Journal of Economics and Finance
https://doi.org/10.1007/s12197-024-09702-w

The market ecosystem in the age of algorithms: An analysis of trading dynamics and market quality

John Paul Broussard[1,3] · **Andrei Nikiforov**[1] · **Sergey Osmekhin**[2]

Accepted: 4 December 2024
© The Author(s) 2025

Abstract
This paper examines the impact of algorithmic trading on market quality using a unique NASDAQ OMX Nordic dataset from 2010–2011. We classify traders into algorithmic, institutional, professional, and retail categories. Using two-way fixed effects models and instrumental variables estimation, we find that algorithmic traders enhance liquidity by reducing bid-ask spreads by 0.28 basis points relative to retail traders, with similar effects from institutional traders. These effects persist during high volatility periods, while professional traders are associated with wider spreads. Surprisingly, retail traders emerge as significant liquidity providers, while algorithmic traders exhibit higher order cancellation rates. These findings contribute to the debate on algorithmic trading's role in modern markets and offer implications for market design and regulation.

Keywords Algorithmic trading · HFT · Market quality · Market microstructure

JEL Classification G20 · G14 · L10

1 Introduction

The landscape of financial markets has undergone a profound transformation in recent decades, with algorithmic trading becoming a dominant force in most major financial centers (O'Hara 2015; Brogaard & Garriott 2019). This shift towards automation has brought about significant changes in market dynamics, including faster executions and often enhanced liquidity. However, the impact of algorithmic trading

✉ Andrei Nikiforov
andrei.nikiforov@rutgers.edu

[1] Rutgers School of Business, Rutgers University, 227 Penn Street, Camden, NJ 08102, USA

[2] Department of Finance and Statistics, Hanken School of Economics, P.O. Box 479, 00101 Helsinki, FI, Finland

[3] Estonian Business School, University in Tallinn, Tallinn, Estonia

Published online: 25 March 2025

on market quality remains a subject of ongoing debate among researchers, practitioners, and regulators alike (Kirilenko et al. 2017; van Kervel & Menkveld 2019).

Our study contributes to this critical dialogue by addressing several key gaps in the existing literature and providing new insights into the role of algorithmic traders within the broader market ecosystem. Specifically, we leverage a unique dataset from NASDAQ OMX Nordic covering the period from June 1, 2010, to November 30, 2011, to examine how different types of market participants, including algorithmic traders, affect various dimensions of market quality. Through robust empirical methods including two-way fixed effects models with clustered standard errors and instrumental variables estimation, we establish causal relationships between trader behavior and market quality measures.

The primary contributions of our study are threefold:

1. Comprehensive Trader Classification: Unlike previous studies that often focus solely on high-frequency traders (HFTs) or treat all algorithmic traders as a homogeneous group, we classify market participants into four distinct categories: algorithmic traders, institutional traders using NASDAQ's algorithms, "professional" investors without algorithms, and retail traders.
2. Multifaceted Analysis of Market Quality: We provide a holistic assessment of market quality by examining the impact of different trader types on bid-ask spreads, trading volume at the National Best Bid and Offer (NBBO), and overall market depth. This comprehensive approach, supported by careful econometric identification strategies, extends recent work on market quality dynamics (e.g., Brogaard et al. 2022.)
3. Liquidity Provision and Order Cancellation Analysis: We investigate the determinants of liquidity provision and order cancellation behaviors among different trader types. This analysis provides novel insights into the strategies employed by algorithmic traders and their impact on market dynamics, building on recent research on order flow toxicity (e.g., Easley et al. 2021).

Our results reveal several important findings that contribute significantly to the existing literature:

First, we find that both algorithmic traders and institutional traders significantly reduce spreads compared to retail traders, with algorithmic traders reducing spreads by 0.28 basis points and institutional traders by 0.43 basis points. These effects remain robust to various empirical specifications, including instrumental variables estimation using lagged algorithmic trading activity.

Second, contrary to some expectations, we observe no adverse impact from algorithmic traders on spreads during periods of high volatility. Their impact remains consistent across different volatility levels. Instead, we find that professional non-algorithmic traders are associated with wider spreads (0.69 basis points increase) during volatile conditions, potentially being a primary source of market quality deterioration under such circumstances. This result contributes to the ongoing debate about the role of different trader types in market stability.

Third, our analysis reveals that retail traders are significant liquidity providers, surpassing other trader types including algorithmic traders in this aspect. Algorithmic traders, while contributing to reduced spreads, show lower levels of liquidity provision compared to retail traders. This finding offers new insights into the complex interplay between different market participants and challenges some preconceived notions about the role of retail investors in market liquidity.

While our dataset covers a period from 2010 to 2011, which predates the current market environment, it offers distinct advantages for our analysis. This era captures a key phase in the evolution of algorithmic trading, providing valuable historical insight into the early effects of algorithmic trading on market quality. As noted by Menkveld (2016), studying early market structures can reveal patterns that remain relevant over time. Moreover, many emerging and frontier markets are now at a similar stage of algorithmic trading adoption, making our findings particularly relevant for understanding markets currently undergoing similar transitions (Yan et al. 2022).

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature and develops our hypotheses. Section 3 describes our data and methodology. Section 4 presents and discusses our empirical results. Section 5 presents our robustness checks. Finally, Section 6 concludes and discusses implications for market participants and regulators.

2 Literature review and hypotheses development

The impact of algorithmic trading on financial markets has been a subject of extensive research in recent years. A significant strand of literature focuses on the role of algorithmic trading in price discovery and market efficiency. Hendershott and Riordan (2013) establish that algorithmic trades and quotes contain value-relevant information, contributing positively to price discovery. Brogaard et al. (2014) demonstrate that High-Frequency Trading (HFT) enhances market efficiency by aligning with permanent price changes and countering temporary mispricings. More recently, Hu and Murphy (2020) found that the full automation of NYSE's closing auctions led to improved auction quality.

The relationship between algorithmic trading and market liquidity is more contentious. Korajczyk and Murphy (2019) highlight the ambivalent role of HFTs in market making, noting their reduction of spreads for small orders while simultaneously increasing costs for large institutional orders. Van Kervel and Menkveld (2019) observe that HFTs' liquidity provision tends to be transient, with a tendency to withdraw during one-sided market moves.

The impact of volatility on algorithmic trading behavior has been extensively studied. While some studies suggest that HFT market makers withdraw during high volatility periods (Kirilenko et al. 2017; Ait-Sahalia and Saglam 2024), others find a more nuanced relationship. Hasbrouck and Saar (2013) argue that algorithmic trading can dampen short-term volatility. Brogaard et al. (2018) show that HFTs provide liquidity during extreme single-stock events but demand liquidity during market-wide downturns. Aït-Sahalia and Brunetti (2020) and Zhou et al. (2020) further support the notion that HFTs may actually mitigate price pressures during volatile periods.

