Received: 19 April 2021 | Accepted: 8 May 2022

DOI: 10.1002/fut.22362

RESEARCH ARTICLE

FUTURES MARKETS WILEY

Algorithmic trading and market quality: Evidence from the Taiwan index futures market

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Abstract

This study examines the effects of different algorithmic traders on market quality and the price discovery process, considering the impact of different trading strategies and market conditions. Algorithmic foreign institutions and proprietary firms act strategically, by monitoring market conditions. During stable market conditions, they supply liquidity, and this strategic activity both improves price efficiency and increases fundamental volatility. In more turbulent market conditions, algorithmic foreign institutions and proprietary firms instead demand liquidity, and their trading activity leads to an increase in price efficiency and a decrease in excessive volatility. Overall, algorithmic trades do not harm market quality.

KEYWORDS

algorithmic trading, market quality, price discovery, trading activity

JEL CLASSIFICATION

G14, G15, G18

1 | INTRODUCTION

> Markets are different now in fundamental ways .... From the way traders trade, to the way markets are structured, to the way liquidity and price discovery arise—all are now different in the high-frequency world.
>
> –O'Hara (2015, p. 257)

Algorithmic trading (AT) (or high-frequency trading [HFT]) has grown rapidly in major financial markets, reflecting both technology advances and the growing popularity of electronic trading.[1] In automated trading settings, trading speed is very fast, and financial markets are highly competitive. By automating the process, AT helps reduce the intermediary costs of trading. It also changes the way traders execute trades, the structures of markets, and the manners in which both market liquidity and price discovery arise. Noting these relevant features, we use a unique, account-level data set from the Taiwan Futures Exchange (TAIFEX) to perform a comprehensive analysis of whether and how different types of algorithmic traders (i.e., foreign institutions, proprietary firms, domestic institutions, and

[1]HFT is viewed as a subset of AT (Chaboud et al., 2014).

individual traders) influence market quality and price efficiency, while also testing the effects of different trading strategies and market conditions (i.e., either stable or volatile markets).

Computer-based trading has received increasing research attention, but there are disagreements about the effectiveness and impact of automated trading. In particular, the role of algorithmic traders in financial markets remains an empirical issue, and these research gaps motivate our research. We posit that algorithmic traders' role as liquidity demanders or providers may depend on market stability, such that they choose different trading strategies in various market conditions, because market conditions would alter the trading opportunities they encounter. We also seek to determine when and why algorithmic traders might decide to change their roles, from liquidity demanders to providers and vice versa. Finally, we test how changes in algorithmic traders' strategies affect market quality and price efficiency.

With these unique, TAIFEX, account-level data, this study provides a detailed analysis of whether, why, and how different types of algorithmic traders use distinct trading strategies under different market conditions, and then how these different trading activities of various algorithmic traders affect market quality and market efficiency. To the best of our knowledge, no existing literature examines how the AT activities of different trader types affect the market. Most studies address the mean impact of AT (or HFT) on overall market quality (Biais & Woolley, 2011; Brogaard et al., 2014; Brogaard, 2010; Hendershott & Riordan, 2011, 2013; Khandani & Lo, 2011; Hoffmann, 2014; Chaboud et al., 2014; Kirilenko et al., 2017; O'Hara et al., 2014). Yet AT by different types of traders clearly could affect market quality differently. Therefore, we seek to complement extant literature by providing a fuller analysis of whether and how different traders influence market quality under different market conditions. The results provide important implications for regulators concerned about potential welfare gains and losses of different types of market participants due to increasing AT.

Accordingly, we follow Hendershott et al. (2011) and use the number of order submissions per minute by each type of trader as a proxy for AT activity, such that we can investigate the empirical relationship of the trading activities of different algorithmic traders with market quality or price efficiency on the TAIFEX. To distinguish trends in the general increase in trading volume during our sample period, we normalize the AT measures for different traders, using their respective trading volumes. In addition, because existing literature focuses primarily on stock markets when examining the effects of AT, empirical evidence about how it affects futures market is somewhat limited. Futures markets differ from stock markets though, such that they feature higher leverage, lower transaction costs, and easier short selling. Therefore, we predict that the impacts of AT on futures market quality and the price discovery process differ from those in stock markets. In particular, we suggest that algorithmic traders prefer to trade index futures, due to their high liquidity, low information asymmetry, and capacity to function as a financial instrument that can be used to speculate on or hedge against overall market price changes (e.g., Black, 1975; Chan, 1992; Gammill & Perold, 1989; Ko, 2012; Kurov, 2008; Subrahmanyam, 1991).

This study thus makes several contributions to extant literature. First, we show that algorithmic traders actively and closely monitor the market and respond quickly to its changes. These traders face different trading opportunities, depending on market conditions, and thus employ different trading strategies (i.e., liquidity-providing or liquidity-demanding). Understanding the trading strategies of algorithmic traders in different market conditions is important, because it gives insights into dynamic changes in market quality and the price discovery process. In this sense, our findings advance market-making studies that consider whether algorithmic traders can act effectively as market makers, even though they are not subject to the affirmative obligations imposed on traditional market makers. Second, we consider AT activities by different types of traders and their influences on market quality, which has not been addressed previously, largely due to a lack of complete transaction records. Yet as we show, the trading behavior of different types of traders may affect market quality differently. Third, we provide evidence of how AT affects futures markets, moving beyond previous AT studies that mostly focus on stock markets. These results in particular have important policy implications for regulators who need to know how AT influences futures markets. Fourth, our empirical results provide additional implications for policy makers seeking social welfare maximization; they can use our findings to develop appropriate regulations on investments using fast trading technology, such as the "Pigovian tax."[2]

Our results show that AT by foreign institutions and proprietary firms provides market liquidity during normal market conditions. Their trading activities, which supply liquidity, encourage price discovery by posting quotes that

[2]This tax on financial transactions imposes punishment mechanisms on investments using fast trading technology, to mitigate externalities due to differences in market participants' ability to process the vast amount of market information (Biais et al., 2015).

represent quick responses to market information. Furthermore, the process of incorporating market information into prices with increased quote speed results in an increase in “good” (fundamental) volatility. During more turbulent market conditions, AT by foreign institutions and proprietary firms instead consumes liquidity when more arbitrage opportunities appear. Their demand for liquidity leads to more informationally efficient market prices, by making arbitrage opportunities disappear. In addition, arbitrage trading by algorithmic foreign institutions and proprietary firms leads to reductions in “bad” (excessive) volatility, by pulling prices toward to their fundamental values. Overall, AT appears beneficial for the futures market, because this activity lowers “bad” volatility during turbulent periods and increases “good” volatility during quiet periods. Notably, AT also improves price efficiency for both normal and turbulent market conditions, and its positive impact is especially significant during high market volatility periods.

With these findings, policy makers can regulate AT more effectively. A common assumption is that AT generates unnecessary volatility and harms market efficiency, so to control for these presumed negative effects, regulators impose frictions on AT (e.g., taxes and fees). Contrary to these general beliefs though, we find that during quiet periods, higher market volatility corresponds to the incorporation of fundamental information into prices, and AT activity actually contributes positively to price efficiency.

The remainder of this article is organized as follows: Section 2 briefly reviews prior literature. Section 3 describes the methodology. Section 4 introduces the empirical models. Section 5 presents the empirical results, and Section 6 concludes.

2 | LITERATURE REVIEW

Various theoretical and empirical studies explore the relationship of automated trading with market quality and price efficiency. Several theoretical investigations argue that AT (or HFT) contributes positively to markets. For example, Oehmke (2009) anticipates that increasing the speed of arbitrage opportunities disappear significantly reduces mispricing, and Hoffmann (2014) notes that fast traders contribute more to efficient prices by quickly revising their quotes in response to news, which increases trades. Similarly, Martinez and Roşu (2013) predict that with more high-frequency traders, market liquidity, and trading volume increase. Furthermore, fast traders can enhance price efficiency by making inefficient prices disappear quickly, because they trade on news. Consistent with these predictions, various studies confirm that AT (or HFT) improves market conditions. For example, Hendershott and Riordan (2011) argue that AT makes prices more efficient than human trading and does not increase volatility on the Deutsche Boerse. Hendershott et al. (2011) determine that AT induces improvements in liquidity and makes quotes more efficient on the New York Stock Exchange (NYSE). Chaboud et al. (2014) also find that AT contributes more to efficient prices by speeding up price discovery on foreign exchange markets. According to O'Hara et al. (2014), AT has the positive effect of improving price efficiency in odd-lot trades on equity markets. Similarly, Brogaard et al. (2015) show that the increase in trading speed leads to an improvement in market liquidity. Finally, Brogaard et al. (2014) also show that HFT increases price efficiency.

