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Retail investors' trading and stock market liquidity☆

Menachem Meni Abudy

Graduate School of Business Administration, Bar-Ilan University, Ramat Gan, Israel

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ABSTRACT

The paper investigates the relation between retail investors' participation in trading and aggregate stock market liquidity. The findings show a positive and significant relation between retail investors' trading and stock market liquidity. Examination of the determinants of retail investors' trading reveals that, on average, retail investors with more diversified trading activity tend to trade when liquidity is higher, the frequency of their arrival to the market is not affected by the level of liquidity, and retail investors are willing to trade at a lower liquidity level as sellers than as buyers. Moreover, retail investors' trading does not create price noise at the aggregate market level. Overall, the evidence suggests that retail investors contribute to market quality.

1. Introduction

Liquidity is an important determinant of asset pricing. Originally, research on liquidity focused on individual financial assets. However, gradually the understanding that liquidity (along with additional determinants of market microstructure) exhibits commonalities that affect asset classes started to emerge. This led the literature to explore the effect and determinants of aggregate stock market liquidity (e.g., Chordia, Roll, & Subrahmanyam, 2000; 2001;; Chordia, Sarkar, & Subrahmanyam, 2005; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001), and to integrate the effect of aggregate liquidity (also known as market-wide liquidity) in asset pricing models (Acharya & Pedersen, 2005; Jacoby, Fowler, & Gottesman, 2000). Since then, market-wide liquidity has been acknowledged as an important factor of a well-functioning market (e.g., Hanselaar, Stulz, & Van Dijk, 2019; Sadka & Scherbina, 2007) and as a leading indicator of real economic activity (Apergis, Artikis, & Kyriazis, 2015; Ellington, 2018; Florackis, Giorgioni, Kostakis, & Milas, 2014; Naes, Skjeltorp, & Ødegaard, 2011).

This paper investigates whether the participation of retail investors (RIs) in the trading process contributes to aggregate stock market liquidity. During the last decade, there is growing evidence regarding the effect of RI participation in trading (Abudy & Wohl, 2018; Aouadi, Arouri, & Teulon, 2013; Barber, Odean, & Zhu, 2008; Ding & Hou, 2015; Peress & Schmidt, 2020). The literature has examined whether RI trading contains information on the direction of future stock prices, yielding mixed results (Barber et al., 2008; Barrot, Kaniel, & Sraer, 2016; Kaniel, Saar, & Titman, 2008; Kelley & Tetlock, 2013; see Section 2 for details). Moreover, the contribution of RI trading to the liquidity of individual stocks has been explored (Aouadi et al., 2013; Ding & Hou, 2015; Greene & Smart, 1999; Peress & Schmidt, 2020).[1] However, the contribution of RI trading to aggregate stock market liquidity has not been

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E-mail address: menachem.abudy@biu.ac.il.

[1] The contribution of RI trading to the liquidity of individual stocks has been mainly motivated by variations in investors' attention.

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investigated yet. Such examination can further enhance our understanding about the importance of this type of investors to well-functioning capital markets.

To investigate the effect of RI trading on liquidity of the aggregate stock market, I use a proprietary database of the Tel Aviv Stock Exchange (TASE). The database includes transactions executed in the TASE securities, and thus presents a comprehensive picture of the entire stock market. Similar to Abudy and Wohl (2018), I identify about 377,000 "low-volume" investors with an annual trading volume of less than 2 million new Israeli shekels (ILS) in all the TASE securities. As the trading activity of each of these low-volume investors is infrequent, they are almost surely RIs: For example, the mean (median) number of annual trading days, per investor, is 2.15 (0.67). Identifying this investor group allows me to analyze the impact of their direct trading activity on the aggregate stock market liquidity.[2]

To measure RI trading activity, I estimate the proportion of RI trading volume out of the total daily trading volume in the market. As the direction of the causality of the relation between RI trading proportion and aggregate stock market liquidity is unclear, I begin the analysis by employing a Granger causality test. The findings show that RI trading Granger causes aggregate stock market liquidity, while the opposite direction is statistically insignificant (that is, liquidity does not Granger cause RI trading). Additional supportive evidence for the causality of the relation between RI trading and liquidity is provided by the instrumental variable approach of Abudy and Wohl (2018), who show causality between higher RI trading and lower bid–ask spreads in the TASE corporate bond market. Based on these Granger test results, I measure the effect of the proportion of RI trading volume on two measures of liquidity: the bid–ask spread, which is an estimate of the cost of a small round-trip transaction, and Amihud's (2002) measure ILLIQ, which is a proxy for price impact. For both measures, I find a contemporaneous and significant relation, indicating that, on average, higher participation of RI trading increases market liquidity.