Recent research has also examined the interplay between market fragmentation, algorithmic trading, and price discovery. Cox (2020) investigates the effects of dark and lit market fragmentation around earnings announcements and surprises, finding that dark fragmentation reduces post-earnings announcement drift (PEAD) for stocks with positive earnings surprises but strengthens it for stocks with negative surprises.

The strategies employed by algorithmic traders, particularly in terms of liquidity provision and order cancellation, have attracted significant attention. Hagströmer and Norden (2013) note that market making constitutes a major part of HFTs' volume. The introduction of maker-taker fee structures has further complicated the liquidity provision landscape, with studies by Colliard and Foucault (2012), Malinova and Park (2015), and Foucault et al. (2013) exploring its implications for market quality and trading behavior.

Based on this literature, we formulate the following hypotheses:

H1: Algorithmic traders contribute to narrower bid-ask spreads compared to other trader types, particularly during periods of high market volatility.
H2: The presence of algorithmic traders is associated with increased trading volume at the NBBO, enhancing price discovery and market efficiency, even during periods of high volatility.
H3: Algorithmic traders exhibit distinct patterns of liquidity provision and order cancellation compared to other market participants, reflecting their unique trading strategies and technological advantages.

By testing these hypotheses, our study aims to provide a more comprehensive understanding of the role of algorithmic trading in modern financial markets, addressing key gaps in the existing literature and offering novel insights into the complex dynamics of the market ecosystem.

3 Data specification and methodology

Our study utilizes a comprehensive dataset from NASDAQ OMX Nordic covering June 1, 2010, to November 30, 2011. While this period predates the current market environment, it offers valuable insights into a critical phase of algorithmic trading evolution, as highlighted by Menkveld (2016). This era captures the early impact of algorithmic trading, providing a benchmark for comparison with current market dynamics and insights relevant to emerging markets at similar stages of algorithmic trading adoption (Yan et al. 2022).

Our dataset uniquely isolates the impact of algorithmic traders in a less saturated market, enabling clearer identification of its effects. This approach aligns with Boehmer et al. (2021), who studied algorithmic trading's impact on market quality across 42 equity markets from 2001 to 2011. Their use of an even earlier sample period validates the relevance of historical data in understanding algorithmic trading's effects. They found that algorithmic trading generally improves liquidity and informational efficiency, with benefits more pronounced in larger stocks. Their international focus also underscores the importance of our study for

emerging markets, as many are currently experiencing or will soon undergo similar stages of algorithmic trading adoption. Our 2010–2011 data thus provides insights not only into the historical evolution of algorithmic trading but also into potential future impacts in developing markets. Moreover, the 2010–2011 period, characterized by high volume and volatility, bears similarities to post-2020 market conditions, enhancing the relevance of our findings to current volatile environments.

Our final sample consists of 382 trading days, excluding non-trading days. The dataset classifies traders into four distinct categories:

1. Algorithmic traders: Employing proprietary algorithms, including diverse High-Frequency Trading (HFT) strategies.
2. Institutional traders: Executing large orders via NASDAQ-approved algorithms (e.g., VWAP, TVWAP).
3. Professional investors: Operating without algorithmic assistance.
4. Retail traders: Predominantly non-algorithmic, with a marginal subset (1.4% of volume) utilizing algorithms reclassified into the algorithmic trader category.

Figure 1 illustrates the changing market composition over time, demonstrating a rise in algorithmic trading at the expense of other trader types. Figure 2 details the proprietary algorithmic trading volume, which nearly doubled but stabilized at approximately 40% in the final four months of observation.

Key variables in our dataset include date, order book, order execution metrics (Acks, Executions, Cancels), account type, liquidity provision, volume, relative time-weighted average spread (RTWAS), and order book depth measures (TVOB Volume, TVOA Volume). Additional data on prices and market capitalization are included. After filtering for liquidity and price range, following Hendershott et al. (2011), our final sample consists of 156 unique stocks and 458,813 observations.

It's important to note that our dataset contains daily summaries for each stock, detailing trading volumes by trader category and liquidity provision status, rather

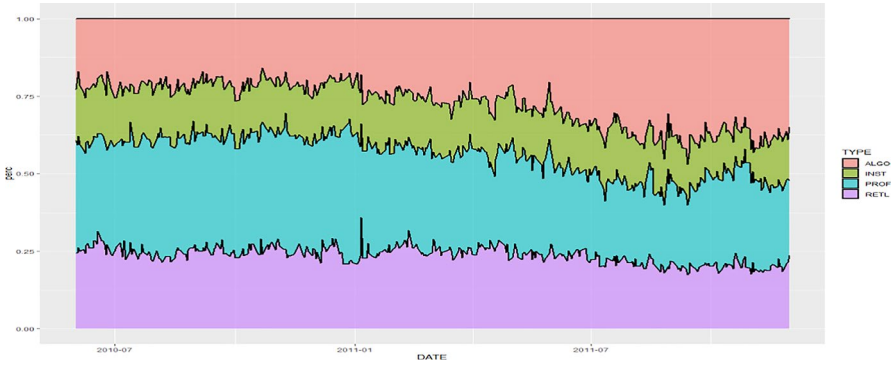


Fig. 1 The figure shows the distribution of trading volume across trader categories (algorithmic, institutional, professional, and retail) in the NASDAQ OMX Nordic market from June 2010 to November 2011. The data demonstrates a progressive increase in algorithmic trading activity relative to other trader categories during the sample period

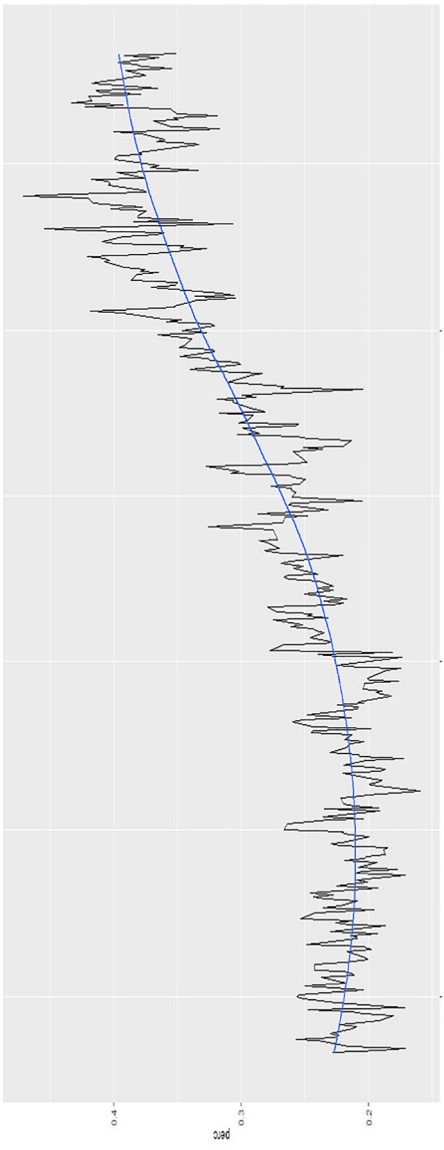


Fig. 2 The figure tracks proprietary algorithmic trading as a percentage of total market volume in the NASDAQ OMX Nordic market from June 2010 to November 2011. Algorithmic trading volume nearly doubled during the observation period before stabilizing at approximately 40% in the final four months

than trade-level data. NASDAQ classifies the total volume into various binary categories and determines whether trades were adding or removing liquidity using its internal classification rules. There are up to eight observations per each Date/Ticker: combined trades for the four TYPEs aggregated by whether they provide liquidity (MAKE = 1, limit orders) or remove liquidity (MAKE = 0, market orders).

