Bank of Israel **Research Department**

The strategies employed by algorithmic traders on the Tel Aviv Stock Exchange and the connection between Them and indicators of trading quality *

Orry Kaz[A] and Roy Stein[B]

Discussion Paper 2018.06
July 2018

Bank of Israel; http://www.boi.org.il

[A] Orry Kaz – email: orry.kaz@gmail.com

[B] Roy Stein Research Department, Bank of Israel – email: roy.stein@boi.org.il

* Thank you to the Tel Aviv Stock Exchange for intra-day trading data and for support in promoting the research. Thank you to the participants of the Bank of Israel Research Department seminar, to Prof. Avi Wohl, Prof. Yishai Yaffe, Prof. Haim Levy-Kedar, and Itamar Caspi for their helpful comments that enriched the analysis and the findings. Special thanks to Nadav Keinan for his assistance in the initial stages of the research.

חטיבת המחקר, בנק ישראל ת״ד 780 ירושלים 91007

Research Department, Bank of Israel. POB 780, 91007 Jerusalem, Israel

The strategies employed by algorithmic traders on the Tel Aviv Stock Exchange and the connection between them and indicators of trading quality

Orry Kaz and Roy Stein

Abstract

In recent years, securities trading algorithms have been developed, and they have allowed automated high-frequency trading (HFT) without human intervention. HFT has changed the face of trading: it is widely considered to have a marked impact on its quality, and it can be established that it is responsible for a notable share of its quantity, including on the Tel Aviv Stock Exchange (TASE). HFT reflects various trading strategies, and this paper identifies the main ones based on intraday data on securities trading. Its findings indicate that the various strategies have different connections with trading-quality indicators: while HFT that functions as a market maker reduces transaction costs and volatility, and improve the price discovery process, other strategies are not characterized by the same connections and sometimes are even negatively correlated with the quality of trading. It was also found that HFT that functions as a market maker significantly decreases its activity on noisy days. This phenomenon indicates that HFT probably creates phantom liquidity, which enhances the systemic risk in the secondary market. These findings cast doubt on the advantages of the algorithmic trading tools functioning with the various strategies, and particularly question the advantages of HFT that does not function as a market maker.

האסטרטגיות שנוקטים מחוללי הציטוטים בבורסה לניירות ערך בתל אביב והקשר בינן לבין מדדים לאיכות המסחר

אורי קז ורועי שטיין

תקציר

בשנים האחרונות פותחו אלגוריתמים למסחר בניירות ערך, והם אִפשרו מסחר אוטומטי, ללא מגע יד אדם. כלים אוטומטיים אלה – מחוללי הציטוטים – שינו את פני המסחר: רבים מייחסים להם השפעה ניכרת על איכותו, ואפשר לקבוע כי הם אחראים לנתח נכבד מכמותו, לרבות בבורסה לניירות ערך בתל אביב. מחוללי הציטוטים בבורסת תל אביב מגלמים אסטרטגיות השקעה שונות, ומחקר זה מזהה את העיקריות שבהן על יסוד הנתונים התוך-יומיים על המסחר בניירות ערך. ממצאיו מראים כי לאסטרטגיות השונות יש קשרים שונים עם המדדים לאיכות המסחר: בשעה שהמחוללים הפועלים כעושי שוק מפחיתים את עלויות העסקה והתנודתיות ומשפרים את תהליך גילוי המחיר, שאר האסטרטגיות אינן מתאפיינות באותם קשרים ולעיתים אף פוגעות באיכות המסחר. עוד נמצא כי המחוללים הפועלים כעושי שוק מפחיתים באופן מובהק את פעילותם בימים רועשים; תופעה זו מעידה כי ייתכן שהם מייצרים נזילות מדומה, דבר שמגביר את הסיכון המערכתי בשוק המשני. ממצאים אלו מטילים בספק את יתרונותיהם של מחוללי הציטוטים הפועלים באסטרטגיות השונות, ובמיוחד את יתרונות המחוללים שאינם עוסקים בעשיית שוק.

1. Background

Securities trading has undergone many changes over the past decades, most notably the automation of trading venues and of investment actions, as well as increased transparency of trading platforms. In the past two decades, essentially all aspects of trading on the capital market have become automated. Automation includes sending transaction orders as well as concurrent control by back offices (algo traders). The transition to a market structure incorporating automation has contributed to reduced brokerage and other transaction costs, increased asset liquidity, and improved price discovery[1], which in turn have reduced the cost of issuing equity and debt for the business sector. Subsequently, high frequency automated trading was added to the market, referring to robots that continuously monitor relevant information for asset pricing and that automatically send buy and sell orders.

At first, algo traders primarily used trading methods that reduce the transaction cost, since the algorithms first and foremost divide orders into lots, thereby reducing the transaction cost and its impact on the asset price; at that early stage, these were mainly used by brokers and investment houses. But later on, algo traders were equipped with advanced data analysis capacity and with the ability to respond at a high frequency (High Frequency Trading, or HFT) and became common among all traders (including day traders) and started to generate the majority of orders sent to major trading venues across the world.

Over the years, algo trading activity and its impact on securities trading have drawn the attention of capital market participants and regulators. Algo traders may contribute to trading quality, because they quickly reflect new information, which reduces information asymmetry and accelerates the price discovery process, thereby increasing asset liquidity. However, at the same time, algo traders may take advantage of their high frequency response capability, acting as informed traders, thereby increasing information asymmetry and adversely impacting asset liquidity.

Awareness of the risk associated with algo trading increased in the aftermath of events such as the Flash Crash (May 2010)[2], the Knight Capital Group trade orders (August 2012)[3], and the sharp volatility on October 15, 2014 in prices of US Government bonds[4], which led to more extensive research focused on monitoring their effects. Researchers agree that over the past 20 years, algo trading has brought about dramatic change in the market dynamics for trading financial assets, but disagree on the impact of algo trading on trading quality. When researchers focused on quality benchmarks commonly used in academic literature, they found that algo traders improve trading by providing market liquidity (see, for

[1] Price discovery is the reflection of current news in the asset price.

[2] SEC (2010). "Regulating High-Frequency Trading: An Examination of U.S. Equity Market Structure in Light of the May 6, 2010 "Flash Crash" (http://www.sec.gov/comments/s7-02-10/s70210-341.pdf); and Kirilenko et al. (2017).

[3] Securities Exchange Act of 1934, Release No. 70694 / October 16, 2013, https://www.sec.gov/litigation/admin/2013/34-70694.pdf

[4] Joint Staff Report: The U.S. Treasury Market on October 15, 2014, https://www.treasury.gov/press-center/press-releases/Documents/Joint_Staff_Report_Treasury_10-15-2015.pdf

example, Menkveld (2013)). However, in recent years, studies have focused on trading quality at different points in time or in small markets, often finding that the various trading quality benchmarks suffer from significant shortcomings. Some of the current research is focused on attempting to identify which of the strategies applied by algo traders has the more decisive effect on trading quality of financial assets. The various strategies include the following major ones: Market making, arbitrage, directional strategies and structural strategies.[5] (For elaboration see literature overview.)

Research conducted in other countries[6] has shown that high-frequency algo trading contributes about one half of the trading volume in securities in the US and 40 percent of the volume in Europe. In Israel, too, the volume attributed to algo trading has grown, but the increase is mostly in the number of buy and sell orders. We have found that in June 2015, algo traders submitted 98 percent of orders for corporate bonds, 90 percent of orders for shares included in the Tel Aviv 25 Index and over 90 percent of orders for smaller shares. However, they only carried out 35 percent of transactions in shares included in the Tel Aviv 25 Index, 23 percent of transactions in smaller shares and 30 percent of transactions in corporate bonds. The share of orders submitted by algo traders in Israel is high by comparison to the rest of the world[7], while their share of transactions is significantly lower, indicating their diverse and unique activity in Israel.

The Israel Securities Authority has published a paper providing an overview and preliminary findings with regard to algo trading activity in options on the Tel Aviv Stock Exchange.[8] This study shows that from the start of 2008 through mid-2011, the number of algo traders increased three-fold and they have reached a 50 percent share of transactions in options. Tobolsky (2014) has studied the impact of algo trading on the 20 largest corporate bond series (Tel-Bond 20) and found that they were highly active on the Stock Exchange, primarily on the order book, but she did not find that they had a significant impact on asset liquidity. However, Tobolsky regarded the algo trading strategies as a single batch.

This research analyzes the impact of algo traders in more detail, reviewing in particular the link between the various strategies and trading quality in various assets and on different trading days. This research refers to major financial assets—those included in the Tel Aviv 25 (large-cap), Tel Aviv 75 (mid-cap), Yeter 50 (small cap), Tel Bond 20 (large-cap bond series) and Tel Bond 40 (mid-cap bond series) indices—first by regarding the various strategies as a single bunch and then by defining them by type of strategies. This allows us, *inter alia*, to consider the extent to which empirical findings in the literature are valid for

5 Strategies are listed in descending order of contribution to trading efficiency. We use the definition of efficiency as provided in *Concept* Release on Equity Market (2010 SEC).

6 "Understanding High Frequency Trading", *World Federation of Exchanges, 2013*.

7 See, for example, Zang and Riordan (2011).

8 G. Gershgorn, A. Michaeli and A. Rephaeli (2013), "Algo Trading and HFT, Overview and Preliminary Findings from the Israeli Capital Market", Israeli Securities Authority, draft working paper.

each of the strategies, and in particular those other than market making. We measure trading quality by (1) trading cost (buy price/sell price spread); (2) price discovery speed (serial auto correlation of price changes); and (3) volatility (standard deviation of price changes). Together, these benchmarks allow us to distinguish between "good" volatility, due to faster price discovery, and "bad" volatility, which hampers price discovery. The analysis is based on a specific, unique database of trading of financial assets.[9]

The rest of this paper consists of the following: Section 2 provides an overview of the literature, Section 3 describes the data and attributes of algo trading activity by trading strategy, Section 4 shows descriptive statistics of the data, Section 5 shows the statistical links between algo trading activity and trading quality benchmarks, Section 6 presents the key findings and Section 7 concludes.

