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The influence of tick prices on high-frequency trading on market quality in LQ-45 Indonesia

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ABSTRACT

This research aims to determine the influence of tick prices on high-frequency trading on market quality in LQ-45 Indonesia. This study employs a quantitative approach. This study employed the Fixed Effect, Random Effect and Common Effect. The research data source used secondary data, with 37 stocks identified that met the criteria for High-Frequency Trading (HFT). The data analysis technique utilized panel data method. Three findings were revealed in the results of this research: first, it demonstrates a significant impact of tick price on High-Frequency Trading (HFT) activity; second, it reveals a positive influence of HFT on market quality, as evidenced by the metrics of spread, volatility, and risk-adjusted return. HFT activity in this research substantiates a positive impact on market quality, measured through spread, volatility, and risk-adjusted return. However, when assessing market quality based on liquidity, the research indicated that HFT volume and trades exert a noteworthy impact on diminishing market liquidity; and third, High-Frequency Trading (HFT) generally exhibits a notable impact on reducing spreads, even though its strength is not conclusively proven in the HFT volume test. The practical implications of this research offer insights into the positive impact of tick prices on the escalation of High-Frequency Trading (HFT) activity.

Contribution/Originality: This research can provide further information about the impact of tick prices on the escalation of High-Frequency Trading (HFT) activity. This study's findings support the impact of tick prices on the escalation of High-Frequency Trading (HFT) activity. The beneficial effect of tick price is more pronounced in HFT trades when compared to HFT volume.

1. INTRODUCTION

The evolution of theories with the objective of elucidating diverse phenomena and activities in the capital market is becoming progressively specific to individual variables. One of the theories concentrating on microvariables within the capital market is market microstructure. According to Mann and O'Hara (1996), market microstructure is a theory that specifically centers on the mechanism of shaping stock prices by considering various microvariables, including spreads, returns, volatility, tick prices, and so forth. Along with the development of technology, the theory and approach of market microstructure have been adapted to explain the phenomena or conditions that occur in the capital market. One approach to the conditions of the capital market, which has been predominantly influenced by technology and digitization, is High-Frequency Trading (HFT). Kirilenko, Kyle, Samadi, and Tuzun (2017) elucidate that High-Frequency Trading (HFT) is a component of trading algorithms

(AT), representing a combination of algorithms within a computer system. These algorithms assist investors in swiftly placing, canceling, and buying shares on a millisecond time scale.

High-Frequency Trading (HFT) emerged as a result of technological advancements, leading to the transformation of computer-controlled markets from operating on a minute timescale to a microsecond timescale. The favorable influence of High-Frequency Trading (HFT) activity on liquidity is demonstrated by an upswing in the number of trades, whereas the adverse impact is evidenced by a reduction in the number of trades, which serves as an indicator of liquidity. The results of various previous studies found evidence that the presence of HFT increases liquidity due to various factors. Kirilenko et al. (2017) found that HFT is able to provide liquidity during extreme events, but only if these extreme events refer to a single stock. Research by Emory (2011) explains that the increase in liquidity caused by HFT is due to reduced trade selection costs . In addition to this, the increase in liquidity can also be due to information efficiency (Boehmer, Li, & Saar, 2018). A decrease in liquidity demonstrates the negative impact of HFT. As found by Brogaard, Hendershott, and Riordan (2017), when the HFT short sell ban actually worsens liquidity or decreases. Short-term trading has the potential to worsen the market because short sells tend to rely less on fundamentals and prioritise information, which in some caseses overreaction from investors.

Other research explains that the aggressive HFT model encourages higher transaction speeds, which increase the selection of liquidity providers, resulting in decreased liquidity (Foucault, Hombert, & Roşu, 2016). HFT trading that can absorb a lot of liquidity reduces the possibility of differences between bid and ask prices, which is one measure of the spread (Baron, Brogaard, Hagströmer, & Kirilenko, 2019). In line with the character and results of previous research on HFT, it shows that the greater the level of HFT activity, the lower the spread value of a stock. Previous research states that the rate of price increase (tick price) influences the escalation or reduction of High-Frequency Trading (HFT) activity. In relation to stock prices, the tick price on large stocks will be much larger than the tick price on lower-priced stocks (O'Hara, Saar, & Zhong, 2019). This research differs from previous research.