Table 1 provides summary statistics for our key variables, including trading variables, market quality indicators, and execution metrics. Panel C of Table 1 disaggregates statistics by trader type, revealing higher average daily turnover among non-algorithmic professionals, while algorithmic traders lead in order modifications.

Table 2 documents variable correlations, providing insights into market dynamics and liquidity provision.

This study offers a comprehensive view of all algorithmic traders, extending beyond just HFT market makers, thus providing a broader analysis of their market activity (Tables 3 and 4).

4 Results and discussion

To address potential unobserved heterogeneity in our panel dataset, we employ two-way fixed effects in all our regression specifications. This approach, following Korajczyk and Murphy (2019) and Boehmer et al. (2021), allows us to control for both time-invariant stock characteristics and market-wide temporal effects. Specifically, for our baseline specification, we estimate:

$$RTWAS_\{i,t\} = \alpha_i + \gamma_t + \beta_1 TYPE_\{i,t\} + \beta_2 TURN_\{i,t\} + \beta_3 VLT_\{i,t\} + \beta_4 log(CLOSE_\{i,t\}) + \beta_5 log(MCAP_\{i,t\}) + \varepsilon_\{i,t\}$$

where α_i captures stock fixed effects and γ_t represents time (daily) fixed effects. This specification ensures that our estimates reflect within-stock variation in trading behavior while controlling for market-wide temporal patterns, following the approach of Hendershott and Riordan (2013).

We implement our estimation using the plm package in R for the fixed effects regression, followed by the multiwayvcov package to compute standard errors clustered at both the stock and date levels. This two-way clustering approach, as recommended by Pedersen (2009), accounts for potential correlation in the error terms both within stocks across time and within days across stocks, which is particularly important in market microstructure studies where both cross-sectional and temporal dependencies are likely to be present.

4.1 The effect of different types of traders on relative spreads

4.1.1 The effect of different types of traders on market quality measures

To investigate the impact of different trader types on market quality, we employ a series of regression models examining three key market quality indicators: the

Table 1 Descriptive statistics. The descriptive statistics for all major variables during our sample period from June 2010 to December 2011. TOTVOL is the average daily trading volume in shares. TURN is the ratio of shares to the total shares outstanding, MCAP is the market capitalization in billions of Euros. ACKS are partially executed orders, EXEC – the fully executed orders, CANCELS are orders that were cancelled, and PRICE is the average daily price in euros. Panel B describes the market quality variables. RTWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book respectively. TVOBR and TVOAR are the same variables multiplied by the price in euros. VLT is a volatility variable measures as the difference between High and Low price during a day scaled by the Closing price. Panel C presents some variable characteristics separated by trader type where ALGO represents all trades completed through proprietary algorithms, INST – all trades submitted through standard and exchange-approved execution algorithms (VWAP, TVAP, etc.), PROF – all orders that were submitted "manually", and RETL – are all orders that come from the retail investors

Panel A. Trading Variables

	TOTVOL	TURN	MCAP, €B	ACKS	EXEC	CANCELS	PRICE
Min	0	0.000%	0.02	1	1	1	2.19
1st Qu	7,175.00	0.008%	0.71	431.00	133.00	338.00	6.92
Median	28,870.00	0.023%	1.64	1,873.00	440.00	1,622.00	11.54
Mean	149,361.00	0.044%	4.45	9,530.00	1,074.00	11,017.00	17.67
3rd Qu	105,740.00	0.051%	4.42	6,310.00	1,293.00	5,745.00	20.05
Max	42,481,766	26.380%	66.20	2,559,620	67,772	2,590,058	119.61
Std. Dev	73,011	0.032%	3	4,355	859	4,005	10
N	458,813	458,813	458,813	458,813	458,813	458,813	458,813

Panel B. Market Quality Variables

	RTWAS	TVOBV	TVOBR	TVOAV	TVOAR	VLT, %
Min	0.03	31.70	890.00	337.00	6,030.00	0.28%
1st Qu	0.11	812.70	11,256.00	21,997.00	264,582.00	1.72%
Median	0.17	1,868.90	19,156.00	51,819.00	614,936.00	2.47%
Mean	0.27	4,004.80	36,700.00	125,078.00	1,332,398.00	2.97%
3rd Qu	0.37	3,997.20	40,990.00	128,732.00	1,608,029.00	3.61%
Max	9.58	2,033,229	4,211,052	11,071,906	43,494,537	58.02%
Std. Dev	0	2,358.89	22,025	79,063	995,146	1.40%
N	458,813	458,813	458,813	458,813	458,813	458,813

Panel C. Variables by Trader type

TYPE	TURN	ACKS	EXEC	CANCELS	MAKING	CORR
1 ALGO	0.037%	30,030	1,184	37,045	42.0%	0.946
2 INST	0.029%	2,477	745	2,249	47.1%	0.829
3 PROF	0.068%	3,978	1,388	3,485	52.2%	0.979
4 RETL	0.040%	3,010	978	2,729	55.2%	0.858

relative time-weighted average spread (RTWAS), the average number of shares at the best levels of the order book (TVOBV), and the average number of shares across all levels of the order book (TVOAV). We analyze the effects of algorithmic traders (ALGO), institutional traders using NASDAQ-approved algorithms (INST), and professional investors without algorithmic assistance (PROF),

Table 2 Correlations. The table presents Spearman correlations between the main market quality variables. TWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book respectively. VLT is a volatility variable measures as the difference between High and Low price during a day scaled by the closing price. TURN is the number of shares traded scaled by the number of shares outstanding. MAKING is the average ratio of the trading volume that supplies liquidity to the total trading volume for the day

	RTWAS	TVOBV	TVOAV	TURN	MAKING	VLT
RTWAS	1	0.0189	(0.1798)	(0.0641)	0.0184	0.3202
TVOBV	0.0189	1	0.5702	0.0264	0.0105	(0.0137)
TVOAV	(0.1798)	0.5702	1	0.1207	0.0522	(0.0010)
TURN	(0.0641)	0.0264	0.1207	1	0.0402	0.2221
MKTK	0.0184	0.0105	0.0522	0.0402	1	0.0048
VLT	0.3202	(0.0137)	(0.0010)	0.2221	0.0048	1

All correlations are significant at 5% level

controlling for turnover (TURN), volatility (VLT), closing price (CLOSE), and market capitalization (MCAP).

