inadequate sample size, stocks with prices below $0.100 are omitted from all tests performed in this study.

Group (SIG), Tower Research Capital, and Virtu Financial, the terms "low-latency trading" (LLT) and "low-latency traders" (LLTs) are adopted instead. This distinction clarifies the study's focus lies in capturing broader patterns of rapid, algorithmic trading activities, rather than strictly analysing firms explicitly classified as HFT.

Four primary proxies are employed to estimate LLT activity: the message-to-trade ratio, algorithmic trading ratio, total number of high-frequency orders (HFO), and HFO's message ratio. Each metric leverages data typically available in order-book datasets, enhancing the replicability of this methodology across diverse markets and over extended time periods. Nonetheless, this indirect approach introduces limitations, as the findings may not exclusively capture HFT firm activity but rather encompass a broader group of traders engaged in low-latency algorithmic strategies.

a. Message-to-trade ratio

The message-to-trade ratio (MTR) is derived by dividing the total number of *ENTER*, *AMEND*, or *DELETE* messages in the order book by the total trades executed on a given day. LLTs typically place numerous limit orders at multiple price levels and frequently adjust them in response to new information. Thus, stocks with elevated MTRs (i.e. higher quoting intensity) are often linked to high LLT activity. A high MTR indicates active quoting, agility, and a low tolerance for adverse selection – characteristics aligned with LLT strategies and risk preferences. The MTR is widely accepted as a proxy for LLT liquidity provision, evidenced by its use in prior studies (e.g., Aquilina & Ysusi, 2016; ASIC, 2013, 2015; Brogaard et al., 2015; Friederich & Payne, 2015; Frino et al., 2015; Hagstromer & Norden, 2013).[6] The formula for calculating MTR is presented in Equation 1, where a higher (lower) MTR suggests a greater (lower) degree of LLT activity, and a ratio of one indicates that every submitted order results in a trade:

$$MTR_{i,t} = \frac{\sum_{1}^{i,t} Message_{i,t}}{\sum_{1}^{i,t} Trade_{i,t}}$$

(Equation 1)

[6] Yao and Ye (2018), on the other hand, argue that the MTR is an ineffective proxy for HFT activity, particularly for liquidity provision. Contrary to the conventional assumption that high MTRs correlate with increased HFT activity, their findings reveal a negative relationship between HFT presence and MTR values. This insight stems from the queuing channel mechanism they propose, where the interaction of tick size, price controls, and time priority creates competitive dynamics favouring speed. Thus, the use of MTR as a universal cross-sectional indicator of HFT presence can be challenged, and suggest that, in some contexts, it may be inversely related to HFT liquidity provision.

where $\sum_1^{i,t} Message_{i,t}$ represents the total number of *ENTER*, *AMEND*, and *DELETE* messages on stock i on day t,[7] and $\sum_1^{i,t} Trade_{i,t}$ is the total number of *TRADE* messages on stock i on day t.[8] For brevity, the in-text explanation is based solely on information from the AETH dataset.

b. Algorithmic trading ratio

The datasets used in this study do not specify whether an order is placed by an algorithm or a human trader, making it infeasible to directly monitor algorithmic trading activities. Following Hendershott et al. (2011), who used electronic message traffic as a proxy for algorithmic trading, this study employs the algorithmic trading ratio (ALGO) to capture the efficiency and intensity of algorithmic trading in liquidity provision, particularly in fast-paced market conditions. Hendershott et al. (2011) assert that variations in message traffic primarily capture algorithmic liquidity provision, as algorithmic arbitrage activity often involves market orders rather than limit orders. Although ALGO may not precisely quantify LLT activity, LLT is a subset of AT, allowing ALGO to approximate general LLT attributes. ALGO is calculated as the sum of daily trading value (in dollars) normalised by the total number of *ENTER*, *AMEND*, or *DELETE* messages, multiplied by negative one, as shown in Equation 2. Higher (lower) ALGO values indicate more (less) algorithmic trading activity:

$$ALGO_{i,t} = \frac{\sum Trading\ Value_{i,t}}{\sum_1^{i,t} Message_{i,t}} \times (-1)$$

(Equation 2)

where $\sum Trading\ Value_{i,t}$ represents the daily trading value for stock i on day t, and $\sum_1^{i,t} Message_{i,t}$ is the total number of messages recorded as ENTER, AMEND, or DELETE for stock i on day t.[9]

c. High-frequency orders

LLTs are distinguished by their speed, allowing them to quickly update quotes in response to new information, resulting in rapid sequences of related messages. Building on Hasbrouck and Saar (2013) and Boehmer et al. (2018), this study identifies high-frequency orders (HFOs) based on extended sequences of linked messages, typically involving at least ten messages. Hasbrouck and Saar (2013) note that runs longer than ten messages capture a significant proportion of low-latency activity. Additionally, if an LLT algorithm detects adverse selection risks or fleeting profit opportunities, it will quickly adjust or cancel limit orders, resulting in brief order resting times. Subrahmanyam and Zheng (2016) found that LLT orders for large, medium, and small-cap firms

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[7] Message: AETH = *ENTER*, *AMEND*, *DELETE*; ITCH = *A*, *U*, *D*

[8] Trade: AETH = *TRADE*; ITCH = *E*, *C*

[9] Trading value: AETH = *Value* when *Record Type* is equal to *TRADE*; ITCH = (*Price* × *Quantity*) when *Message Type* is equal to *E* or *C*.

average survival times of 28.74, 33.03, and 51.89 seconds, respectively, implying that LLT orders resting less than three seconds are indicative of rapid trading strategies.[10] With unique OrderIDs in the AETH and ITCH datasets, the study tracks each order from entry to withdrawal via cancellation or execution.[11,12] Orders submitting at least ten messages and with average resting times under three seconds are classified as HFOs. In essence, HFO reflects the core characteristic of LLT, which is to place, cancel, or amend orders at very high frequencies, indicative of LLT activity. The formula to calculate HFO is shown by Equation 3:

$$OrderDuration_{j,i,t} = OrderID_{j,i,t,\max(d)} - OrderID_{j,i,t,\min(d)}$$

$$ORT_{j,i,t} = \frac{OrderDuration_{j,i,t}}{\sum_{1}^{j,i,t} Messages_{j,i,t}}$$

$$\sum_{1}^{i,t} HFO_{i,t} = \sum_{1}^{j,i,t}\left[\left(ORT_{j,i,t} \leq 3 \text{ seconds}\right) \,\&\, \left(\sum_{1}^{j,i,t} Message_{j,i,t} \geq 10 \text{ messages}\right)\right]$$

(Equation 3)

where $OrderDuration_{j,i,t}$ is the duration of OrderID j on stock i on day t, $ORT_{j,i,t}$ is the resting time, and $\sum_{1}^{i,t} HFO_{i,t}$ is the count of orders on stock i on day t meeting the criteria of ten messages and a resting time of three seconds or less.

d. HFO message ratio

The HFO message ratio (HFOR) calculates the proportion of total market messages generated by high-frequency orders. This metric indicates the extent to which HFOs dominate message traffic, providing a measure of their influence on the order book, as expressed in Equation 4:

$$HFOR_{i,t} = \frac{\sum_{1}^{HFO,i,t} Message_{HFO,i,t}}{\sum_{1}^{i,t} Message_{i,t}}$$

(Equation 4)

where $\sum_{1}^{HFO,i,t} Message_{HFO,i,t}$ denotes the total number of messages from HFOs on stock i on day t, and $\sum_{1}^{i,t} Message_{i,t}$ is the total number of messages for stock i on day t.

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[10] This is due to the fact that only large and medium-sized firms were included in the study's sample.

[11] This includes everything in between, such as order modification and/or incomplete execution (if any). When an order is modified, it may lose its queue position in the limit order book if: (1) its price is changed; and (2) its modified quantity is greater than the original amount. In these cases, the order is pushed to the back of the queue.

[12] This study excludes any high-frequency orders (HFOs) with an average resting time below five milliseconds. Although this threshold is somewhat arbitrary, setting a minimum resting time is essential to avoid misidentifying HFOs due to the order book's inherent mechanics. For instance, when a large buy limit order enters the market and is progressively executed against multiple small sell market orders, numerous *AMEND* messages are generated to update the remaining balance of the original order after each transaction. This process inflates the total message count in the order book, potentially leading to an overestimation of LLT activity if left unfiltered. Establishing a minimum resting time for HFO calculation thus ensures a more accurate representation of true high-frequency trading activity.