Next, I explore how the determinants of RI trading affect aggregate stock market liquidity. The determinants are based on measures that can be extracted from the trading data. Specifically, I calculate the average number of securities and the average number of trading days that each RI traded during each year. Then, for each trading day, I calculate the average number of securities and trading days for the RIs who participated in trading. The average number of securities serves as a proxy for the diversification of the RI group that traded on day t, because trading in a higher number of securities is identified with a more diversified investment in the financial instruments traded on the stock exchange. The average number of trading days serves as a proxy for the frequency that RIs arrive to the market. I find that there is a positive relation between aggregate stock market liquidity and the number of securities that RIs traded in. This indicates that more diversified RIs require a higher level of liquidity to trade. With respect to the average frequency of RI trading, I find no relation between the average number of trading days of RIs and stock market liquidity.

Moreover, I find that when RIs act on the sell side, they are willing to trade at a lower level of liquidity than when they act on the buy side. This finding is in line with previous literature that examines traders' behavior—and not just RIs—in the stock market (see Brennan, Chordia, Subrahmanyam, & Tong, 2012; Kalay, Sade, & Wohl, 2004; Ranaldo, 2004). A possible reason for this difference is that because of limitations/costs of short selling, it is easier to act upon positive information, which drives the buy side, than upon negative information, which drives the sell side. An additional possible explanation is that sellers might need more immediate execution than buyers. Therefore, they are willing to act at higher spreads.

Finally, as the evidence thus far has focused on the contribution of RIs to stock market liquidity, I also examine a potential downside of RI trading on market quality, namely, the price noise it might induce. If RIs create price noise during their trading activity, it can have a distortive effect on their cash flows, which can in turn influence future prices (Kelley & Tetlock, 2013). Consistent with the focus of the paper, I conduct this examination at the aggregate stock market level. Detecting price noise is based on the relation between RI cash flows (net buying) and subsequent returns. To examine potential damage to market quality, I first confirm the causality between RI cash flows and subsequent returns using the Granger causality test. Then, I test whether RI trading generates price noise and find that there is practically no distortive effect of RI trading on cash flows at the aggregate market level.

The paper has several contributions. First, the paper presents evidence for the contribution of RI participation in trading to aggregate stock market quality. This finding is important because, according to existing literature, aggregate stock market liquidity is an important factor of capital markets and in predicting real economic activity. Sadka and Scherbina (2007) find that higher aggregate stock market liquidity accelerates the convergence of prices to fundamentals in stocks with high analysts' disagreement, and Hanselaar et al. (2019) show that equity issuance are positively related to stock market liquidity. Moreover, Apergis et al. (2015), Florackis et al. (2014), Naes et al. (2011), and Ellington (2018) find that aggregate stock market liquidity is a leading indicator of real economic activity such as gross domestic product (GDP) and consumption. Second, the findings indicate that the group of RIs is not uniform, and specific characteristics of these investors have stronger impacts on aggregate stock market liquidity compared with other characteristics. Such findings may assist policymakers and market designers in forming financial literacy programs that will have a positive effect on both the investors and the aggregate stock market. Such programs have been documented to have a positive impact on investor diversification (see Abreu & Mendes, 2010; Mouna & Jarboui, 2015). Third, relative to existing literature, the paper's findings present a complete view of a stock market rather than relying on data from a specific broker. This enables me to capture an examination of costs and benefits of RI participation in trading at the aggregate level.

The remainder of this paper is organized as follows: Section 2 reviews related literature. Section 3 describes the TASE trading process, the data, and the sample of traders. Section 4 describes the contribution of RIs to stock market liquidity. Section 5 reports the determinants of RI trading. Section 6 reports that RI trading does not distort future prices at the aggregate stock market level, and

[2] The detected trading activity is conducted by the RIs themselves through online access to the exchange or through a specific instruction to a broker to submit orders. That is, the RIs have full discretion over their trading activity.

Section 7 summarizes the findings.

2. Related literature

The literature on RI trading addresses several distinct research questions. One prominent question relates to the informational content of this investor group and examines whether RI trading contains information regarding the direction of future prices. The empirical evidence on this research question presents mixed results. Kaniel et al. (2008) find that individual investors' trades at the NYSE are informative about future prices. These findings are consistent with Kelley and Tetlock (2013), who investigate transactions records of certain retail brokers in the US and find that they predict stocks' returns and news. Barrot et al. (2016) investigate a database of a large online broker in Europe. They find that the clients of this broker predict the next day's returns, but on the trading day they incur some losses. In contrast to these findings, Barber and Odean (2000) investigate long-term performance of clients of a discount broker during 1991–1996 and report sizable losses for these investors, and Barber, Lee, Liu, and Odean (2009) find trading losses in horizons of several months for individuals in Taiwan.