Our analysis reveals significant differences in how trader types impact market quality, particularly relative spreads (RTWAS). Algorithmic traders (ALGO) and institutional traders (INST) both show a significant negative impact on RTWAS, with coefficients of −0.0028 (t-statistic = −3.47) and −0.004 (t-statistics = −5.4) for both. This indicates that a higher presence of these traders is associated with narrower bid-ask spreads, supporting our first hypothesis (H1) that algorithmic traders contribute to improved market liquidity.

In contrast, professional traders (PROF) are associated with wider spreads (coefficient = 0.007, t-statistic = 8.6). These effects persist when controlling for turnover (TURN), volatility (VLT), closing price (CLOSE), and market capitalization (MCAP).

While our primary focus is on RTWAS, we also observe that institutional traders consistently show positive effects on order book depth measures (TVOBV and TVOAV), while professional traders show negative effects. Algorithmic traders have a small negative effect on TVOBV but no significant effect on TVOAV.

4.2 The sensitivity of algorithmic traders to increased turnover

To examine how different trader types respond to changes in trading volume, we incorporate interaction terms between trader type dummy variables and daily turnover (TURN). For RTWAS, the base effect of turnover is strongly negative (−81, t-statistic = −55,), indicating that higher overall trading activity is associated with tighter spreads.

However, the interaction terms reveal important differences across trader types. Algorithmic traders (ALGO * TURN) show a positive coefficient (41.7, t-statistic = 25.8), suggesting that their spread-reducing effect diminishes as turnover increases. Institutional traders (INST * TURN) become slightly more effective at

Table 3 The impact of trader types on market quality measures: Two-way fixed effects estimation. The table presents the results of regression model in Sect. 4.1. RTWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book respectively. VLT is a volatility variable measure as the difference between High and Low price during a day scaled by the closing price

Panel A: ALGO			
Variable	RTWAS	TVOBV	TVOAV
I(TYPE = = "ALGO")	−0.0028 (−3.47)***	0.0050 (3.91)***	0.0021 (1.90)
TURN	−18.6374 (−57.93)***	23.0268 (45.69)***	26.5868 (61.52)***
VLT	2.1122 (85.04)***	−0.3755 (−9.65)***	0.7295 (21.87)***
log(CLOSE)	−0.1117 (−24.85)***	−1.2030 (−170.80)***	−0.9212 (−152.52)***
log(MCAP)	−0.1861 (−40.60)***	0.6828 (95.12)***	0.4851 (78.80)***
Adj. R-Squared	0.0759	0.1069	0.1050
N (Observations)	458,813	458,813	458,813
Panel B: INST			
Variable	RTWAS	TVOBV	TVOAV
I(TYPE = = "INST")	−0.0043 (−5.40)***	0.0045 (3.54)***	0.0071 (6.53)***
TURN	−18.7329 (−58.08)***	23.0944 (45.72)***	26.7780 (61.82)***
VLT	2.1133 (85.08)***	−0.3757 (−9.66)***	0.7267 (21.78)***
log(CLOSE)	−0.1116 (−24.82)***	−1.2031 (−170.81)***	−0.9213 (−152.55)***
log(MCAP)	−0.1862 (−40.62)***	0.6830 (95.14)***	0.4852 (78.83)***
Adj. R-Squared	0.0759	0.1068	0.1050
N (Observations)	458,813	458,813	458,813
Panel C: PROF			
Variable	RTWAS	TVOBV	TVOAV
I(TYPE = = "PROF")	0.0069 (8.60)***	−0.0089 (−7.05)***	−0.0095 (−8.85)***
TURN	−18.9675 (−58.47)***	23.4309 (46.11)***	27.0690 (62.13)***
VLT	2.1178 (85.23)***	−0.3822 (−9.82)***	0.7210 (21.60)***
log(CLOSE)	−0.1116 (−24.82)***	−1.2032 (−170.83)***	−0.9213 (−152.56)***
log(MCAP)	−0.1862 (−40.63)***	0.6831 (95.15)***	0.4853 (78.83)***
Adj. R-Squared	0.0760	0.1070	0.1051
N (Observations)	458,813	458,813	458,813
Panel D: All Together			
Variable	RTWAS	TVOAV	TVOAV
TYPEALGO	−0.0023 (−2.31)*	0.0041 (2.66)**	0.0013 (0.94)
TYPEINST	−0.0034 (−3.47)***	0.0037 (2.39)*	0.0049 (3.77)***
TYPEPROF	0.0050 (5.18)***	−0.0063 (−4.15)***	−0.0075 (−5.72)***
TURN	−19.0067 (−58.55)***	23.4687 (46.16)***	27.1321 (62.23)***
VLT	2.1187 (85.26)***	−0.3832 (−9.85)***	0.7200 (21.57)***
log(CLOSE)	−0.1116 (−24.82)***	−1.2032 (−170.83)***	−0.9214 (−152.57)***
log(MCAP)	−0.1862 (−40.63)***	0.6830 (95.15)***	0.4853 (78.84)***
Adj. R-Squared	0.0760	0.1069	0.1051
N (Observations)	458,813	458,813	458,813

Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels. T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

Table 4 Volume interaction effects on market quality: Two-way fixed effects estimation. The table presents the results of regression model in Sect. 4.2 where we interact the trader type dummy variable and the daily turnover, TURN defined as the ratio of number of shares traded to the total number of shares outstanding. RTWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book respectively. VLT is a volatility variable measure as the difference between High and Low price during a day scaled by the closing price

Variable	RTWAS	TVOBV	TVOAV
TYPEALGO	−0.0198 (−16.85)***	0.0493 (26.87)***	0.0350 (22.23)***
TYPEINST	−0.0074 (−6.17)***	0.0075 (3.95)***	0.0062 (3.85)***
TYPEPROF	−0.0233 (−20.48)***	0.0351 (19.70)***	0.0275 (17.99)***
TURN	−81.3814 (−55.81)***	123.1355 (53.92)***	109.1821 (55.74)***
VLT	2.3944 (95.14)***	−0.8307 (−21.07)***	0.3385 (10.01)***
log(CLOSE)	−0.1086 (−24.24)***	−1.2007 (−171.18)***	−0.9208 (−153.06)***
log(MCAP)	−0.1899 (−41.60)***	0.6813 (95.29)***	0.4854 (79.16)***
ALGO*TURN	41.6617 (25.76)***	−113.8218 (−44.93)***	−84.1958 (−38.75)***
INST*TURN	−8.8529 (−4.22)***	23.1337 (7.03)***	25.4678 (9.03)***
PROF*TURN	67.9670 (46.20)***	−102.8746 (−44.65)***	−85.9871 (−43.51)***
Adj. R-Squared	0.0841	0.1149	0.1127
N (Observations)	458,813	458,813	458,813

Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels. T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

reducing spreads as turnover increases, albeit with a relatively small effect (−8.85, t-statistic = −4.22).