3.3.2. Explanatory variables

a. Independent variable

This study's primary objective is to assess whether relative tick size influences LLT activity. Relative tick size is calculated as the ratio of nominal tick size $\left(Tick\ Size_{i,t}\right)$ to closing price $\left(Close_{i,t}\right)$, as shown in Equation 5:

$$RTS_{i,t} = \frac{Tick\ Size_{i,t}}{Close_{i,t}}$$

(Equation 5)

To examine this effect, specific sample groups that capture variations in relative tick size values is defined, referred to as $\text{RTS}_{\text{SMALL}}$ and $\text{RTS}_{\text{LARGE}}$. A dummy variable is then assigned to these observations, where a value of one represents the $\text{RTS}_{\text{SMALL}}$ group, and zero otherwise.

b. Control variables

Several control variables are included in the study, reflecting factors that have been shown to significantly affect LLT activity, including volatility, liquidity, and firm size.

Volatility

Prior research indicates that higher volatility is associated with increased LLT activity, suggesting a positive relationship between the two (see Boehmer et al., 2020; Ersan & Ekinci, 2016; Hasbrouck & Saar, 2013; Lee, 2015; Manahov, 2016; Yılmaz et al., 2015). Volatility in this study is proxied by the daily trading range, calculated as the difference between the daily high $\left(High_{i,t}\right)$ and low $\left(Low_{i,t}\right)$ prices, divided by their average, as specified in Equation 6:

$$VOLATILITY_{i,t} = \frac{High_{i,t} - Low_{i,t}}{\left(\frac{High_{i,t} + Low_{i,t}}{2}\right)}$$

(Equation 6)

Liquidity

Studies also indicate that LLT activity is more prevalent in highly liquid stocks (Brogaard et al., 2014; Bhattacharya et al., 2020; Ersan & Ekinci, 2016). To measure liquidity, this study uses the spread measure developed by Corwin and Schultz (2012), as detailed in Equation 7. This measure accounts for bid-ask spreads and, though negative values are theoretically possible, Corwin and Schultz (2012) recommend substituting them with zero for practical applications:

$$LIQUIDITY_{i,t} = \frac{2(e^{\alpha_{i,t}} - 1)}{1 + e^{\alpha_{i,t}}}$$

where:

$$\alpha_{i,t} = \frac{\sqrt{2\beta_{i,t}} - \sqrt{\beta_{i,t}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3 - 2\sqrt{2}}}$$

$$\beta_{i,t} = \left(\ln \frac{High_{i,t-1}}{Low_{i,t-1}}\right)^2 + \left(\ln \frac{High_{i,t}}{Low_{i,t}}\right)^2$$

$$\gamma_{i,t} = \left(\ln \frac{max\{High_{i,t-1}, High_{i,t}\}}{min\{Low_{i,t-1}, Low_{i,t}\}}\right)^2$$

(Equation 7)

Firm Size

LLT activity is also expected to correlate positively with firm size, as larger firms tend to attract higher trading volumes and greater market attention. Firm size is proxied by the natural logarithm of market capitalisation, calculated as shown in Equation 8:

$$SIZE_{i,t} = \ln(Market\ Capitalisation_{i,t})$$

(Equation 8)

3.3.3. Model specification

To test the first hypothesis, the analysis begins with a univariate analysis, comparing the mean LLT activity between the RTS_{SMALL} and RTS_{LARGE} groups using a parametric t-test. While this method provides initial insights, it does not account for other factors influencing LLT activity, as highlighted in the literature. Therefore, a multiple regression analysis is used to examine the effect of relative tick size on LLT activity while controlling for firm-specific factors, including volatility, liquidity, and firm size. The model for this analysis is presented in Equation 9:

$$HFT_{i,t} = \beta_0 + \beta_1(DSMALL_{i,t}) + \beta_2(CONTROL_{i,t-1}) + \varepsilon_{i,t}$$

(Equation 9)

In this model, DSMALL is a dummy variable set to one if the observation for firm i on day t belongs to the RTS_{SMALL} group and zero otherwise. The regression can yield three outcomes: (i) no significant effect, implying that LLT activity is unaffected by relative tick size; (ii) a significantly positive effect, indicating increased LLT activity with smaller tick sizes; or (iii) a significantly negative effect, indicating reduced LLT activity with smaller tick sizes. CONTROL includes the three control variables: VOLATILITY, LIQUIDITY, and SIZE, representing daily trading range, Corwin-Schultz spread, and natural logarithm of market capitalisation, respectively, for firm i on day $t - 1$. Lagged values are used for these controls to mitigate potential reverse causality. Additionally, firm and day fixed effects are included to control for unobserved heterogeneity across firms and over time.

For the second hypothesis, the study applies a difference-in-differences (DID) method. DID serves as a quasi-experimental method that can address endogeneity issues by isolating the impact of exogenous shifts in relative tick size resulting from the "tick size border-crossing" events. These events cause sudden changes in relative tick size without directly altering LLT activity, providing a natural experiment framework to assess causality. This approach allows the study to attribute observed changes in LLT activity specifically to shifts in relative tick size. The events are categorised as UPWARDS or DOWNWARDS, based on the relative tick size position before and after the event (see Table 4). Since UPWARDS and DOWNWARDS events exhibit opposite effects on relative tick size, combining them into a single analysis would obscure their distinct impacts on LLT activity, thus, they are analysed separately.

In the DID framework, two groups are defined: TREATMENT and CONTROL. The TREATMENT group comprises all crossing events classified as either UPWARDS or DOWNWARDS, as outlined in Table 5. The CONTROL group consists of matched samples that do not experience a crossing event but meet the following criteria: (i) they do not belong to the TREATMENT group, and (ii) their daily low and high prices are within a set range across PRE_CROSS and POST_CROSS days – between A$1.00 and A$1.995 for UPWARDS events, and between A$2.00 and A$3.99 for DOWNWARDS events.[13]

Each observation in both the TREATMENT and CONTROL groups is further subdivided into PRE_CROSS and POST_CROSS periods based on the timing relative to the crossing event, allowing the study to evaluate the following differences to assess the RTS effect on LLT activity:

i. $DIFF_{PRE\_CROSS}$: Difference in LLT activity between TREATMENT and CONTROL groups before the crossing event.
ii. $DIFF_{POST\_CROSS}$: Difference in LLT activity between TREATMENT and CONTROL groups after the crossing event.
iii. $DIFF_{POST\text{-}PRE}$: Difference due to the RTS change, calculated as $DIFF_{POST\_CROSS} - DIFF_{PRE\_CROSS}$

The multivariate DID regression model for this analysis is specified in Equation 10:

$$HFT_{i,t} = \beta_0 + \beta_1\left(DTREATMENT_{i,t}\right) + \beta_2\left(DPOST_{i,t}\right) + \beta_3\left(DTREATMENT_{i,t} \times DPOST_{i,t}\right) + \beta_4\left(CONTROL_{i,t-1}\right) + \varepsilon_{i,t}$$

(Equation 10)

[13] The highest relative tick size value for stocks with a nominal tick size of A$0.01 is 0.50% at A$2.00, which is the same as stocks priced at A$1.00 with a nominal tick size of A$0.005. Similarly, the lowest relative tick size value for stocks with a nominal tick size of A$0.005 is 0.2506% at A$1.995, which is the same as stocks priced at A$3.99 with a nominal tick size of A$0.01. The price ranges stated in the main text for RTS_{SMALL} and RTS_{LARGE} are decided based on these price and relative tick size limits.

In this model, DTREATMENT is a dummy variable set to one if the observation for firm i on day t belongs to the TREATMENT group and zero otherwise; DPOST is a dummy variable set to one if the observation belongs to the POST_CROSS period and zero otherwise. The interaction term DTREATMENT×DPOST captures the effect of relative tick size change on LLT activity. The control variables remain consistent with those in Equation 9, and firm and day fixed effects are also included to mitigate potential omitted variable bias.

4. Results, analyses, and discussions

4.1. LLT activity across different RTS groups categorised by nominal tick sizes

4.1.1. Descriptive statistics

Table 6 presents the dataset used to examine the first hypothesis, which tests the impact of relative tick size (RTS) on low-latency trading (LLT) activity, categorised by nominal tick sizes of either half-cent (Panel I) or one-cent (Panel II).[14] Observations within each nominal tick size category are further divided into four subgroups: $RTS_{SMALL\_0.005}$, $RTS_{LARGE\_0.005}$, $RTS_{SMALL\_0.01}$, and $RTS_{LARGE\_0.01}$, based on their relative tick sizes. The observed values of PRICE and RTS in each subgroup adhere to the conditions specified in the sample selection criteria.