The literature also examines the relation between RI trading and the liquidity of individual stocks. To do so, it examines the effects of investor attention.[3] That is, it examines whether changes in investor attention cause changes in a stock's liquidity. In this respect, Greene and Smart (1999) find a positive relation between noise trading and stock liquidity; Ding and Hou (2015) and Aouadi et al. (2013) find that RI attention improves stock liquidity, and Peress and Schmidt (2020) find that news that distracts the attention of retail investors (i.e., news not related to the economy, such as reporting on the verdict in the O. J. Simpson trial) decreases the liquidity of stocks with high retail ownership.[4] On the basis of these empirical findings, Ruan and Zhang (2016) present a theoretical model showing that higher RI attention leads to higher stock liquidity. Empirical examinations of retail trading and stock liquidity *not* via investor attention are performed by Wang and Zhang (2015) and Bloomfield, O'Hara, and Saar (2009). Wang and Zhang (2015) find that stocks that are more heavily traded by individual investors have higher liquidity; Bloomfield et al. (2009) use a laboratory experiment of a simulated market and find that uninformed trading reduces bid–ask spreads. However, their findings will not necessarily prevail in a study that is based on actual trading data.

This paper investigates the effect of RI trading on aggregate stock market liquidity. Prior studies rely on measures of retail trading that may lead to biased inferences regarding RIs as they are based on an incomplete market picture (e.g., inferences based on a single broker, orders selectively routed to a single exchange, or an indirect proxy; see Kelley and Tetlock, 2013). However, in this paper I have the complete transaction record of the market. This enables me to measure the effect of RI trading on stock market liquidity directly, and not via changes in investor attention.

Liquidity is an important factor of capital markets—not only at the security level but also at the aggregate market level. Hanselaar et al. (2019) show that changes in equity issuance are significantly and positively related to lagged changes in the local stock market liquidity. Sadka and Scherbina (2007) find that an increase in aggregate stock market liquidity accelerates the convergence of prices to fundamentals in stocks with high analysts' disagreement. Moreover, aggregate stock market liquidity serves as a leading factor of real economic activity. Apergis et al. (2015) find that when liquidity deteriorates, investors should anticipate lower GDP, investments, and consumption, and higher unemployment rates. Naes et al. (2011) find that aggregate stock market liquidity can serve as a leading indicator of macroeconomic variables in the US and Norway. Moreover, Florackis et al. (2014) find that stock market illiquidity is the best forecast estimator of future UK GDP growth (by documenting a negative relation between these two variables) compared with other variables usually examined, such as term spread of interest rates, short-term interest rates, and real money supply. Ellington (2018) finds that stock market illiquidity is linked to the business cycle in the UK, and that it also yields predictive power for future recessionary periods.

3. Market description and data

3.1. Market description

The Tel Aviv Stock Exchange (TASE) is the only exchange in Israel. It is classified as a developed market according to all data providers (Russell, FTSE, MSCI, S&P, and Dow Jones). All publicly traded securities are traded through the TASE: stocks, government bonds, corporate bonds, warrants, convertibles, exchange-traded funds (ETFs), and various types of derivatives. The major stock indices are the TA-25 and the TA-100, which include the 25 and 100 stocks, respectively, with the highest market capitalization that match certain criteria (the TA-100 index includes the TA-25).[5] The stock lists of the major indices are updated twice a year (at the end of June and the end of December) or following stock listings and de-listings. The stocks are traded by an electronic limit order book

[3] Investor attention relates to the level of attention that investors allocate to financial assets. While in theory investors incorporate new information immediately into security prices—which requires full attention—in practice the attention is limited and therefore asset prices are adjusted accordingly (Da, Engelberg, & Gao, 2011).

[4] Mugerman, Steinberg, and Wiener (2019) show that an increase in information salience, by adding an exclamation mark ("!") designed to highlight risk to the mutual fund's name, plays a significant role in affecting RI behavior, and Aharon and Qadan (2020) find that changes in the volatility index affect investor attention.

[5] In February 2017 (which is after our sample period), the number of stocks in the TA-25 and TA-100 was increased to 35 (from 25) and 125 (from 100), respectively.