In contrast, some theoretical contributions assert that AT (or HFT) might induce negative effects on markets. Stein (2009) and Kozhan and Tham (2012) indicate that if traders simultaneously implement the same strategy, using computers, to exploit the same arbitrage opportunity, AT will deteriorate market efficiency. Biais et al. (2015) argue that fast trading generates adverse selection costs for other market participants and thus creates negative externalities, which lowers overall welfare. Furthermore, Foucault et al. (2016) reveal that high-frequency traders do not improve the process of price discovery without asymmetric information. Empirical findings consistent with these arguments in turn indicate that AT (or HFT) deteriorates market quality. For example, Khandani and Lo (2011) investigate the August 2007 mini-crash on the NYSE and find that fast trading affects market quality negatively if algorithmic traders use similar strategies at the same time. A downward spiral in the market may initiate if many algorithmic traders experience a shock at the same time and react similarly. Boehmer et al. (2021) also conclude that greater AT intensity exacerbates market volatility. According to Kirilenko et al. (2017), the response of high-frequency traders to unusually large selling pressure aggravates market volatility during a flash crash.

These ambiguous findings about the effects of AT could reflect the lack of agreement about the nature of algorithmic traders' strategies, that is, whether they employ a liquidity-providing or a liquidity-demanding strategy. We offer another argument, namely, that algorithmic traders dynamically use liquidity-providing or liquidity-demanding strategies, depending on the trading opportunities they encounter in different market conditions. We propose that studying AT under different market environments facilitates overall understanding of how technological progress affect financial markets. Therefore, we investigate the impact of AT on market liquidity, volatility, and the price discovery process during both normal and turbulent market periods, according to trading behavior that algorithmic traders display in these different periods. In turn, we can specify whether AT is beneficial or harmful to markets when they are volatile versus stable. To the best of our knowledge, no prior theoretical and empirical evidence exists regarding the effects of AT strategies on market quality and price efficiency in different market conditions.

As another interesting issue to address, we consider whether algorithmic traders exert varying influences on markets. Fast algorithmic traders have access to advanced trading techniques and the advantage of low trading latency, so they can access better, more real-time market information than slow traders (Biais et al., 2015; Brogaard et al., 2015; Chaboud et al., 2014; Hendershott & Riordan, 2013; Martinez & Roşu, 2013). In turn, they might be better able to choose when to provide liquidity to the market or take it away, compared with slow algorithmic traders. Furthermore, fast algorithmic traders might impose adverse selection costs on slower traders, through their superior ability to access, process, and respond to information (Biais et al., 2015; Brogaard et al., 2017; Chaboud et al., 2014; Hendershott & Riordan, 2013; Hoffmann, 2014; Jovanovic & Menkveld, 2016; Martinez & Roşu, 2013).

With a detailed, account-level data set, we divide algorithmic traders into four types: algorithmic foreign institutions, algorithmic proprietary firms, algorithmic domestic institutions, and algorithmic individual traders. Therefore, we explore the trading behavior and profitability of different types of algorithmic traders, as well as whether each type of algorithmic trader has unique effects on market quality and the price discovery process in different market conditions. We anticipate that they adopt different trading strategies, according to the market conditions (i.e., normal vs. turbulent), which create distinct trading opportunities. According to Brogaard (2010), on average days, when asset prices are steady and fewer arbitrage opportunities exist, sophisticated traders who use computer algorithms to trade automatically supply liquidity to market participants who demand liquidity. However, on the most volatile days, when asset prices are volatile and more arbitrage opportunities exist, these sophisticated traders demand liquidity by making more marketable trades. They are willing to supply liquidity because, unlike traditional market makers, they incur less risk of being picked off, and these specialist traders also can quickly adjust their quotes to the arrival of new information, which protects them against unfavorable executions (Brogaard et al., 2015; Conrad et al., 2015; Jovanovic & Menkveld, 2016; Malinova et al., 2013). Therefore, the liquidity provision of AT traders should differ, depending on market conditions. During normal market conditions, algorithmic traders can employ a liquidity-providing strategy; they have fewer arbitrage opportunities, when prices are relatively steady. But during turbulent market conditions, they instead step in and employ a liquidity-demanding strategy, because they have more arbitrage opportunities in this market with its relatively volatile prices. Overall, we suggest that algorithmic traders monitor market conditions to optimize their activities, whether supplying or taking liquidity.

Then, we offer explanations for how these trading strategies affect market quality and price efficiency. A common view holds that algorithmic traders engage in market making (liquidity-providing strategy).[3] In this case, they generally benefit the market by enhancing competition and increasing market liquidity (Brogaard et al., 2015; Hoffmann, 2014; Jovanovic & Menkveld, 2016). However, AT traders do not have affirmative obligations, similar to those imposed on traditional market makers, so they could create market disruptions if they exit the market at their own discretion.[4] In addition, algorithmic liquidity providers might contribute to price discovery by quickly adjusting their quotes after the arrival of public information (Chaboud et al., 2014; Conrad et al., 2015; Hendershott et al., 2011; Hoffmann, 2014), but they would contribute less information to prices if they exit at their own discretion. Alternatively, algorithmic traders might engage in arbitrage or directional trading (liquidity-demanding strategy).[5] In this case, algorithmic liquidity demanders make prices more informationally efficient (Kondor, 2009; Martinez & Roşu, 2013; Oehmke, 2009), but their AT also pushes prices farther from fundamental values, because they simultaneously perform the same trade, triggering the same (or similar) arbitrage strategies (Kozhan & Tham, 2012; Stein, 2009). Ultimately, the process of incorporating market information into prices through liquidity-providing and liquidity-demanding strategies should increase "good" (fundamental) volatility during quiet periods and decrease "bad" (excessive) volatility during turbulent periods (Brogaard et al., 2014; Chaboud et al., 2014).

[3]Fast traders who implement automated computer trading act like market makers and perform market-making tasks (Brogaard et al., 2014; Gerig & Michayluk, 2010; Jovanovic & Menkveld, 2016; Menkveld, 2013).

[4]Traditional market makers have positive obligations, which requires them to stand ready to supply liquidity at any time, as well as obligations that limit their ability to demand liquidity. The absence of these two obligations allows algorithmic traders to exit the market at their discretion.

[5]Fast traders that demand liquidity employ arbitrage or directional trading strategies (Brogaard et al., 2014; Hagströmer & Nordén, 2013).

Prior studies offer mixed findings about the information advantages of foreign and domestic investors on non-US markets. Grinblatt and Keloharju (2000), Seasholes (2004), Chang et al. (2009), Chiang et al. (2010), Chen et al. (2014), and Chuang et al. (2019) argue that foreign institutional investors have information advantages over domestic investors. Yet Choe et al. (2001), Hau (2001), and Dvořák (2005) instead suggest that domestic investors possess information advantages over foreign investors. Chen et al. (2014) further specify that among domestic investors, institutional investors and proprietary firms are more informed than individual investors.

In previous studies, individual investors often represent uninformed traders, because of their inferior trading profitability. However, these studies tend to rely on the mean trading performance by individual investors, which obscures the wide variation in trading performance across individual investors who potentially have vastly different trading abilities. Some individual investors might be skilled traders with superior information; Barber et al. (2014) acknowledge that most individual traders tend to be unskilled but identify some Taiwanese individual investors who are skilled traders with information advantages. Therefore, some individual investors likely represent informed traders with superior trading ability. Using a unique data set from the TAIFEX, this study examines how AT affects the market and its implications for the information advantages of different trader types.