Professional traders (PROF * TURN) show a large positive coefficient (67.97, t-statistic = 46.2), indicating that they are associated with wider spreads during periods of high turnover, potentially due to increased information asymmetry or inventory risk.

4.3 The sensitivity of algorithmic traders to volatility

We examine how different trader types respond to changes in market volatility by incorporating interactions between trader type dummy variables and volatility measures. Table 5 presents results using both continuous volatility (Panel A) and volatility quintiles (Panel B).

For RTWAS, the base effect of volatility (VLT) is strongly positive (2.07, t-statistic = 53.6), confirming that higher volatility generally corresponds to wider spreads. The interaction between algorithmic traders and volatility (ALGO x VLT) shows a small negative effect (−0.10, t-statistic = −2.08), while institutional traders (INST x VLT) exhibit a similar pattern (−0.09, t-statistic = −1.81). In contrast, professional traders (PROF x VLT) demonstrate a strong positive coefficient (0.42, t-statistic = 8.43), indicating significantly wider spreads during volatile periods.

The quintile analysis in Panel B reinforces these findings. While algorithmic and institutional traders maintain relatively stable spread impacts across volatility quintiles, professional traders show progressively larger spread-widening effects in higher volatility quintiles, with the strongest effect in the highest quintile (0.009, t-statistic = 3.07).

These results suggest that algorithmic traders help maintain market quality during volatile periods, while professional traders may contribute to spread widening under these conditions. This contrast highlights the stabilizing role of algorithmic trading in modern markets, particularly during periods of market stress, and suggests that market structure considerations should account for these differential behaviors across trader types.

4.4 The effect of market making activities

We examine market making activities' impact on market quality by incorporating a MAKE dummy variable indicating liquidity addition (MAKE = 1) versus removal (MAKE = 0). Table 6 presents results for the interaction between MAKE and trader types, analyzing effects on RTWAS, TVOBV, and TVOAV.

The uninteracted MAKE coefficient (0.0028, t-statistic = 2.02) represents the baseline effect of retail traders' liquidity provision, showing that retail market making is associated with slightly wider spreads. This likely reflects a compensation for risk-taking. Relative to this retail baseline, algorithmic traders demonstrate improved market quality when providing liquidity (ALGO × MAKE: −0.0041, t-statistic = −2.08), with positive effects on both best-level depth (0.0069, t-statistic = 2.23) and overall depth (0.0051, t-statistic = 1.92).

Professional traders show no significant differential impact relative to retail traders when providing versus consuming liquidity (PROF × MAKE coefficients statistically insignificant), suggesting their market making activities affect market quality similarly to retail traders. Institutional traders' net effect on spreads when providing liquidity is also minimal, though they show improvement in overall depth (INST × MAKE: 0.0058, t-statistic = 2.22,).

These findings indicate that while algorithmic traders contribute positively to market quality through their liquidity provision relative to retail traders, professional and institutional traders' market making activities have more modest effects. The results suggest that market structure designs should consider the varying effectiveness of different participant types in liquidity provision roles, with particular attention to the beneficial role of algorithmic traders.

4.5 Determinants of liquidity supplying activities and order cancellation rates

Using two-way fixed effects regressions controlling for both stock and time variations, we analyze the determinants of liquidity provision (MAKE_FRAC) and order cancellation rates (CANCELLED_FRAC). Table 7 presents our findings.

Table 5 Volatility sensitivity analysis: Two-way fixed effects estimation. The table shows the effects of interacting the trader types with volatility from Sect. 4.3. TURN defined as the ratio of number of shares traded to the total number of shares outstanding. The dependent variable, RTWAS, is the relative Bid-Ask spread weighted by time, which is the results presented in this Table. (TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book respectively, whose results are available upon request). VLT is a volatility variable measure as the difference between High and Low price during a day scaled by the closing price. Volatility quintiles are calculated by sorting all stock/days based on VLT from Q1 (the "calmest") to Q5 (the "stormiest")

Panel A. Using continuous volatility measure	
	RTWAS
ALGO	0.0008 (0.43)
INST	−0.0008 (−0.47)
PROF	−0.0071 (−4.06)***
VLT	2.0704 (53.57)***
TURN	−19.69 (−59.73)***
log(CLOSE)	−0.1113 (−24.75)***
log(MCAP)	−0.1867 (−40.73)***
ALGO*VLT	−0.1033 (−2.08)*
INST*VLT	−0.0890 (−1.81)
PROF*VLT	0.4164 (8.43)***
Adj. R-Sq	0.0763
N	458,813
Panel B. Using Volatility Quintiles	
	RTWAS
TYPEALGO	0.0018 (0.82)
TYPEINST	−0.0016 (−0.75)
TYPEPROF	0.0008 (0.38)
SQSQ2	0.0426 (19.45)***
SQSQ3	0.0599 (27.02)***
SQSQ4	0.0791 (34.99)***
SQSQ5	0.1104 (46.65)***
TURN	−15.72 (−49.02)***
log(CLOSE)	−0.12 (−26.98)***
log(MCAP)	−0.19 (−41.74)***
TYPEALGO*SQSQ2	−0.0037 (−1.18)
TYPEINST*SQSQ2	−0.0001 (−0.02)
TYPEPROF*SQSQ2	0.0011 (0.37)
TYPEALGO*SQSQ3	−0.0039 (−1.25)
TYPEINST*SQSQ3	−0.0011 (−0.35)
TYPEPROF*SQSQ3	0.0025 (0.83)
TYPEALGO*SQSQ4	−0.0051 (−1.63)
TYPEINST*SQSQ4	−0.0018 (−0.58)
TYPEPROF*SQSQ4	0.0034 (1.11)
TYPEALGO*SQSQ5	−0.0070 (−2.24)*
TYPEINST*SQSQ5	−0.0039 (−1.26)
TYPEPROF*SQSQ5	0.0094 (3.07)**
Adj. R-Squared	0.0740
N (Observations)	458,813

Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels. T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

Table 6 Market making activities and market quality: Two-way fixed effects estimation. The table presents the results of a regression from Sect. 4.4, where in addition to the trader type dummy variable we also add MAKE dummy variable. MAKE is an indicator variable (supplied by the NASDAQ OMX) that signifies whether the trade was adding (MAKE = 1) or removing (MAKE = 0) liquidity. Daily turnover, TURN defined as the ratio of number of shares traded to the total number of shares outstanding. RTWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book, respectively. VLT is a volatility variable measure as the difference between High and Low price during a day scaled by the closing price