Table 1
Summary statistics of the TA-100 stocks. The table reports the cross-section statistics of the 130 stocks of our sample, which were traded on the TA-100 index of the TASE during 2012–2014. The statistics are calculated for the days that the stocks were included in the TA-100 index. *Average return* and *STD* are the average and standard deviation of the daily stock return, respectively. *Daily volume* is the average daily ILS volume. *Number of daily transactions* is the average number of daily transactions. *Size* is the market capitalization calculated at the end of each day and averaged across the sample period for each stock. *Proportion of trading on opening* (*Proportion of trading on closing*) is the average daily ILS volume relative to the total trading volume of the stock during the opening (closing) trading stage.

	N	Mean	SD	Median	Min	Max
Average return	130	−0.04%	0.25%	0.05%	−1.34%	0.24%
STD	130	2.02%	1.00%	1.69%	0.54%	7.53%
Daily volume (in millions ILS)	130	6.24	11.89	1.98	0.23	70.58
Number of daily transactions	130	320	375	152	14	2086
Size (in billions ILS)	130	5.33	15.72	1.65	0.47	153.34
Proportion of trading on opening (%)	130	3.72%	4.29%	1.64%	0.09%	23.82%
Proportion of trading on closing (%)	130	10.75%	4.43%	9.99%	3.40%	23.86%

market. The trading day consists of three stages: an opening and closing sessions, which are call auctions, and a continuous bilateral stage throughout the day. A minimum amount of 5,000 (2,000) ILS on the TA-25 stocks (TA-100 stocks) applies for orders placed in the continuous stage. The opening stage of the trading day for TA-100 stocks occurs between 9:45 and 9:50, the exact time for each stock being arbitrary; the pre-opening stage, where orders are posted, starts at 9:00 am. In the first half of the sample period, the closing call auction stage occurs at 16:28, with the pre-closing stage starting at 16:15. On June 16, 2013, the trading day was extended by an hour from Monday to Thursday, and thus the pre-closing stage now starts at 17:15 and the closing auction occurs at 17:28. In all stages, the limit orders are executed by price and time priority.[6]

During the sample period (2012–2014), there were 27 exchange members at the TASE. These are banks and brokerage firms through which traders submit orders. The exchange members provide their clients with online access to the exchange without any human intervention: The clients can see the status of the order book online and submit orders that are transmitted immediately (after computerized checks) to the exchange. In addition, the exchange members transmit information (status of the book, transactions, etc.) to computerized traders, receive their orders, and transmit them to the exchange. During the sample period, all the traders were able to observe the three best bids and offers of each side of the market.[7] The identity of the exchange members and traders submitting orders is unknown to the market participants.

In Israel, there are no alternative trading systems, such as dark pools. Trading off the exchange is possible, and it is used for very large blocks of securities. For example, according to the TASE website, in 2012 trading off the exchange in TA-100 stocks was 8.95% of the total ILS volume. Some of the stocks on the TASE are dual-listed, mostly in the US.

3.2. The TASE database

I use a unique and proprietary database of the TASE that contains transaction records in which both sides of the transaction are identified using unique trader identification. The identification includes a combination of the identity of the exchange member and a code that identifies the trader among the member's clients.[8] The database does not include the trader's classification (such as retail or institutional). In addition, I use a TASE file that contains updates of the three upper layers in the limit order book. The information available in this file is the time of the update, the quantity, and the proposed price for the security. However, the limit order book information does not include an order code or trader identification.

3.3. Sample description

The sample period is 2012–2014. Market participants during this sample period are similar to market participants in other developed markets, and include various types of participants such as RIs, mutual funds, computerized algo traders, index funds, foreign investors, and institutional investors.[9] Table 1 reports the summary statistics of the stock sample: 130 stocks that were included in the

[6] Hidden orders were introduced in October 2014, but according to the TASE they were rarely used. The TASE also allowed "fill or kill" and "immediate or kill" orders during the sample period, but they were rarely used.

[7] Starting in November 2014, traders are able to observe the five best bids and offers.

[8] For example, if each of two exchange members has client codes of 100, 101, and 102, it will result in six different identification codes that are a combination of the client code and the exchange member code. These numbers are coded to prevent revealing the actual identity of brokers and clients. In addition, to prevent the possibility of identifying the most active traders, the ten most active traders in each year (according to their number of transactions) are represented by one identification code.

[9] Abudy and Wohl (2018) indicate that participants in the Israeli corporate bond market and their market share are similar to those in other developed markets.