3 | METHODOLOGY

3.1 | Institutional setting

Before proceeding, it is useful to characterize the TAIFEX. The TAIFEX is an order-driven futures market with no designated market makers and is operated by the automated trading system. Trading on the TAIFEX is carried out from 8:45 a.m. to 1:45 p.m., from Mondays to Fridays (excluding public holidays), with the price limits on the TAIFEX being ±7% of the previous day's close. The Taiwan index futures market is special in terms of the composition of traders. Unlike other mature index futures markets, which are dominated by institutional investors (Cheng & Li, 2014),[6] major participants on the TAIFEX are individual investors. Domestic individual investors account for roughly 71% of the total trading volume during our sample period. Futures proprietary firms rank second (18%), and foreign institutions rank third (8%) in terms of the trading volume. Domestic institutions account for only 3% of the trading volume, the smallest fraction of the total market trading volume in the TAIFEX. By using a unique data set from the TAIFEX, our study contributes to the existing literature by investigating the impact of the AT trading of individual traders on market quality and how AT activities of different institutional traders (i.e., foreign institutions, proprietary firms, and domestic institutions) affect the market, an area that has rarely been explored before.

3.2 | Data and samples

As the technology at exchanges and in the possession of traders improves, the significance of the influence of HFT on futures markets has increased. According to the Aite Group, HFT accounted for nearly 25% of the global trading volumes on futures markets in 2009. In addition, according to a study by the Tabb Group consultancy, there is a rapid growth in HFT in Asia-Pacific markets, as they undergo developments similar to those witnessed previously in the US and European markets (i.e., improved technology for trading platforms, enhanced ability to deliver real-time market data).[7] Thus, HFT has become an important part of futures markets around the globe, and its role is growing with advancing technology for exchanges and traders, especially for the Asia-Pacific markets.

We focus on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) futures contracts traded on the TAIFEX, where the Taiwan index futures has an important role to play on futures exchanges and financial markets

[6]On the US stock index futures market, around 80% of the total market trading volume comes from institutional investors. The stock index futures market in Japan similarly is dominated by institutional investors, which account for roughly 90% of the total trading volume. In Korean stock index futures markets, institutional investors contribute roughly 65% of the total trading volume, and domestic individual investors account for 35%. Similarly, in the Hong Kong stock index futures market, institutional investors are the main traders.

[7]See the reports of Tabb: "European Equity Trading 2010: Maneuvering in the Market" (October 2010) and "Next-Generation Algorithms: High Frequency for Long Only" (December 2010).

around the world.[8] The trading unit for TAIEX futures is the index value of the TAIEX × 200 New Taiwan Dollars (NT$). In our empirical analyses, we use the nearest contracts, to focus on the most liquid futures contracts. The detailed data set we obtained from the TAIFEX intraday futures database contains a detailed history of order flows, order books, and traders' identities, for all transactions of TAIEX futures between January 1, 2004 and March 31, 2009.[9] For each order, the transaction data report the time stamp of arrival, its sign (buy or sell), the quantity demanded or offered, and the traders. According to the trader codes, we can categorize them into four types: foreign institutions, domestic institutions, proprietary firms, and individual traders. We winsorized all variables at the 1st and 99th percentiles to avoid the influence of extreme values.

We provide detailed variable definitions in Table 1, along with summary statistics for subsamples, defined by subperiods and trader types. To examine whether and how different market conditions (i.e., stable or turbulent) influence the trading strategies of different types of algorithmic traders and further affect market quality and price efficiency, we conduct univariate tests of variables across different subperiods. The division of the sample period into two subperiods (stable vs. turbulent) reflects the timing of the subprime mortgage crisis that began in August 2007. The stable period is before the crisis (January 1, 2004–July 31, 2007), and the turbulent period is after it (August 1, 2007–March 31, 2009).

Table 1 contains the averages of all variables for both stable and turbulent periods and the differences between them. The mean AT activity for foreign institutions, futures proprietary firms, and individual traders during the turbulent period is significantly higher than that in the stable period, at a 1% level. That is, compared with the stable period, the AT activity of foreign institutions, futures proprietary firms, and individual traders increases in the turbulent period. The increase in AT activity for foreign institutions and futures proprietary firms is particularly greater than that of individual traders, indicating that AT activity for foreign institutions and proprietary firms is much more aggressive during turbulent market conditions. Furthermore, we find that the market liquidity, volatility, and price efficiency measures during the turbulent period are significantly higher than those during the stable period, at a 1% level. Thus, the AT trading strategies of different trader types appear to have different impacts on market quality and price efficiency, according to different market conditions.

In addition, the trading volume of individual traders is significantly greater than that of other trader types in both the stable and turbulent periods. The proportions of trading volume for different trader types across periods indicate that individual traders account for the largest proportion of trading volume in both periods. For example, the trading volume of individual traders accounts for 71.7% and 66.5% of all trades in the stable period and the turbulent period, respectively. Futures proprietary firms rank second (stable period 17.8% and turbulent period 18.2%), followed by foreign institutions (stable period 6.9% and turbulent period 10.8%). Domestic institutions account for a small fraction of the total trading volume in both periods. Overall, the investor structure in the Taiwan futures market is significantly different from those in developed markets (e.g., the United States) when individual traders contribute the biggest trading volume in the market.

3.3 | Variable definition

To examine the relationship of AT activity with market quality, we consider the impacts of different types of algorithmic traders. We investigate several dimensions of market quality, including market liquidity, volatility, and price efficiency, as we detail next.

3.3.1 | AT measure

We cannot observe directly whether a particular order reflects AT or not. Because AT activity generally relates to fast order submissions and cancellations (Hasbrouck & Saar, 2013), we use the sum of order submissions in a minute as a proxy for AT.[10] Similarly, a proxy based on the number of order submissions is widely used by market participants

[8]According to Euromoney TRADEDATA, stock index futures contracts traded on the TAIFEX ranked 10th among global exchanges in 2017.
[9]The account-level data are only available until March 31, 2009, because the Personal Information Protection Act enacted at that time prohibited the TAFEX to release new account-level data.
[10]As a robustness check, we use the sum of order cancelations per minute as a proxy and obtain similar results.

TABLE 1 Univariate statistics by subsample

	The stable period (1) mean	The stable period standard deviation	The turbulent period (2) mean	The turbulent period standard deviation	Difference (2) − (1)
$Espread_t(10^{-4})$	1.186	0.347	1.298	0.369	0.112***
$Rspread_t(10^{-4})$	0.270	0.896	0.524	1.235	0.254***
$Advselection_t(10^{-4})$	0.916	1.019	0.774	1.204	−0.142**
$Volatility_t$	0.840	0.373	1.523	0.533	0.683***
$PE_t(10^{-4})$	1.039	0.781	1.572	1.022	0.533***
AT_t^{all}	−1.462	0.200	−0.968	0.150	0.494***
$AT_t^{foreign}$	−2.133	1.163	−0.836	0.536	1.297***
$AT_t^{domestic}$	−1.937	0.392	−1.966	0.343	0.029
$AT_t^{proprietary}$	−2.337	0.763	−0.785	0.409	1.552***
$AT_t^{individual}$	−1.368	0.134	−1.156	0.078	0.212***
$Volume_t^{foreign}(10^4)$	0.492	0.428	1.588	0.677	1.096***
$Volume_t^{domestic}(10^4)$	0.240	0.131	0.628	0.241	0.388***
$Volume_t^{proprietary}(10^4)$	1.226	0.574	2.761	0.947	1.535***
$Volume_t^{individual}(10^4)$	4.886	1.896	10.036	3.143	5.150***
$Per\_Volume_t^{foreign}$	0.069	0.044	0.108	0.048	0.039***
$Per\_Volume_t^{domestic}$	0.035	0.014	0.043	0.017	0.008***
$Per\_Volume_t^{proprietary}$	0.178	0.036	0.182	0.025	0.004**
$Per\_Volume_t^{individual}$	0.717	0.068	0.665	0.063	−0.052***
$Inv\_price(10^{-4})$	1.493	0.213	1.648	0.459	−0.155***

Note: This table presents differences in means of the variables with daily data across two subperiods. All variables are winsorized at the 1st and 99th percentiles. $Espread_t = Rspread_t + Advselection_t$ is the effective spread; $Rspread_t = Q_t(P_t - M_{t+5})/M_t$ is the realized spread, where P_t is the trade price, Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, M_t is the midpoint of the prevailing ask and bid quotes, M_{t+5} is the quote midpoint 5 min after the trade, and $Advselection_t = Q_t(M_{t+5} - M_t)/M_t$ is the 5-min adverse selection (price impact) of a trade. $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility, where $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. Then PE_t is the pricing error for the trade price based on Hasbrouck (1993). The algorithmic trading by type i traders is defined as AT_t^i, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively; AT is the negative value of total trading volume divided by the number of order submission within a minute. In addition, $Volume_t^i$ refers to the trading volume by type i traders, $Per\_Volume_t^i$ refers to the ratio of trading volume by type i traders to all trades, and Inv_price denotes the inverse of the daily closing price. The stable period is January 1, 2004–July 31, 2007, and the turbulent period is from August 1, 2007 to March 31, 2009. ** and *** indicate significance at the 5% and 1% levels, respectively.