Variable	RTWAS (A)	RTWAS (B)	TVOBV(C)	TVOAV (D)
ALGO	−0.0023 (−2.31)*	−0.0002 (−0.17)	0.0007 (0.32)	−0.0013 (−0.68)
INST	−0.0034 (−3.46)***	−0.0025 (−1.81)	0.0021 (0.98)	0.0021 (1.12)
PROF	0.0050 (5.18)***	0.0055 (3.98)***	−0.007 (−3.06)**	−0.0079 (−4.30)***
MAKE		0.0028 (2.02)*	−0.0037 (−1.70)	−0.0027 (−1.48)
VLT	2.1187 (85.26)***	2.119 (85.28)***	−0.38 (−9.87)***	0.7192 (21.55)***
TURN	−19.01 (−58.57)***	−19.04 (−58.6)***	23.53 (46.2)***	27.17 (62.26)***
log(CLOSE)	−0.1116 (−24.82)***	−0.11 (−24.8)***	−1.20(−170.8)***	−0.92 (−152.57)***
log(MCAP)	−0.1862 (−40.64)***	−0.186 (−40.6)***	0.683(95.16)***	0.4853 (78.85)***
ALGO*MAKE		−0.0041 (−2.08)*	0.0069 (2.23)*	0.0051 (1.92)
INST*MAKE		−0.0018 (−0.92)	0.0031 (1.02)	0.0058 (2.22)*
PROF*MAKE		−0.0008 (−0.42)	0.0005 (0.15)	0.0009 (0.33)
Adj. R-Sq	0.0760	0.0760	0.1069	0.1051
N	458,813	458,813	458,813	458,813

Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels. T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

4.5.1 Determinants of market making activity (Panel A)

Relative to retail traders, other trader types show lower proportions of liquidity-providing trades, with algorithmic traders showing the strongest contrast (TYPEALGO: −0.13, t-statistic = −173.52). This finding complements our earlier analysis in Sect. 4.4, suggesting that while algorithmic traders are more effective at improving market quality when providing liquidity, they are more selective in choosing when to do so. Market conditions influence liquidity provision, with both higher turnover and volatility associated with reduced liquidity-providing trades. Market quality measures show that wider spreads and greater market depth correlate with increased liquidity provision, suggesting compensation for risk-taking behavior. These patterns indicate a sophisticated liquidity provision strategy by algorithmic traders: they provide liquidity less frequently than retail traders but do so more effectively when they choose to participate, consistent with our hypothesis about their distinct trading strategies and technological advantages (H3).

Table 7 Determinants of liquidity provision and order cancellation: Two-way fixed effects estimation. The table presents the results of regressions from Sect. 4.5, where the dependent variables are changed to MAKE_FRAC and CANCELLED_FRAC. MAKE_FRAC is a ratio of liquidity supplying volume to the total volume for each stock/day (as presented in Eq. (5)) and CANCELLED_FRAC is a ratio of cancelled orders to total orders for each day/stock. Both equations are estimated with beta regression. Daily turnover, TURN defined as the ratio of number of shares traded to the total number of shares outstanding. VLT is a volatility variable measure as the difference between High and Low price during a day scaled by the closing price. MAKE is an indicator variable (supplied by the NASDAQ OMX) that signifies whether the trade was adding (MAKE = 1) or removing (MAKE = 0) liquidity. RTWAS is the relative Bid-Ask spread weighted by time, TVOBV and TVOAV are the average number of shares at the Best and ALL levels of order book, respectively

Panel A. Market Making Determinants	
TYPEALGO	−0.1311 (−176.91)***
TYPEINST	−0.0771 (−105.77)***
TYPEPROF	−0.0294 (−40.40)***
TURN	−0.3297 (−1.35)
VLT	0.1348 (7.19)***
log(CLOSE)	0.0047 (1.35)
log(MCAP)	0.0009 (0.27)
log(RTWAS)	0.0253 (22.40)***
log(TVOBV)	−0.0088 (−11.49)***
log(TVOAV)	0.0013 (1.48)
Adj. R-Squared	0.0730
N	458,813
Panel B. Cancelled Orders Determinants	
(Intercept)	0.18 (40.80)***
TYPEALGO	0.12 (253.74)***
TYPEINST	0.00 (−9.47)
TYPEPROF	−0.03 (−54.82)***
TURN	−1.49 (−10.06)***
VLT	−0.14 (−15.68)***
log(CLOSE)	0.00 (−1.01)
log(MCAP)	0.01 (22.71)***
log(RTWAS)	0.00 (0.40)
log(TVOBV)	−0.02 (−67.76)***
log(TVOAV)	0.02 (81.89)***
Adj. R-Sq	0.22
N	458,813

Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels.T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

4.5.2 Determinants of order cancellation (Panel B)

Algorithmic traders exhibit significantly higher order cancellation rates (TYPEALGO: 0.12, t-statistic = 253.74), reflecting dynamic order management strategies, while professional traders show more stable order placement (TYPEPROF: −0.03, t-statistic = −54.82). Higher turnover and volatility correspond to reduced cancellations, suggesting increased execution likelihood during active market periods. Market depth has opposing effects at different levels: greater depth at best prices reduces cancellations while greater overall depth increases them.

These findings, robust to stock and time fixed effects, reveal systematic differences in trading strategies across participant types and market conditions, with important implications for market structure design.

5 Robustness checks

To ensure the validity and reliability of our findings, we conduct an instrumental variable (IV) analysis to address potential endogeneity concerns. This approach is particularly important given that our baseline analysis relies on two-way fixed effects regressions with clustered standard errors.

5.1 Addressing endogeneity concerns

Our primary analysis investigates the impact of algorithmic trading on market quality, specifically on the relative time-weighted average spread (RTWAS). While our two-way fixed effects results suggest that algorithmic trading improves liquidity by reducing spreads, it's crucial to address potential endogeneity concerns. The relationship between algorithmic trading activity and spreads could be simultaneously determined, as algorithmic traders might be more active when spreads are already low.

To address this potential endogeneity, we implement an instrumental variable (IV) approach, following the methodology used in several seminal papers in the field. We utilize the panel structure of our data, using the lagged value of algorithmic trading volume (TURN by ALGO) as an instrument. This approach is similar to that of Brogaard et al. (2014), who use lagged high-frequency trading as an instrument in their analysis of price efficiency. Our choice is based on the rationale that past trading activity by algorithmic traders is likely correlated with current trading activity but less likely to be directly correlated with the current spread, apart from its effect through algorithmic trading.

The first-stage regression results, presented in Table 8, Panel B, strongly support the relevance of our instrument. The coefficient on lagged algorithmic trading volume (lag_TURN_ALGO) is highly significant (0.1974, t-statistic = −196.33), indicating that our instrument is strongly correlated with current algorithmic trading activity. The F-statistic of 10,180 ($p < 0.001$) far exceeds the conventional threshold for weak instruments, providing strong support for our instrument's validity.