This research is associated with the evaluation of High-Frequency Trading (HFT), specifically focusing on tick price to test and demonstrate that tick price influences the level of HFT activity in LQ-45 Composite Stocks. Based on this literature, this research aims to determine the influence of tick prices on high-frequency trading on market quality in LQ-45 Indonesia.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1. High-Frequency Trading, Tick Prices, Market Quality in LQ-45 Indonesia

The definition of HFT in the *Nasdaq glossary* is a trade that refers to computerisation using proprietary algorithms. Several studies using HFT data from exchanges were conducted by Baldauf and Mollner (2020); Brogaard, Garriott, and Pomeranets (2014); Brogaard et al. (2017); Pelger (2020); Weller (2019), and so on. But there are also several studies that use HFT data based on the classification of predetermined criteria, Baron et al. (2019);Anagnostidis and Fontaine (2020); Ammar, Hellara, and Ghadhab (2020), and Conrad, Wahal, and Xiang (2015).

Tick price, or price fraction, serves as a metric for tracking stock price fluctuations in a single increment of increase or decrease. The determination of the *tick price* value for stock prices is contingent upon the policies established by each exchange within individual countries. An exchange can adjust the trick price value to improve market performance and attract investors. For example, the Indonesia Stock Exchange (IDX) changed the *tick price* in 2014 from five types to three types and changed back to five types in 2016 based on the nominal share price. This shows that the number of types or variants as well as the nominal value of the *tick price* greatly affects market performance. As in the IDX, *tick price* changes are also made on developed country exchanges, such as the pilot programme to determine the impact of *tick price* changes on stock performance. Through the pilot programme, several studies explained the impact of *tick price* changes on trading strategies and trading costs.

The explanation of the effect of HFT activity on volatility was previously related to the effect on *risk-adjusted return*. In some studies, *risk-adjusted return is* measured by several methods, one of which is the *cumulative abnormal return* (CAR). Lower CAR values demonstrate the positive impact of HFT activity, and vice versa. Research by Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) and Boehmer et al. (2018) found that a 56% increase in *returns* with trading strategies was correlated with the presence of HFT. Furthermore, in their research, Brogaard (2010) and Hendershott and Riordan (2013) found that the level of HFT participation plays an important role in price efficiency and the price discovery process. Malceniece, Malcenieks, and Putniņš (2019) explain that an increase of one standard deviation in HFT increases the *co-return* movement by one-fifth of the average and liquidity simplification by two-fifths of the average value. Discussion of *returns* in the capital market is inseparable from risk, and the return *of the* presence of HFT has a positive impact on investor risk management. While the negative impact of HFT activity on CAR was found by Brogaard et al. (2017) who found that the temporary price impact of large trades caused price disturbances due to price pressures arising from liquidity demand by long-term investors. By focusing on flash cras events Weller (2019) and Kirilenko et al. (2017) found evidence that the presence of HFT that drives increased volatility is associated with extreme price decline events. Another explanation for the negative impact of HFT is that it allows stock manipulation. Menkveld (2013) explains that HFT is useful as a market maker, implying that HFT can directly influence prices through the availability of liquidity and increased *spreads*.

The beneficial effect of High-Frequency Trading (HFT) activity on spreads is illustrated by a reduction in the disparity between bid and ask prices, while the adverse impact is manifested by an increase in spreads. There are some previous studies that prove the positive impact of the presence of HFT on reducing or reducing the value of spreads, namely research from Hendershott and Riordan (2013); Boehmer et al. (2018); Baron (2019); Hasbrouck and Saar (2013);Menkveld (2013). One explanation of the effect of HFT activity on spreads from research by Baron (2019) is that the decrease in spreads by the presence of HFT is due to utilising superior speed in various ways that can reduce trading costs so that order information from each investor can be received at the same time. Meanwhile, the difference between the higher bid and ask prices demonstrates the negative impact on HFT activity on spreads. Malinova and Park (2015) found evidence of an increase in retail investors' trading costs due to HFT. The increase in trading costs further widens or increases the distance between the bid and ask values on the spread. In addition, the increase in spreads can also be due to the ability of HFT to quickly cancel orders, as explained in the research of Ye, Yao, and Gai (2012), where each session the demand-supply of traders is slow, so that it causes a widening of the bid-ask, (Malinova, Park, & Riordan, 2018). Budish, Cramton, and Shim (2015) predict that HFT competition creates a non-zero spread but one invariant to the number of HFTs and the bid-ask spread gets worse with each increase in the number of HFTs.

