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Working Paper 2018-03

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Abstract

We analyze the relation between algorithmic trading and liquidity using a novel data set from the Austrian equity market. Our sample covers almost 4.5 years, it identifies the market share of algorithmic trading at the stock-day level, and it comes from a market that has hitherto not been analyzed. We address the endogeneity problem using an instrumental variables approach. Our results indicate that an increase in the market share of algorithmic trading causes a reduction in quoted and effective spreads while quoted depth and price impacts are unaffected. They are consistent with algorithmic traders on average acting as market makers.

Keywords: algorithmic trading; Austrian stock market; market liquidity

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JEL: G10, C58

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Algorithmic Trading and Liquidity: Long Term Evidence from Austria

Abstract: We analyze the relation between algorithmic trading and liquidity using a novel data set from the Austrian equity market. Our sample covers almost 4.5 years, it identifies the market share of algorithmic trading at the stock-day level, and it comes from a market that has hitherto not been analyzed. We address the endogeneity problem using an instrumental variables approach. Our results indicate that an increase in the market share of algorithmic trading causes a reduction in quoted and effective spreads while quoted depth and price impacts are unaffected. They are consistent with algorithmic traders on average acting as market makers.

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This Draft: January 3, 2018

1 Introduction

Trading in financial markets has seen a tremendous shift towards algorithmic trading (AT). Regulators are concerned about potential negative effects of AT on market quality and have taken action to limit its extent. The naked access ban imposed by the SEC (Chakrabarty et al., 2014), the tax on high frequency trading imposed in Italy (Rühl and Stein, 2014) and the German High Frequency Trading Act (Haferkorn and Zimmermann, 2014) are cases in point. Thanks to Michael Lewis' bestseller *Flash Boys* the issue has also attracted considerable public attention.

Algorithmic traders employ both active (liquidity-seeking) and passive (liquidity-supplying) strategies. While passive AT may increase liquidity (but may crowd out non-AT liquidity suppliers), active AT may have a detrimental effect on liquidity, in particular when AT exploits short-lived informational advantages and thus imposes adverse selection costs on other traders. The impact of AT on market quality is thus an empirical question. The evidence available so far is mixed. While several papers report that liquidity improves when there is more AT (e.g. Hendershott, Jones and Menkveld, 2011; Hasbrouck and Saar, 2013; Jarnecic and Snape, 2014; Boehmer, Fong and Wu, 2015; and Lyle and Naughton, 2015), other papers find opposing results (e.g. Shkilko and Sokolov, 2016; and Broogard, Hendershott and Riordan, 2017).

Analyzing the effect of AT on liquidity requires accurate identification of AT activity. Several authors use potentially noisy proxies for AT activity such as order-to-trade ratios (e.g. Boehmer, Fong and Wu, 2015), lifetime of orders (e.g. Hasbrouck and Saar, 2013), or message traffic (e.g. Hendershott, Jones and Menkveld, 2011). NASDAQ provides data on trades and quotes by 26 high frequency trading firms in 120 stocks covering 2008 and 2009. It has, among others, been used by Carrion (2013), Brogaard, Hendershott and Riordan

(2014; 2017), O'Hara, Yao and Ye (2014), Brogaard et al. (2017) and Zhang (2018). Other authors have access to proprietary account-level data on trades made by AT firms (e.g. Breckenfelder, 2013; Hagströmer and Nordén, 2013; Hendershott and Riordan, 2013; Brogaard et al., 2014; Jarnecic and Snape, 2014; Benos and Sagade, 2016;). Note that most of these data sets only cover short sample periods (several months at most).[1]

The present paper contributes to this literature in several ways. We use a novel data set from the Austrian stock market. It spans 52 months, a much longer sample period than most previous studies, and it allows for accurate identification of the market share of AT at the stock-day level. We provide out-of-sample evidence by analyzing a non-US market that has not previously been analyzed. The Austrian equity market has the additional advantage that the market share of the Vienna Stock Exchange has been rather stable throughout our sample period. This is in sharp contrast to incumbent exchanges in other countries which have suffered considerable declines in market shares over the same period.