(e.g., consultants Aite Group and Tabb Group), exchanges (e.g., National Association of Securities Dealers Automated Quotations [NASDAQ] and NYSE), and researchers (e.g., Boehmer et al., 2021; Hendershott et al., 2011).

However, we might capture only the increase in trading volume, which is not related to AT, if we were to adopt raw message traffic measure, without normalizing it by electronic messages. To normalize message traffic, we redefine our AT proxy as the negative value of trading volume divided by the number of messages. This normalization is consistent with Hendershott et al.'s (2011) and Boehmer et al.'s (2021) analyses. For our regression analyses, because the normalized value represents negative volume associated with each message, a higher normalized measure indicates greater AT activities.

3.3.2 | Liquidity measures

We investigate the impact of AT on market liquidity using various liquidity measures, including the effective spread, the realized spread, and adverse selection, all measured as proportions of the midpoint of prevailing ask and bid quotes. We start with the effective spread,[11] for which a reduction implies an increase in market liquidity. The effective spread for the tth trade is

$$Espread_t = Q_t(P_t - M_t)/M_t, \tag{1}$$

where Q_t is the buy–sell indicator, equal to +1 for buy orders and −1 for sell orders; P_t is the trade price; and M_t is the midpoint of the prevailing ask and bid quotes of the tth trade, which provides the proxy for the true value of the asset. Next, we decompose the effective spread into two components, realized spread and adverse selection (or price impact). The realized spread captures revenues to liquidity providers; adverse selection measures the losses that liquidity providers suffer from informed liquidity demanders. We then estimate the 5-min realized spread. The realized spread of the tth trade is defined as

$$Rspread_t = Q_t(P_t - M_{t+5})/M_t, \tag{2}$$

where P_t is the trade price; Q_t is the buy–sell indicator, equal to +1 for buy orders and −1 for sell orders; M_t is the quote midpoint prevailing ask and bid quotes at the time of the tth trade; and M_{t+5} is the quote midpoint 5 min after the trade. For adverse selection, we take the 5-min price impact of a trade, so the adverse selection of the tth trade is defined as

$$Adveselection_t = Q_t(M_{t+5} - M_t)/M_t, \tag{3}$$

and the variables are as defined for Equation (2). For all liquidity measures, we calculate the daily liquidity as the trade-weighted average of all trades during the day. Finally, to define the relations among the effective spread, the realized spread, and adverse selection, we use[12]

$$Espread_t = Rspread_t + Advselection_t. \tag{4}$$

3.3.3 | Volatility measure

We employ the realized volatility proposed by Andersen et al. (2001) as a proxy for market volatility. The realized volatility is[13]

$$Volatility_t = \frac{100 * \sum_{k=1}^{K}(R_{t,k})^2}{K}, \tag{5}$$

where $R_{t,k}$ is the 1-min intraday return, and K is the number of 1-min intraday returns within a trading day. In turn, $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the prevailing bid–ask midpoint at the end of the 1-min interval.

3.3.4 | Pricing error measure

We estimate pricing error, in line with Hasbrouck's (1993) assertion that an observed transaction price can be decomposed into an efficient price component and a pricing error component. The efficient price should follow a random walk process, defined as a security's expected value, conditional on all public information and private information that can be inferred from the order flow. The pricing error instead is a zero-mean covariance-stationary process that measures the temporary deviation between the efficient price and the actual transaction price, such that it captures information-unrelated market frictions (e.g., price discreteness, inventory control effects, and transaction costs

[11]As a robustness check, we account for the quoted spread, $Qspread_t = (Ask_t - Bid_t)/M_t$, and find similar results.

[12]As a robustness check, we follow Hendershott et al. (2011) and use a 30-min horizon after the reference quote to calculate the 30-min realized spread and 30-min adverse selection; our conclusions remain unchanged.

[13]As a robustness check, we use 5-min intraday returns to calculate the realized volatility; the results are very similar, and our conclusions do not change.

incurred by traders). The standard deviation of the pricing error reflects the magnitude of deviation relative to the efficient price, so it provides a good proxy for price efficiency. A lower standard deviation in the pricing error reflects better price discovery and market quality.

In an empirical setting, Hasbrouck (1993) estimates the following bivariate vector autoregression (VAR):

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \cdots + b_1 x_{t-1} + b_2 x_{t-2} + \cdots + v_{1,t}, \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \cdots + d_1 x_{t-1} + d_2 x_{t-2} + \cdots + v_{2,t}, \end{aligned} \tag{6}$$

where r_t indicates price changes, and x_t is the signed trade variable. Inverting this VAR provides a vector moving average:

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \cdots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \cdots, \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \cdots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \cdots. \end{aligned} \tag{7}$$

With an expanded representation of pricing error, in line with Beveridge and Nelson's (1981) identification restriction, we determine

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \cdots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \cdots, \tag{8}$$

where $\alpha_j = -\sum_{k=j+1}^{\infty} a_k^*$, $\beta_j = -\sum_{k=j+1}^{\infty} b_k^*$. Then the variance of the pricing error (σ_s^2) may be computed as

$$\sigma_s^2 = \sum_{j=0}^{\infty} [\alpha_j \beta_j] Cov(v) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix}. \tag{9}$$

We use the tick data of price changes (r_t) and signed trades (x_t) to estimate the pricing error variance (σ_s^2) on a daily basis and measure price efficiency in the futures market.

4 | EMPIRICAL MODELS

To establish the causal relationship between AT and market quality, we follow Boehmer et al. (2021) and use the instrumental variable method.[14] We seek an instrument that is not causally related to our market quality variables and is closely related to AT activity. As suggested by Boehmer et al. (2021), we use the introduction of the direct market access (DMA) service as our instrument.[15] The TAIFEX adopted the DMA service on July 17, 2007. According to its definition of DMA, it is an individual trader that effectively places orders directly to the exchange, through brokers' computer systems, without any interventions from brokers. Therefore, DMA allows a trader's order submission algorithm to interact with the exchange with minimal latency. To implement our instrumental variable method, we construct a dummy variable, *DMA*, which equals 0 before DMA service and 1 after the DMA service. We employ the 2SLS in estimating the models. In the first stage, we regress our AT proxy, AT_t^i, on *DMA* and control variables and save the predicted value, $AT\_hat_t^i$. In the second stage, we estimate the second stage regression models with the predicted AT value.[16]

We first investigate the impact of AT on market liquidity, volatility, and informational efficiency during a stable period,[17] while considering the AT activities of different types of traders. We control for several other factors that might affect market quality and price efficiency (Hendershott et al., 2011). For market liquidity, we specify the following regression model:

[14]We thank an anonymous referee for providing this valuable suggestion.

[15]Boehmer et al. (2021) suggest the introduction of colocation and DMA services are two possible instruments. We use the introduction of the DMA service because only the DMA service event occurred in TAIFEX during our sample period.

[16]The same set of control variables is used in both the first- and second-stage regressions. To ensure the explanatory variables are predetermined, we follow Boehmer et al. (2021) to lag all control variables by 1 day.