The measurement of market returns' standard deviation demonstrates volatility, which represents the extent of price fluctuations. A higher volatility value indicates a more favorable market, while conversely, a lower value suggests the opposite. The positive influence of High-Frequency Trading (HFT) activity on volatility is manifested in reduced volatility, and conversely, the negative impact of HFT activity is reflected in increased volatility. The results of previous studies that prove the increase in HFT activity has a positive impact on volatility (Ang, 2015; Boehmer et al., 2018; Chaboud et al., 2014; Hagströmer & Nordén, 2013; Siregar, 2019) explains that the decline in volatility is due to the reduced level of *spreads* and high demand for liquidity. Although the research of Hagströmer and Nordén (2013) only found the effect of HFT activity in reducing short-term volatility. However, reduced HFT activity in certain situations can actually increase volatility and worsen market quality. Too large an increase in volatility in stocks indicates the negative impact of HFT activity. Increased volatility can be caused by various factors, such as transaction costs, investor behavior, and asymmetric information (Siregar, 2019). In addition, investor behaviour that *overreacts* to information can cause temporary price reversals (Brasiano, Hanafi, & Arief, 2019). Research by Dalko and Wang (2020) explains that the uncertainty of price trends generates uncertainty among affected investors. Since HFT generates a large number of trades in a very short period of time, the frequency of price reversals and other volatility risks increases substantially.

2.2. Hyphotesis Development

Investors with short-term trading goals (HFT) are more likely to choose stocks with lower prices. Conversely, investors with long-term investment goals will choose stocks with a larger tick price value. Based on this explanation, it shows that the higher the stock tick price value, the higher the level of HFT activity, and vice versa, the lower the stock tick price, the lower the level of HFT activity. Following previous research conducted by Malceniece et al. (2019);Hendershott and Riordan (2013) and Boehmer et al. (2018), the measurement of HFT uses two models, namely, HFT trade and HFT vol. Therefore, the formulation of hypothesis 1 (H1) is as follows:

H_1: Larger tick price level affects the increase in HFT trade or HFT vol activity in LQ-45 stocks.

Research outcomes from Hendershott and Riordan (2013) elucidate that the augmented liquidity attributed to Algorithmic Trading (AT) or High-Frequency Trading (HFT) is a result of diminished trade selection costs. Additionally, alongside this evidence, increased liquidity can also stem from enhanced information efficiency. This explanation leads us to conclude that an increase in market liquidity is proportional to the level of HFT activity. Therefore, the formulation of hypothesis 2 (H2) is as follows:

H_2: The level of HFT activity volume in LQ-45 stocks affects the increase in market liquidity.

A decrease in spreads was found in the research of Hendershott and Riordan (2013); Boehmer et al. (2018); Hasbrouck and Saar (2013); Menkveld (2013), and Baron (2019). Where the effect of reducing the spread is due to the speed of transactions owned by HFT, so as not to provide time for continuous order cancellation. Based on this explanation, the third hypothesis (H3) can be formulated is as follows:

H_3: The level of HFT activity volume in LQ-45 stocks affects the decline in spreads.

Boehmer et al. (2018) present evidence indicating that the decrease in volatility is a consequence of diminished *spread* levels and a heightened demand for liquidity. A lower *spread* value suggests that there is no significant disparity between demand and supply prices or price fluctuations. In addition, with an increase in high liquidity, either from sales or purchases, it can reduce price fluctuations, which further reduces the value of volatility. This explanation leads to the conclusion that a market's volatility value decreases as HFT activity levels increase. Based on a review studies described above, the first hypothesis (H4) is as follows:

H_4: The level of HFT activity volume in LQ-45 stocks affects the decrease in market volatility.

High-Frequency Trading (HFT) diminishes instances of mispricing by investors. In support of this, Brogaard et al. (2017), along with Hendershott and Riordan (2013), discovered that the extent of HFT participation plays a crucial role in price efficiency and the price discovery process. Furthermore, Malceniece et al. (2019) explain that a one-standard deviation increase in HFT increases CAR movements by one-fifth of the mean and liquidity simplification by two-fifths of the mean. Some explanations from previous research show that HFT activity has a statistically negative effect on *risk-adjusted return*. This shows that an increase in HFT activity cannot increase returns but can encourage a decrease in the risk of a stock, and vice versa. Therefore, it can be concluded that the greater the level of High-Frequency Trading (HFT) activity, the higher the Cumulative Abnormal Return (CAR) value of a stock or market, and vice versa. Based on a review of the theory and previous studies described above, the first hypothesis (H5) is as follows:

H_5: The level of HFT activity volume in LQ-45 stocks has an effect on risk-adjusted stock returns.