While AT may affect market quality, it may also be true that market conditions affect the amount of AT, resulting in a potential endogeneity problem. We follow Hasbrouck and Saar (2013) and instrument the market share of AT in a stock on a day by the average AT market share of all other stocks on that day. Our results indicate that AT has a positive effect on liquidity. An increase in the share of algorithmic trading causes a reduction in quoted and effective spreads while it does not affect quoted depth. We also find that AT has no effect on the price impact, implying that AT do not predominantly trade on private information. Taken together, our results do not provide support for regulatory activities to curb AT.

Our paper proceeds as follows. Section 2 introduces data and preliminary results. Section 3 outlines methodology and presents empirical findings. Section 4 concludes the paper.

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[1] An exception is a data set from the National Stock Exchange in India. It is used in studies by Boehmer and Shankar (2014) and Aggarwal and Thomas (2014) and contains complete order book and trade information for several years as well as an AT flag that allows for accurate identification of AT trading.

2 Market structure, data and preliminary analysis

The Vienna Stock Exchange (VSE) is one of the world's oldest exchanges and operates Austria's only securities exchange. Trading is organized as an electronic open limit order book on the Xetra® platform which is also used by the exchanges in Germany and Ireland. The continuous trading session starts and ends with a call auction. A third call auction takes place at noon. Stocks listed in the prime market, the top segment of the VSE, have one specialist and in addition may have (and in practice do have) one or several designated market makers. Specialists and market makers are subject to quotation obligations, maximum spread and minimum depth requirements. The obligations for the specialist are more restrictive than those for the market makers.[2]

Our sample consists of 20 stocks, and covers 52 months (September 2011 to December 2015). The sample stocks are almost identical to the components stocks of the Austrian benchmark index ATX and are all listed in the prime market. During our sample period, the VSE has an average daily market share of approximately 70% (with a standard deviation of 5.5%[3]) in trading ATX constituents stocks. Thus, our sample captures the bulk of trading in the sample stocks. Cross-market trading is thus less of an issue in the Austrian market than it is in most other developed markets.

2.1 Algorithmic trading data

Following a request from the Austrian Financial Market Authority the VSE required its members to identify their accounts as either AT or non-AT accounts from 2011 onwards. When an account is declared "AT" all trading conducted via this account is classified as

[2] In fact, the specialist position is assigned in a yearly tender procedure for each stock to the market maker who offers the best "package" of maximum spread and minimum depth restrictions. For details see Wiener Börse (2017).

[3] The data is taken from www.bats.com (accessed February 9, 2017) and relates to trading on regulated markets and multilateral trading facilities (MTFs) during our sample period. The corresponding values for the constituents of the German DAX traded on XETRA® and the UK FTSE100 constituents traded by LSE Group are 62% (standard deviation 4.5%) and 54% (standard deviation 3.4%), respectively.

algorithmic. Based on this classification the VSE reported the market share of AT for each stock and each day on its website from 2011 to 2015. Designated market makers and specialists (who, together, account for approximately 25-30% of total trading on the VSE[4]) were exempted from the reporting requirement. Their trading activity is thus not counted as AT.

Table 1 provides descriptive statistics on the sample stocks. The average market capitalization amounts to € 3.15 billion. On average there are 534 transactions on a trading day and the average daily turnover is € 626,500. Market capitalization and turnover are skewed, as can be seen from the difference between the means and medians. The last line shows the percentage of AT in the total trading volume. It amounts to 17.3% on average. This value is lower than percentages given for other markets (see e.g. Brogaard et al., 2014 who report a 27.7% AT market share for their mid-sized stocks, a sample which is comparable in terms of market capitalization to ours). However, as noted above, trades by the specialists and market makers are not counted as AT in our sample.