2. Literature overview

In recent years, many studies have been published about how algo trading affects securities trading quality. These publications have come out at a faster pace since 2010, when the US Securities and Exchange Commission (SEC) urged researchers to study questions with regard to technology changes in the market structure, and in particular with regard to increased activity by algo traders. SEC members elaborated in detail the unique attributes of algo traders and posed questions as to their inherent trading strategies, their impact on liquidity, information asymmetry among traders, intra-day volatility and the price discovery process, as well as with regard to intraday changes in such effects, since they may vary extensively based on developments in capital markets.

Some of the relevant questions for this research included:

1. What are the most common algo trading strategies and what are their features?
2. Do algo traders provide liquidity for all types of securities?
3. Do algo traders provide phantom liquidity, i.e., stop providing liquidity when it is most needed?
4. Do algo trading strategies benefit market trading or detract from its quality?
5. Are there regulatory tools that could address strategies that detract from trading quality without impacting strategies that benefit it?

Preliminary research in this area has primarily focused on measuring the bid-ask spreads, trading volumes and transaction frequency. It was concluded that algo trading benefits liquidity. One could argue that when fast players join in, they expect to increase liquidity and benefit the dynamic price discovery process. Therefore, one may deduce that the technological advances achieved by algo traders reduce pricing anomalies and reduce financial friction (see Hendershott, Jones and Menkveld, 2011). Hendershott and Riordan (2013) studied the top 30 shares traded on the Dutch stock exchange in 2008 and found algo

[9] This data were made available to us by the Tel Aviv Stock Exchange management.

trading to be more active in liquidity monitoring, consuming liquidity when spreads are low and providing liquidity when spreads are high.

Zhou, Kalev and Lian (2014) studied algo trading activity on the Australia Securities Exchange (ASX) on volatile trading days. These researchers found that algo traders "smooth out" the change in share prices, whereas traders other than algo traders act with the changed direction and amplify it. Brogaard, Hendershott and Riordan (2014) separated the change in asset prices into two groups—permanent change and temporary change ("noise")—and found that algo traders improve asset price discovery, because they trade with the permanent change direction and against the temporary change direction. Therefore, they claimed that algo traders reduce "noise" during trading. Moreover, these researchers have examined whether macroeconomic news results in differences in the number of orders in which algo traders provided and consumed liquidity.[10] They found that algo traders continued to provide liquidity even after negative news came out which resulted in higher volatility in asset prices—a finding that contradicts claims of phantom liquidity, which disappears when the market is highly volatile.

Along with research reporting the advantages of algo trading, there is also research that indicates negative effects. Jiang, Lo and Valente (2014) found that algo trading significantly increased the bid-ask spread prior to publication of macroeconomic announcements whose timing was known to the public. The researchers linked this to the fact that algo traders withdrew their orders due to market uncertainty ahead of the announcement being made. Boehmer, Fong and Wu (2012) focused on unusual days (days of relatively higher volatility) and studied how algo trading affected shares with low degrees of liquidity. They found that algo trading reduced liquidity and increased volatility of small-cap shares. Boehmer, Fong, and Wu (2015) studied the effect of algo trading on trading quality of shares over 10 years across 42 stock markets and found that in general, they improved liquidity and price discovery, but increased volatility. In smaller stock markets and/or on days when markets were "tighter", the effect on liquidity was decreased and the effect on volatility was increased.

Hagstromer and Norden (2013) focused on high-frequency algo trading on NASDAQ OMX Stockholm, separated by activity—market making or "opportunistic" activity. They found that, indeed, most of the activity involves market making, which contributes to asset liquidity and to market efficiency, but this is not the case for the other strategies.

Gerig (2015) studied the US stock market and summarized his findings by claiming that algo trading makes the financial system as a whole more fragile. Partington, Kwan, and Philip (2015) reached a similar conclusion: They claimed that algo trading detracted from trading quality of financial assets more than it benefited it.

[10] Providing liquidity (supply)—trading orders that reach the order book and await execution; Consuming liquidity (demand)—trading orders that are immediately executed.

Algo trading is intensive in the US Government bond market as well, the most liquid market in the world. On October 15, 2014, within less than one hour, the 10-year note series experienced especially high volatility. A joint team[11] studied the causes for this using trading data by investor type. The report, released on July 15, 2015, stated that algo trading acted more aggressively and with significant imbalance in the order book, amplifying the price change. The sharp spike in trading of the Swiss franc on January 15, 2015 (a 30 percent increase in 20 minutes), after the central bank, in a surprise move, removed its support for the bottom exchange rate of CHF vs. EUR, was due to the involvement of algo trading in those 20 minutes. Thereafter, algo trading stopped, resulting in a significant liquidity shortage. This event is yet another example showing that the current market structure is more fragile, especially on days when new, relevant information is made public.[12]

The regulator in Australia[13] also studied the effect of algo traders and found that they were successful in profiting from their transactions, and in fact increased costs for institutional investors, including mutual funds. Mudassir (2013) studied the effect of algo trading on the Canadian stock market, and found that it indeed increased the transaction volume and narrowed the bid-ask spread, but concurrently increased intraday volatility. He claimed that the algo trading increases the hidden cost for natural investors, which raises questions about the total cost created by algo trading. Kervel (2015) studied trading data on the UK market and found many order cancellations, and that the volume of such cancellations depended on the number of players who had access to several trading venues simultaneously. These studies do not refute the positive impact of algo trading on trading of securities, but highlight the fact that the shortcomings of algo trading may yet be under-weighted in analysis of their impact on market structure.

Kwan and Philip (2015) studied whether algo traders increased transaction costs for regular traders.[14] The researchers found that costs for regular traders were higher than for algo traders, which they attributed to the fact that algo trading was typically involved in front running the orders given by regular traders.

Biais, Foucault, and Moinas (2015) found that when the market consisted of multiple trading venues[15], algo traders indeed managed to find lower-priced quotes. However, they

---

11 The members of the Joint Staff Report: U.S. Treasury; Board of Governors of the Federal Reserve System; Federal Reserve Bank of New York; U.S. Securities and Exchange Commission; U.S. commodity Futures Trading Commission.

12 See the financial stability overviews by the UK central bank: http://www.bankofengland.co.uk/publications/Documents/fsr/fsrboxes/1512box4.pdf, www.bankofengland.co.uk/publications/Documents/fsr/2015/fsrfull1507.pdf. and Breedon et al. (2018)

13 Australia Industry Super Network, (2013) "Some Costs of High Frequency Trading in Low Latency Markets".

14 See also the research by Tong (2013).

15 Stock trading in the US and in Europe typically involves multiple trading hubs. For example, in 2008 there were over 50 hubs operating in the US. See O'Hara and Ye (2011).

were also successful in obtaining information faster than other traders and in conducting their transactions rapidly, thereby actually increasing the risk of adverse selection for traders. Therefore, the researchers claim that in case of multiple trading venues, there is a certain logic in imposing a Pigovian tax on companies using algo trading in order to maximize social benefit. It is important to note that for most of the financial assets in Israel there is a single trading venue, which is also the case for all financial assets studied in this research.[16] Therefore, this work may make a further contribution to research literature: It would show how algo trading affects trading quality in markets where financial assets have but a single trading venue.

3. Sample, data and attributes of algo trading activity

Data in this research are taken from the transaction book and from the order book, and refer to all assets included in price indices of key financial assets—the Tel Aviv 25, Tel Aviv 75, Yeter 50, Tel-Bond 20 and Tel-Bond 40. One of the key advantages of this research lies in the data's detail and quality: We have received the full trading data for each order (transmission, modification and cancelation) and for each transaction. Each trading account was assigned a coded identifier that allowed us to monitor all of the orders and transactions and to classify the strategy type applied by each trading account. Thus, we were able to study how the different strategies contribute to trading quality in financial assets. This data also allows us identify which side of a transaction provided liquidity and which side consumed it for each one of the transactions.

The sample period covers two years: It begins in January 2014, the date after which it is mandatory to register algo traders on stock exchange accounts, and ends in December 2015.[17] The sample was studied over time and by dividing it into "ordinary" and "noisy" days, i.e., days of sharp fluctuations in asset prices, as described in Appendix 1. This analysis made it possible to study algo traders' effect on trading quality under different trading conditions. However, it is important to highlight that we defined noise relative to typical volatility for the estimated period, which did not include exceptional days that caused significant liquidity pressures on the financial markets.

We used the intra-day data as described above to classify algo traders under the following strategies[18]:

1. Market makers—algo traders who simultaneously send buy and sell orders for the same asset.
2. Official market makers—trading accounts authorized by the stock exchange to act as market makers for a list of assets (stocks and bonds) with very low turnovers.

---

[16] Government bonds in Israel are traded on the Tel Aviv Stock Exchange, but also on a closed system for primary market makers—MTS.

[17] Due to memory capacity limitations, order data is abbreviated for a partial period: January–April 2014, December 2014, February 2015 and June 2015.

[18] Appendix 1 precisely lists all of the calculations made in this study.

3. Arbitragers—algo traders with typically high liquidity demand who simultaneously send buy and sell orders for multiple assets at market price.
4. Others—all other algo traders.

We have also classified and tagged algo traders applying the various strategies, especially directional ones, by the following attribute: Algo traders who remain balanced at the end of each trading day in each asset (day-trading). Such tagging allows us to study in more detail the links between strategies and trading quality.