3. RESEARCH METHODS

3.1. Research Samples and Data

The study used secondary data. Sample selection is based on non-probability sampling with a purposive sampling method. Research data was collected from Ver 3.0 trading application from Mirae Asset Securities. The data was collected using LQ-45 stock trading tick data, with 37 stocks identified that satisfied the criteria for High-Frequency Trading (HFT). The sample selection in the research focused on one group of shares with high liquidity provided by the IDX, namely LQ-45 shares. Investors consistently trade stocks with high liquidity, resulting in large trading volumes. This research data uses tick-type data, where every transaction made on these shares can be known. For example, in TLKM (Telkom) shares on May 5, 2021, recorded transactions reached 25,600 trades.

Regarding the use of time in this research, it starts from 09.00 (market opening) to 11.30 (rest time) and 13.30 to 15.15 (market closing). The initial start of research or sampling was carried out from April 12, 2021, to September 30, 2021, and the second period was carried out from April 1, 2022, to May 31, 2022, with a total of 150 trading days. All data processing uses the reviews program (Lee, 2020).

3.2. Operational Definitions of Variables

The measurement of HFT as a dependent variable refers to the previous studies by Malceniece et al. (2019); Hendershott and Riordan (2013) and Boehmer et al. (2018). Furthermore, HFT volume and HFT trade are developed into two measurements, namely accumulation and individual. The following is the basic measurement of the individual HFT model:

$$\text{HFT Volume}_{i.t} = \frac{dVol\ i.t}{100\ messages\ i.t}$$

$$\text{HFT trades}_{i.t} = \frac{messages\ i.t}{trades\ i.t}$$

Where; i (stock), t (trading interval), dvol (combined trading volume), and messages are the number of orders. The second proxy for HFT is number of trades per day.

O'Hara et al. (2019) define *tick price* as a unit of increase and decrease of a stock over time. Following research from Malceniece et al. (2019), the measurement of market liquidity is explained as follows:

$$LIQ_{ihsg} = -Log\ [1 + \sum_{h=1}^{H} (\frac{1}{H} \frac{\{r.ihsg.t.h\}}{dvol.ihsg.t.h})]$$

Where r.i is the return in basis points on stock i at time t and period h, dvol.i is the accumulated volume per second of stock i at time t and period h, r.ihsg is the return in basis points (bps) on the JCI at time t and period h, dvol.i is the accumulated volume per second at JCI at time t and period h.

The spread calculation follows previous research conducted by Malceniece et al. (2019), as follows:

$$SPREAD_{i.t} = \sum_{h=1}^{H} (\frac{1}{H} \frac{Ask.i.t. - Bid.i.t}{\frac{Ask.i.t. + Bid.i.t}{2}})$$

Where *ask* the *offer* price of stock *i*at time *t* and period *h*. *Bid* the asking or *bid* price for stock *i*at time *t* and period *h*. In this research, the authors assessed the volatility variable by employing either the variance or standard deviation of market *returns*. Risk adjusted return in research is shown through the amount of CAR (cumulative abnormal return). The greater the CAR value, the greater the risk of a stock.

Effect of Tick price on HFT is:

$$HFT_{vol.1} = \beta_0 + \beta_1 TP_{it} + + e_{it} \quad (1)$$

$$HFT_{vol.2} = \beta_0 + \beta_1 TP_{it} + + e_{it} \quad (2)$$

$$HFT_{trade.1} = \beta_0 + \beta_1 TP_{it} + + e_{it} \quad (3)$$

$$HFT_{trade.2} = \beta_0 + \beta_1 TP_{it} + + e_{it} \quad (4)$$

HFTvol.1 is accumulated number of HFT orders of stock i period t, HFTvol.2 is Value of stock i's HFT order quantity period t. HFTtrade.1 is value of the number of HFT transactions of stock i in period t, HFTtrade.2 is Accumulated number of stock i HFT trades period t, TP it : Percentage level of tick price of stock i in period t, β0 is intercept or constant and β1 TP it is regression coefficient of tick price of stock i in period t.