[17]We divide the sample period into two subperiods (stable vs. turbulent), according to the timing of the subprime mortgage crisis that began in August 2007. The stable period is before the crisis (January 1, 2004–July 31, 2007), and the turbulent period is after the crisis (August 1, 2007–March 31, 2009).

$$Liquidity_t^s = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}, \tag{10}$$

where liquidity ($Liquidity_t^s$) denotes the market liquidity measure on day t. Our liquidity measures include the effective spread ($Espread_t$), the realized spread ($Rspread_t$), and the price impact ($Advselection_t$). Our main explanatory variable is $AT\_hat_t^i$, the algorithmic activity for type i traders, where $i = all$, *foreign*, *domestic*, *proprietary*, or *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. To control for the effect of market conditions on liquidity, we also include trading volume ($Volume_{t-1}$), market volatility based on the realized volatility ($Volatility_{t-1}$), and the inverse of trade price (Inv_price_{t-1}), in the regression. Finally, we add a time dummy variable D to examine the effects of AT during turbulent periods.

We test for the effect of AT on market volatility as follows:

$$Volatility_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Espread_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}, \tag{11}$$

where volatility ($Volatility_t$) is a function of AT activity by type i traders ($AT\_hat_t^i$), as defined previously. We measure volatility by realized volatility. The other explanatory variables are daily trading volume ($Volume_{t-1}$), the effective bid–ask spread ($Espread_{t-1}$), and the inverse of the futures price (Inv_price_{t-1}). We again include the time dummy variable D.

The equation for testing the effect of AT on price efficiency is as follows:

$$PE_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}, \tag{12}$$

where pricing error (PE_t) is a function of the AT activity by type i traders ($AT\_hat_t^i$), as defined previously. The control variables and the time dummy variable are the same as those in Equation (11). For all regression models, we employ Newey and West's (1987) robust heteroskedasticity, autocorrelation-consistent standard errors to address potential heteroskedasticity and autocorrelation in the regression errors.

5 | EMPIRICAL RESULTS

5.1 | Market liquidity

We regress the various liquidity measures ($Liquidity_t^s$) on AT activities (AT_t^i) and some control variables. The empirical estimates of the effective spread equations are in Table 2.[18] Column (1) reflects the results for overall AT; Models (2)–(5) pertain to each of the four trader types. In the general results, we find that the coefficient of $AT\_hat_t^{all}$ in Column (1) is significantly negative; overall, the effective spread decreases with an increase in AT activity. That is, we show empirically that AT increases market liquidity in normal market conditions. Across the different types of traders, the coefficients of $AT\_hat_t^{foreign}$ and $AT\_hat_t^{proprietary}$ also are significantly negative in Table 2. These empirical results affirm that the AT activities of foreign institutions and proprietary firms narrow the effective spread, such that they function to improve liquidity in a period of relatively stable market conditions.

To investigate the effects of AT during more turbulent market conditions, we include the interaction term between $AT\_hat_t^i$ and D in our regression, which reveals the links of AT activities by different types of traders and market liquidity measures. The empirical results in Table 2 show that the integration term between D and the AT activities of all traders ($D * AT\_hat_t^{all}$) is significantly positive. Therefore, greater liquidity demand with increased AT activities arises in turbulent markets. The algorithmic traders provide liquidity to relatively stable markets but take liquidity in response to market turbulence. Accordingly, we confirm that algorithmic traders perform different liquidity provision roles, depending on the market conditions. Furthermore, for the different types of traders, the coefficients of

[18]We estimate the augmented Dickey–Fuller (ADF) tests both with and without a time trend for the effective spread, which indicates that the effective spread series is stationary.

TABLE 2 Regression analysis on effective spread

Variables	Column (1) $i = all$	Column (2) $i = foreign$	Column (3) $i = proprietary$	Column (4) $i = domestic$	Column (5) $i = individual$
$Intercept(10^{-4})$	0.106*	0.227***	0.173***	0.302***	0.066
	(0.061)	(0.035)	(0.039)	(0.049)	(0.085)
$D(10^{-4})$	0.142	0.004	0.032	−0.139*	−1.204***
	(0.099)	(0.031)	(0.036)	(0.083)	(0.273)
$AT\_hat_t^i(10^{-4})$	−0.115***	−0.035***	−0.030***	0.024	−0.095
	(0.039)	(0.007)	(0.011)	(0.019)	(0.063)
$D * AT\_hat_t^i(10^{-4})$	0.226***	0.105***	0.167***	−0.010	−0.943***
	(0.094)	(0.024)	(0.033)	(0.043)	(0.225)
$Volume_{t-1}(10^{-9})$	−0.706***	−0.681***	−0.653***	−0.721***	−0.695***
	(0.057)	(0.057)	(0.058)	(0.057)	(0.076)
$Volatility_{t-1}(10^{-4})$	0.705***	0.702***	0.691***	0.690***	0.687***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.036)
Inv_price_{t-1}	0.378***	0.355***	0.394***	0.402***	0.438***
	(0.024)	(0.024)	(0.028)	(0.024)	(0.024)
Adjusted R^2	0.619	0.627	0.624	0.616	0.627

Note: This table reports the regression results of the following model: $Espread_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where $Espread_t = Q_t(P_t - M_t)/M_t$ is the effective spread on day t; P_t is the trade price, Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, and M_t is the midpoint of the prevailing ask and bid quotes. The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, $foreign$, $domestic$, $proprietary$, and $individual$, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume, and $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility, where $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. In addition, Inv_price_t denotes the inverse of the daily closing price. The dummy variable D equals 1 during the crisis period and 0 otherwise. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

$D * AT\_hat_t^{foreign}$ and $D * AT\_hat_t^{proprietary}$ are significantly positive in Columns (2) and (3), but the coefficient of $D * AT\_hat_t^{individual}$ is significantly negative in Column (5). This empirical evidence indicates that during a period of relatively high volatility, increased trading activities by algorithmic foreign institutions and proprietary firms lead to a marginal increase in the effective spread, but more algorithmic activity by individual traders leads to a marginal decrease in the effective spread. Therefore, market liquidity decreases with an increase in AT by foreign institutions and proprietary firms; market liquidity increases with an increase in AT by individual traders. Overall, algorithmic foreign institutions and proprietary firms take liquidity during more turbulent market conditions, but algorithmic individual traders supply liquidity in such periods. Our empirical results are consistent with Chae et al. (2013) predictions that algorithmic individual traders have an important role in relation to liquidity provision.

5.2 | Decomposition of liquidity

With increased AT activity, effective spreads could narrow (widen) due to lower (higher) realized spreads, lower (higher) adverse selection, or some combination of the two. To understand the effect of AT on liquidity provisions in more detail, we decompose the effective spread into two components, realized spread and adverse selection.

We first discuss sources of changes to the effective spread during normal market conditions. Tables 3 and 4 contain estimation results for the realized spread and adverse selection, respectively. In both tables, Column (1) pertains to overall AT, and Columns (2)–(5) represent the results involving the different types of traders. In Column (1) in Table 3, the coefficient of $AT\_hat_t^{all}$ is significantly positive; the realized spread increases significantly with an increase in AT.