Table 1: Summary statistics - market characteristics

Variable	Unit	Mean	Std. dev.	Median	Q1	Q3
Market cap.	10^6 EUR	3151.2	2475.3	2256.8	1465.4	4477.6
Return	%	-0.005	0.035	-0.005	-0.022	0.013
Std. dev. of return	%	1.873	0.507	1.734	1.604	2.128
Turnover value	10^3 EUR	626.5	1055.9	316.1	95.1	655.7
Number of trades	1	533.7	440.4	389.8	226.8	781.9
Trading volume	10^3 #	8374.2	8990.9	4506.7	2707.8	13050.7
Proportion of algo trading	%	17.3	3.7	16.8	15.0	20.2

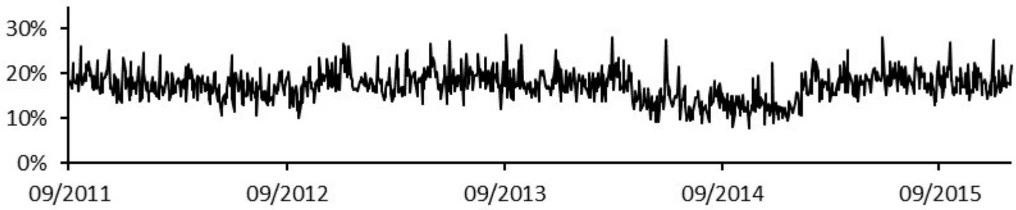
This table provides summary statistics on average daily measures of market characteristics for our sample of 20 stocks at the Vienna Stock Exchange. Sample period: September 2011 to December 2015. Q1 (Q3) denotes the first (third) quartile.

Figure 1 shows the time series of the daily (equally-weighted) average share of algorithmic trading. The figure reveals that there is considerable time-series variation in the

[4] This figure was revealed to us in private conversation with market participants. We are not aware of any official statistic.

AT share. However, no clear upward or downward trend is apparent during our sample period.

Figure 1: Temporal dynamics of algorithmic trading



The figure plots the time series of daily equally weighted cross sectional means of the proportion of algorithmic trading for our sample of 20 stocks at the Vienna Stock Exchange. Sample period: September 2011 to December 2015.

2.2 Data on market liquidity

We use trade and quote data obtained from the Vienna Stock Exchange to construct standard measures of liquidity.[5] Specifically, we use the percentage quoted spread, the percentage effective spread, the quoted depth in Euros (defined as the average of the quoted depth at the best bid and the best ask price) and the percentage 1-minute price impact (defined as the relative change in the quote midpoint from the time of the trade to 60 seconds after the trade, multiplied by +1 [-1] for buyer-initiated [seller-initiated] trades). The price impact is a measure of the adverse selection cost. To obtain daily values we calculate time-weighted averages of the quoted spreads and depths, and transaction-size weighted averages of the effective spreads and price impacts.

Table 2 reports descriptive statistics on the liquidity measures. Average percentage quoted and effective spreads amount to 0.225% and 0.253%, respectively. The average 1-minute price impact is 0.102%, corresponding to slightly more than 80% of the effective half-spread. The average depth at the inside quotes amounts to € 11,710. The figures provided for the

5 Data on bid and ask quotes is missing for May 14, 2014.

first and third quartile indicate that there are significant liquidity differences across the stocks in our sample.

Table 2: Summary statistics - liquidity

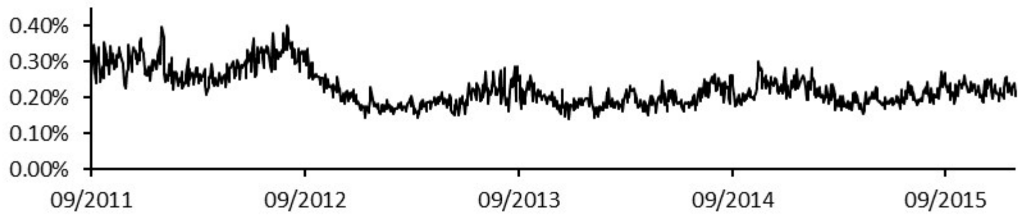
Variable	Unit	Mean	Std. dev.	Median	Q1	Q3
RQS	%	0.225	0.107	0.199	0.153	0.283
RES	%	0.253	0.118	0.232	0.173	0.315
RPI^{1min}	%	0.102	0.030	0.103	0.075	0.125
DEP	10^3 EUR	11.710	3.608	10.811	9.550	14.339

This table provides summary statistics on average daily liquidity measures for our sample of 20 stocks at the Vienna Stock Exchange. Sample period: September 2011 to December 2015. RQS…relative quoted spread; RES…relative effective spread; RPI^{1min}…relative 1-minute price impact; DEP… average Euro depth. Q1 (Q3) denotes the first (third) quartile.