Effect of HFT on Liquidity is:

$$LIQ_{IHSG.t} = \beta_0 + \beta_1 HFT_{vol.1} + \beta_2 HFT_{vol.2} + e_{it} \quad (5)$$

$$LIQ_{IHSG.t} = \beta_0 + \beta_3 HFT_{trade.1} + \beta_4 HFT_{trade.2} + e_{it} \quad (6)$$

Where LIQ_{IHSG} : Market liquidity levels, $HFT_{vol.1}$: Accumulated number of HFT orders of stock i period t, $HFT_{vol.2}$: Value of stock i's HFT order quantity period t, $HFTtrade_{.1}$: Value of the number of HFT transactions of stock i in period t and $HFTtrade_{.2}$: Accumulated number of stock i HFT trades period t

Effect of HFT on Spreads is:

$$SPREAD_{it} = \beta_0 + \beta_1 HFT_{vol.1} + \beta_2 HFT_{vol.2} + e_{it} \quad (7)$$

$$SPREAD_{it} = \beta_0 + \beta_3 HFT_{trade.1} + \beta_4 HFT_{trade.2} + e_{it} \quad (8)$$

Where $SPREAD_{it}$ is Spread rate of stock i period t

Effect of HFT on Volatility is:

$$\sigma R_{IHSG.t} = \beta_0 + \beta_1 HFT_{vol.1} + \beta_2 HFT_{vol.2} + e_{it} \quad (9)$$

$$\sigma R_{IHSG.t} = \beta_0 + \beta_3 HFT_{trade.1} + \beta_4 HFT_{trade.2} + e_{it} \quad (10)$$

Where: $\sigma R_{JCI.t}$ is the market volatility rate

Effect of HFT on CAR is:

$$CAR_{i.t} = \beta_0 + \beta_1 HFT_{vol.1} + \beta_2 HFT_{vol.2} + e_{it} \quad (11)$$

$$CAR_{i.t} = \beta_0 + \beta_3 HFT_{trade.1} + \beta_4 HFT_{trade.2} + e_{it} (12)$$

Where CAR i.t is the risk adjusted return of stock i period t

3.3. Analysis Methods and Techniques

This study employed the Fixed Effect (FEM), Random Effect (REM), and Common Effect (CEM), with explanations or assumptions from the model, namely based on criteria from research samples that have t or the number of time series data more than n or the number of cross-section units, which are more effective for using static panel data regression. The basic premise of the fixed effects model is that the intercept and slope have different values for each variable or time (Bintarti, 2015; Vukovic, Spitsina, Gribanova, Spitsin, & Lyzin, 2023). This study assumes that the slope is constant, but the intercept varies between units. The fixed effects model chose the minor square dummy variable technique, also known as ordinary least squares (OLS), because it included dummy variables to explain differences in intercepts between individuals (Lee, Chen, & Lee, 2019). The required dummy variable is k-1 where k is number of companies (Vinod, 2022). The random effects model selection estimates panel data where disturbance variables may be interconnected over time or between individuals. The appropriate method for estimating the random effects model is generalized least squares, which can be processed directly using Eviews software (Ji, Wei, & Xu, 2023).

4. RESEARCH RESULTS AND DISCUSSION

4.1. Tick Price and HFT

The initial hypothesis test had the objective of ascertaining the impact of *tick prices* on High-Frequency Trading (HFT). As previously explained, this investigation categorizes HFT into four types: HFT-Vol1, HFT-Vol2, HFT-Trade1, and HFT-Trade2. This classification involves three types of *tick prices*, determined by existing price fractions, and spans five distinct time intervals. The first hypothesis is divided into two parts, namely H1a: *Tick price* (TP) has a positive effect on HFT-Trade activity. H1b: *Tick price* (TP) has a positive effect on HFT-Vol activity.

Table 1. Results of testing the effect of tick price on HFT.