TABLE 3 Regression analysis on realized spread

Variables	Column (1) $i = all$	Column (2) $i = foreign$	Column (3) $i = proprietary$	Column (4) $i = domestic$	Column (5) $i = individual$
$Intercept(10^{-4})$	0.438	−0.215	−0.171	−0.224	0.844**
	(0.027)	(0.158)	(0.174)	(0.210)	(0.341)
$D(10^{-4})$	−1.048**	0.029	−0.027	−0.577	−1.252
	(0.438)	(0.138)	(0.162)	(0.492)	(1.467)
$AT\_hat_t^i(10^{-4})$	0.525***	0.107***	0.190***	−0.027	0.868***
	(0.173)	(0.029)	(0.051)	(0.073)	(0.229)
$D * AT\_hat_t^i(10^{-4})$	−0.972**	0.022	0.137	−0.354	−1.026
	(0.418)	(0.109)	(0.150)	(0.253)	(1.248)
$Volume_{t-1}(10^{-9})$	0.490*	0.374	0.430*	0.498*	0.608**
	(0.252)	(0.255)	(0.258)	(0.294)	(0.294)
$Volatility_{t-1}(10^{-4})$	−0.230**	−0.171*	−0.245**	−0.159	−0.248*
	(0.099)	(0.098)	(0.099)	(0.130)	(0.133)
Inv_price_{t-1}	0.420***	0.488***	0.632***	0.272**	0.411***
	(0.108)	(0.107)	(0.123)	(0.117)	(0.119)
Adjusted R^2	0.026	0.028	0.030	0.022	0.027

Note: This table reports the regression results of the following model: $Rspread_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where $Rspread_t = Q_t(P_t - M_{t+5})/M_t$ is the realized spread on day t; P_t is the trade price, Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, M_t is the midpoint of the prevailing ask and bid quotes, and M_{t+5} is the quote midpoint 5 min after the trade. The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume and $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility, where $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. In addition, Inv_price_t denotes the inverse of the daily closing price. The dummy variable D equals 1 during the crisis period and 0 otherwise. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

It seems likely that AT activity enables liquidity providers to earn greater revenues, due to their superior ability to choose when to provide liquidity to the market (Carrion, 2013). In Column (1) of Table 4, we also find that the coefficient of $AT\_hat_t^{all}$ is significantly negative, so the price impact decreases significantly with increasing AT activity under normal market conditions. Their AT activity helps liquidity suppliers incur fewer losses, possibly because they are less likely to be adversely selected when AT enables them to incorporate real-time information quickly into their quotes and thus protects them against unfavorable executions (Conrad et al., 2015). In addition, Tables 3 and 4 reveal that more revenue earned by liquidity providers is offset by fewer losses among liquidity providers, due to informed liquidity demanders, so overall market liquidity increases.

The empirical estimates of the realized spread and adverse selection for different types of traders are in Columns (2)–(5) of Tables 3 and 4, respectively. Increased AT by foreign institutions and proprietary firms helps liquidity providers capture more revenue and experience smaller losses to informed liquidity demanders. Moreover, AT activities by foreign institutions and proprietary firms induce decreases in losses to informed liquidity demanders that are greater than the increase in revenues earned from providing liquidity, resulting in an increase in market liquidity. Therefore, algorithmic foreign institutions and proprietary firms provide liquidity in normal market conditions. Our empirical findings are consistent with the argument that fast liquidity providers generally are willing to narrow the bid–ask spread and provide more market liquidity when they face less risk of being adversely selected, leading to a decrease in their adverse selection costs (Brogaard et al., 2015; Hoffmann, 2014; Jovanovic & Menkveld, 2016; Malinova et al., 2013). In more turbulent market conditions, as Column (1) of Table 3 shows, the coefficient of $D{*}AT\_hat_t^{all}$ is significantly negative, a marginal decrease in the realized spread with an increase in AT activity when the market is

TABLE 4 Regression analysis on permanent price impact

Variables	Column (1) $i = all$	Column (2) $i = foreign$	Column (3) $i = proprietary$	Column (4) $i = domestic$	Column (5) $i = individual$
$Intercept(10^{-4})$	−0.636**	0.345**	0.107	0.499**	−1.157***
	(0.286)	(0.167)	(0.184)	(0.229)	(0.374)
$D(10^{-4})$	1.267***	0.090	0.346**	0.237	−0.773
	(0.462)	(0.146)	(0.171)	(0.392)	(1.038)
$AT\_hat_t^i(10^{-4})$	−0.837***	−0.146***	−0.200***	0.064	−1.150***
	(0.182)	(0.031)	(0.054)	(0.087)	(0.257)
$D * AT\_hat_t^i(10^{-4})$	1.212***	0.255**	0.506***	0.250	−0.628
	(0.439)	(0.114)	(0.158)	(0.200)	(0.871)
$Volume_{t-1}(10^{-9})$	−1.136***	−1.023***	−0.924***	−1.177***	−1.230***
	(0.265)	(0.269)	(0.272)	(0.267)	(0.265)
$Volatility_{t-1}(10^{-4})$	0.958***	0.885***	0.895***	0.847***	0.936***
	(0.105)	(0.104)	(0.105)	(0.105)	(0.106)
Inv_price_{t-1}	−0.061	−0.092	−0.065	0.152	0.088
	(0.114)	(0.113)	(0.130)	(0.111)	(0.114)
Adjusted R^2	0.077	0.078	0.076	0.064	0.079

Note: This table reports the regression results of the following model:
$Advselection_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where $Advselection_t = Q_t(M_{t+5} - M_t)/M_t$ is the 5-min adverse selection (price impact) of a trade on day t (permanent price impact on day t); Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, M_t is the midpoint of the prevailing ask and bid quotes, and M_{t+5} is the quote midpoint 5 min after the trade. The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume, and $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility, where $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. The dummy variable D equals 1 during the crisis period and 0 otherwise. In addition, Inv_price_t denotes the inverse of the daily closing price. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

more volatile. Therefore, liquidity providers earn less profit with increased AT activity. Such AT likely makes the realized spread smaller because competition among algorithmic liquidity suppliers provides incentives for them to update their quotes (Conrad et al., 2015). An increase in competition among traders also seems plausible, considering the level of investments in fast trading technology and trade infrastructure (Conrad et al., 2015).

Furthermore, Column (1) of Table 4 indicates that the coefficient of $D*AT\_hat_t^{all}$ is significantly positive; a marginal increase in adverse selection with greater AT. Therefore, liquidity providers face more losses to informed traders due to AT during periods marked by high volatility. This finding is consistent with a prediction by Brogaard et al. (2017), namely, that the adverse selection costs imposed by fast traders may be unusually high in turbulent market conditions. Algorithmic liquidity demanders impose higher adverse selection costs on liquidity providers, perhaps because they have better skills in terms of accessing, processing, and responding to information than do slow traders (Biais et al., 2015; Brogaard et al., 2015; Chaboud et al., 2014; Hendershott & Riordan, 2013; Martinez & Roşu, 2013). In addition, from Column (1) of Tables 3 and 4, we find that liquidity providers increase effective spreads to make up for some of the losses in revenues due to increased adverse selection. For the different types of traders, the empirical estimates of the realized spread and the adverse selection in Columns (2)–(5) indicate that liquidity providers experience greater losses to informed liquidity demanders, due to increased AT activities by foreign institutions and proprietary firms. That is, AT activities of foreign institutions and proprietary firms induce increases in losses to informed liquidity demanders for liquidity providers, resulting in a reduction in market liquidity.

Overall then, in more turbulent market conditions, when asset prices are volatile, algorithmic foreign institutions and proprietary firms tend to consume more liquidity. In contrast, during normal market conditions, when asset prices are stable, algorithmic foreign institutions and proprietary firms prefer to provide liquidity. These outcomes likely arise because algorithmic foreign institutions and proprietary firms face more (less) arbitrage trading opportunities in volatile (stable) markets. Algorithmic foreign institutions and proprietary firms accordingly behave differently in terms of their liquidity provision when market conditions vary.

The results in Tables 2 and 4 also indicate that the coefficients of $D * AT\_hat_t^{foreign}$ and $D * AT\_hat_t^{proprietary}$ in Columns (2) and (3) are both positive. During periods of relatively high volatility, the AT of foreign institutions and proprietary firms increases the level of adverse selection and makes the market less liquid. When algorithmic foreign institutions and proprietary firms have information advantages, in terms of access to market information, their liquidity demand behavior imposes higher adverse selection costs on slow liquidity providers (Biais et al., 2015; Chaboud et al., 2014; Hendershott & Riordan, 2013; Martinez & Roşu, 2013), who accordingly post wider bid–ask spreads, reduce their trades, or even quit the market (Biais et al., 2015; Brogaard et al., 2015; Cartea & Penalva, 2012; Foucault et al., 2016; Foucault et al., 2017; Hendershott & Riordan, 2013). Finally, our empirical results imply that if AT sufficiently increases the level of adverse selection, it might worsen overall welfare, because of a costly arms race triggered by AT (e.g., Hendershott & Riordan, 2013; Hoffmann, 2014).