[Insert Table 6 here]

The data in Table 6 reveal that samples in the RTS_{SMALL} groups (both half-cent and one-cent) exhibit lower volatility and wider spreads compared to their RTS_{LARGE} counterparts. Market capitalisation, however, shows a marked difference: stocks in the RTS_{SMALL} groups have significantly higher market capitalisations than those in RTS_{LARGE}. Specifically, the average firm size in the $RTS_{SMALL\_0.005}$ subgroup is nearly twice as large as in $RTS_{LARGE\_0.005}$, while in the $RTS_{SMALL\_0.01}$ subgroup, it is almost seven times larger than in $RTS_{LARGE\_0.01}$. These results suggest that stocks with higher prices (RTS_{SMALL}) tend to have smaller intraday price ranges, narrower spreads, and greater market capitalisation relative to lower-priced stocks (RTS_{LARGE}).

4.1.2. Univariate and Multivariate Analysis

Table 7 shows the univariate test results comparing LLT activity as represented by message-to-trade ratio (MTR), ALGO, high-frequency orders (HFO), and HFO-contributed message ratio (HFOR), between the RTS_{SMALL} and RTS_{LARGE} groups within each nominal tick size category (half-cent in Panel I and one-cent in Panel II). A two-sample t-test was employed to examine the mean differences of these LLT proxies between RTS_{SMALL} and RTS_{LARGE} groups.

[Insert Table 7 here]

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[14] It is not possible to test stocks with $0.001 (one-tenth of once-cent) due to the limited number of observations available at this nominal tick size group.

The univariate results indicate statistically significant differences in LLT activity between RTS_{SMALL} and RTS_{LARGE} groups, with RTS_{SMALL} groups generally exhibiting higher levels of MTR, ALGO, HFO, and HFOR. An exception is observed for ALGO in the one-cent tick size category, where the result, although positive, is statistically insignificant. This evidence suggests that LLT activity is more prominent in stocks with smaller relative tick sizes, particularly within the one-cent tick size category. However, it is essential to note that firm-level characteristics such as volatility, liquidity, and size differ across RTS_{SMALL} and RTS_{LARGE} groups (see Table 6), which could confound the observed relationships. Therefore, a multivariate regression analysis is conducted to control for these factors and further assess the influence of relative tick size on LLT activity.

Table 8 presents the results of a multiple regression analysis examining the impact of a small relative tick size on LLT activity, distinguished by nominal tick size values of A$0.005 (half-cent) and A$0.01 (one-cent). In Panel I, the regression results for the half-cent category reveal that stocks with a small relative tick size are associated with a statistically significant increase in HFO ($\beta = 0.484$). However, this variable does not significantly explain the variation in other LLT activity measures. These findings imply that the differences in LLT activity between the RTS_{SMALL} and RTS_{LARGE} groups identified in previous univariate tests may be driven by factors other than relative tick size itself. Notably, all LLT measures are significantly influenced by at least one of the control variables, including volatility, liquidity, and firm size.

[Insert Table 8 here]

Panel II reports the regression results for the once-cent category, demonstrating that stocks with a small relative tick size exhibit significantly higher LLT activity across all measures: message-to-trade ratio (MTR: $\beta = 135.552$), algorithmic trading (ALGO: $\beta = 11.870$), HFO ($\beta = 1.802$), and HFO-contributed message ratio (HFOR: $\beta = 6.815$). These results suggest that the substantial differences in LLT activity between the RTS_{SMALL} and RTS_{LARGE} groups observed in the prior univariate tests can indeed be attributed to variations in relative tick size, even after controlling for other factors such as volatility, liquidity, firm size, as well as firm- and day-fixed effects, thereby reinforcing the robustness of these findings.

The regression outcomes lend support to the undercutting hypothesis, which posits that LLTs are more likely to participate in stocks with smaller relative tick sizes, as they can leverage their speed advantage to gain execution priority. This effect is prominently observed in the one-cent tick size category, whereas it is mostly absent in the half-cent category. This discrepancy may be better understood by referring to the relative tick size values in Table 6, which describes the data used for these regression models.

The average relative tick size for the $RTS_{SMALL\_0.005}$ group is 0.275%, only marginally lower than the 0.344% average for the $RTS_{LARGE\_0.01}$ group. This similarity suggests that stocks in the half-cent category with a "small" relative tick size (RTS_{SMALL}) are practically indistinguishable from those with a "large" relative tick size (RTS_{LARGE}) in the one-cent category, implying that the relative tick size in the $RTS_{SMALL\_0.005}$ group is not sufficiently small to attract LLTs.

Conversely, the $RTS_{SMALL\_0.01}$ group provides a more definitive example of a setting with a very small relative tick size, with an average relative tick size of just 0.026% – approximately one-tenth of the values in the $RTS_{SMALL\_0.005}$ and $RTS_{LARGE\_0.01}$ groups. This exceptionally small tick size allows LLTs to gain execution priority by quoting minimally better prices (Werner et al., 2023). Consequently, this environment becomes less appealing for non-LLT participants to establish price priority in the order book, resulting in shorter queues at each price level (Angel, 2011). This setup also permits LLTs to frequently modify or cancel limit orders without the risk of losing queue priority, as they can quickly re-quote at a better price. Overall, these findings indicate that LLTs are likely to engage in order-undercutting strategies only when the relative tick size is sufficiently small, thus supporting the proposed hypothesis.

4.2. LLT activity around tick size crossing events

4.2.1. Descriptive statistics

Table 9 presents the descriptive statistics for testing Hypothesis 2, which investigates how LLT activity adjusts in response to tick size changes when stocks cross regulatory tick size thresholds. The data show notable differences in market characteristics between Treatment and Control groups, both before and after crossing events. For UPWARDS tick size changes, the Treatment group demonstrates higher volatility, narrower bid-ask spreads, and larger market capitalisations than the Control group, both pre- and post-event. Upon crossing the tick size threshold upwards, the Treatment group's average intraday price range increased by 0.1486%, the bid-ask spread widened by 0.716%, and market capitalisation rose by A$0.231 billion. In contrast, the Control group experienced minimal changes, with volatility decreasing by 0.107%, the bid-ask spread narrowing by 0.077%, and market capitalisation increasing by A$0.04 billion.

[Insert Table 9 here]

For DOWNWARDS tick size changes, the Treatment group showed higher pre-event volatility, narrower bid-ask spreads, and smaller market capitalisations than the Control group. Following the downward crossing, the Treatment group's intraday price range surged by 1.003%, the bid-ask spread expanded by 0.864%, and market capitalisation fell by A$0.259 billion. Adjustments in the Control group were more subdued, with a 0.107% rise in intraday price range, a 0.072% increase in bid-ask spread, and a decrease in market capitalisation of A$0.109 billion.

These results suggest that crossing tick size thresholds impacts volatility, liquidity, and market capitalisation for the Treatment group, with effects varying by direction of the crossing. For UPWARDS crossings, the Treatment group experienced moderate increases in volatility and bid-ask spreads, while DOWNWARDS crossings triggered more pronounced rises in volatility and bid-ask spreads. Changes in market capitalisation appear largely mechanical, driven by shifts in stock price, explaining the higher (lower) market capitalisation observed in UPWARDS (DOWNWARDS) crossings. The relative stability of the Control group indicates these effects are primarily due to tick size changes in the Treatment group. These findings align with prior research, which shows that tick size adjustments influence trading dynamics, particularly among LLTs who rapidly adapt to evolving price grids (Yao & Ye, 2018; Werner et al., 2023).

4.2.2. Difference-in-Differences Analysis

Table 10 presents the univariate DID analysis for tick size crossing events, focusing on LLT activity under UPWARDS and DOWNWARDS conditions. Panel I present the UPWARDS events, where results indicate that pre-event LLT activity in the Treatment group was significantly higher than in the Control, shown by higher high-frequency orders (HFO) and HFO-contributed messages (HFOR). Post-event, LLT activity in the Treatment group decreased, as evidenced by reduced algorithmic liquidity provision (ALGO) values. The DID analysis confirms that a sudden increase in relative tick size is associated with a significant drop in ALGO, signalling reduced LLT activity. These results align with literature suggesting that larger tick sizes dampen LLT engagement by constraining pricing flexibility and lengthening order queues (O'Hara et al., 2019).

[Insert Table 10 here]

Panel II summarises the results for DOWNWARDS events, the Treatment group displayed lower LLT activity than the Control before the event, indicated by lower message-to-trade ratios (MTR), HFO, and HFOR. However, post-event, while LLT activity remained lower in the Treatment group, the gap in MTR with the Control narrowed. The DID analysis shows that a sudden decrease in relative tick size led to significantly higher HFO and HFOR, suggesting an increase in LLT activity following the reduction. Collectively, the evidence implies that decreases (increases) in relative tick size stimulate (suppress) LLT activity, as finer pricing grids allow LLTs to leverage speed advantages in executing rapid, small profit trades (Angel et al., 2011; Chordia et al., 2013).