Table 2

The activity of retail investors. The sample period is 2012–2014. The table describes the activity of 377,260 retail investors (RIs) who traded in the stock sample and whose annual trading volume in 2012–2014 in TASE's securities (including stocks, government bonds, corporate bonds, ETNs, and warrants, but not options) was below 2 million ILS. The annual trading volume was calculated as the ILS trading volume of the investor divided by the number of years in which they traded. This is called *annual volume in all securities. Annual volume in the stock sample* is the average annual ILS volume in the sample of stocks defined in Table 1. *Number of trading days per year on the TASE* is the number of trading days on which the RI was involved in at least one transaction in TASE securities (excluding options) divided by the number of years that they were active. *Number of trading days per year in the stock sample* is the number of trading days on which the RI was involved in at least one transaction in the stock sample divided by the number of years that they were active. *Number of traded securities per year on the TASE* is the number of securities on the TASE in which the investor had at least one transaction divided by the number of years that they were active. *Number of traded stocks per year in the stock sample* is the number of stocks from our sample in which the investor had at least one transaction divided by the number of years that they were active. *Number of transactions per year in the stock sample* is the number of transactions of the investor in the stock sample divided by the number of years that they were active.

	N	Mean	SD	Median	90% percentile	Max
Annual volume in all securities (in ILS)	377,260	251,588	355,802	103,488	711,990	1,999,865
Annual volume in the stock sample	377,260	55,939	131,300	13,912	133,655	1,930,639
Number of trading days per year on the TASE	377,260	4.83	9.64	2.00	10.67	244.33
Number of trading days per year in the stock sample	377,260	2.15	5.50	0.67	4.33	238.00
Number of traded securities per year on the TASE	377,260	3.91	4.91	2.00	10.00	360.67
Number of traded stocks per year in the stock sample	377,260	1.23	1.65	0.67	3.00	33.67
Number of transactions per year in the stock sample	377,260	4.98	14.23	1.33	11.00	2,392.00

TA-100 index during the sample period. The table reports statistics only for days when the stocks were included in the TA-100. At the daily level, the stocks are aggregated to obtain estimates at the market level. Specifically, as the direct activity of traders occurs at the individual stock level, aggregating the direct activity of the traders can provide meaningful results on their market impact.

According to Table 1, the stocks have a mean (median) daily return of −0.04% (0.05%) and a mean (median) daily standard deviation of 2.02% (1.69%). Their average (median) daily volume is 6.24 (1.98) million ILS, and 3.72% (10.75%) of the average daily volume is during the opening (closing) trading phase. At the aggregate level, during the sample period the TA-100 index had a daily average (median) return of 0.040% (0.065%) with a daily standard deviation of 0.70%. These estimates are similar to studies conducted on the TASE (Abudy & Shust, 2020).

3.4. The sample of traders

The database does not include information about the traders' type (retail, institutional, etc.). Therefore, following Abudy and Wohl (2018), I rely on trading information to classify traders and identify small RIs. I identify a trader as an RI if their average annual trading volume in all TASE securities (including stocks, government and corporate bonds, exchange-traded notes [ETNs], and warrants) is less than 2 million ILS during the years that they were active (roughly $544,000 in the sample period 2012–2014).[10] These investors are very likely retail.[11] Note that a cutoff of an average annual trading volume of 2 million ILS may be restrictive, because it is possible that there are RIs with higher trading volumes. However, non-retail investors with such low trading volumes are probably rare. As a robustness check, I also examine a cutoff of 1.5 million ILS and a cutoff of 3 million ILS to identify RIs. All the main findings of the paper remain qualitatively similar.

Table 2 reports the summary statistics of the activity of these investors. I find 377,260 RIs who traded in the stock sample during the sample period, which represents 95% of the traders in the stock sample. The table shows that per investor, their trading activity is relatively low and infrequent. The average (median) annual trading volume, per investor, in all TASE securities (excluding options) is 251,588 (103,488) ILS. In our sample of TA-100 stocks, the average (median) annual trading volume, per investor, is 55,939 (13,912) ILS. Per investor, the average (median) number of annual trading days on the TASE—out of an average of 244.3 possible trading days per year—is 4.83 (2.00). The investor in the ninetieth percentile of annual trading days traded on 10.67 trading days per year. The average (median) number of annual trading days for the sample of stocks is 2.15 (0.67). However, while these estimates point out that on the individual level, RI trading is low, because the number of RIs is relatively high, their aggregate volume is not negligible: 7.6% of the double-sided trading volume. This estimate is similar to the retail trading proportion found by Boehmer, Jones, Zhang, and Zhang (2019), who report that according to their identification, 6.91% of the average total traded shares is traded by RIs in the US equity market.