Based on the transaction and order books, we calculated, for each asset in the sample, the following variables:

1. Liquidity measures: Bid-ask spread relative to the midpoint[19], turnover and number of transactions.
2. Volatility measures: Standard deviation of change in midpoint, for both transaction prices and order prices, for every 1 minute, 5 minutes, 10 minutes, 20 minutes and 30 minutes.[20] We also calculated the absolute daily price change and the difference (in percent) between the highest transaction price and the lowest transaction price for all transactions conducted on that day.
3. Informational efficiency measures: The serial autocorrelation of change in midpoint price, for both transactions and orders, for every 1 minute, 5 minutes, 10 minutes, 20 minutes and 30 minutes. When this autocorrelation limits to zero the informational efficiency is the best.
4. Scope of activity by algo traders in each asset and on each trading day: The number of transactions/turnover attributable to algo traders relative to all transactions/turnover; and number of quotes attributable to algo traders relative to all quotes. We calculated these measures for each of the aforementioned strategies.

Note that with regard to Sections 2 and 3 the research not only studied the intra-day volatility, but also its source, in order to determine whether it improved trading quality ("good") or negatively impacted it ("bad"). Good intra-day volatility is due to fast, efficient price discovery—a process made possible, *inter alia*, by low trading friction, wider variety of trader types and lower information asymmetry among the different traders. Conversely, bad intra-day volatility is due to a market structure that makes it difficult to discover the price based on new information made public. Bad volatility is indicated by a series autocorrelation of change in prices other than zero. Therefore, in order to test the effect of algo trading on trading quality, we estimate intra-day volatility along with this series autocorrelation.

[19] The midpoint is calculated as the average of the best buy and sell prices.

[20] The various calculation methods and time windows were used for econometric testing of the stability of estimates.

4. Descriptive statistics

In this section, we present in detail statistical data about the activity of algo traders on the Tel Aviv Stock Exchange, by different strategies, and we also provide a quantitative description of the trading quality measures we have calculated in this study, as described in Section 3.

4.1 Transactions and orders

Tables 1 and 2 present the scope of activity of algo traders for orders and for transactions, respectively. It is evident that their activity for orders is much higher than that of regular traders, but this is not the case for transactions. Moreover, the transactions conducted by algo traders typically have significantly lower volumes than those conducted by regular traders, hence their share of turnover is even lower. As for the number of accounts operated by algo traders, it is still low relative to the number of accounts operated by regular traders, but it is growing markedly, and for corporate bonds, algo traders' accounts' reach to one-quarter of the number of regular accounts and are responsible for 99 percent of the orders. One of the key findings in these tables is with regard to the number of orders canceled by algo traders: it is significantly higher than cancellations by regular traders. Table 2 shows that algo traders conduct most of their transactions with regular traders, and only a very small percentage of transactions are conducted between algo traders. This finding indicates that regular traders suffer from adverse selection in their transactions, due to the fast operation of algo traders.

When comparing algo trading activity on various stock exchanges around the world, we find that such activity in Israel is unique in accounting for a higher percentage of orders and a lower percentage of transactions. Zhang and Riordan (2011) studied algo traders active in stock trading on NASDAQ and found that they accounted for 73.7 percent of all orders but only for 43.7 percent of all transactions. On the Japanese Stock Exchange, too, algo trading accounted for 70 percent of the order book and for 50 percent of the transaction book.[21] The Canadian market supervisor (IIROC) reports that algo trading on the Canadian Stock Exchange accounts for 94 percent of orders, but only for 36 percent of transactions. Algo trading activity in the Canadian order book is similar to that reported in this article, but their total transactions are higher than in Israel, although lower by international comparison.

[21] Explanatory document dated April 19, 2016 issued by the FSA: http://www.fsa.go.jp/en/newsletter/weekly2016/193.html

Table 1

Order data by account type: Algo traders (Algo) and regular traders (Reg)

Daily average per asset

		January–May 2014	**June 2015**
Tel Aviv 25	Total orders	4,819	12,735
	Percentage of orders sent by algo traders	70%	91%
	Total accounts of algo traders	11	20
	Average number of orders per algo trader account	311	570
	Percentage of self-cancellation, algo traders	95%	97%
	Total accounts of regular traders	232	227
	Average number of orders per regular account	6	5
	Percentage of self-cancellation, regular traders	50%	45%
Tel Aviv 75	Total orders	2,831	9,991
	Percentage of orders sent by algo traders	79%	97%
	Total accounts of algo traders	7	10
	Average number of orders per algo trader account	301	995
	Percentage of self-cancellation, algo traders	90%	98%
	Total accounts of regular traders	109	72
	Average number of orders per regular account	6	4
	Percentage of self-cancellation, regular traders	60%	47%
Yeter 50	Total orders	1,783	3,759
	Percentage of orders sent by algo traders	86%	96%
	Total accounts of algo traders	5	7
	Average number of orders per algo trader account	279	541
	Percentage of self-cancellation, algo traders	99%	99%
	Total accounts of regular traders	48	38
	Average number of orders per regular account	5	4
	Percentage of self-cancellation, regular traders	63%	47%
Tel-Bond 20	Total orders	2,931	11,369
	Percentage of orders sent by algo traders	91%	98%
	Total accounts of algo traders	6	10
	Average number of orders per algo trader account	414	1062
	Percentage of self-cancellation, algo traders	98%	99%
	Total accounts of regular traders	56	54
	Average number of orders per regular account	5	4
	Percentage of self-cancellation, regular traders	58	44
Tel-Bond 40	Total orders	4,216	12,579
	Percentage of orders sent by algo traders	95%	99%
	Total accounts of algo traders	7	10
	Average number of orders per algo trader account	606	1256
	Percentage of self-cancellation, algo traders	99%	99.9%
	Total accounts of regular traders	35	37
	Average number of orders per regular account	6	4
	Percentage of self-cancellation, regular traders	66%	46%

Table 2
Transaction data by account type: Algo traders (Algo) and regular traders (Reg)

Daily average per asset (monetary amounts in NIS thousands)

		January–May 2014				June 2015			
		All trans-actions	**One side Algo and other side Reg**	**Both sides Algo**	**Both sides Reg**	**All trans-actions**	**One side Algo and other side Reg**	**Both sides Algo**	**Both sides Reg**
Tel Aviv 25	Number (percentage) of transactions	686 (100%)	204 (30%)	17 (3%)	465 (68%)	817 (100%)	396 (48%)	86 (11%)	336 (41%)
	Turnover (percentage)	16,926 (100%)	4,447 (26%)	316 (1.9%)	12,163 (72%)	19,121 (100%)	8,153 (43%)	1,518 (7.9%)	9,450 (49%)
	Average turnover per transaction	24	22	18	26	23	21	18	28
Tel Aviv 75	Number (percentage) of transactions	199 (100%)	55 (28%)	3 (1%)	142 (71%)	179 (100%)	87 (48%)	10 (6%)	82 (46%)
	Turnover (percentage)	2,493 (100%)	562 (23%)	23 (1%)	1,909 (77%)	1,651 (100%)	518 (31%)	46 (2.8%)	1,088 (66%)
	Average turnover per transaction	13	10	9	14	9	6	5	13
Yeter 50	Number (percentage) of transactions	65 (100%)	20 (31%)	1.0 (2%)	44 (68%)	66	27 (41%)	2 (3%)	37 (56%)
	Turnover (percentage)	622 (100%)	143 23%	6 (0.9%)	473 (76%)	542	167 (31%)	9 (1.6%)	366 (68%)
	Average turnover per transaction	10	7	6	11	8	6	5	10
Tel-Bond 20	Number (percentage) of transactions	102 (100%)	42 (41%)	1.7 (2%)	59 (58%)	134 (100%)	62 (47%)	7 (6%)	64 (48%)
	Turnover (percentage)	4,927 (100%)	1,284 (26%)	50 (1.0%)	3,593 (73%)	6,533 (100%)	1,771 (27%)	161 (2%)	4,601 (70%)
	Average turnover per transaction	48	31	29	60	48	28	23	70
Tel-Bond 40	Number (percentage) of transactions	66 (100%)	29 (45%)	1.4 (2%)	35 (53%)	92 (100%)	41 (45%)	5 (6%)	45 (49%)
	Turnover (percentage)	2,944 (100%)	786 (27%)	34 (1.1%)	2,125 (72%)	4,585 (100%)	1,168 (25%)	125 (3%)	3,292 (72%)
	Average turnover per transaction	45	27	25	61	49	28	24	72

Over the sample period, algo traders continued to increase their trading activities, and Tables 1 and 2 show this in numbers:

- Total orders sent by algo traders increased three-fold during the sample period, while the number of transactions increased only slightly.
- The number of orders sent by algo traders increased significantly, due to both an increase in the number of accounts and an increase in the average number of orders per account. Yet at the same time, the number of regular trader accounts decreased, primarily those involved in mid-size and small shares, and the average number of orders per regular account decreased as well.
- The number of transactions conducted by algo traders increased across all asset types, with most of the increase being vis-à-vis regular traders, which probably indicates the growing impact of adverse selection across the sample period. Figure 1 shows this data for shares included in the Tel Aviv 25 index.
- Algo traders increased the percentage of order cancellations, reaching over 99 percent of their total orders. Conversely, regular traders reduced the cancellation percentage to below 50 percent.

It may be that the increase in number of algo trader accounts active on the stock exchange results in a more efficient market, since it expands the activity of faster traders, with the extent of cancellations indicating that indeed, new information is reflected faster in prices. In contrast, it may be that the decrease in number of regular trader accounts results in a less heterogeneous and more fragile market, which may impact trading quality. We consider this question in Section 5.