These findings underscore an asymmetric response of LLT activity to relative tick size changes triggered by tick size border crossings. When tick sizes decrease, allowing for a finer pricing grid, LLT activity intensifies, consistent with literature indicating that smaller tick sizes attract LLTs seeking to avoid adverse selection risks and maximise order undercutting opportunities (Yao & Ye, 2018). Conversely, an increase in tick size appears to suppress LLT activity, as coarser grids impose limitations on LLTs' agility, reducing their willingness to queue for order priority.

4.2.3. Multivariate Analysis

Table 11 displays the results of a multivariate regression analysis examining the influence of abrupt relative tick size changes on LLT activity. Here, the DTREATMENT coefficient represents the general effect of the Treatment group on LLT activity, encompassing pre- and post-event impacts due to relative tick size changes. Similarly, DPOST captures the aggregate influence of the post-event period on LLT activity across both Treatment and Control groups. To isolate the specific impact of tick size changes, the interaction term DPOST×DTREATMENT is analysed.

[Insert Table 11 here]

For UPWARDS events, the DPOST×DTREATMENT coefficients are significantly negative for ALGO ($\beta = -2.946$), HFO ($\beta = -0.201$), and HFOR ($\beta = -0.569$), as shown in Panel I. These indicate that the increase in relative tick size restricts LLT activity in the Treatment group, thereby widening the LLT activity gap with the Control. This finding is consistent with studies that show a coarser pricing grid deters LLT participation by reducing flexibility in order placement and increasing adverse selection risk (O'Hara et al., 2019; Werner et al., 2023). In contrast, the DPOST×DTREATMENT coefficients for DOWNWARDS events as shown in Panel II, are significantly positive for HFO ($\beta = 0.476$) and HFOR ($\beta = 0.902$). This outcome implies that the decrease in relative tick size enhances LLT activity in the Treatment group, rendering it more active than the Control. These results suggest that smaller tick sizes amplify LLT activity, consistent with literature that argues finer pricing grids allow LLTs to exploit small price improvements swiftly, minimising adverse selection risk and maximising rapid turnover (Angel et al., 2011; Yao & Ye, 2018).

Regression analysis of control variables further reveals that: (i) higher volatility is linked to decreased MTR and ALGO but increased HFO and HFOR; (ii) wider bid-ask spreads correlate with higher MTR and ALGO; and (iii) larger market capitalisation is associated with lower ALGO but higher HFO and HFOR. These results align with prior studies on volatility and market depth, where LLTs adjust their strategies based on liquidity and volatility conditions to maintain a balance between speed and profitability (Chordia et al., 2013; Li et al., 2021).

In summary, this study demonstrates a clear inverse relationship between LLT activity and relative tick size on the ASX. LLTs show a strong preference for undercutting strategies that optimise speed and minimise adverse selection risk, thriving in finer tick environments. In coarser tick environments, while potential returns may be higher for market makers willing to queue, LLTs typically avoid this approach due to the increased risk exposure it entails. Thus, these findings suggest that LLT activity on the ASX could be strategically influenced by adjusting nominal tick sizes, potentially aiding policymakers in calibrating market dynamics to achieve desired levels of liquidity and stability (Bacidore, 1997; O'Hara et al., 2019).

5. Conclusion

This study examines the role of relative tick size in shaping low-latency trading (LLT) behaviour within the Australian equity market, leveraging a robust dataset from the ASX spanning 2008 to 2017. By analysing key LLT metrics – quoting intensity (MTR), algorithmic liquidity provision (ALGO), high-speed OrderIDs (HFO), and HFO-contributed messages (HFOR) – this research provides insights into how LLT responses vary according to tick size shifts in two primary contexts: stocks within the same nominal tick size and those crossing the tick size threshold in either direction.

The findings challenge the initial hypothesis that larger relative tick sizes attract higher LLT activity due to enhanced order-queuing opportunities. Instead, LLTs exhibit a distinct preference for smaller relative tick sizes, particularly within the one-cent category, where LLTs favour order undercutting over queuing. This suggests that LLTs are not incentivised by queuing potential within larger tick sizes but rather by the ability to engage flexibly in a finer pricing grid, which reduces adverse selection risks. Stocks in the half-cent category, where relative tick sizes differ minimally, show no significant change in LLT behaviour, underscoring that only sufficiently small relative tick sizes attract LLT engagement on the ASX.

The results support the second hypothesis, indicating that LLT activity declines when a stock's tick size crosses the A$2.00 border upwards and increases when crossing downwards. This asymmetry reveals LLTs' preference for finer pricing grids that facilitate swift entry and exit, essential for minimising adverse selection exposure. The inverse relationship between relative tick size and LLT activity implies that LLTs, particularly market makers on the ASX, adopt a highly risk-sensitive approach, prioritising undercutting strategies over order queuing. Such behaviour aligns with observations that LLTs strategically minimise exposure to adverse selection risk by focusing on low-risk, high-speed trading activities (Angel et al., 2011; Chordia et al., 2013).

These findings diverge from prior research on U.S. markets, which often posits that larger relative tick sizes promote LLT market-making (e.g., Angel, 2011; O'Hara et al., 2019; Werner et al., 2023). Structural differences likely account for this divergence. The ASX's lower market fragmentation and absence of designated market makers reduce competitive pressures on LLTs, enabling greater revenue capture from liquidity provision, particularly in high-priced stocks with minimal relative tick sizes. The ASX's minimum trading unit of one share may further compel LLTs to manage their exposure strategically, as informed traders can more easily conceal large orders, intensifying the adverse selection risk to LLTs. Consequently, ASX-based LLTs favour small tick sizes to enable strategic undercutting, reflecting a risk-averse approach that aligns with the need for minimal adverse selection exposure.

In conclusion, this study highlights LLTs' fundamental risk aversion, where risk minimisation takes precedence over aggressive profit maximisation. By targeting stocks with smaller relative tick sizes, LLTs generate cumulative profits through frequent, low-risk trades, which compound into significant returns with limited loss exposure (Netherlands Authority of Financial Markets (NAFM), 2010; Zhang, 2010). These insights extend current understandings of LLT strategies, particularly their reliance on high-frequency, risk-sensitive trade executions in response to tick size dynamics.

The implications suggest that a dynamic tick size regime could serve as an effective policy tool for optimising LLT activity. Regulators might consider assigning smaller tick sizes to less liquid stocks to encourage LLTs-driven liquidity, while larger tick sizes might be implemented in highly liquid stocks to curb “toxic” LLT effects, enforcing price-priority and enhancing order queuing. This approach aligns with Chordia et al. (2013), who argue for balancing HFTs' impact on market welfare. A well-calibrated tick size policy could thus enable the ASX to manage LLT activity more effectively, fostering liquidity in areas where it is needed while mitigating adverse effects in more liquid segments.

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TABLES

Table 1. Tick size structure in the Australian and U.S. equity markets

This table compares the tick size structures applied in the Australian and U.S. equity markets. Tick size refers to the nominal tick size used in each market. The relative tick size is calculated by dividing the nominal tick size by the price.

Australia (A$)			
Price Range	$0.001 - $0.099	$0.100 - $1.995	$2.00 - $99,999,990
Tick Size	$0.001	$0.005	$0.01
Highest relative tick size	100.00%	5.00%	0.50%
Lowest relative tick size	≈1.01%	0.25%	≈0.00%
United States (US$)			
Price Range	p < $1.000	p ≥ $1.000	
Tick Size	$0.0001	$0.01	
Highest relative tick size	100.00%	1.00%	
Lowest relative tick size	≈0.01%	≈0.00%	

Table 2. Data Summary from AETH and ITCH Datasets

This table provides a comprehensive overview of the datasets used in this study, sourced from SIRCA. Columns *AETH* and *ITCH* present the information obtained from the Australian Equities Tick History and ASX ITCH, respectively. *Period* refers to the date range of which the data of the study is retrieved from. *Firms* refer to the number of unique firms, while *Observations* refers to the total number of firm-day observations. *Timestamp Precision* refers to the smallest precision unit for time used to record the messages in the order book. *Rows* refers to the number of lines in the order book for the specified time period. *Size on disc* refers to the size of the dataset used in this study as recorded on the hard drive. *Order Entry Types* refers to how a message is recorded in the databases' order books. *Daily Prices* refers to the key price points on each trading day, while *Identifiers* refer to unique identification code assigned to distinguish each order. *Volume* represents the quantity of shares traded, and *Value* reflects the dollar value of these transactions.