[10] I divide each trader's ILS volume during 2012–2014 by the number of years that they were active (i.e., had at least one transaction in the year).

[11] While it is possible that a trader trades through different exchange members or through different accounts of a given exchange member, casual observation suggests that RIs tend to concentrate their trading activity in one account. In any case, an account that trades less than 2 million ILS per year is likely to be an account of an RI.

Table 3

Examining Granger causality. The table reports a Granger causality test between the changes in the daily market's bid–ask spread, BAS, and the changes in daily retail trading proportion in the market, PROP_RI. The market bid–ask spread is calculated as follows: For each stock, I estimate an hourly observation of half the difference between the ask price and the bid price, divided by the mid-quote, calculated at six time points each trading day, namely, on the hour from 10:00 to 16:00. This hourly observation is winsorized if the value is greater than 10% or if there is no valid bid–ask spread. The $BAS_{j,t}$ of stock *j* is the average of these intra-daily observations on day *t*. The market's BAS_t is the average of $BAS_{j,t}$ across TA-100 stocks on day *t*. ΔBAS_t is the change in the market's BAS from day *t-1* to day *t*. $PROP\_RI_t$ is calculated as the average of the daily retail investors' trading volume as buyers and sellers, divided by the daily total trading volume in the stock market. $\Delta PROP\_RI_t$ is the change in this daily retail proportion.

	ΔBAS_t		$\Delta PROP\_RI_t$	
	(1)	(2)	(3)	(4)
Intercept	−0.0002	−0.0002	0.0074	0.0078
	(−0.23)	(−0.22)	(0.09)	(0.10)
ΔBAS_{t-1}	−0.4786	−0.4598		2.9003
	(−13.46)	(−12.59)		(0.95)
ΔBAS_{t-2}	−0.2803	−0.2612		−0.3729
	(−7.89)	(−7.15)		(−0.12)
$\Delta PROP\_RI_{t-1}$		−0.0011	−0.6398	−0.6468
		(−2.47)	(−18.32)	(−17.97)
$\Delta PROP\_RI_{t-2}$		−0.0009	−0.3356	−0.3330
		(−2.02)	(−9.61)	(−9.24)
R^2	0.2077	0.2153	0.3163	0.3174
Granger *F*-test	3.532			
			0.580	
Granger *p*-value	0.030			
			0.560	
N	130	130	130	130

4. Retail investors and stock market liquidity

This section presents evidence on the contribution of RIs to stock market liquidity. As the direction of the causality between RI trading and liquidity is unknown, I begin by examining the direction of the causality between these variables. The causality examination is based on the Granger (1969) causality test. The liquidity is measured using the average of the daily half bid–ask spreads (BAS) over the stocks included in the TA-100 index (see the Appendix for a formal definition). RIs' trading activity is measured using their proportion in the daily trading activity, measured as RI daily trading volume out of the total daily trading volume in the market, denoted as PROP_RI. The unrestricted model in the Granger causality test is[12]

$$\Delta BAS_t = \alpha_1 + \sum_{i=1}^{2} \beta_i \cdot \Delta BAS_{t-i} + \sum_{i=1}^{2} \lambda_i \cdot \Delta \mathrm{PROP}_R I_{t-i} + u_t \tag{1}$$

and the restricted model is

$$\Delta BAS_t = \alpha_1 + \sum_{i=1}^{2} \beta_i \cdot \Delta BAS_{t-i} + e_t \tag{2}$$

where $\Delta BAS_t = BAS_t - BAS_{t-1}$ and $\Delta PROP_R I_t = PROP_R I_t - PROP_R I_{t-1}$.

The findings, presented in Table 3, show a statistically significant Granger causality between RI proportion and liquidity. The *p*-value (*F*-test) of the Granger test is 0.030 (3.532).[13] That is, the direction of the causality is that a change in RI proportion affects the level of liquidity. To complete the causality examination, I also employ a Granger causality test to examine causality in the opposite direction (where $\Delta PROP_R I_t$ is the dependent variable). That is, I examine whether the change in the bid–ask spreads Granger cause RI proportion, and find that it is statistically insignificant, with an *F*-test of 0.58 (see Table 3). As additional supportive evidence note that the instrumental variable approach of Abudy and Wohl (2018) shows causality between RI trading and low bid–ask spreads in the TASE corporate bond market.