Time interval	Dependent variable	Tick price		Tick price 5		Tick price 10		Tick price 25	
		Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Second	HFT_VOL1	-0.0008	-233.48***	-0.001	-195.060***	-0.0004	-183.746***	0.0001	13.307***
	HFT_VOL2	0.0011	2.725***	0.002	1.545***	-0.001	-11.564***	0.003	17.466***
	HFT_TRADE1	-0.563	-3.001***	-0.437	-1.651*	0.979	1.716*	-3.079	-10.989***
	HFT_TRADE2	0.302	26.974***	0.299	22.315***	0.281	6.469***	0.341	63.292***
Minute	HFT_VOL1	0.0002	5.9473***	0.0002	2.707***	-0.0002	-8.955***	0.0005	18.473***
	HFT_VOL2	0.0051	3.42***	0.009	2.568**	-0.001	-10.542***	0.002	18.292***
	HFT_TRADE1	2.167	1.25	-2.782	-0.713	4.661	1.42	1.723	0.906
	HFT_TRADE2	1.395	2.416**	2.366	3.650***	1.066	9.303***	0.918	8.593***
15 Minute	HFT_VOL1	0.0002	1.584	0.0003	0.909	-0.0003	-3.101***	0.0005	4.811***
	HFT_VOL2	0.001	2.035**	0.003	1.969**	-0.001	-6.425***	0.0004	3.120***
	HFT_TRADE1	0.601	4.099***	1.449	6.773***	1.066	5.047***	-0.508	-1.778*
	HFT_TRADE2	0.34	6.123***	1.4	18.249***	0.207	2.265**	-0.618	-5.811***
1 Hour	HFT_VOL1	0.0002	0.764	0.0003	0.472	-0.0004	-1.886*	0.0004	2.025**
	HFT_VOL2	0.0003	0.889	0.001	0.982	-0.0008	-2.907***	0.0001	0.894
	HFT_TRADE1	0.462	2.473**	1.153	5.209***	0.93	3.928***	11504.25	11938.13
	HFT_TRADE2	0.331	3.420***	1.248	9.146***	0.307	1.830*	-0.445	-1.1226
Daily	HFT_VOL1	0.0002	0.414	0.001	0.917	-0.0007	-1.855***	0.085	0.085
	HFT_VOL2	0.0002	0.414	0.001	0.917	-0.0007	-1.854**	0.086	0.086
	HFT_TRADE1	0.399	2.47**	0.528	2.131**	0.663	1.768***	-0.01	-0.0428
	HFT_TRADE2	0.399	2.47**	0.528	2.130**	0.663	1.766*	-0.01	-0.0431

Note: * : Sig on df 10%.
** : Sig on df 5%.
***: Sig on df 1%.

Table 1 presents a summary of the results for testing hypothesis 1a concerning High-Frequency Trading (HFT) volume and 1b for HFT trade. In the examination of HFT volume, it is apparent that a tick price of 10 exerts a more pronounced effect on HFT volume across all time intervals, as indicated by a negative t-statistic value. Thus, the results of testing hypothesis 1a conclude that a smaller tick price level has an effect on increasing HFT volume. As for HFT trade, tick price 5 has a stronger significant effect on HFT trade than tick prices 10 and 25, with positive t-statistic values in eight cases. Hence, the decision on hypothesis 1b concludes that smaller tick prices have an effect on increasing HFT trade.

The outcomes reported align with outcomes from prior studies conducted by Frino, Mollica, and Zhang (2015) and Mahmoodzadeh and Gençay (2017), as well as Hagströmer and Nordén (2013). These studies collectively support the assertion that smaller *tick prices* indeed have an impact on the escalation of High-Frequency Trading (HFT) activity. Meanwhile, the results of hypothesis one disagree with the research of O'Hara et al. (2019) and Yao and Ye (2018), who found evidence that larger *tick prices* affect the level of HFT activity. The firm size effect may be one explanation for smaller tick prices having an effect on increasing HFT may be due to the *firm size effect*. HFT investors prefer low-tick-priced stocks with the assumption that the investment capital in the stock is less and has the opportunity to get more returns. So that HFT investors will be more interested in trading stocks with small tick prices when compared to stocks with larger tick prices.

4.2. HFTs and Market Quality

The impact of High-Frequency Trading (HFT) on market quality is examined through the testing of four hypotheses. Hypothesis two explores the influence of HFT on market liquidity, hypothesis three assesses its effect on spreads, hypothesis four examines its impact on volatility, and hypothesis five investigates its effect on risk-adjusted return. We subdivide the independent variable, HFT, into four categories: volume 1, HFT volume 2, HFT trade 1, and HFT trade 2. The test results of each hypothesis that has been carried out to select an effective model of panel data regression are summarised in Table 2:

4.3. HFTs dan Market Liquidity

Examining the outcomes presented in Table 2 for the testing of High-Frequency Trading (HFT) volume (2a) and HFT trade (2b) on market liquidity, a positive t-statistic is observed exclusively in two test scenarios, namely HFT volume 1 and HFT trade 2. These results show that HFT does not have a bigger effect on markets more liquid, especially when compared to the negative t-statistic and the fact that other test cases did not show any significance. Therefore, hypothesis two rejects Ha, where HFT has no effect on increasing market liquidity or HFT has an effect on decreasing market liquidity. The results of hypothesis two that reject Ha are consistent with some results from previous studies, as explained by Foucault et al. (2016), who found that aggressive HFT encourages higher order speeds and reduces liquidity provision. The decrease in liquidity is because HFT tends to negatively select limit orders (Dalko & Wang, 2020). Another statement from, O'Hara et al. (2019) is that HFTs that increase undercutting of rest limit orders can cause a temporary decrease in liquidity in stocks with smaller *tick price* values.