	AETH	**ITCH**
Period	1/1/2008 – 31/5/2016 (1887 days)	1/6/2016 – 31/12/2017 (657 days)
Firms	171	113
Observations	209,644	39,806
Timestamp Precision	Millisecond	Nanosecond
Rows	5,550,425,473	1,783,656,562
Size on Disc	739 GB	217 GB
Order Entry Types	▪ ENTER: Entry of a new order into the order book. ▪ DELETE: Deletion of an order from the order book. ▪ AMEND: Modification of existing order. ▪ TRADE: A trade between two orders.	▪ A: Add order message. ▪ D: Order delete message. ▪ U: Order replace message. ▪ E: Order executed message. ▪ C: Order executed message (with price).
Daily Prices	Open, Close, High, Low (recorded as "TRADE")	Open, Close, High, Low (recorded as "C" or "E")
Identifiers	OrderID (combination of BuyID and AskID)	OrderID (unique per order book and side)
Volume and Value	Share Quantity, Dollar Value	Quantity, Value (Price × Quantity)

Table 3. Data description for the samples used to test the first hypothesis

This table describes the data used to test the first hypothesis. The top and bottom sections of the table display the data for the A$0.005 and A$0.01 tick size categories, accordingly. RTS_{SMALL} and RTS_{LARGE} denotes the group of observations with low and high relative tick size values, respectively. *Observations*, *Highest price,* and *Lowest price* refer to the number of observations, the highest and lowest closing prices for each RTS group, accordingly.

	$\mathbf{RTS_{SMALL}}$	$\mathbf{RTS_{LARGE}}$
Tick size: A$0.005		
Observations	6,022	6,041
Highest price (A$)	1.995	0.880
Lowest price (A$)	1.510	0.100
Tick size: A$0.01		
Observations	43,596	43,526
Highest price (A$)	199.700	4.400
Lowest price (A$)	22.050	2.000

Table 4. Identification and classification of tick size crossing events

This table presents the potential scenarios for tick size crossing events and how they are classified. *CROSS* denotes the day on which a crossing event occurred; hence, their relative tick size values are recorded as '*Nil*'. *PRE_CROSS* and *POST_CROSS* refer to the immediate trading days before and after the occurrence of either a single-day or multiple-day CROSS event. RTS_{SMALL} and RTS_{LARGE} signify the relative tick size position during PRE_CROSS and POST_CROSS days. Event classification refers to the decision to classify whether an event is accepted or rejected. An *UPWARDS* event starts with $\text{RTS}_{\text{SMALL}}$ on the PRE_CROSS day and ends with $\text{RTS}_{\text{LARGE}}$ on the POST_CROSS day, whereas a *DOWNWARDS* event starts with $\text{RTS}_{\text{LARGE}}$ on the PRE_CROSS day and ends with $\text{RTS}_{\text{SMALL}}$ on the POST_CROSS day. Events with any combination other than the aforementioned scenarios are classified as *Rejected*. Panel A shows the possible combinations involving a single-day crossing event, while Panel B depicts potential scenarios involving multiple days of crossing events in a row.

Panel A: Single-day crossing

PRE_CROSS	*CROSS*	*POST_CROSS*	*Event classification*
$\text{RTS}_{\text{SMALL}}$	Nil	$\text{RTS}_{\text{LARGE}}$	UPWARDS
$\text{RTS}_{\text{SMALL}}$	Nil	$\text{RTS}_{\text{SMALL}}$	Rejected
$\text{RTS}_{\text{LARGE}}$	Nil	$\text{RTS}_{\text{SMALL}}$	DOWNWARDS
$\text{RTS}_{\text{LARGE}}$	Nil	$\text{RTS}_{\text{LARGE}}$	Rejected

Panel B: Multiple-days crossing

PRE_CROSS	*CROSS*	*CROSS*	*POST_CROSS*	*Event classification*
$\text{RTS}_{\text{SMALL}}$	Nil	Nil	$\text{RTS}_{\text{LARGE}}$	UPWARDS
$\text{RTS}_{\text{SMALL}}$	Nil	Nil	$\text{RTS}_{\text{SMALL}}$	Rejected
$\text{RTS}_{\text{LARGE}}$	Nil	Nil	$\text{RTS}_{\text{SMALL}}$	DOWNWARDS
$\text{RTS}_{\text{LARGE}}$	Nil	Nil	$\text{RTS}_{\text{LARGE}}$	Rejected

Table 5. Data description of the crossing events selected to test the second hypothesis

This table describes the data of the tick size crossing events selected to test the second hypothesis. *UPWARDS* and *DOWNWARDS* reflect the category of tick size crossing events, as detailed in the preceding table. *Average*, *Highest*, and *Lowest prices* reflect the mean, maximum, and minimum closing prices for the PRE_CROSS and POST_CROSS groups, while *Average*, *Highest*, and *Lowest differences* represent the mean, maximum, and minimum closing prices differences between the POST_CROSS and PRE_CROSS periods, respectively. *Accepted* and *Rejected events* indicate the number of tick size crossing events that were accepted and rejected in the final sample, respectively. *Total observations* shows the number of firm-day observations resulting in tick-size border crossings.

	UPWARDS	**DOWNWARDS**
PRE_CROSS		
Average price (A$)	1.931	2.093
Highest price (A$)	1.995	3.740
Lowest price (A$)	1.495	2.000
POST_CROSS		
Average price (A$)	2.085	1.884
Highest price (A$)	2.500	1.990
Lowest price (A$)	2.000	0.940
Difference (POST - PRE)		
Average difference (A$)	0.154	-0.210
Highest difference (A$)	0.755	-0.015
Lowest difference (A$)	0.025	-2.270
Duration (POST - PRE)		
Average duration	4.309 days	4.617 days
Longest duration	14 days	15 days
Shortest duration	2 days	2 days
Accepted events	95	111
Rejected events	370	399
Total observations	**1072**	

Table 6. Descriptive statistics of the data used to test Hypothesis 1

This table describes the data employed to test the first hypothesis, which are categorised by nominal tick sizes of either A$0.005 (*Panel I*) or A$0.01 (*Panel II*). *Panels* RTS_{SMALL} and RTS_{LARGE} refer to the observations in the first and fifth quintile based on their closing prices, respectively. *N*, *Mean*, *S.D.*, *Minimum*, and *Maximum refer* to the number of observations, average, standard deviation, lowest value, and highest value, accordingly. *PRICE* refer to the closing price; *RTS* indicates the relative tick size, which is calculated by dividing nominal tick size by closing price (Equation 5); *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 7); and *SIZE* is the actual dollar value of market capitalisation.

	Panel I: Tick size = A$0.005					**Panel II: Tick size = A$0.01**				
	N	**Mean**	**S.D.**	**Min.**	**Max.**	**N**	**Mean**	**S.D.**	**Min.**	**Max.**
RTS_{SMALL} (5th qu.)										
PRICE ($)	6,022	1.822	0.086	1.510	1.995	43,596	45.555	23.137	22.050	199.700
RTS (%)	6,022	0.275	0.013	0.251	0.331	43,596	0.026	0.009	0.005	0.045
VOLATILITY (%)	6,022	2.627	1.917	0.289	32.749	43,596	2.050	2.076	0.000	162.557
LIQUIDITY (%)	6,012	0.626	0.892	0.000	9.845	43,545	0.412	0.632	0.000	14.485
SIZE ($ billion)	6,022	3.817	1.915	0.339	10.590	43,596	34.530	36.530	1.035	166.000
RTS_{LARGE} (1st qu.)										
PRICE ($)	6,041	0.558	0.172	0.100	0.880	43,526	3.007	0.528	2.000	4.400
RTS (%)	6,041	1.041	0.553	0.568	5.000	43,526	0.344	0.064	0.227	0.500
VOLATILITY (%)	6,041	5.232	5.109	0.612	73.684	43,526	2.760	1.914	0.277	67.410
LIQUIDITY (%)	6,020	1.205	1.902	0.000	26.430	43,460	0.634	0.892	0.000	24.975
SIZE ($ billion)	6,041	1.893	1.381	0.056	6.355	43,526	5.103	6.219	0.393	50.150

Table 7. Mean comparison of HFT activity categorised by nominal tick sizes

This table displays the results of a univariate analysis using observations classified by their nominal tick sizes to test the first hypothesis. The findings from the A$0.005 and A$0.01 categories are shown in *Panels I* and *II*, respectively. *Obs.* and *Mean* refer to the number of observations and the average values of each HFT measure, accordingly. *Difference* represents the difference between the mean values of RTS_{SMALL} and RTS_{LARGE}. Message-to-trade ratio (MTR), average trade size (ALGO), high-frequency orders (HFO), and HFO-contributed message ratio (HFOR) are the variables used as proxies for measuring HFT activity. The formulas are illustrated in Equations 1, 2, 3, and 4, respectively. Data are winsorised at three standard deviations (3-sigma) from their respective means.