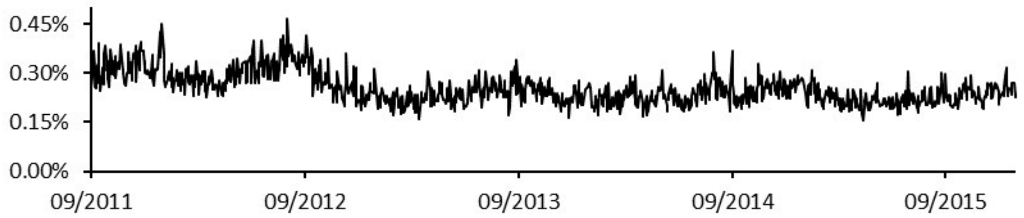
Panels A - D of Figure 2 illustrate the time-series variation in our sample. It shows daily (equally-weighted) cross-sectional averages of our four liquidity measures. The figure documents a noticeable decline in quoted and, to a lesser extent, in effective spreads in the second half of 2012. The price impact exhibits a slight downward trend in the first half of the sample period while quoted depth appears to be relatively stable throughout the sample period.

Figure 2: Temporal dynamics of market liquidity measures

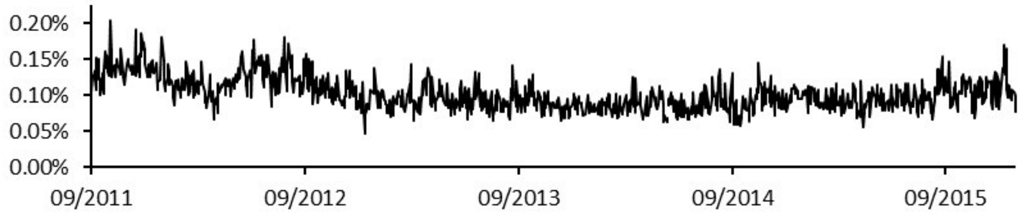
Panel A: Relative quoted spread (%)



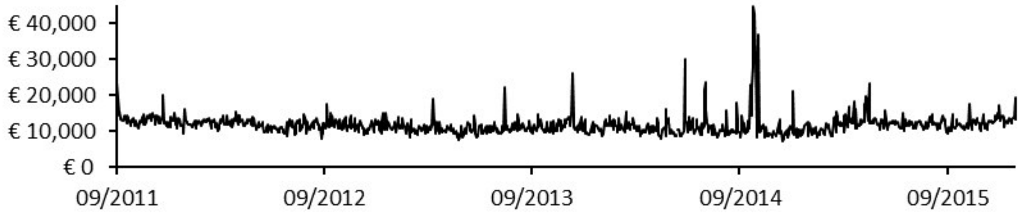
Panel B: Relative effective spread (%)



Panel C: Relative 1-minute price impact (%)



Panel D: Euro depth (€)



The figures plot the time series of daily equally weighted cross sectional means of the relative quoted spread (Panel A), the relative effective spread (Panel B), the relative 1-minute price impact (Panel C) and Euro depth (Panel D) for our sample of 20 stocks at the Vienna Stock Exchange. Sample period: September 2011 to December 2015.

3 Methodology, results and discussion

We present our results in two steps. In the first step we report correlations and OLS estimates, thereby ignoring the endogeneity issue. In the second step we use an instrumental variables approach to explicitly address the endogeneity concern.

3.1 Ignoring endogeneity

We start by calculating time-series correlations between the AT share and our four liquidity measures for each stock and then consider the equally-weighted cross-sectional mean and median. Similar to Hendershott, Jones and Menkveld (2011) and Aggarwal and Thomas (2014) we find the proportion of daily AT to be significantly negatively correlated with the relative quoted spread (mean -0.10; median -0.06), the relative effective spread (mean -0.16; median -0.14) and the relative 1-minute price impact (mean -0.11; median -0.10). The negative correlations imply that spreads and price impacts are lower on days with more algorithmic trading. The correlation between algorithmic trading and average Euro depth is also negative but is much smaller in magnitude (mean: -0,04; median: -0,03).