Table 8 Instrumental variables analysis of algorithmic trading effects. This table presents instrumental variable (IV) estimates of trader types' impact on relative time-weighted average spreads (RTWAS). See Sect. 5. Panel A compares OLS and IV estimates, using lagged algorithmic trading volume as an instrument for current algorithmic trading. Panel B presents first-stage regression results. The dependent variable is RTWAS in all specifications. Independent variables include trader type indicators (ALGO, INST, PROF), daily turnover (TURN), volatility (VLT), and controls for price and market capitalization (in logs)

Panel A		
	RTWAS	
Variable	OLS	IV REG
(Intercept)	7.20 (711.78)***	7.17 (682.19)***
TYPEALGO	−0.02 (−13.87)***	−0.03 (−14.84)***
TYPEINST	−0.02 (−9.37)***	−0.03 (−14.74)***
TYPEPROF	0.03 (15.59)***	0.05 (29.89)***
TURN	−93.79 (−181.20)***	−191.10 (−125.27)***
VLT	5.30 (165.98)***	6.61 (172.52)***
log(CLOSE)	−0.09 (−117.78)***	−0.09 (−114.89)***
log(MCAP)	−0.41 (−834.40)***	−0.41 (−800.05)***
Adj. R-sq	0.71	0.68
N	458,813	458,813
Panel B		
	RTWAS	
Variable	Coefficients	t-statistics
lag_TURN_ALGO	0.1974^{***}	−196.33
TYPEALGO	-0.0000352^{***}	(−7.31)
TYPEINST	-0.0001068^{***}	(−22.21)
TYPEPROF	0.0002787^{***}	−58.26
VLT	0.0112^{***}	−126.11
log(CLOSE)	0.0000069^{**}	−3.17
log(MCAP)	-0.0000246^{***}	(−17.18)
Constant	0.0004379^{***}	−14.76
Adj. R-sq	0.1395	
N	439,730	
F-statistics	10,180 ($p < 0.001$)	

Note: Results from two-way (stock and time) fixed effects panel regressions with standard errors clustered at both stock and date levels.T-statistics are in parentheses. The t-statistics are based on standard errors that have been adjusted for heteroskedasticity, serial correlation, and cross-sectional dependence using the two-way clustering method, as recommended by Pedersen (2009). ***, **, and * denote the level of significance at 1%, 5%, and 10% respectively

Furthermore, the control variables in the first stage show expected relationships, with volatility (VLT) positively associated with algorithmic trading activity (0.0112, t-statistic = 126.11) and market capitalization (log(MCAP)) showing a small negative association (−0.0000246, t-statistic = −17.18).

The second-stage results, presented in Table 8, Panel A, compare our baseline OLS estimates with the IV regression estimates. The Hausman test comparing these models yields a p-value of 0.11, which is above the conventional threshold for statistical significance (typically < 0.05). This result suggests that endogeneity is not a significant concern in our data. However, we observe some interesting differences in the magnitude of coefficients between the OLS and IV specifications.

Most notably, the coefficient on TURN (turnover) is substantially larger in magnitude in the IV specification (−191.10, t-statistic = −125.27) compared to the OLS estimate (−93.79, t-statistic = −181.20). This suggests that the OLS estimates may actually understate the impact of trading activity on spreads. The coefficients on our trader type indicators (TYPEALGO, TYPEINST, and TYPEPROF) maintain their signs and statistical significance across both specifications, though with slightly larger magnitudes in the IV estimation. This provides robust evidence that our main conclusions about the differential impact of trader types on market quality are not driven by endogeneity concerns.

The consistency of our results across both the baseline two-way fixed effects models (presented in earlier sections) and this IV specification provides strong support for our main findings. The significant negative association between algorithmic trading and spreads persists across all specifications, indicating a robust relationship between algorithmic trading activity and improved market liquidity. These results align with the broader literature on algorithmic trading and market quality (e.g., Hendershott et al. 2011; Brogaard et al. 2014).

Given that our baseline analysis already incorporates two-way fixed effects and clustered standard errors, and considering the results of our IV analysis, we can be confident that our findings are robust to both time-invariant unobserved heterogeneity and potential endogeneity concerns. The similarity in results across specifications, combined with the strong performance of our instrument in the first stage, provides compelling evidence for the causal interpretation of our findings regarding the impact of algorithmic trading on market quality.

6 Conclusion

This study provides a comprehensive analysis of algorithmic traders' role within the broader market ecosystem, offering novel insights into their impact on market quality and trading dynamics. By leveraging a unique dataset from NASDAQ OMX Nordic and employing a nuanced classification of market participants, combined with robust econometric methods including two-way fixed effects and instrumental variables estimation, we contribute to the ongoing debate surrounding the effects of algorithmic trading on financial markets.

Our findings, supported by multiple empirical specifications, reveal that algorithmic traders significantly enhance market liquidity by reducing bid-ask spreads, with effects that persist even after controlling for potential endogeneity and unobserved heterogeneity. Specifically, algorithmic traders reduce spreads by approximately 0.28 basis points compared to retail traders, with institutional traders showing similar benefits (0.43 basis points reduction). Contrary to some concerns, algorithmic traders do not adversely affect market quality during periods of high volatility. Instead, professional non-algorithmic traders are associated with wider spreads (0.69 basis points increase), particularly during volatile conditions, emerging as the primary source of potential market quality deterioration.

We uncover a surprising role of retail traders as significant liquidity providers, while algorithmic traders exhibit more selective liquidity provision patterns. Our analysis of order cancellation rates reveals that algorithmic traders maintain significantly higher cancellation rates compared to other market participants (12 percentage points higher than retail traders), consistent with their use of dynamic order placement strategies. These findings remain robust to various empirical specifications, including our instrumental variables analysis using lagged algorithmic trading activity.

These results have important implications for market design, regulation, and our understanding of modern market microstructure. Policies encouraging algorithmic trading participation could enhance overall market efficiency and liquidity, though regulators should consider the implications of increased order cancellations. The significant role of retail traders in liquidity provision warrants further investigation and may have implications for market structure and retail investor protection policies.

The differential impact of professional traders' activities on market quality during volatile periods suggests a need for more nuanced regulatory approaches that consider the varying behaviors of different market participant types under different market conditions. Our empirical findings, supported by both fixed effects and instrumental variables analyses, provide strong evidence that these differences are not merely correlational but likely reflect causal relationships.

While our study provides valuable insights, it also opens up several avenues for future research. Further investigation into the long-term effects of algorithmic trading on market stability and efficiency is warranted, particularly as markets continue to evolve technologically. Additionally, exploring the interaction between algorithmic traders and other market participants in different market structures and asset classes could yield valuable insights. Future studies might also benefit from applying our methodological framework to more recent data, particularly given the continued evolution of algorithmic trading strategies and market structures.

In conclusion, our study contributes to the growing body of literature on algorithmic trading and market microstructure by providing a more nuanced and methodologically robust understanding of the role of different market participants in shaping market quality. Our findings, supported by careful econometric analysis addressing both unobserved heterogeneity and potential endogeneity, offer valuable insights for market designers and regulators. As financial markets continue to evolve, such empirically grounded insights will be crucial for ensuring efficient, fair, and stable markets that serve the needs of all participants.