Figure 1
Number of Daily Transactions in Assets on the Tel Aviv 25 Index by Account Type: Algo Traders (Algo) and Regular Traders (Reg), Monthly Average, January 2014 to December 2015

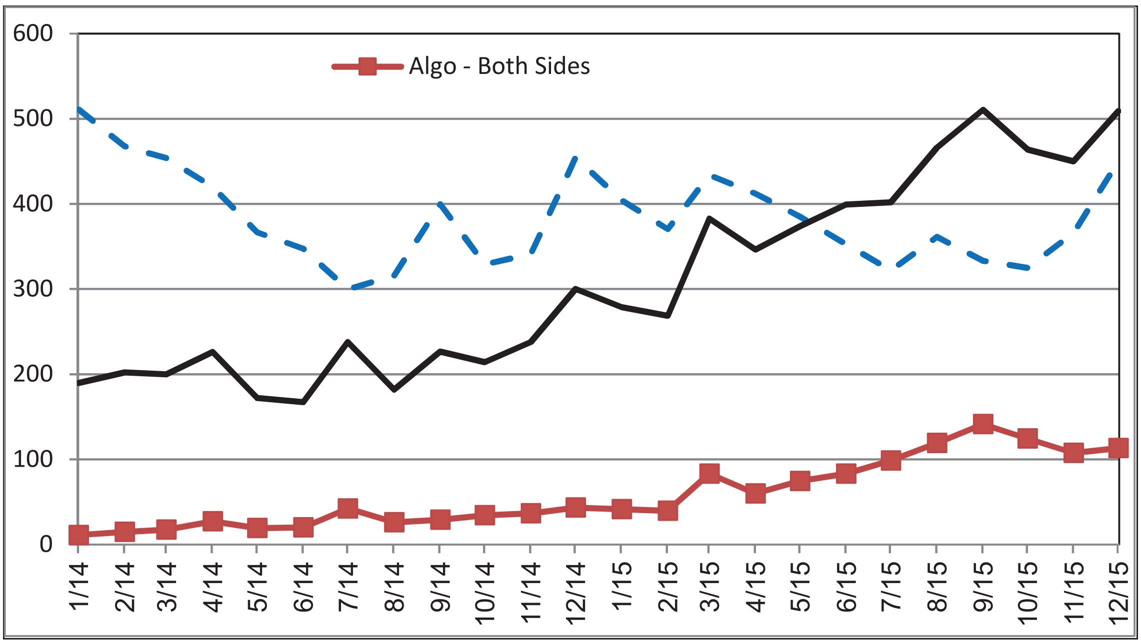

Table 3

Transactions conducted by algo traders with regular traders: Percentage of transactions that algo traders served as liquidity provider, in percent

	January–May 2014	June 2015
Tel Aviv 25	64	56
Tel Aviv 75	75	67
Yeter 50	75	79
Tel-Bond 20	80	77
Tel-Bond 40	79	74

Table 3 shows that algo traders provide more liquidity for trading of small shares and bonds, assets with less liquid trading, thereby improving liquidity for assets where it is most needed. This finding shows that market making is a dominant strategy for them. The table also shows that liquidity provided by algo traders decreased over the period, primarily for large and mid-size equity indices, but also for bond indices. Based on this decrease, we may deduce that most of the algo traders who joined during the sample period applied a strategy other than market making.

4.2 Algo trading activity by strategy

Table 4
Activity in trading accounts by trading strategy

	Number of accounts	Percentage of accounts	Number of transactions (in thousands)	Percentage of transactions	Number of orders (in thousands)	Percentage of orders	Ratio of transactions to orders
All accounts	222,194		7,673		125,683		6%
Regular accounts	221,165	99.5%	5,815	75.8%	13,570	11%	43%
Regular accounts excluding[1]	117,089	52.9%	4,655	60.7%	9,282	7%	50%
Algo traders	1029	0.5%	1,858	24.2%	112,113	89%	2%
Of which: Market makers	76	7%	604	32%	60,946	54%	1.0%
Arbitragers	31	3%	130	7%	147	0.1%	88%
Others	922	90%	1,124	61%	51,021	46%	2.2%
Balanced accounts[2]	859	83%	1,255	68%	86,231	77%	1.5%

All assets included in the five indices studied, across entire period

1 Regular accounts excluding very small accounts, i.e., accounts from which no more than two orders were sent.

2 A balanced account acts in each asset with no significant change in position, i.e., for each individual asset, total change as percentage of total activity (total trading volume) is less than 7 percent.

Table 4 shows that the different strategies have significant differences in activity. Algo traders hold only 0.5 percent of all accounts on the stock exchange, but account for 89 percent of orders and 24 percent of transactions conducted. The ratio of transactions to orders sums up these differences well: Regular accounts execute more than 50 percent of their transmitted orders, whereas algo traders only execute around 2 percent. Review of algo trading activity by strategy reveals, once again, significant differences. For arbitragers, there is a very high ratio of orders to transactions—88 percent, but for market makers, this ratio is only 1 percent. Algo trading applying other strategies account for a significant share of all algo trading, and this activity differs from market making, primarily in the ratio of transactions to orders.

Table 4a lists the top 100 most active accounts on the order book, showing that trading accounts for balanced algo trader accounts have the highest number of transactions per account. We have found that most of these serve as market makers, but some accounts apply a strategy other than market making and their daily positions, too, do not change significantly. It is interesting to note that in these accounts, the ratio of transactions to orders is very low. This finding shows that algo traders applying this strategy have the highest trading volume on the stock exchange, and are likely to impact trading quality significantly.

Table 4a
Trader activity in top 100 accounts[1]
In all assets included in the five indexes studied, across entire period

	Number of accounts	Number of transactions per account per day	Number of orders per account per day	Ratio of transactions to orders
Regular accounts	66	161	393	41%
Algo traders	34	551	23,155	2.4%
Of which:	9	619	43,688	1.4%
Arbitragers	5	414	423	98%
Others	20	555	19,599	2.8%
Balanced accounts	15	809	40,810	2.0%

[1] The top trading accounts were selected by number of orders across the sample period.

4.3 Algo trading activity on noisy days

Thanks to the unique data available to us, we can study algo traders applying the different strategies, distinguishing between ordinary days and noisy days, in terms of intra-day fluctuation. Table 5 divides the sample into noisy days and ordinary days, showing a significant difference between these categories in trading quality benchmarks, in particular in spread and series autocorrelation. The share of market makers in both orders and transactions is significantly lower on noisy days, with all other strategies significantly increasing their activity in both orders and transactions. It is interesting to note that indeed there were significant changes in balanced algo trading activity on noisy days, but it would appear that their share of the order book decreased, while their share of the transaction book increased. The following section reviews these findings in the estimation equation, in order to estimate the differences in algo trading activity for the different strategies.

Table 5
Differences between ordinary days and noisy days[1]
In trading quality benchmarks and in algo trading activity, daily average per asset

	Bid-ask spread	Intraday standard deviation	Series autocorrelation	Number of orders issued by algo traders	Number of transactions executed by algo traders	Natural logarithm of total trading volume
Ordinary days (24,698)	0.00927	0.054	0.105	4,204	175	14
Noisy days (2,708)	0.0106	0.0611	0.1495	7,256	401	14.8
Significance[2]	0.0014	0.17	0.0001	0.0001	0.0001	0.0001

Activity in order book by strategy:

	Share of algo traders	Share of market makers	Share of official market makers	Share of arbitragers	Share of other strategies	Share of balanced accounts
Ordinary days (24,698 observations)	0.835	0.41	0.0046	0.13	0.42	0.65
Noisy days (2,708 observations)	0.815	0.28	0.0052	0.1	0.55	0.63
Significance[2]	0	0	0.2	0.015	0	0

Activity in transaction book by strategy:

	Share of algo traders	Share of market makers	Share of official market makers	Share of arbitragers	Share of other strategies	Share of balanced accounts
Ordinary days (24,589 observations)	0.22	0.137	0.01	0.127	0.07	0.313
Noisy days (2,707 observations)	0.234	0.095	0.0065	0.115	0.127	0.322
Significance[2]	0	0	0.0007	0.165	0	0.0096

1 See definition of "noisy days" in Appendix 1. It is important to emphasize that this definition is not endogenous for algo trading activity, and only groups together the material price changes in the asset during the trading day. Moreover, intraday standard deviation on ordinary days is not significantly different than on noisy days, which is empirical proof of this not being endogenous.

2 The lower the value than 0.05, the more significant is the difference between these two series.

4.4 Algo trading activity: Correlation between changes in scope of activity by strategy

We have studied the correlation between changes in the scope of activity among trading accounts applying the same strategy, because as the correlation increases, so does the probability of a systemic crisis, which makes the market fragile; for the market making strategy, this phenomenon may also increase liquidity risk for assets in which these accounts are active. To calculate this correlation, we omitted accounts with relatively low activity over the sample period, and focused on accounts that traded in a particular asset on at least 10 trading days and issued at least 10 orders per day, on average, for such asset.[22] We identified whether this was a regular account or an account operated by an algo trader, and for the latter we also identified the trading strategy. We calculated the correlations between daily change for each account in activity in each asset and the daily change in activity in the same asset across all other accounts applying the same strategy. As shown in Table 6, there is a significant positive correlation among algo traders in the balanced market maker group, whereas the correlation is low for all non-balanced other accounts, and for regular accounts.

Table 6

Activity in trading accounts by the main strategy

Trading accounts	Number of accounts	Daily average orders per asset	Average number of assets per account	Correlation between changes in activity scope	Minimum correlation	Maximum correlation	Standard deviation of correlation coefficients
Balanced market makers	25	1250	29	78.8	30	81	12.1
Balanced others	19	256	87	32	8	64	15.7
Non-balanced market makers	13	785	31	25.1	2.6	58	14.4
Non-balanced others	52	158	21	14	-27	49.4	16.5
Regular	361	12	18	13.6	-68.6	91.5	21.2

It is important to note that balanced market makers conduct, on average, the highest number of orders per asset, which amplifies their impact on total trading.

[22] Trading accounts of algo traders met another criteria—they sent at least 1,000 orders. See Appendix 1.

5. Methodology framework for studying different strategies applied by algo traders

Below we refer to some of the questions posed by the SEC that in our view have not been studied in a satisfactory manner in empirical literature. We ask:

1. What is the correlation between the different algo trading strategies and trading quality measures, in particular "bad" volatility?
2. Does the nature of algo trading activity change on noisy days (days in which asset prices changed significantly, presumably due to new information) and was the liquidity provided on such days affected?
3. Do statistical relations between algo traders and trading quality change when moving from large, liquid shares to smaller, less liquid ones?