	RTS_{SMALL} (5th qu.)		**RTS_{LARGE} (1st qu.)**		**Difference**
	Obs.	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
Panel I: (TS = A$0.005)					
MTR (%)	6,022	503.189	6,041	449.623	53.566***
ALGO	6,022	-13.770	6,041	-17.300	3.531***
HFO (Ln)	6,022	2.323	6,041	1.404	0.919***
HFOR (%)	6,022	3.269	6,041	2.439	0.83***
Panel II: (TS = A$0.01)					
MTR (%)	43,596	612.243	43,526	511.546	100.697***
ALGO	43,596	-16.362	43,526	-16.389	0.028
HFO (Ln)	43,596	5.129	43,526	2.450	2.679***
HFOR (%)	43,596	17.179	43,526	3.532	13.647***

*** p<0.01, ** p<0.05, * p<0.10

Table 8. Regression analysis on HFT activity categorised by nominal tick sizes

This table shows the results of multivariate regression analysis using observations categorised by their nominal tick sizes to test the first hypothesis. The findings from the A$0.005 and A$0.01 categories are shown in *Panels I* and *II*, respectively. Dependent variables are the HFT activity measures, namely message-to-trade ratio (*MTR*), average trade size (*ALGO*), high-frequency orders (*HFO*), and HFO-contributed message ratio (*HFOR*). The formula are shown in Equations 1, 2, 3, and 4, respectively. The independent variable is *DSMALL*, which is a dummy variable assigned with a value of one if the observation belongs to the group with low relative tick size (RTS_{SMALL}), and zero otherwise. The control variables are the one-day lagged (t – 1) values of *VOLATILITY*, *LIQUIDITY*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 7); and *SIZE* is the natural log of market capitalisation (Equation 8), respectively. All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel I: (TS = A$0.005)				**Panel II: (TS = A$0.01)**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
DSMALL	-9.296	2.514	0.484***	0.134	135.552***	11.870***	1.802***	6.815**
	(18.474)	(2.463)	(0.144)	(0.427)	(33.918)	(2.612)	(0.165)	(3.233)
VOLATILITY	-2.496*	-0.243**	0.039***	0.064***	-6.336***	-0.235**	0.079***	0.488***
	(1.343)	(0.112)	(0.007)	(0.019)	(0.879)	(0.103)	(0.007)	(0.106)
LIQUIDITY	1.372	0.386***	-0.018***	-0.043*	8.658***	1.026***	-0.009**	-0.025
	(1.098)	(0.103)	(0.005)	(0.024)	(0.823)	(0.087)	(0.004)	(0.042)
SIZE	-8.725	-4.341***	0.254***	0.355	35.744*	-5.531***	0.649***	6.153**
	(14.439)	(1.286)	(0.077)	(0.243)	(18.557)	(2.000)	(0.138)	(2.643)
Constant	577.616*	72.096**	-6.024***	-8.082	-611.204	62.196	-16.419***	-149.395**
	(322.408)	(27.801)	(1.708)	(5.298)	(422.390)	(45.126)	(3.142)	(59.909)
Observations	12,047	12,047	12,047	12,047	86,994	86,994	86,994	86,994
R-squared	0.463	0.344	0.6634	0.3617	0.492	0.561	0.799	0.471
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 9. Descriptive statistics of the data used to test Hypothesis 2

This table describes the data used to test the third hypothesis, which are organised by the direction of the tick size crossing events. *Panels I (a)* and *(b)* represent the data for the PRE-EVENT$_{UPWARDS}$ and POST-EVENT$_{UPWARDS}$, whereas *Panels II (a)* and *(b)* refer to the PRE-EVENT$_{DOWNWARDS}$ and POST-EVENT$_{DOWNWARDS}$, respectively. *PRE-EVENT* and *POST-EVENT* refer to the values in the period before and after a tick size crossing event occurrence, accordingly. *Treatment* refers to all observations classified as accepted tick size crossing events, while *Control* refers to non-crossing observations that fulfil the criteria outlined in the model specification section. *N*, *Mean*, *S.D.*, *Min.*, and *Max. refer* to the number of observations, average, standard deviation, lowest value, and highest value, accordingly. *PRICE* refer to the closing price; *RTS* indicates the relative tick size, which is calculated by dividing nominal tick size by closing price (Equation 5); *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 7); and *SIZE* is the actual dollar value of market capitalisation (Equation 8).

	Panel I (a): PRE-EVENT$_{UPWARDS}$					**Panel I (b): POST-EVENT$_{UPWARDS}$**				
	N	**Mean**	**S.D.**	**Min.**	**Max.**	**N**	**Mean**	**S.D.**	**Min.**	**Max.**
Treatment										
PRICE ($)	95	1.933	0.070	1.495	1.995	95	2.080	0.070	2.000	2.310
RTS (%)	95	0.259	0.011	0.251	0.334	95	0.481	0.015	0.433	0.500
VOLATILITY (%)	95	3.839	3.903	0.855	27.429	95	3.987	3.600	0.499	30.769
LIQUIDITY (%)	94	0.226	0.797	0.000	6.744	95	0.942	1.280	0.000	5.548
SIZE ($ billion)	95	3.383	2.064	0.3572	10.51	95	3.614	2.178	0.4287	11.23
Control										
PRICE ($)	691	1.455	0.257	1.005	1.975	691	1.472	0.257	1.010	1.985
RTS (%)	691	0.355	0.065	0.253	0.498	691	0.351	0.063	0.252	0.495
VOLATILITY (%)	691	3.618	2.554	0.607	20.921	691	3.511	2.370	0.557	19.380
LIQUIDITY (%)	686	0.853	1.196	0.000	8.440	690	0.776	1.223	0.000	9.855
SIZE ($ billion)	691	2.86	1.529	0.1917	8.039	691	2.9	1.553	0.1981	8.465
	Panel II (a): PRE-EVENT$_{DOWNWARDS}$					**Panel II (b): POST-EVENT$_{DOWNWARDS}$**				
Treatment										
PRICE ($)	111	2.093	0.177	2.000	3.740	111	1.886	0.140	0.940	1.990
RTS (%)	111	0.480	0.027	0.267	0.500	111	0.267	0.031	0.251	0.532
VOLATILITY (%)	111	4.380	3.075	0.990	20.833	111	5.383	7.709	0.757	73.498
LIQUIDITY (%)	111	0.227	0.569	0.000	3.417	111	1.091	2.237	0.000	16.830
SIZE ($ billion)	111	3.339	2.069	0.4117	10.91	111	3.08	1.977	0.3312	10.49
Control										
PRICE ($)	1,689	3.027	0.506	2.020	3.970	1,654	2.969	0.506	2.010	3.960
RTS (%)	1,689	0.340	0.060	0.252	0.495	1,654	0.347	0.062	0.253	0.498
VOLATILITY (%)	1,689	3.231	2.454	0.254	41.745	1,654	3.338	2.463	0.281	43.826
LIQUIDITY (%)	1,689	0.692	1.044	0.000	9.683	1,654	0.764	1.153	0.000	8.268
SIZE ($ billion)	1,689	4.981	6.459	0.4042	48.28	1,654	4.872	6.336	0.4117	48.03

Table 10. Univariate difference-in-difference analysis of HFT activity measures for tick size crossing events

This table presents the results of univariate difference-in-difference analysis to test the second hypothesis. *Panels I* and *II* represent the UPWARDS and DOWNWARDS tick size crossing events, respectively. *Treatment* refers to all observations classified as accepted tick size crossing events, while *Control* refers to non-crossing observations that fulfil the criteria outlined in the model specification section. $DIFF_{PRE}$ and $DIFF_{POST}$ refers to the difference between the values observed in Treatment and Control in the period before and after the crossing events, respectively. *DIFF-IN-DIFF* refers to the difference-in-difference values produced by subtracting the $DIFF_{POST}$ with $DIFF_{PRE}$. Message-to-trade ratio (MTR), average trade size (ALGO), high-frequency orders (HFO), and HFO-contributed message ratio (HFOR) are the variables used as proxies for measuring HFT activity. The formula is illustrated in Equations 1, 2, 3, and 4, respectively. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel I: $RTS_{UPWARDS}$				**Panel II: $RTS_{DOWNWARDS}$**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
Pre-event								
Treatment (T)	481.13	-14.92	2.32	3.23	435.63	-19.51	1.68	2.28
Control (C)	459.25	-13.96	1.93	2.68	475.21	-19.94	2.11	2.89
$DIFF_{PRE}$ (T – C)	21.88	-0.95	0.39**	0.55*	-39.58***	0.43	-0.43***	-0.61**
	(19.00)	(1.34)	(0.18)	(0.33)	(13.78)	(1.48)	(0.15)	(0.29)
Post-event								
Treatment (T)	467.91	-19.10	2.11	2.78	426.45	-16.96	2.21	3.27
Control (C)	459.15	-14.60	1.89	2.73	476.64	-18.24	2.16	2.95
$DIFF_{POST}$ (T – C)	8.76	-4.49***	0.22	0.05	-50.18***	1.28	0.05	0.32
	(19.98)	(1.63)	(0.17)	(0.36)	(14.25)	(1.42)	(0.17)	(0.36)
DIFF-IN-DIFF								
$DIFF_{POST}$ – $DIFF_{PRE}$	-13.12	-3.54*	-0.17	-0.50	-10.61	0.85	0.48**	0.93**
	(27.57)	(2.11)	(0.25)	(0.48)	(19.82)	(2.05)	(0.22)	(0.46)