5.3 | Market volatility and price efficiency

Tables 5 and 6 show the results of the market volatility and pricing error tests for stable and volatile market conditions, respectively.[19] Columns (2) and (3) in Table 5 indicate significantly positive coefficients of $AT\_hat_t^{foreign}$ and $AT\_hat_t^{proprietary}$, whereas the similar models in Table 6 reveal significantly negative coefficients of $AT\_hat_t^{foreign}$ and $AT\_hat_t^{proprietary}$. Therefore, increases in AT by foreign institutions and proprietary firms increase market volatility and decrease pricing errors under normal market conditions. Their AT activities accordingly improve the informational efficiency of prices, and this price discovery process induces an increase in fundamental market volatility.

Combining the results in Tables 2 and 6, we find that the coefficients of $AT\_hat_t^{foreign}$ and $AT\_hat_t^{proprietary}$ in Columns (2) and (3) are both significantly negative. The algorithmic foreign institutions and proprietary firms act as liquidity suppliers, and their AT behavior improves price efficiency under normal market conditions. The high-speed quote updates to the arrival of public information likely represent improved market liquidity and allow for more information to be impounded into prices, consistent with Hoffmann (2014), Chaboud et al. (2014), and Conrad et al. (2015). Overall, the AT activities of foreign institutions and proprietary firms which provide liquidity increase "good" market volatility (fundamental volatility) by incorporating more new information into futures prices.

For relatively more turbulent market conditions, we again examine the relationship of AT with market volatility and price efficiency. To test for the role of AT in these conditions, we include the interaction of $AT\_hat_t^i$ and D. In Models (2) and (3) in Tables 5 and 6, the interactions of the dummy variable D with the trading activities of algorithmic foreign institutions ($D * AT\_hat_t^{foreign}$) and proprietary firms ($D * AT\_hat_t^{proprietary}$) relate significantly negatively to market volatility and pricing error in the trade price. In this sense, AT by foreign institutions and proprietary firms leads to a margin decrease in market volatility and pricing error; that is, they decrease market volatility and improve price efficiency in turbulent market conditions. These findings might reflect increased arbitrage trading by algorithmic foreign institutions and proprietary firms.

Combining the results from Columns (2)–(3) of Tables 2, 5, and 6, we note that by taking liquidity, algorithmic foreign institutions and proprietary firms appear to improve price efficiency by speeding up the price discovery process, because they aggressively trade on existing arbitrage opportunities. Once price inefficiencies appear and arbitrage opportunities arise, these algorithmic foreign institutions and proprietary firms quickly take advantage of the opportunity. Therefore, the relative information advantages of foreign institutions and proprietary firms are more significant during the turbulent periods, because their AT trading takes advantage of the arbitrage opportunities presented during this period. These empirical findings support prior evidence (Chang et al., 2009; Chen et al., 2014; Chiang et al., 2010; Chuang et al., 2019; Grinblatt & Keloharju, 2000; Seasholes, 2004) that foreign institutions and proprietary firms are more informed. In periods of high volatility, their arbitrage trading strategies prompt smaller price changes, by pushing prices back toward their true values,[20] which lowers market noise and reduces "bad" market

[19]We conduct ADF tests both with and without a time trend for market volatility, which indicate that the market volatility series is stationary.

[20]An arbitrage (or convergence) trading strategy is defined as "strategies taking long-short positions in assets with identical underlying cash flows that temporarily trade at different prices" (Chaboud et al., 2014, p. 2046). Oehmke (2009) and Kondor (2009) note that price efficiency increases with the number of arbitrageurs who implement an arbitrage trading strategy.

TABLE 5 Regression analysis on market volatility

Variables	Column (1) *i = all*	Column (2) *i = foreign*	Column (3) *i = proprietary*	Column (4) *i = domestic*	Column (5) *i = individual*
$Intercept(10^1)$	−0.103***	−0.103**	−0.104**	−0.096***	−0.496***
	(0.038)	(0.041)	(0.040)	(0.034)	(0.090)
$D(10^1)$	0.015	−0.071***	−0.064**	−0.009	0.365***
	(0.061)	(0.022)	(0.026)	(0.044)	(0.104)
$AT\_hat_t^i(10^1)$	0.010	0.015***	0.024***	0.009	−0.317***
	(0.018)	(0.005)	(0.007)	(0.014)	(0.051)
$D * AT\_hat_t^i(10^1)$	0.022	−0.028***	−0.030**	0.007	0.334***
	(0.040)	(0.008)	(0.013)	(0.021)	(0.077)
$Volume_{t-1}(10^{-5})$	0.447**	0.555***	0.398*	0.495**	0.450**
	(0.205)	(0.178)	(0.206)	(0.207)	(0.197)
$Spread_{t-1}$	0.584***	0.608***	0.643***	0.560***	0.443***
	(0.157)	(0.157)	(0.157)	(0.144)	(0.131)
$Inv\_price_{t-1}(10^4)$	0.802***	0.745***	0.843***	0.811***	1.023***
	(0.151)	(0.149)	(0.156)	(0.164)	(0.161)
Adjusted R^2	0.096	0.106	0.099	0.097	0.112

Note: This table reports the regression results of the following model:
$Volatility_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Espread_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility on day t, $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume, and $Espread_t = Q_t(P_t - M_t)/M_t$ is the effective spread, where P_t is the trade price, Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, and M_t is the midpoint of the prevailing ask and bid quotes. In addition, Inv_price_t denotes the inverse of the daily closing price. The dummy variable D equals 1 during the crisis period and 0 otherwise. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

volatility (excessive volatility). Our results are thus consistent with Brogaard et al. (2014) and Chaboud et al. (2014), and they support the idea that algorithmic traders improve price efficiency through effective arbitrage.

In Tables 2 and 6, we also find an interesting result, in that the improvement in price efficiency comes predominantly from increased AT activity by algorithmic foreign institutions and proprietary firms that consume liquidity by hitting posted quotes under turbulent market conditions, not from their activities to provide liquidity by posting quotes that are hit under normal market conditions. The demand for liquidity by algorithmic foreign institutions and proprietary firms contributes more to moving prices toward the efficient price; their supply of liquidity contributes more to efficient prices through more efficient quotes. These empirical results are consistent with a prediction by Hendershott and Riordan (2011) that AT activities associated with both demanding and supplying liquidity make prices more efficient.

Algorithmic foreign institutions and proprietary firms appear to act strategically, in monitoring market conditions and improving price efficiency. They contribute to efficient prices by providing liquidity when market volatility is low and taking liquidity when market volatility is high. From the viewpoint of improving price discovery, their AT activities are equally beneficial in stable or turbulent markets, because the varied activities consistently make markets more efficient.

5.4 | Market volatility with efficient price changes

To measure market volatility due to efficient price changes, we estimate the standard deviation of the efficient price. We capture the efficient price by using the method proposed by Hasbrouck (1993) (see Section 3.3.4 for a more detailed discussion). It provides a good proxy for market volatility, derived from efficient price changes. We repeat the tests in

TABLE 6 Regression analysis on market efficiency

Variables	Column (1) i = *all*	Column (2) i = *foreign*	Column (3) i = *proprietary*	Column (4) i = *domestic*	Column (5) i = *individual*
Intercept	0.083	−0.013***	−0.011***	0.003	0.026
	(0.220)	(0.004)	(0.003)	(0.019)	(0.026)
$D(10^{-1})$	−0.032	−0.643***	−0.241**	−0.539	−0.008
	(1.457)	(0.166)	(0.094)	(0.396)	(0.169)
$AT\_hat_t^i(10^{-1})$	0.823	−0.090**	−0.068***	0.067	0.251
	(2.025)	(0.036)	(0.025)	(0.131)	(0.207)
$D * AT\_hat_t^i\ (10^{-1})$	−0.315	−0.203***	−0.044	−0.264	−0.063
	(0.944)	(0.069)	(0.039)	(0.196)	(0.146)
$Volume_{t-1}(10^{-6})$	−0.108	0.117**	0.042	−0.097	−0.089
	(0.068)	(0.045)	(0.026)	(0.072)	(0.065)
$Volatility_{t-1}(10^{-2})$	0.649**	0.011	0.018	0.646**	0.716***
	(0.271)	(0.017)	(0.029)	(0.306)	(0.254)
$Inv\_price_{t-1}(10^{2})$	0.074	−0.157	0.205	0.555	0.065
	(0.842)	(0.233)	(0.144)	(0.392)	(0.287)
Adjusted R^2	0.049	0.054	0.058	0.0501	0.056