We estimate the set of relations between algo trading activity and trading quality measures using an estimation equation of the following general form:

(1) $$MQ_{i,t} = \alpha_i + \tau_t + \beta * AT_{i,t} + \delta * X_{i,t} + \varepsilon_{i,t}$$

Where[23]

$MQ_{i,t}$ – Trading quality measures (for asset i, on day t), as defined in this study:

BAS – Bid-ask spread relative to midpoint price. The midpoint price is equal to the average of the best buy price and best sell price;

STD – Intra-day volatility of change in transaction and midpoint prices.

AR – Series autocorrelation of change in transaction and midpoint prices.

α_i – dummy variable for asset.

τ_t – dummy variable for time.

$AT_{i,t}$ – Algo trading activity relative to all activity (in asset i, on day t);

This activity is measured twice: Based on the order book and based on the transaction book.

This activity is measured for all strategies combined and for each strategy separately. $X_{i,t}$ – Vector of various control measures:

Absolute value of daily change in asset;

Natural logarithm of daily trading volume;

Bid-ask spread volatility;

The other two trading quality measures (not used as dependent variables).

Equation 1 estimates the statistical relations between algo trading activity and trading quality measures, ignoring the endogenous nature of such testing (it may be that algo trading activity started due to the change in quality measures, rather than caused such change); therefore, it is not possible to deduce how algo trading activity impacts trading quality.[24] However, we estimate the relations between algo trading activity and quality

[23] Appendix 2 presents a statistical description of variables in the estimation equation.

[24] It is important to note that this issue cannot be resolved using Vector Auto-Regression (VAR) equations, which describe the inter-effects between variables. That is because the equations have a daily frequency, whereas the aforementioned effect takes place simultaneously (within seconds or less), hence causality cannot be proven.

benchmarks using dummy variables per asset (firm-fixed effects) at each point in time (time-fixed effects)—a method commonly used in literature and for testing relations between algo trading and various liquidity measures (Hendershott, et al. 2011). The estimation equation uses (a) a dummy variable for each asset (i), which explains the differences between asset types, and (b) a dummy variable for each time unit (t), which explains the differences at each point in time, which causes the remaining variables, including algo trading activity, to only explain the specific differences in the explained variable (trading quality measures) for each asset at each point in time.

6. Key findings

In this section, we present the estimation results from equation 1, studying the differences between noisy days and ordinary days. We studied the statistical relations both for algo trading activity as a whole, and for algo trading activity in three major strategies: market making, arbitrage and all other strategies. We also estimated these relations separating balanced accounts from all other accounts. It is important to emphasize that when market makers are balanced, they take less market risk and are typically required to consume liquidity near the end of the trading day. Therefore, we would expect to see statistical differences between the different strategies studied in this research.

The estimation results are presented in Table 7, indicating significant statistical relations between algo trading activity and trading quality measures for the various assets: There is a significant negative correlation between their activity as percentage in the order book and in the transaction book, and all other quality measures. Thus, we can say that their total activity is correlated with lower spread, lower volatility and faster price discovery.

When estimating equation 1 separating the various strategies, we find significant differences between these strategies (Table 7a). Market makers typically reduce the spread, standard deviation and series autocorrelation, but volatility increases as the number of their transactions increases. Algo traders applying other strategies increase the standard deviation and series auto-correlation in their transaction book activity—findings indicating higher bad volatility in trading. Balanced algo trading activity in the order book is correlated with higher spreads. Therefore, when market makers and others maintain asset balance at the end of each trading day—i.e., execute transactions opposed to their position accumulated during the trading day—they are more weakly correlated with increases in trading quality measures. Arbitragers do not account for a large share of trading, certainly not in the order book, and therefore lack significant statistical relations with quality measures. Finally, we note the findings with regard to official market makers (market makers for financial assets with low trading volumes). Indeed, their activity is correlated with lower spreads, but is positively correlated with the series autocorrelation—meaning that they slow down the price discovery, which is even worse on noisy days, a result of significant information published. From this we can deduce that these market makers are unsuccessful in performing their role, but rather act in line with the trend of changes in prices of assets in which they are trading.

In summary, when algo trading activity applying other strategies is not only correlated with higher intra-day standard deviation, but also with higher series autocorrelation, it is positively correlated with bad volatility.

Other findings from the estimation equation:

- There is a significant positive correlation among all three trading quality measures.
- When estimating the equation based on noisy days only, we see higher correlation between market maker activity and lower spread and series autocorrelation, but we also see a significant decrease in their activity (Table 6).
- When we study the correlations between algo trading activity and quality measures for the various asset types, we find no significant differences between these types—corporate bonds vs. stocks—and between assets with higher and lower trading volumes.

Table 7
Results of estimation of equation 1

	Algo activity in order book			Algo activity in transaction book		
	Bid-ask spread (BAS)	**Standard deviation (STD)**	**Series auto-correlation (AR)**	**Bid-ask spread (BAS)**	**Standard deviation (STD)**	**Series auto-correlation (AR)**
Spread		**0.526****	**1.13****		**0.57****	**1.31****
Standard deviation[1]	**0.336****		**0.162****	**0.325****		**0.162****
Series autocorrelation[1]	**0.0053****	**0.0012****		**0.0053****	**0.0011****	
Algo share of activity	**-0.005****	**-0.005****	**-0.095****	**-0.0088**	**0.034****	**-0.059****
Natural logarithm of total turnover	**-0.003****	**0.0006****	**0.008****	**-0.003****	**0.0007****	**0.009****
Standard deviation of spread	**0.0175****	**0.02****	**-0.42****	**0.0177****	**0.02****	**-0.43****
Constant	**0.0405****	**-0.016****	**0.209****	**0.0336****	**-0.023****	**0.125****
Fixed effect for asset	+	+	+	+	+	+
Fixed effect for day	+	+	+	+	+	+
Equation goodness of fit (R^2)	**0.44**	**0.38**	**0.2**	**0.456**	**0.385**	**0.2**
Number of observations	**27,272**	**27,272**	**27,272**	**27,170**	**27,170**	**27,170**

* Significant at the 1% level
** Significant at the 5% level

[1] The variables listed were calculated based on the order book. When calculated based on the transaction book, the results are not materially different.

Table 7a

Estimation of algo trading activity by strategy[1]

	Algo activity in transaction book		**Algo activity in order book**	
Bid-ask spread	**Ordinary days**	**Noisy days**	**Ordinary days**	**Noisy days**
Market makers	**-0.0081****	**-0.0223****	**-0.0085****	**-0.0214****
Official market makers in small shares	**-0.0051****	-0.0209	-0.0044	-0.0135
Arbitragers	-0.0013	-0.0105	-0.0095	-0.0155
All other strategies	**-0.0083****	**-0.0115****	**-0.0061****	**-0.0138****
Balances	-0.0005	-0.0005	**0.0036****	0.0040
Standard deviation				
Market makers	**0.0042****	-0.0054	**-0.0058****	0.0034
Official market makers in small shares	**-0.0115****	0.0092	-0.0051	0.0148
Arbitragers	0.0011	-0.0050	-0.0218	0.0018
All other strategies	**0.0071****	-0.0009	0.0003	0.0015
Balances	-0.0007	0.0038	**-0.0033****	-0.0024
Series autocorrelation				
Market makers	**-0.0789****	**-0.212****	**-0.111****	**-0.14****
Official market makers in small shares	**0.0776****	**0.4193****	0.0637	**0.6286****
Arbitragers	0.0248	0.2165	-0.1335	1.5761
All other strategies	**0.0422****	-0.1315	**-0.0746****	**-0.153****
Balances	**-0.037****	0.0076	0.0025	0.0298

*   Significant at the 1% level
** Significant at the 5% level

[1] The relation between algo trading activity and trading quality remains stable in different assets including in the sample.

7. Summary and potential implications for regulation

This study shows that preliminary research into trading quality was primarily focused on measurement of bid-ask spreads and turnovers; these studies found that algo trading made a positive contribution to liquidity. It is important to emphasize that adding new, fast players indeed increases liquidity and price discovery. However, algo trading has other effects on trading, which vary by the trading strategies applied. When researchers focused on their effect at extreme points in time and on less liquid markets, they often found a negative impact on trading quality. Below are the key findings of this research:

- Algo trading activity expanded in 2014 and 2015, both by increased number of accounts and increased average activity per account. Such activity is extensive in the order book, but not so in the transaction book.
- Regular traders have reduced their activity, seen in both a reduced number of accounts and reduced average activity per account. Algo traders have replaced regular traders to some extent, in particular for mid-size and small shares.
- Algo traders conduct most of their transactions with regular traders, and only a very small share of their transactions with other algo traders. This indicates a possibility that regular traders are subject to adverse selection in their transactions, due to the rapid action by algo traders.
- When considering algo trading in terms of number of orders, we found that these are mostly concentrated in providing liquidity through market making, a strategy that improves liquidity. However, algo traders acting as market makers significantly reduce their activity on noisy days, hence they may be creating phantom liquidity. This finding is also supported by Raman et al. (2014) and by Anand and Venkataraman (2014).
- As for algo traders not acting as market makers, their activity is not correlated with improvement in quality measures and sometimes may even weaken those measures—as reflected in, for example, analyzed balanced algo traders.
- Activity of algo traders acting as balanced market makers constitutes a significant part of all algo trading activity in Israel, and these algo traders show a significant positive correlation with the scope of activity among them, unlike algo traders applying other strategies. Hence, this activity may increase fragility of the secondary market, thereby increasing systemic financial risk.
- Official market makers—traders nominated by the stock exchange to provide market making in financial assets with low turnover—indeed reduce bid-ask spreads to some extent, but the increase in series autocorrelation, which is even worse on noisy days, indicates their inefficiency as market makers.[25]

It is important to note that algo traders are faster in trading on the basis of new information[26], resulting in increased information asymmetry between them and regular

[25] This finding shows, more than anything, that market makers for small shares act without a well-ordered lending facility, which increases their position risk and impacts their operations as market makers.