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 11. Regression analysis on HFT activity using tick size crossing events

This table presents the results of multivariate regression analysis using tick size crossing events to test the second hypothesis. *Panels I* and *II* represent the *UPWARDS* and *DOWNWARDS* tick size crossing events, respectively. Dependent variables are the HFT activity measures, namely message-to-trade ratio (*MTR*), average trade size (*ALGO*), high-frequency orders (*HFO*), and HFO-contributed message ratio (*HFOR*). The formula are shown in Equations 1, 2, 3, and 4, respectively. The independent variables are *DTREATMENT*, *DPOST*, and *DTREATMENT×DPOST*, where *DTREATMENT* is a dummy variable that equals to one if the observation is identified as a tick size crossing event (see model specification section), and zero otherwise; *DPOST* is a dummy variable assigned with a value of one if the observation belongs to the post-event period, and zero otherwise; and the interaction term, *DTREATMENT×DPOST*, estimates the effect of changes in relative tick size due to tick size crossing event on HFT activity. The control variables are the one-day lagged (t – 1) values of *VOLATILITY*, *LIQUIDITY*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 7); and *SIZE* is the natural log of market capitalisation (Equation 8), respectively. All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel I: UPWARDS ($RTS_{SMALL} \rightarrow RTS_{LARGE}$)				**Panel II: DOWNWARDS ($RTS_{LARGE} \rightarrow RTS_{SMALL}$)**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
DTREATMENT	9.327	-1.319	-0.029	-0.190	-1.532	0.480	-0.156**	-0.280
	(15.256)	(1.370)	(0.054)	(0.250)	(11.112)	(1.081)	(0.075)	(0.253)
DPOST	4.813	6.061***	0.185	-1.579***	0.629	2.169	-0.376	-0.416
	(25.301)	(1.245)	(0.239)	(0.451)	(19.113)	(4.157)	(0.254)	(0.363)
DTREATMENT×DPOST	-6.129	-2.946**	-0.201***	-0.569**	-3.379	0.634	0.476***	0.902***
	(17.982)	(1.172)	(0.064)	(0.243)	(8.547)	(1.153)	(0.063)	(0.234)
VOLATILITY	-5.195***	-0.3128***	0.019	0.088*	-4.009***	-0.110	0.055***	0.098***
	(1.680)	(0.109)	(0.015)	(0.050)	(1.217)	(0.215)	(0.008)	(0.024)
LIQUIDITY	4.148*	0.642***	-0.011	0.002	3.212*	0.409	-0.004	-0.071
	(2.095)	(0.224)	(0.012)	(0.056)	(1.845)	(0.261)	(0.013)	(0.046)
SIZE	4.977	-6.643***	0.578***	1.293***	12.202	-5.031***	0.317***	0.646
	(17.156)	(0.990)	(0.126)	(0.440)	(13.140)	(1.741)	(0.089)	(0.406)
Constant	176.045	117.477***	-12.532***	-28.391***	16.310	49.289	-7.293***	-14.650
	(373.188)	(22.129)	(2.707)	(9.565)	(292.432)	(39.032)	(2.003)	(9.065)
Observations	1,559	1,559	1,559	1,559	3,563	3,563	3,563	3,563
R-squared	0.538	0.463	0.770	0.364	0.561	0.452	0.768	0.347
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