We next estimate a fixed effects panel regression of the form

$$LIQ_{it} = \mu_i + \alpha \cdot AT_{it} + \beta \cdot X_{it} + \varepsilon_{it} \qquad (1)$$

LIQ_{it} is one of our liquidity measures (RQS, RES, RPI^{1min}, DEP) for stock i on day t, μ_i denotes stock fixed effects, AT_{it} is the relative AT market share, and X_{it} is a vector of control variables. We follow Hendershott, Jones and Menkveld (2011) and Boehmer, Fong and Wu (2015) and include return volatility (derived from 5-minute midpoint changes), log share turnover, log market capitalization, the inverse of the closing stock price, and the lagged market liquidity measure, LIQ_{it-1}. All variables are at daily frequencies. Robust standard errors are calculated by clustering the data along both dimensions, stock and time. As a robustness check we re-estimate the model after winsorizing the data at the 1% and 99% percentiles. The results are very similar to those discussed below and are therefore omitted.

Table 3: Algorithmic trading and market liquidity: OLS estimates

	RQS		RES		RPI^{1min}		DEP	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
algo_volume_prop	-3.82E-04**	-4.97	-1.40E-03**	-12.48	-5.11E-04**	-8.98	-4.11E-04**	-5.31
midpoint_vola_5min	7.98E+01**	17.81	1.30E+02**	19.19	1.02E+02**	19.12	-1.95E+01**	-7.58
log(turnover)	-3.43E-04**	-24.98	-3.77E-04**	-19.17	-8.44E-05**	-9.12	2.04E-04**	7.04
log(market cap.)	-3.92E-04**	-12.56	-5.42E-04**	-11.85	-1.02E-04**	-3.29	-1.36E-05	-0.30
1/close_price	2.05E-03**	7.19	3.14E-03**	7.42	1.83E-03**	6.86	-2.59E-03**	-4.37
LIQ_lag1	5.21E-01**	42.37	2.82E-01**	23.95	1.01E-01**	9.94	5.10E-01**	4.26
Adj. R-Squared	0.4839		0.2666		0.2592		0.2859	
F-statistic (p-value)	3335.37 (< 2.2e-16)		1295.89 (< 2.2e-16)		1247.31 (< 2.2e-16)		1426.63 (< 2.2e-16)	

This table reports one-stage OLS estimates and t-statistics for a stock fixed effects panel regression model that for our sample of 20 stocks at the Vienna Stock Exchange relates the proportion of algorithmic trading (algo_volume_prop) and several control variables to market liquidity. Liquidity measures LIQ include relative quoted spread (RQS), relative effective spread (RES), relative 1-minute price impact (RPI^{1min}) and average Euro depth (DEP). Standard errors are computed using the Driscoll and Kraay (1998) robust covariance matrix estimator and are double-clustered by stock and time. Sample period: September 2011 to December 2015. ** and * indicate statistical significance at 1% and 5% levels.

Results in Table 3 are fully consistent with those of the correlation analysis presented above. The coefficient of the AT share is negative and statistically significant in all four models, implying that higher AT share is associated with lower quoted and effective spreads, lower price impact but also lower depth. These results are consistent with algorithmic traders submitting small limit orders at competitive prices, thus contributing to lower spreads while also lowering depth.

The coefficients for the control variables are in line with expectations. All four market liquidity variables exhibit significant first-order serial correlation. An increase in volatility is associated with higher spreads, higher price impact and lower depth. Spreads are lower and depth is higher on days with higher turnover. Spreads and price impacts are decreasing in market capitalization. The inverse of the daily closing price is positively related to the spread and price impact measures, and negatively related to depth, implying that higher price levels are associated with higher liquidity.

3.2 Dealing with simultaneity

The fixed effects regression model in (1) assumes all explanatory variables to be exogenous. However, while the amount of AT may affect liquidity it may also be true that the activity level of algorithmic traders depends on market conditions in general, and on liquidity in particular. In this case, however, a standard fixed effects regression will yield inconsistent estimates.