Based on the Granger causality test results, I estimate the impact of RI trading on stock liquidity. I employ two specifications: The first specification is where the dependent variable is the log of a stock's bid–ask spread, BAS_j. The second specification is where the dependent variable is Amihud's (2002) liquidity measure ILLIQ. While the bid–ask spread measures the cost of a small quantity round-trip transaction, Amihud's (2002) measure ILLIQ is a proxy for measuring the price impact in the market (intuitively, ILLIQ measure can be interpreted as the price change that is associated with one unit of trading volume). Each of the liquidity measures is regressed on

[12] As BAS and PROP_RI are not stationary, I use ΔBAS and ΔPROP_RI to achieve stationarity in the latter variables.

[13] I also perform a Granger causality test where the independent variable is Amihud's (2002) liquidity measure ILLIQ. The results are similar to the ones in Table 3.

Table 4

The effect of retail investors' trading on the bid–ask spread. The table reports regressions that examine the relation between retail investor (RI) trading participation and market liquidity. In columns (1) and (2), the dependent variable is LOG_BAS_j. For each stock, I estimate an hourly observation of half the difference between the ask price and the bid price, divided by the mid-quote, calculated at six time points each trading day, namely, on the hour from 10:00 to 16:00. This hourly observation is winsorized if the value is greater than 10% or if there is no valid bid–ask spread. LOG_BAS_j of stock *j* is the log of the average of these intra-daily observations (within days and then across days). In columns (3) and (4), the dependent variable is ILLIQ. For each stock, it is the average of the absolute value of the daily stock return divided by the daily trading volume (in millions ILS). $PROP\_RI_j$ is the trading volume of RIs out of the total trading volume. STD_j is the standard deviation of the daily returns of stock *j*. LOG_SIZE_j is the log of the stock's market value. TA-25 is a dummy variable that equals 1 in the case the stock is included in the TA-25 index and zero otherwise.

	LOG_BAS		ILLIQ	
	(1)	(2)	(3)	(4)
Intercept	6.262	7.104	30.085	30.085
	(7.84)	(9.80)	(7.71)	(7.71)
$PROP\_RI_j$		−0.048		−0.077
		(−5.86)		(−2.50)
STD_j (%)	−0.111	−0.027	0.333	0.457
	(−3.07)	(−0.78)	(2.22)	(2.90)
LOG_SIZE_j	−0.521	−0.563	−2.011	−1.944
	(−9.40)	(−11.31)	(−7.04)	(−7.00)
TA-25	−0.258	−0.302	1.937	1.575
	(−1.89)	(−2.49)	(3.31)	(2.70)
R^2	0.7315	0.7894	0.5467	0.5581
N	130	130	130	130

a set of explanatory variables that are characteristics that affect liquidity, each of them calculated across the entire sample period. The sample consists of 130 stocks that were included in all or part of the sample period in the TA-100 index. The results are presented in Table 4. The analysis uses three exogenous stock characteristics that affect liquidity. First, prior literature relates between volatility and bid–ask spreads (e.g., Copeland & Galai, 1983; Glosten & Milgrom, 1985). Hence, we control for the standard deviation of daily returns (STD_j). Moreover, spreads are known to relate to firm size (Stoll & Whaley, 1983). This determinant is controlled for using the log of the stock's market value (LOG_SIZE_j). Last, we use a dummy variable called TA-25 that equals 1 in the case the stock is included in the TA-25 index and zero otherwise.[14] Inclusion of this dummy variable is aimed to capture an additional dimension of firm size, as this index includes the largest stocks in the TASE.

Columns (1) and (2) of Table 4 show the results for the bid–ask spread as the independent variable. As expected, the coefficients of the control variables are negative and significant, indicating that, on average, more volatile and larger stocks are more liquid. Regression (2) adds the proportion of RI volume out of the total volume of the stock, $PROP\_RI_j$. The coefficient of this variable is −0.048, indicating that a 1% increase in $PROP\_RI_j$ is related to a decrease of about 4.7% in the stock's BAS_j ($e^{-0.048} - 1 \approx -0.047$). To the extent that RI trading can be identified with noise trading, this result is consistent with Kyle's (1985) prediction that noise trading increases market liquidity.

A similar picture arises when we use Amihud's (2002) liquidity measure, ILLIQ, as the independent variable. The results appear in columns (3) and (4) of Table 4. Similar to the bid–ask spread, a higher (lower) value of ILLIQ indicates a lower (higher) level of liquidity. The inclusion of $PROP\_RI_j$ improves the explanatory power of the regression. The coefficient of this variable equals −0.077 and is statistically significant, indicating that a 1% increase in $PROP\_RI_j$ is related to a decrease of about 7.7% in the stock's $ILLIQ_j$.