Table 2. Test results of the effect of HP on market quality.

Time interval	Independent variable	LIQ-IHSG			Spread.it			Volatilitas			CAR		
		Model	Coefficient	t-statistic	Model	Coefficient	t-statistic	Model	Coefficient	t-statistic	Model	Coefficient	t-statistic
Second	HFT_VOL1	REM	0.0042	169.864***	FEM	3.262	592.776***	FEM	0.004	63.941***	FEM	0.168	12.739***
	HFT_VOL2		-3.99E-06	-18.093***		0.001	22.343***		-1.79E-06	-3.576***		-8.05E-05	-0.692
	HFT_TRADE1	REM	-1.94E-09	-4.223***	FEM	2.32E-06	22.963***	FEM	-4.36E-09	-4.182***	FEM	3.13E-08	0.1293
	HFT_TRADE2		-2.63E-08	-3.406***		-8.77E-05	-51.876***		3.48E-07	19.900***		-9.66E-06	-2.378**
Minute	HFT_VOL1	REM	-0.0005	-2.118**	FFEM	4.088	88.018***	FFEM	-0.001	-26.468***	FFEM	-0.067	-9.218***
	HFT_VOL2		-1.37E-05	-2.107**		-0.007	-5.673***		3.72E-08	0.0519		0.0001	0.69
	HFT_TRADE1	REM	-6.28E-08	-12.120***	FFEM	-2.53E-06	-2.640***	FFEM	-7.32E-09	-12.767***	FFEM	-1.37E-07	-0.918
	HFT_TRADE2		5.88E-08	3.403		-6.14E-07	-0.192		3.61E-09	1.885*		3.39E-07	0.684
15 Minute	HFT_VOL1	CEM	-0.005	-6.187***	FEM	5.106	20.847***	FEM	-0.011	-4.099***	FEM	-0.108	-2.721***
	HFT_VOL2		-0.0002	-0.858		-0.283	-3.988***		0.001	1.1232		0.009	0.784
	HFT_TRADE1	CEM	1.80E-06	2.265**	FEM	-0.00021	-0.969	FEM	-1.31E-05	-5.335***	FEM	-8.56E-05	-2.412**
	HFT_TRADE2		-7.75E-06	-3.816***		-0.011	-18.304***		5.97E-05	9.004***		-0.000513	-5.365***
1 hour	HFT_VOL1	CEM	-0.003	-1.065	REM	6.697	7.956***	REM	-0.071	-3.680***	REM	-0.14	-0.93
	HFT_VOL2		-0.002	-0.79		-1.518	-2.474**		0.035	2.501**		0.038	0.349
	HFT_TRADE1	CEM	3.16E-06	1.192	REM	-0.0004	-0.632	REM	-4.01E-05	-2.416**	REM	-0.000167	-1.2795
	HFT_TRADE2		-4.68E-06	-0.944		-0.013	-9.292***		0.0001	3.129***		-0.000112	-0.439
Daily	HFT_VOL1	CEM	-0.044	-0.292	REM	126.182	3.236***	REM	3.622	0.772	FEM	0.933	0.135
	HFT_VOL2		0.041	0.27		-121.001	-3.104***		-3.578	-0.763		-1.026	-0.149
	HFT_TRADE1	CEM	0.0002	1.385	REM	-0.076	-2.262**	REM	0.0002	0.052	FEM	-0.002787	-0.4703
	HFT_TRADE2		-0.0002	-1.394		0.055	1.624		-0.001	-0.22		0.003377	0.5683

Note: *: Sig on df 10%.
**: Sig on df 5%.
***: Sig on df 1%.