[26] This information may originate from news coverage in mass media, as well as from monitoring of orders and transactions on the markets at any given time.

traders; this increases the risk of adverse selection for regular traders. Therefore, as long as algo traders and regular traders operate in the same venue, the latter would continue to pay the price for the market's assimilation of new technology.

Unusual events in major stock exchanges around the world have provided regulators with incentive to review the impact of algo traders and to find ways to supervise their operations. To avoid similar events in the future and to avoid negative impact, regulators around the world propose both *ex ante* provisions—to identify algo trading activity in order to reduce the possibilities for negative impact to trading quality—and *ex post* provisions—to act following such negative impact to limit its extent (Morelli, 2017). IOSCO, the International Organization of Securities Commissions, is acting to set uniform international policy and measures for member organizations; in 2012, IOSCO issued a report recommending regulatory measures to be applied in order to improve market efficiency and to minimize the negative implications of such activity. These measures limit the impact of algo traders during unusual events, but do not provide a solution for the information issue they have created on the capital market, such as manipulation and phantom liquidity—which would ultimately increase the transaction costs for regular traders.

Given the key findings in this research—algo trading activity in Israel is high compared to world-wide levels, some of the strategies are negatively correlated with trading quality measures, and some algo trading activity is correlated (homogeneous activity), which increases systemic risk in the market—it is important to consider limiting algo trading activity across all traded financial assets, even if this would entail some decrease in liquidity, because such limitation would contribute to reduced risk of failure and manipulation.

References

Anand, A. and K. Venkataraman, (2014). “Should Exchanges Impose Market Maker Obligations?”, working paper.

Raman, V., M. Robe, and P. Yadav, (2014). "Electronic Market Makers, Trader Anonymity and Market Fragility", Chicago Futures Trading Commission manuscript.

Bain, S. and S. Mudassir (2013). “Evolution of Canadian Equity Markets.” RBC Capital Markets Global Electronic Trading.

Biais, B., T. Foucault, and S. Moinas (2015). "Equilibrium Fast Trading", Journal of Financial Economics, 116.

Boehmer, E., K. Fong and J. Wu (2012). "Algorithmic Trading and Changes in Firms' Equity Capital", Working Paper EDHEC Business School.

Boehmer, E., K. Fong and J. Wu (2015). "International Evidence on Algorithmic Trading", Manuscript, EDHEC Business School. Also in: http://ssrn.com/abstract=2022034.

Breedon, Francis, Louisa Chen, Angelo, Ranaldo and N. Vause, (2018). "Judgement Day: Algorithmic Trading Around the Swiss Franc Cap Removal", Staff Working Paper No. 711, Bank of England.

Brogaard, J., T. Hendershott, and R. Riordan (2014). "High-Frequency Trading and Price Discovery", Review of Financial Studies, 27.

Dennis, P. J. and D. Strickland (2002). "Who Blinks in Volatile Markets, Individuals or Institutions?" Journal of Finance, 57.

Gerig, A. (2015). "High-Frequency Trading Synchronizes Prices in Financial Markets", DERA (Division of Economic and Risk Analysis) Working Paper Series, Jan. 21, 2015.

Gur-Gershgoren, G., I. Michaeli, G. Sabach, and E. Refaeli (2013). "Algorithmic Trading and High Frequency Trading in the Israeli Capital Market—Review and Initial Findings", Working Paper, Israel Securities Authority.

Hagstromer, B. and L. Norden (2013). "The Diversity of High-Frequency Trading", Journal of Financial Markets, 16, 4.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). "Does Algorithmic Trading Improve Liquidity?", Journal of Finance, LXVI, 1.

Hendershott, T. and R. Riordan (2013). "Algorithmic Trading and the Market for Liquidity", Journal of Financial and Quantitative Analysis, 48, 4.

Jiang, G. J., I. Lo, and G. Valente (2014). "High-Frequency Trading around Macroeconomic News Announcements: Evidence from the U.S. Treasury Market", Bank of Canada Working Paper, 2014-56.

Menkveld, A. J. (2013). "High Frequency Trading and the New Market Makers", Journal of Financial Markets, 16.

Miller, R. S. and G. Shorter (2016). "High Frequency Trading: Overview of Recent Development", Congressional Research Service 7-5700.

Morelli, M. (2017). "Implementing High Frequency Trading Regulation: A Critical Analysis of Current Reforms", Michigan Business & Entrepreneurial Law Review 6, 2.

O'Hara, M. and M. Ye (2011). "Is Market Fragmentation Harming Market Quality?", Journal of Financial Economics, 100.

Partington, G., A. Kwan, and R. R. Philip (2015). "Is High Frequency Trading Beneficial to Market Quality?", CIFR Paper No. 083/2015.

Van Kervel (2015). "Competition for Order Flow with Fast and Slow Traders", The Review of Financial Studies, 28, 7.

Kirilenko, A. and A. S. Kyle, M. Samadi and T. Tuzun (2017). "The Flash Crash: High-Frequency Trading in an Electronic Market", Journal of Finance, 72, Issue 3.

Kwan, A. and R. Philip (2015). "High-Frequency Trading and Execution Costs", *Financial Management Association Annual Meeting*, Orlando, United States. Also in: Centre for International Finance and Regulation (CIFR) Conference: The Design and Regulation of Securities Markets, Sydney, Australia, 12th August 2015.

Tobolsky, T. (2014). "The High-Frequency Algorithmic Trading Method", Periodic Papers 2014.03, Bank of Israel (in Hebrew).

Tong (2013). "A Blessing or a Curse? The Impact of High Frequency Trading on Institutional Investors", Fordham University Working Paper.

Zang, S. and R. Riordan (2011). "Technology and Market Quality: The Case of High Frequency Trading", ECIS 2011 Proceeding, 95.

Zhou H., P. S. Kalev, and G. Lian (2014). *"Algorithmic Trading in Volatile Markets*", SSRN, https://ssrn.com/abstract=2316040.

Appendix 1

Database

This research covers all assets included in the three major equity indices in Israel (Tel Aviv 25, Tel Aviv 75 and Yeter 50) and in two major corporate bond indices (Tel-Bond 20 and Tel-Bond 40)[27], and it is based on transaction data over two consecutive years and on order data transmitted over 7 selected months.[28] The following table lists the sample period and number of observations.

	Transaction data	Order data
Sample period	January 1, 2014 – December 31, 2015	January 1, 2014 – April 30, 2014 December 1, 2014 – December 31, 2014 February 1, 2015 – February 28, 2015 June 1, 2015 – June 16, 2015
Number of observations	44,157,076	626,955,483
Of which: contiguous observations	35,265,378	615,496,200

Definitions and calculation methods

1. Noisy and ordinary days

We distinguished between noisy and ordinary days in two ways:

(1) We calculated the absolute daily change in price of each asset (the difference between the closing price and the base price) for each trading day in such asset.

(2) We calculated the maximum intra-day change in price of each asset (the difference between the highest price and the lowest price).

We included under noisy days 10 percent of the days in which the highest absolute change in price of each asset was generated.[29]

The combination of these two methods allowed us to analyze algo trading activity by distinguishing between days with large changes and days with large fluctuations that were offset intra- day.

[27] This research excludes Government bonds, makam short-duration bills and ETFs.

[28] We only included 7 select months due to considerations of storage space and processing speed, but the Tel Aviv Stock Exchange has provided to us order data transmitted over the entire two-year period.

[29] Unlike Dennis and Strickland (2002), since they chose an absolute benchmark – namely days in which the relevant asset price index (the reference index) changed by 2% or more. We chose a relative benchmark to obtain a sufficiently high number of noisy days.

We chose this definition of noisy days to represent days on which new, material information emerged that resulted in a relatively large change within the trading day.

These variables are not endogenous to algo trading activity nor to any other activity that correlates with turnover and intra-day standard deviation.

2. Liquidity providers (Makers) and liquidity consumers (Takers)

Transaction data allowed us to identify liquidity providers and liquidity consumers. Each transaction in the database contains a unique identifier for the specific order that resulted in the transaction, as well as for each of the two sides to the transaction. Because orders are numbered in chronological order, we could identify which side issued the order first, and thus identify which side provided the liquidity and which side consumed it.

3. Autocorrelation and intra-day standard deviation based on transaction data

We calculated the series autocorrelation and the standard deviation for the rate of change in transaction prices at fixed, predefined time intervals, based on intra-day data for transactions in the asset. We specified three different time intervals: 10 minutes, 20 minutes and 30 minutes. We chose these time intervals because we found that often there was no transaction executed within a time interval shorter than 10 minutes, especially in the less liquid assets. For these assets there was no transaction executed even in a (short) time interval we chose. To address this issue, we included for each asset a control variable that reflects the portion of the trading day in which no transactions were executed in the time intervals we tested. Using this variable, we flagged those assets where the calculation of series autocorrelation and standard deviation was less reliable. Below is the average, standard deviation, and correlation table for these variables in the time intervals we chose.

Statistical data and correlation table for standard deviation and series auto-correlation

for changes in transaction prices for various intra-day time intervals

Indicator	Number of observations	Average	Standard deviation	Median
autocor_deal_10	25,591	-0.06992	0.278979	-0.05813
autocor_deal_20	25,588	-0.05168	0.310768	-0.03992
autocor_deal_30	25,585	-0.058	0.345112	-0.05015
std_deal_10	25,619	0.002712	0.002896	0.001936
std_deal_20	25,619	0.002988	0.003123	0.002212
std_deal_30	25,619	0.003224	0.003367	0.002404

	autocor_deal_10	autocor_deal_20	autocor_deal_30	std_deal_10	std_deal_20
autocor_deal_10	1				
autocor_deal_20	0.71	1			
autocor_deal_30	0.52	0.6947	1		
std_deal_10	-0.10	-0.1216	-0.1335	1	
std_deal_20	-0.01	-0.0802	-0.0929	0.9707	1
std_deal_30	0.05	0.0007	-0.069	0.9366	0.9676

4. Bid-ask spread, autocorrelation and intra-day standard deviations based on order data

Based on order data, we calculated the bid-ask spread for each asset in each index at each point in time during the trading day. We included in our calculation a one-layer spread, defined as the difference between the best sell (ask) price and the best buy (bid) price at each point in time. We then calculated the rate of change in bid price, ask price, midpoint price and spread relative to midpoint price for each of the following time intervals: 1 minute, 5 minutes, 10 minutes, 20 minutes and 30 minutes. Unlike transaction data, order data includes many more variables for each time interval, allowing us to conduct our calculations for shorter time intervals. Here, too, we included a control variable to represent the portion of the trading day in which no orders were transmitted during time intervals, which we used to flag those assets for which the calculations were less reliable. For each time interval we made two calculations: One considered the bid price and the ask price as the last observation in each time interval, whereas the other was based on a time-weighted average of all bid and ask prices in the time interval. We then calculated the daily average, series autocorrelation and standard deviations for the rate of change in these prices. The various calculation methods were used for statistical robustness tests.