Note: This table reports the regression results of the following model:
$PE_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Volatility_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where PE_t is the pricing error of Hasbrouck (1993). The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume, and $Volatility_t = 100 * \sum_{k=1}^{K}(R_{t,k})^2/K$ is the realized volatility, where $R_{t,k}$ is the 1-min intraday return, such that $R_{t,k} = \ln(M_{t,k}) - \ln(M_{t,k-1})$, where $M_{t,k}$ is the bid–ask midpoint at the end of the 1-min interval, and K is the number of 1-min intraday return. In addition, Inv_price_t denotes the inverse of the daily closing price. The dummy variable D equals 1 during the crisis period and 0 otherwise. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5 but also consider a volatility measure that purges pricing errors; these results are in Table 7. Regarding AT activities across different types of traders, Columns (2)–(3) in Table 7 indicate significantly positive coefficients of $AT\_hat_t^{foreign}$ and $AT\_hat_t^{proprietary}$. Therefore, the AT activities of foreign institutions and proprietary firms induce an increase in efficient price market volatility during normal market conditions. However, we do not find similar results pertaining to the effects of AT activities for other trader types. From the results in Table 2 (regression analyses of market liquidity) and Table 7, we note that foreign institutions' and proprietary firms' AT activities supply market liquidity, which allows more information to be incorporated into prices in normal market conditions.

To determine the effects of AT activities during more turbulent market conditions, we include the interaction term of $AT\_hat_t^i$ and D in the regression. In Column (2) in Table 7, the interactions of the dummy variable D with the AT activities of foreign institutions ($D * AT\_hat_t^{foreign}$) and proprietary firms ($D * AT\_hat_t^{proprietary}$) are significantly negatively. That is, AT activities of foreign institutions and proprietary firms contribute negatively to efficient price market volatility during turbulent market conditions. Column (2) results across Tables 2 and 7 signify that the AT activities of foreign institutions and proprietary firms tend to marginally decrease efficient price market volatility during turbulent market conditions, likely because that foreign institutions and proprietary firms demand liquidity during such periods. A liquidity-demanding strategy contributes more to changes in the deviation between the efficient price and the transaction price; a liquidity-providing strategy instead contributes more to changes in the efficient price. Therefore, during more turbulent conditions, when foreign institutions and proprietary firms use AT to demand liquidity, efficient price market volatility becomes smaller. Overall, we again confirm that during stable periods, the AT activities of foreign institutions and proprietary firms tend to provide liquidity, which increases fundamental volatility by incorporating more new information into futures prices. When their AT activities demand liquidity, it decreases excessive volatility by pushing prices back toward their true values during turbulent periods.

TABLE 7 Regression analysis on market volatility derived from efficient price changes

Variables	Column (1) *i = all*	Column (2) *i = foreign*	Column (3) *i = proprietary*	Column (4) *i = domestic*	Column (5) *i = individual*
$Intercept(10^{-2})$	−0.068***	−0.070***	−0.063***	−0.072***	−0.314***
	(0.012)	(0.009)	(0.009)	(0.011)	(0.026)
$D(10^{-2})$	−0.053***	−0.278***	−0.024***	−0.021*	0.136***
	(0.019)	(0.005)	(0.007)	(0.012)	(0.029)
$AT\_hat_t^i(10^{-2})$	0.005	0.010***	0.018***	−0.001	−0.204***
	(0.011)	(0.003)	(0.004)	(0.004)	(0.020)
$D * AT\_hat_t^i(10^{-2})$	−0.020	−0.007***	−0.012***	0.001	0.155***
	(0.015)	(0.003)	(0.004)	(0.006)	(0.024)
$Volume_{t-1}(10^{-8})$	0.222***	0.150**	0.187***	0.213***	0.145**
	(0.067)	(0.068)	(0.067)	(0.067)	(0.060)
$Spread_{t-1}(10^{-3})$	0.451***	0.470***	0.413***	0.448***	0.429***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.037)
$Inv\_price_{t-1}(10^{1})$	0.426***	0.478***	0.505***	0.418***	0.535***
	(0.041)	(0.039)	(0.040)	(0.039)	(0.035)
Adjusted R^2	0.631	0.643	0.648	0.629	0.699

Note: This table reports the regression results of the following model: $EP\_Volatility_t = \alpha_{10} + \alpha_{11}D + \alpha_{12}AT\_hat_t^i + \alpha_{13}D * AT\_hat_t^i + \alpha_{14}Volume_{t-1} + \alpha_{15}Espread_{t-1} + \alpha_{16}Inv\_price_{t-1} + \varepsilon_{1t}$, where $EP\_Volatility_t$ is the market volatility derived from efficient price changes on day t. The predicted value of algorithmic trading by type i traders is defined as $AT\_hat_t^i$, where $i = all$, *foreign*, *domestic*, *proprietary*, and *individual*, denoting all traders, foreign institutions, domestic institutions, proprietary firms, and individual traders, respectively. $Volume_t$ refers to the daily trading volume, and $Espread_t = Q_t(P_t - M_t)/M_t$ is the effective spread, where P_t is the trade price, Q_t is the buy–sell indicator that is equal to +1 for buy orders and −1 for sell orders, and M_t is the midpoint of the prevailing ask and bid quotes. In addition, Inv_price_t denotes the inverse of the daily closing price. The dummy variable D equals 1 during the crisis period and 0 otherwise. The sample period is from January 1, 2004 to March 31, 2009. We use Newey and West's (1987) procedure to correct the standard errors for the presence of heteroskedasticity and autocorrelation in the regression errors. The robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6 | CONCLUSIONS

We address questions about how different types of algorithmic traders affect market quality and price efficiency, in consideration of various trading strategies adopted in different market conditions. During periods of relatively stable market conditions, algorithmic foreign institutions and proprietary firms provide liquidity, because they encounter fewer arbitrage opportunities. This activity of providing liquidity enables them to earn greater revenues and incur fewer losses, as well as improve overall price efficiency by posting quotes as rapid responses to public information. In addition, the process of incorporating information into trade prices with quick quotes leads to beneficial increases in fundamental market volatility.

However, in more turbulent market conditions, algorithmic foreign institutions and proprietary firms adopt a different role and take liquidity, because they have more arbitrage opportunities in this period. Their trading behavior also leads to more informationally efficient market prices, because they take advantage of these arbitrage opportunities. Their arbitrage trading leads to lower price volatility (excessive volatility) and causes prices to revert to their fundamental values in turbulent markets. Overall, AT thus appears beneficial for futures markets. Algorithmic trades lower "bad" (excessive) volatility during turbulent periods and enhance "good" (fundamental) volatility in stable markets. That is, AT improves price efficiency, regardless of market conditions.

These findings can help policy makers devise more effective AT trading rules. Regulators often express concern about AT, seemingly because they assume that it generates unnecessary volatility and harms market efficiency. Thus, they seek to discipline AT by levying taxes or charging fees to control for these presumed negative effects. But with our findings that show that greater volatility corresponds to the incorporation of fundamental information into prices during stable market conditions, we reveal that AT actually contributes positively to the price discovery process. Its contribution in terms of reducing "bad" volatility and increasing pricing efficiency also provides benefits in turbulent market periods. Thus, in contrast with a widespread assumption among regulators, we show that AT activity is beneficial to price discovery, regardless of market conditions, and its positive impact is especially significant in turbulent markets. Our results advance extant literature and provide more detailed insights into how AT activities by different trader types affect both market quality and the price discovery process.

ACKNOWLEDGMENT

Ya-Kai Chang gratefully acknowledges the financial support from the Ministry of Science and Technology of Taiwan (MOST 109-2410-H-033-005-MY2).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the TAIFEX intraday futures database. Restrictions apply to the availability of these data, which were used under license for this study.

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How to cite this article: Chang, Y.-K., & Chou, R. K. (2022). Algorithmic trading and market quality: Evidence from the Taiwan index futures market. *Journal of Futures Markets*, 42, 1837–1855.
https://doi.org/10.1002/fut.22362