4.4. HFTs and Spreads

The examination of the impact of High-Frequency Trading (HFT) volume (3a) on spreads revealed four instances with notably negative t-statistic values. Similarly, in the case of HFT trading (3b), five instances exhibited significant negative t-statistic values. These outcomes indicate a more pronounced effect compared to results that were either insignificant or showed significant positive t-statistic values. So that in testing hypothesis 3, we conclude that HFT has an effect on reducing spreads or accepting Ha. This proof is consistent with research from Hendershott and Riordan (2013);Boehmer et al. (2018);Baron (2019); Hasbrouck and Saar (2013); and Menkveld (2013), who explain that the decrease in *spreads* in the presence of HFT is due to utilising superior speed in various ways that can reduce trading costs so that order information from each investor can be received at the same time. As explained in various literatures, the success of HFT lies in the speed of transactions and information. This has a positive impact on the possibility of price jumps of a few *ticks* because each bid and ask price can be automatically entered in the transaction order queue list.

4.5. HFTs and Volatility

The impact of High-Frequency Trading (HFT) on volatility, as evidenced by the results in Table 2, indicates that a significantly negative t-statistic value holds more strength than a significantly positive t-statistic value. These outcomes affirm that heightened HFT activity correlates with diminished volatility. Previous research by Siregar (2019) elucidates that heightened activity can mitigate the incidence of price jumps, serving as an indicator of reduced volatility. In addition to this, based on the explanations of Hendershott and Riordan (2013); Boehmer et al. (2018); Baron (2019); Hasbrouck and Saar (2013); and Menkveld (2013), the decline in volatility is due to HFT activity that can reduce the level of *spreads*. The question is slightly different, because this research proves that HFT has a direct effect on reducing volatility without going through the variable *spread* reduction.

4.6. HFTs and Risk Adjusted Return

The comprehensive test results for both High-Frequency Trading (HFT) volume and HFT trade demonstrate that a significantly negative t-statistic value holds more influence, as indicated by the five test results. Conversely, significant results with positive t-statistic values are only evident in one test. Therefore, we can conclude that HFT reduces risk-adjusted return (CAR). The CAR value is related to the risk in a stock, where the greater the CAR value, the less good or less efficient the stock is because it produces positive or negative returns that exceed market returns. As explained by Malceniece et al. (2019), who found evidence that increased HFT activity correlates with increased *co-returns*. Furthermore, research from Baron (2019) shows that HFT trading is able to manage the risk of negative selection in passive trading. Complementing this explanation, Aït-Sahalia and Brunetti (2020) find evidence that in the event of a price jump, HFT trading can avoid the event, and research from Vella and Ng (2016) explains that HFT can reduce asymmetric risk.

HFT has a significant effect on market liquidity. The cumulative impact of tick price on High-Frequency Trading (HFT) activity is established as positive. Nevertheless, upon dividing the tick price into various levels, the outcomes indicate that a smaller tick price exerts a significant and more robust influence on either amplifying or diminishing HFT activity. The evaluation of market quality, specifically focusing on liquidity, establishes that High-Frequency Trading (HFT) volume and trade significantly contribute to a reduction in market liquidity. Despite the inconsistency with the outcomes of Hendershott and Riordan (2013); Boehmer et al. (2018); Baron (2019); Hasbrouck and Saar (2013); and Menkveld (2013) in relation to hypothesis two, the test results reveal evidence supporting a significant impact of HFT on liquidity enhancement in only two test cases.

4.7. Effect of Time Interval on Testing

From Table 2, it is evident that the second time interval exhibits the highest count of significant test cases, totaling 30, and consistently demonstrates a more pronounced and significant effect across all tests. In contrast, during the minute interval, certain test cases either showed no significant effect or had a significant count of 22 cases. Whereas in the 15-minute time interval, more test cases were significant compared to the minute time interval, namely 26 test cases. The hourly time interval totalled 16 significant test cases and the fewer the number of test cases, namely only 11 proved, to have a significant effect. Based on the summary of the test results, there is a tendency that the shorter the time interval, the more likely the influence of each independent variable on the dependent variable.

5. CONCLUSIONS

HFT activity in this research substantiates a positive impact on market quality, measured through spread, volatility, and risk-adjusted return. The research has limitations pertaining to the sample, as it solely relies on LQ-45 data, thereby restricting the tick price to only three levels, namely 5, 10, and 25. This research also constrains the use of static panel data for hypothesis testing compared to dynamic panel data. Therefore, future research can facilitate a comparison between the use of dynamic and static panels in hypothesis testing. The advancement of measurements for market quality variables in subsequent studies may consider additional variables that gauge the quality of a country's market.

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