FIGURES

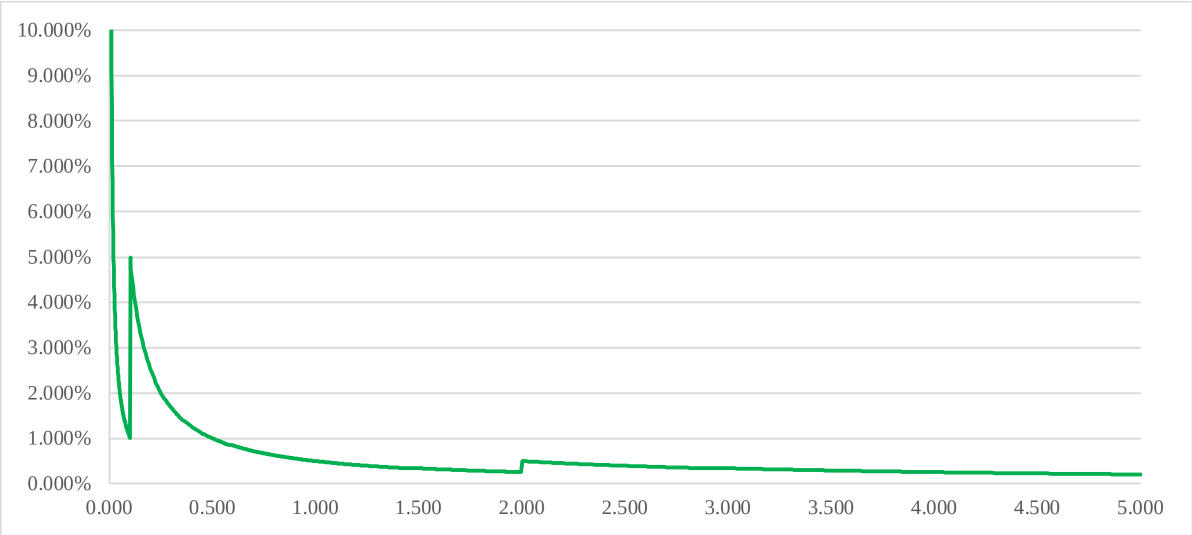

Figure 1: Relative tick size for stock prices ranging from A$0.01 to A$5.00

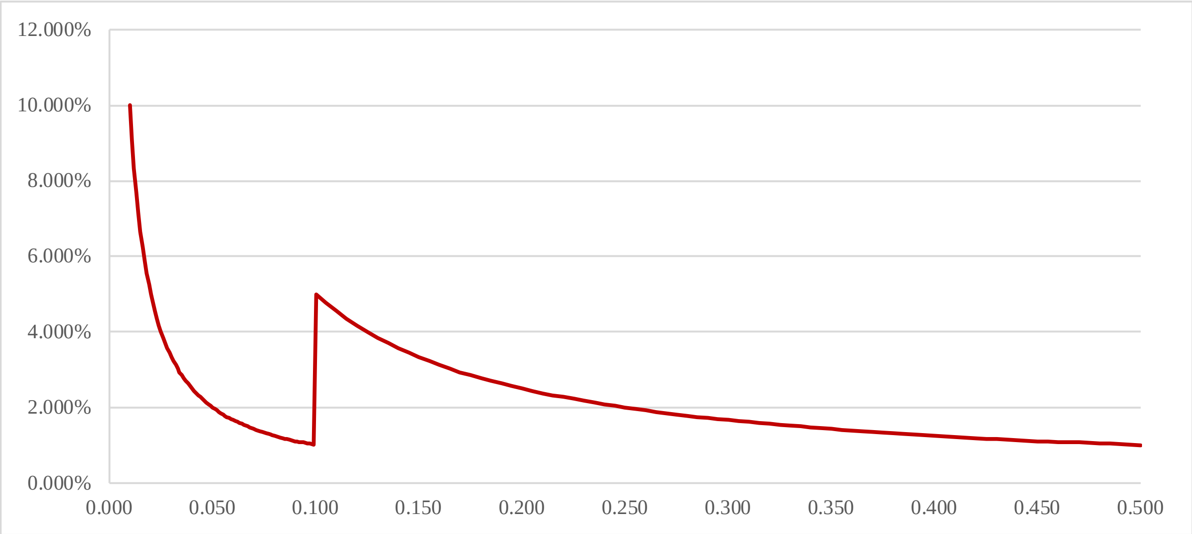

Figure 2: Relative tick size for stock prices surrounding the A$0.10 border

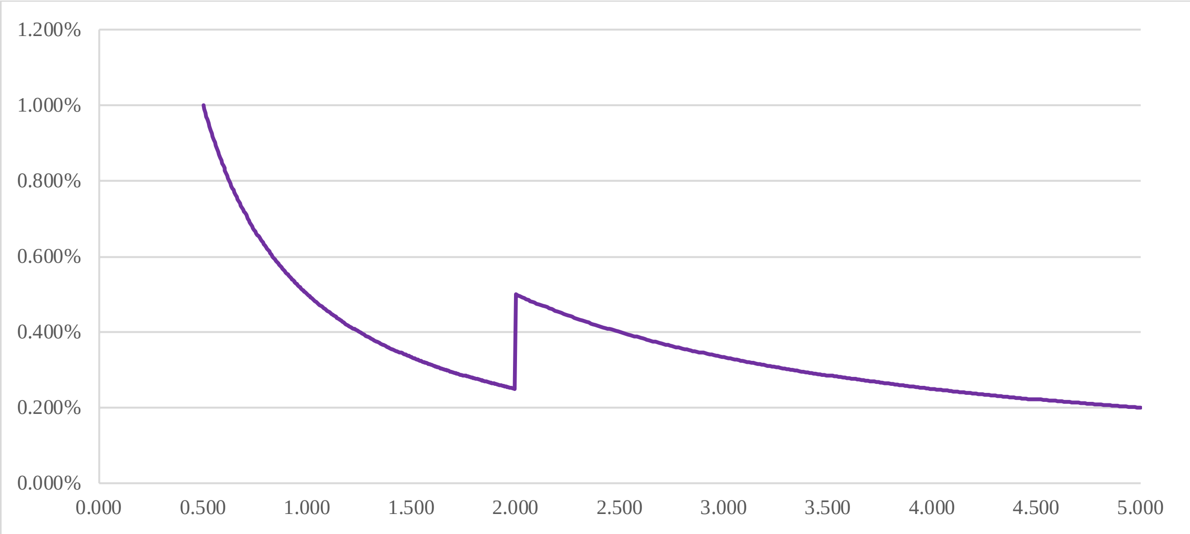

Figure 3: Relative tick size for stock prices surrounding the A$2.00 border

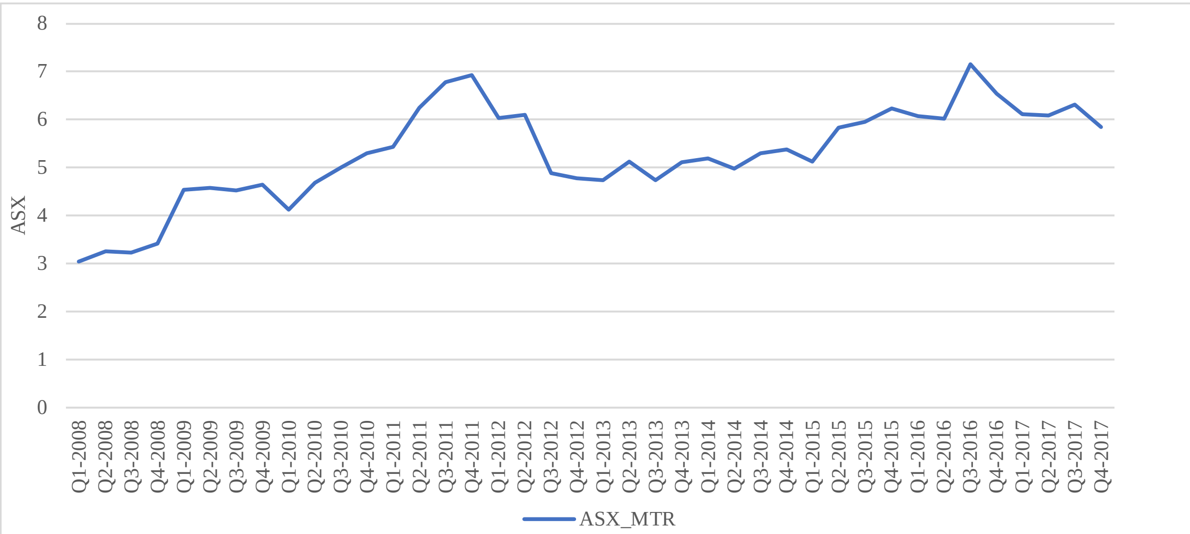

Figure 4: Quarterly average of message-to-trade ratio (MTR) in Australia

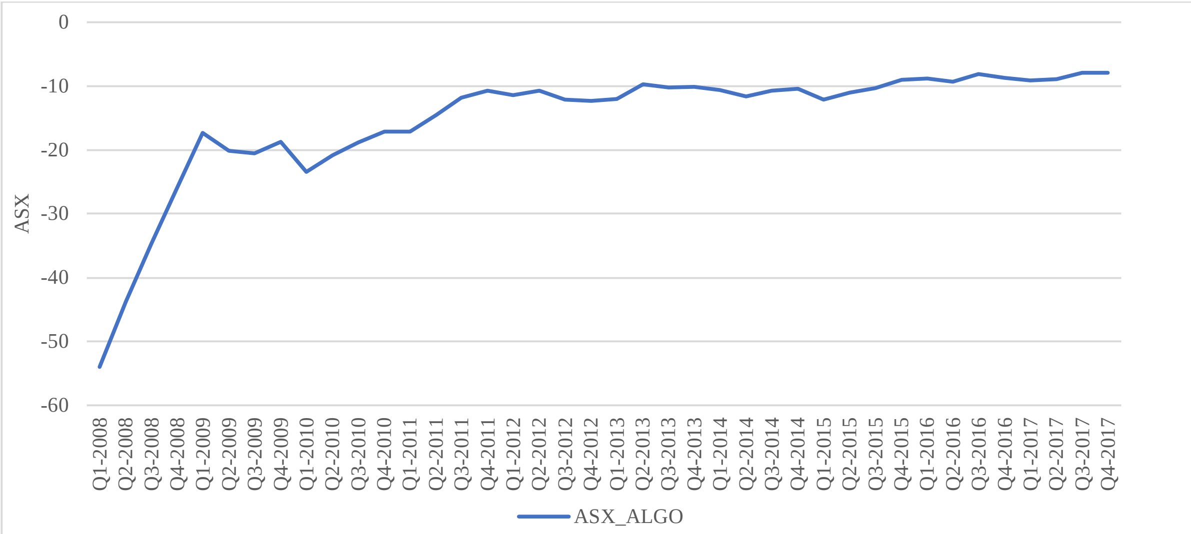

Figure 5: Quarterly average of algorithmic trading ratio (ALGO) in Australia

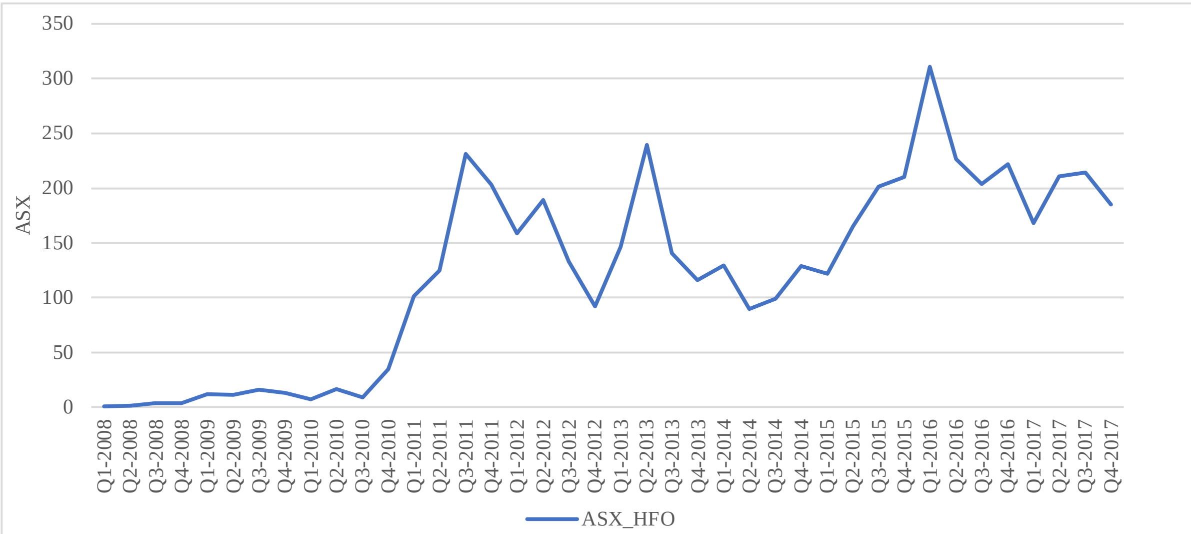

Figure 6: Quarterly average of high-frequency order ID (HFO) in Australia

Figure 7: Quarterly average of HFO's message ratio (HFOR) in Australia