Acknowledgements We extend our sincerest thanks to Frank Hatheway, Henrik Husman, Jakob Hallmer, Petter Dahlström, and the entire NASDAQ OMX Nordic research group for generously providing us with invaluable data. We also deeply appreciate Niklas Ahlgen, Timo Korkeamäki, Juha Joenväärä, Terrence Hendershott, Jonathan Brogaard, Chris Adcock, Emma Fitzgerald, Gordon Alexander, and Campbell Harvey for their insightful discussions and comments that significantly improved our work.

We are also grateful for the constructive feedback received from the discussants at the FMA meetings in Atlanta, GA, and Denver, CO; the European conference in Lyon, France; and the meeting in Helsinki.

Funding Fulbright Suomi -säätiö, Nasdaq OMX, Ella ja Georg Ehrnroothin Säätiö

Data availability The dataset supporting the conclusions of this article is subject to a Non-Disclosure Agreement (NDA) with NASDAQ OMX. As such, the raw data is not publicly available in a repository. However, we are committed to data transparency and will provide the data to researchers subject to the following conditions:

- **NDA Requirements**: Access to the data will be granted upon request to qualified researchers for purposes of replicating the results or for conducting new research, provided that the requester agrees to and signs the requisite NDA with NASDAQ OMX.
- **Request Process**: Requests for data access should be directed to the corresponding author, Andrei Nikiforov, PhD, who will facilitate the signing of the NDA and the subsequent data sharing in accordance with the agreement.

Software and Custom Code: The custom code utilized in our analysis and the generation of results is available upon request. We believe in supporting the scientific community's efforts in replication and further study, and thus:

- **Software Accessibility**: The custom code used for the analysis is available directly from the corresponding author, Dr. Nikiforov, without an NDA or any restrictions.
- **Support for Replication**: We will provide support for replication by offering detailed documentation and assistance in understanding and executing the code.

Declarations

Osmekhin gratefully acknowledges the financial support from the NASDAQ OMX Nordic Foundation and the Ella and Georg Ehrnrooth Foundation. Broussard was Distinguished Fulbright Professor and Visiting Research Professor, Hanken School of Economics when effort began, and acknowledges the financial support of Fulbright, Fulbright Finland, and Hanken.

Data transparency statement This study utilizes proprietary market data from NASDAQ OMX Nordic covering the period from June 1, 2010, to November 30, 2011. The dataset includes comprehensive trading information for 156 unique stocks, resulting in 458,813 observations. While the raw data is subject to NASDAQ OMX's confidentiality agreements, we commit to the following transparency measures:

All statistical code used for data cleaning and analysis will be made available upon request to qualified researchers who have obtained necessary permissions from NASDAQ OMX Nordic.
Detailed documentation of our data filtering procedures, variable construction, and classification methodologies is available in Section 3 of the manuscript and can be replicated using similar market datasets.
Summary statistics, as presented in Tables 1-8, provide comprehensive information about the sample's characteristics without compromising data confidentiality.
Our empirical methodology, including the specifications of all regression models and statistical tests, is fully documented in the manuscript to enable replication with similar datasets.
For inquiries regarding data access, qualified researchers may contact NASDAQ OMX Nordic directly. The authors will provide assistance with statistical code and methodological queries to facilitate replication efforts.

Competing interests One of the authors (Osmekhin) received funding from NASDAQ OMX Nordic, which also provided the dataset used in this study. However, NASDAQ OMX Nordic had no role in the study design, analysis, interpretation of results, writing of the manuscript, or decision to publish. The remaining authors declare no competing interests. All authors affirm that the research was conducted independently and the findings and conclusions presented in this paper represent the authors' own views.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Aït-Sahalia Y, Sağlam M (2024) High frequency market making: the role of speed. J Econ Elsevier, vol 239(2)

Aït-Sahalia Y, Brunetti C (2020) High frequency traders and the price process. J Econ 217(1):20–45

Boehmer E, Fong K, Wu JJ (2021) Algorithmic trading and market quality: International evidence. J Financial Quant Anal 56(8):2659–2688

Brogaard J, Garriott C (2019) High-frequency trading competition. J Financial Quant Anal 54(4):1469–1497

Brogaard J, Hendershott T, Riordan R (2014) High-frequency trading and price discovery. Rev Financial Stud 27(8):2267–2306

Brogaard J, Carrion A, Moyaert T, Riordan R, Shkilko A, Sokolov K (2018) High frequency trading and extreme price movements. J Financ Econ 128(2):253–265

Brogaard J, Nguyen TH, Putnins TJ, Wu E (2022) What moves stock prices? The roles of news, noise, and information. Rev Financial Stud 35(9):4341–4386

Colliard J-E, Foucault T (2012) Trading fees and efficiency in limit order markets. Rev Financial Stud 25(11):3389–3421

Cox J (2020) Market fragmentation and post-earnings announcement drift. J Econ Finance 44(3):587–610

Easley D, López de Prado M, O'Hara M, Zhang Z (2021) Microstructure in the machine age. The Review of Financial Studies 34(7):3316–3363

Foucault T, Kadan O, Kandel E (2013) Liquidity cycles and make/take fees in electronic markets. J Financ 68(1):299–341

Hagströmer B, Norden L (2013) The diversity of high-frequency traders. J Financial Markets 16(4):741–770

Hasbrouck J, Saar G (2013) Low-latency trading. J Financial Markets 16(4):646–679

Hendershott T, Riordan R (2013) Algorithmic trading and the market for liquidity. J Financial Quant Anal 48(4):1001–1024

Hendershott T, Jones CM, Menkveld AJ (2011) Does algorithmic trading improve liquidity? J Financ 66(1):1–33

Hu E, Murphy D (2020) Vestigial tails: Floor brokers at the close in modern electronic markets. Available at SSRN: https://ssrn.com/abstract=3600230

Kirilenko A, Kyle AS, Samadi M, Tuzun T (2017) The flash crash: High-frequency trading in an electronic market. J Financ 72(3):967–998

Korajczyk RA, Murphy D (2019) High-frequency market making to large institutional trades. Rev Financial Studies 32(3):1034–1067

Malinova K, Park A (2015) Subsidizing liquidity: The impact of make/take fees on market quality. J Financ 70(2):509–536

Menkveld AJ (2016) The economics of high-frequency trading: Taking stock. Annu Rev Financ Econ 8:1–24

O'Hara M (2015) High frequency market microstructure. J Financ Econ 116(2):257–270

Pedersen LH (2009) Estimating standard errors in finance panel data sets: Comparing approaches. Rev Financial Stud 22(1):435–480

Van Kervel V, Menkveld AJ (2019) High-frequency trading around large institutional orders. J Financ 74(3):1091–1137

Yan S, Ling X, Cao T, Hu S, Xiong R, Ye H, Zhang R (2022) Algorithmic trading and challenges on retail investors in emerging markets. J Econ, Finance Accounting Stud 4(3):36–41

Zhou H, Kalev PS, Frino A (2020) Algorithmic trading in turbulent markets. Pac Basin Financ J 62:101358

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.