Statistical data and correlation table for standard deviation and auto-correlation for changes in midpoint prices on the order book for intra-day time intervals

Indicator	Number of observations	Average	Standard deviation	Median
autocor_mid_1	27,289	0.144	0.243	0.168
autocor_mid_5	27,283	0.121	0.250	0.152
autocor_mid_10	27,281	0.110	0.260	0.138
autocor_mid_20	27,275	0.096	0.288	0.117
autocor_mid_30	27,267	0.070	0.317	0.087
std_mid_1	27,291	0.004	0.013	0.001
std_mid_5	27,289	0.005	0.021	0.002
std_mid_10	27,289	0.005	0.025	0.002
std_mid_20	27,282	0.006	0.031	0.002
std_mid_30	27,279	0.006	0.035	0.002

	autocor_mid_1	Autocor_mid_5	Autocor_mid_10	Autocor_mid_20
autocor_mid_1	1			
autocor_mid_5	0.2719	1		
autocor_mid_10	0.166	0.4954	1	
autocor_mid_20	0.0866	0.259	0.4162	1
autocor_mid_30	0.0587	0.1799	0.2486	0.5618

	std_mid_1	std_mid_5	std_mid_10	std_mid_20
std_mid_1	1			
std_mid_5	0.9266	1		
std_mid_10	0.8835	0.9715	1	
std_mid_20	0.8456	0.9378	0.9746	1
std_mid_30	0.819	0.9143	0.9578	0.9864

It is evident that the larger the time intervals, the lower the series autocorrelation (the faster the price discovery) and the higher the standard deviation (for both the average and median values). It is also evident that correlation between estimates for the different time intervals is very high for standard deviations and lower for autocorrelations. This finding indicates, first and foremost, that as time intervals become longer, the autocorrelation decreases rapidly and significantly.

5. Algo trader strategies

a. Market making strategy

We used the complete order data to study the scope of market making for all algo traders in each of the different assets. We calculated two estimates: 1) We observed the duration of trading of a particular asset and studied the share of the time in which an algo trader issued at least two simultaneous orders for the asset on both sides of the order book. 2) We observed the duration of operation for each algo trader on the trading day and studied the share of the time in which it issued at least two simultaneous orders on both sides of the order book. This resulted in two estimates of the share of time in which each of the algo traders acted as market maker.

Given these estimates, we determined whether the algo trader acted as market maker as follows:

2) We identified all algo traders that issued orders for both sides of the book for at least 20 percent of the time on average, and whose ratio of transactions to orders was 20 percent or lower. We then took all algo traders active in each day in each asset and calculated, for each day and for each asset, the percentage of algo traders that acted as market makers.

b. Arbitrage strategy

We chose to define the algo traders applying the arbitrage strategy as follows: Algo traders who issued, on the same day, orders for multiple assets in the same index, with a particularly low rate of providing liquidity (lower than 25 percent) and with a particularly high ratio of transactions to orders (higher than 50 percent); the high transaction to order ratio indicates algo traders that issue orders rapidly and, consequently, pay higher transaction costs—features typical of players applying the arbitrage strategy. We emphasize that our definition did not require opposite transactions, i.e., both buy and sell transactions.

6. Trading activity in transaction book and in order book

a. In order to determine the scope of algo trading activity based on the order book, we referred to asset j on date i and aggregated each order sent, modified or deleted. The aggregations were made by each one of the accounts, each one of the strategies and for all algo trader accounts.
b. In order to determine the scope of algo trading as a whole based on the transaction book, we referred to asset j on date i and calculated:

$$AT^{Deals}_{i,j} = \frac{Algo\_One\_Side_{i,j} + Algo\_Two\_Sides_{i,j}/2}{All\_Total\_Deals_{i,j}}$$

Where:

$Algo\_One\_Side_{i,j}$ – Number of transactions executed in asset j on date i between algo trader accounts and regular traders.

$Algo\_Two\_Sides_{i,j}$ – Number of transactions executed in asset j on date i between algo traders and algo trader accounts.

$All\_Total\_Deals_{i,j}$ – Total number of transactions executed in asset j on date i.

7. Correlation between change in scope of activity for trading accounts applying the same strategy

First, we slightly reduced the number of active accounts, in order to base our calculations only on accounts where the number of observations was sufficiently large. We excluded the following accounts:

From accounts operated by algo traders:

- Accounts that issued fewer than 1,000 orders throughout the sample period.
- All observations at account-asset level if the account was active in this asset for fewer than 10 days.
- All observations at account-asset level if the account issued on average fewer than 10 orders per day in this asset.

From ordinary accounts:

- All observations at account-asset level if the account was active in this asset for fewer than 10 days.
- All observations at account-asset level if the account issued on average fewer than 5 orders per day in this asset.

The calculation of correlation coefficients was designed to test for any common trends among trading accounts applying similar strategies. We therefore studied the correlations between daily change for each account in activity in each asset and the daily change in activity in the same asset across all other accounts applying the same strategy.

Table 1.1
Technical explanation of variables calculated in this paper, for each day and each asset

	Variable name	**Noisy days**
1	noise_rule_high1	Dummy variable. Consider each asset separately and calculate the difference between the base price and the closing price for each one of the trading days in the sample; Assign the value 1 to the top decile (days on which the largest difference occurred).
2	noise_rule_ high2	Dummy variable. Consider each asset separately and calculate the difference between the highest price and the lowest price for each one of the trading days in the sample; Assign the value 1 to the top decile (days on which the largest difference occurred).
		Algo trader strategies
4	algo_arbitrager	Algo trader accounts that executed transactions in two or more assets in the index, with a ratio of transactions to orders higher than 50 percent and a ratio of providing liquidity no higher than 25 percent.
5	algo_mmdefined	Algo-trader accounts sent orders to both sides of trading for at least 20 percent of the time and with a ratio of transactions to orders no higher than 20 percent.
6	algo_balanced	Balanced accounts – algo accounts where the cumulative daily change in quantity (buy or sell) is up to 7 percent of the total daily trading volume in the account. $\frac{\lvert Sell\_Vol_{i,j,k} - Buy\_Vol_{i,j,k}\rvert}{Sell\_Vol_{i,j,k} + Buy\_Vol_{i,j,k}} \leq 7\%$ Where Buy_Vol and Sell_Vol represent the sum of all units of asset j which account k bought and sold, respectively, on date i.
7	algo_alwaysoneside	Accounts that were never in the Balanced category.
8	algo_maker_prcnt	The share of transactions (by strategy) where the algo accounts provided liquidity (makers) $\frac{Maker\_Deals_{i,j,k}}{Total\_Deals_{i,j,k}}$ Where Maker_Deals represents the number of transactions on date i in asset j in which account k provided liquidity, i.e., was recorded in the order book before the party with which the transaction was executed.

		Benchmarks for trading quality (for each asset for each day)
9	avg_spread_nis	The spread between the best sell and buy prices at each point in time—time-weighted daily average per asset (based on the duration in which the order existed). $\frac{Ask_{i,j,t} - Bid_{i,j,t}}{2\ Mid_{i,j,t}}$ Where: $Mid = \frac{Ask_{i,j,t} + Bid_{i,j,t}}{2}$ On date i, for asset j and time t. Ask, Bid are the best buy and sell prices at any given time t. To obtain the daily data for date i for each asset j, we calculated a time-weighted average: We took the largest spread at any given time, assigned a weighting based on the duration in which it existed and calculated the average.
10	avg_mid_nis	The midpoint between the best sell and buy prices—time-weighted daily average per asset.
11	avg_spread	Spread in percent—spread from the midpoint price.
12	Autocor_mid/deal	Autocorrelation of the intra-day change in asset price—we calculated prices during the trading day for various time intervals (1, 5, 10, 20 and 30 minutes); the price for each interval is equal to the time-weighted average midpoint price on the order book and the average transaction price, weighted by transaction size. Autocorrelation is the correlation between any price change at time t and a price change at time t-1, i.e., the previous time interval, across the entire trading day.
13	Std_mid/deal	Standard deviation of the intra-day change in asset price—we calculated prices during the trading day for various time intervals (1, 5, 10, 20 and 30 minutes); the price for each interval is equal to the time-weighted average midpoint price on the order book and the average transaction price, weighted by transaction size.
14	std_spread	Standard deviation of intra-day change in spread in percentage points—prices during the trading day were calculated for various time intervals (1, 5, 10, 20 and 30 minutes).