We therefore adopt the methodology of Hasbrouck and Saar (2013) and use the contemporaneous average AT share of all stocks except stock i (denoted $\overline{AT}_{ex\_i,t}$) as an instrument for the AT share in stock i on day t.[6] To test whether the instrument is indeed correlated with the AT share of our sample stocks we regress the AT share of each stock on its instrument, $\overline{AT}_{ex\_i,t}$, and the other independent variables (except for LIQ_{it-1}). The coefficient on the instrument $\overline{AT}_{ex\_i,t}$ is positive and statistically significant for all sample stocks.

[6] In a robustness check, we use as instrument the average AT share of all other stocks in the same size tercile. The results are very similar to those presented in the text.

We estimate the resulting model using panel 2SLS. We first regress the AT share $AT_{i,t}$ on the instrument $\overline{AT}_{ex\_i,t}$ and on all exogenous variables $X_{i,t}$. The predicted values from this regression are then used as instruments in the second-stage liquidity regressions. The results are presented in Table 4. Our previous finding that increased AT activity causes a reduction in quoted and effective spreads is confirmed. However, the magnitude of the coefficients is reduced. We no longer find that AT activity has a significant impact on quoted depth and price impact. The coefficients of the control variables are essentially unchanged. Our findings are consistent with algorithmic traders acting as market makers. Their activity decreases the bid-ask spread through a reduction in the non-information-related components of the spread. This finding is consistent with AT activity reducing rents earned by the suppliers of liquidity.

Table 4: Algorithmic trading and market liquidity: 2SLS estimates

	RQS		RES		RPI^{1min}		DEP	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
IV_algo_volume_prop	-1.03E-03**	-3.51	-1.15E-03**	-3.09	2.11E-04	1.11	-3.32E-04	-1.06
midpoint_vola_5min	7.94E+01**	17.66	1.30E+02**	19.28	1.02E+02**	19.24	-1.94E+01**	-7.56
log(turnover)	-3.48E-04**	-25.18	-3.75E-04**	-18.90	-7.98E-05**	-8.49	2.04E-04**	6.86
log(market cap.)	-3.77E-04**	-11.94	-5.48E-04**	-11.58	-1.19E-04**	-3.88	-1.55E-05	-0.36
1/close_price	2.11E-03**	7.21	3.11E-03**	7.30	1.77E-03**	6.54	-2.60E-03**	-4.36
LIQ_lag1	5.20E-01**	41.78	2.82E-01**	24.03	1.01E-01**	9.86	5.10E-01**	4.26
Adj. R-Squared	0.4812		0.2664		0.2517		0.2859	
F-statistic (p-value)	3298.55 (< 2.22e-16)		1294.27 (< 2.22e-16)		1199.36 (< 2.22e-16)		1426.43 (< 2.2e-16)	

This table reports two-stage least squares (2SLS) estimates and t-statistics for a stock fixed effects panel regression model that for our sample of 20 stocks at the Vienna Stock Exchange relates the instrument of the proportion of algorithmic trading (IV_algo_volume_prop) and several control variables to market liquidity. In the first stage of the 2SLS model we regress the proportion of algorithmic trading in a single stock (algo_vlume_prop) on the average of algo_volume_prop on the same day for all other stocks (IV_algo_volume_prop, which is the instrumental variable) and the control variables. In the second stage we regress each measure of market liquidity LIQ on the fitted values from the first stage regression. Liquidity measures LIQ include relative quoted spread (RQS), relative effective spread (RES), relative 1-minute price impact (RPI^{1min}) and average Euro depth (DEP). Standard errors are computed using the Driscoll and Kraay (1998) robust covariance matrix estimator and are double-clustered by stock and time. Sample period: September 2011 to December 2015. ** and * indicate statistical significance at 1% and 5% levels.

4 Conclusion

We revisit the question of how algorithmic trading affects liquidity. Our paper makes several contributions to the literature. We use a data set in which the market share of algorithmic traders is identified through a classification of traders. It spans 52 months and is thus considerably longer than the data sets used in most previous studies. Our data comes from the Austrian stock market, a market that has hitherto not been investigated. We thus provide out-of-sample evidence. We address the endogeneity problem using an instrumental variables approach.

Our results indicate that an increase in the market share of algorithmic trading causes a reduction in quoted and effective spreads while quoted depth and price impacts (a measure of adverse selection costs) are unaffected. Our results do thus not justify regulatory approaches to curb algorithmic trading activity.

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