Appendix 3 Results of estimation of equation 1[30]

Dependent Variable: avg_spread

Source	SS	df	MS		
Model	5.44786	383	0.01422	Number of obs:	27,272
Residual	6.96475	26,888	0.00026	F(383, 26786):	54.91
Total	12.4126	27,271	0.00046	Prob > F:	0
				R-squared:	0.4389
				Adj R-squared:	0.4309
				Root MSE:	0.01609

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	-0.00523	0.00094	-5.56	0	-0.00708	-0.00339
autocor	0.00532	0.00042	12.75	0	0.0045	0.00614
std_mid	0.3366	0.00442	76.09	0	0.32793	0.34527
ln_volume	-0.0028	0.00012	-23.21	0	-0.00304	-0.00257
std_spread	0.01748	0.00055	31.69	0	0.01639	0.01856
cons	0.04052	0.00283	14.31	0	0.03497	0.04608

Dependent Variable: autocor

	SS	df	MS		
Model	368.077	383	0.96104	Number of obs:	27,272
Residual	1480.07	26,888	0.05505	F(383, 26786):	17.46
Total	1848.14	27,271	0.06777	Prob > F:	0
				R-squared:	0.1992
				Adj R-squared:	0.1878
				Root MSE:	0.23462

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	-0.09521	0.01371	-6.95	0	-0.12208	-0.06835
avg_spread	1.13045	0.08863	12.75	0	0.95672	1.30418
std_mid	0.16199	0.07108	2.28	0.023	0.02266	0.30132
ln_volume	0.00799	0.00178	4.49	0	0.00451	0.01147
std_spread	-0.42113	0.00778	-54.16	0	-0.43637	-0.40589
cons	0.20877	0.04143	5.04	0	0.12757	0.28996

Dependent Variable: std_mid

	SS	df	MS		
Model	6.79149	383	0.01773	Number of obs:	27,272
Residual	10.8917	26,888	0.00041	F(383, 26786):	43.78
Total	17.6832	27,271	0.00065	Prob > F:	0
				R-squared:	0.3841
				Adj R-squared:	0.3753
				Root MSE:	0.02013

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	-0.00517	0.00118	-4.4	0	-0.00748	-0.00287
avg_spread	0.52639	0.00692	76.09	0	0.51284	0.53995
autocor	0.00119	0.00052	2.28	0.023	0.00017	0.00222
ln_volume	0.00058	0.00015	3.78	0	0.00028	0.00088
std_spread	0.02096	0.00069	30.35	0	0.01961	0.02232
cons	-0.01588	0.00355	-4.47	0	-0.02285	-0.00892

[30] In addition to the explanatory variables presented in this appendix, we also used dummy variables for asset and for each point in time.

Dependent Variable: avg_spread if nois e_rule_high==1				Number of obs:	2,639
Source	SS	df	MS	F(383, 26786):	6.13
Model	0.55573	360	0.00154	Prob > F:	0
Residual	0.57344	2,278	0.00025	R-squared:	0.4922
Total	1.12917	2,638	0.00043	Adj R-squared:	0.4119
				Root MSE:	0.01587

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	-0.0152	0.00342	-4.45	0	-0.0219	-0.0085
autocor	0.00304	0.00148	2.06	0.04	0.00014	0.00593
std_mid	0.31308	0.01846	16.96	0	0.27688	0.34928
ln_volume	-0.00355	0.00044	-8.16	0	-0.00441	-0.0027
std_spread	0.02203	0.00223	9.86	0	0.01765	0.02641
cons	0.05778	0.01269	4.55	0	0.03289	0.08266

Dependent Variable: autocor if nois e_rule_high==1				Number of obs:	2,639
Source	SS	df	MS	F(383, 26786):	2.59
Model	47.1999	360	0.13111	Prob > F:	0
Residual	115.176	2,278	0.05056	R-squared:	0.2907
Total	162.376	2,638	0.06155	Adj R-squared:	0.1786
				Root MSE:	0.22486

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	-0.14356	0.04854	-2.96	0.003	-0.23874	-0.04838
avg_spread	0.61027	0.29666	2.06	0.04	0.02852	1.19202
std_mid	0.15051	0.27764	0.54	0.588	-0.39393	0.69496
ln_volume	0.00567	0.00625	0.91	0.365	-0.00659	0.01794
std_spread	-0.47861	0.03075	-15.57	0	-0.5389	-0.41831
cons	0.36479	0.1805	2.02	0.043	0.01084	0.71874

Dependent Variable: std_mid if nois e_rule_high==1				Number of obs:	2,639
Source	SS	df	MS	F(383, 26786):	5.51
Model	0.57123	360	0.00159	Prob > F:	0
Residual	0.65584	2,278	0.00029	R-squared:	0.4655
Total	1.22707	2,638	0.00047	Adj R-squared:	0.3811
				Root MSE:	0.01697

Coef.	Std.	Err.	t	P>t	[95% Conf.	Interval]
algo_orders	0.00095	0.00367	0.26	0.795	-0.00624	0.00815
avg_spread	0.35806	0.02111	16.96	0	0.31666	0.39947
autocor	0.00086	0.00158	0.54	0.588	-0.00224	0.00396
ln_volume	0.00044	0.00047	0.93	0.353	-0.00049	0.00136
std_spread	0.02612	0.00238	10.98	0	0.02145	0.03078
cons	-0.0153	0.01363	-1.12	0.262	-0.04203	0.01143

Dependent Variable: avg_spread

Source	SS	df	MS		
				Number of obs:	27,170
				F(383, 26786):	58.63
Source	SS	df	MS	Prob > F:	0
Model	5.03199	383	0.01314	R-squared:	0.456
Residual	6.00219	26,786	0.00022	Adj R-squared:	0.4483
Total	11.0342	27,169	0.00041	Root MSE:	0.01497

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	-0.00875	0.00104	-8.41	0	-0.01079	-0.00671
autocor	0.00535	0.00039	13.76	0	0.00459	0.00611
std_mid	0.32545	0.00417	77.96	0	0.31727	0.33364
ln_volume	-0.00252	0.00011	-22.19	0	-0.00275	-0.0023
std_spread	0.01769	0.00051	34.41	0	0.01668	0.0187
cons	0.03366	0.0025	13.47	0	0.02876	0.03856

Dependent Variable: autocor

Source	SS	df	MS		
				Number of obs:	27,170
				F(383, 26786):	17.47
Source	SS	df	MS	Prob > F:	0
Model	367.898	383	0.96057	R-squared:	0.1999
Residual	1472.83	26,786	0.05499	Adj R-squared:	0.1884
Total	1840.73	27,169	0.06775	Root MSE:	0.23449

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	-0.0585	0.0163	-3.59	0	-0.09046	-0.02655
avg_spread	1.31236	0.09538	13.76	0	1.12542	1.4993
std_mid	0.16141	0.07243	2.23	0.026	0.01945	0.30338
ln_volume	0.00927	0.0018	5.16	0	0.00575	0.01279
std_spread	-0.42749	0.0078	-54.77	0	-0.44279	-0.41219
cons	0.12514	0.03928	3.19	0.001	0.04815	0.20213

Dependent Variable: std_mid

Source	SS	df	MS		
				Number of obs:	27,170
				F(383, 26786):	43.76
Source	SS	df	MS	Prob > F:	0
Model	6.55601	383	0.01712	R-squared:	0.3849
Residual	10.479	26,786	0.00039	Adj R-squared:	0.3761
Total	17.035	27,169	0.00063	Root MSE:	0.01978

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	0.00341	0.00138	2.48	0.013	0.00071	0.0061
avg_spread	0.5682	0.00729	77.96	0	0.55391	0.58249
autocor	0.00115	0.00052	2.23	0.026	0.00014	0.00216
ln_volume	0.00073	0.00015	4.82	0	0.00043	0.00103
std_spread	0.01956	0.00068	28.59	0	0.01821	0.0209
cons	-0.02281	0.00331	-6.89	0	-0.0293	-0.01632

Dependent Variable: avg_spread
if nois e_rule_high==1

Source	SS	df	MS
Model	0.54828	360	0.00152
Residual	0.56316	2,277	0.00025
Total	1.11145	2,637	0.00042

Number of obs:	2,638
F(383, 26786):	6.16
Prob > F:	0
R-squared:	0.4933
Adj R-squared:	0.4132
Root MSE:	0.01573

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	-0.01671	0.0044	-3.8	0	-0.02534	-0.00808
autocor	0.00354	0.00146	2.42	0.016	0.00067	0.00641
std_mid	0.31316	0.0183	17.12	0	0.27729	0.34904
ln_volume	-0.00311	0.00042	-7.39	0	-0.00394	-0.00228
std_spread	0.02249	0.00222	10.15	0	0.01815	0.02684
cons	0.04211	0.01194	3.53	0	0.01869	0.06553

Dependent Variable: autocor
if nois e_rule_high==1

Source	SS	df	MS
Model	47.0445	360	0.13068
Residual	115.315	2,277	0.05064
Total	162.36	2,637	0.06157

Number of obs:	2,638
F(383, 26786):	2.58
Prob > F:	0
R-squared:	0.2898
Adj R-squared:	0.1775
Root MSE:	0.22504

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	-0.10952	0.06316	-1.73	0.083	-0.23338	0.01433
avg_spread	0.72453	0.29949	2.42	0.016	0.13722	1.31184
std_mid	0.12833	0.27813	0.46	0.645	-0.41709	0.67376
ln_volume	0.00913	0.00609	1.5	0.134	-0.00281	0.02108
std_spread	-0.48222	0.0308	-15.66	0	-0.54262	-0.42182
cons	0.22319	0.17132	1.3	0.193	-0.11277	0.55916

Dependent Variable: std_mid
if nois e_rule_high==1

Source	SS	df	MS
Model	0.57238	360	0.00159
Residual	0.65459	2,277	0.00029
Total	1.22698	2,637	0.00047

Number of obs:	2,638
F(383, 26786):	5.53
Prob > F:	0
R-squared:	0.4665
Adj R-squared:	0.3822
Root MSE:	0.01696

Coef.	Std.	Err.	t	P>t	[95% Conf. Interval]	
algo_deals	0.00138	0.00476	0.29	0.772	-0.00796	0.01072
avg_spread	0.36401	0.02127	17.12	0	0.3223	0.40571
autocor	0.00073	0.00158	0.46	0.645	-0.00237	0.00382
ln_volume	0.0004	0.00046	0.88	0.378	-0.0005	0.00131
std_spread	0.02579	0.00238	10.83	0	0.02112	0.03046
cons	-0.01414	0.01291	-1.1	0.273	-0.03946	0.01117