5. Determinants of retail investors and stock market liquidity

This section explores the determinants of RI trading that may affect aggregate stock market liquidity. These determinants are based on characteristics of RIs that can be extracted from the trading data. The first subsection relates to the determinants of RI presence in the stock market. The second subsection relates to the differential effect that RIs may have on liquidity when they act as sellers vs. when they act as buyers. Notably, both effects are analyzed while controlling for additional factors that affect liquidity.

5.1. Determinants of retail trading

In this subsection, I examine the relation between characteristics of RIs who participate in trading and aggregate stock market liquidity. For each trading day, I refer to the daily trading volume of RIs in the stock market, the average number of securities that each RI traded in during the year, and the average number of trading days that each RI traded on during the year (see the Appendix for variable definitions). The average number of securities serves as a proxy for the diversification of the RI group that participated in

[14] An additional common liquidity driver is trading volume (Copeland & Galai, 1983; Glosten & Milgrom, 1985). However, in the stock sample it is highly correlated with firm size, and therefore causes multicollinearity that biases the results. A robustness check that replaces trading volume with firm size yields similar results to the ones reported in Table 4.

Table 5

Regressions of market bid–ask spread on the index and investor characteristics. The table presents the coefficients from the time-series regressions of the market bid–ask spread on explanatory variables of the underlying index and retail investor (RI) characteristics. The sample period is 2012–2014. The sample is defined in Table 1. In Panel A, the dependent variable is the average of the daily TA-100 stocks' bid–ask spread, BAS_t. For each stock, I estimate an hourly observation of half the difference between the ask price and the bid price, divided by the mid-quote, calculated at six time points each trading day, namely, on the hour from 10:00 to 16:00. This hourly observation is winsorized if the value is greater than 10% or if there is no valid bid–ask spread. The $BAS_{j,t}$ of stock *j* is the average of these intra-daily observations on day *t*. The market's BAS_t is the average of $BAS_{j,t}$ across TA-100 stocks on day *t*. In Panel B, the dependent variable is the market's ILLIQ. Each day for each stock, I divide the absolute value of the stock's return by the daily trading volume of the stock (in millions ILS). The market's ILLIQ is the daily average of the stocks. STD is the daily standard deviation of the TA-100 index. Using the weights of each stock in the TA-100 index, I calculate the index return each minute from 10:00 to 16:00. The daily standard deviation of TA-100 is the standard deviation of these minute returns. MKT_vol is the log of the daily ILS trading volume of the TA-100 index. It is calculated as the sum of the daily ILS trading volume of all TA-100 stock index. RI_traded_vol is the log of the daily ILS trading volume of RIs in the TA-100 index. RI_sec_num is the average number of securities that the RIs who participated on trading day *t* traded per year. For each RI, I calculate the number of securities that they traded during a calendar year. Then, I calculate the daily average of this figure for all the RIs who participated in trading for each trading day. RI_days_num is the average number of trading days that the RIs who participated on trading day *t* traded per year. For each RI, I calculate the number of trading days on which they participated (i.e., made at least one transaction during the continuous trading phase) during a calendar year. Then, I calculate the daily average of this figure for all the RIs who participated in trading for each trading day. Ratio_seller is the daily ratio of the ILS selling trading volume of RIs relative to the sum of the ILS trading volume of RIs in the TA-100 index.

Panel A	(1)	(2)	(3)	(4)	(5)
Intercept	0.874	1.217	1.554	1.182	1.178
	(9.23)	(10.50)	(13.47)	(9.95)	(10.23)
STD	4.504	4.599	4.036	4.557	4.453
	(16.69)	(17.28)	(15.60)	(17.01)	(16.74)
MKT_vol	−0.036	−0.021	−0.023	−0.021	−0.018
	(−7.53)	(−3.71)	(−4.36)	(−3.82)	(−3.34)
RI_Traded_vol		−0.036	−0.036	−0.034	−0.040
		(−4.98)	(−5.37)	(−4.73)	(−5.56)
RI_sec_num			−0.009		
			(−9.35)		
RI_days_num				0.0005	
				(1.32)	
Ratio_seller					0.134
					(3.98)
R^2	0.2803	0.3040	0.3787	0.3057	0.3189
N	734	734	734	734	734
Panel B	(1)	(2)	(3)	(4)	(5)
Intercept	33.167	40.473	45.051	38.498	39.770
	(14.58)	(14.89)	(15.97)	(13.88)	(14.63)
STD	80.606	82.793	75.257	80.340	80.352
	(12.46)	(12.95)	(11.65)	(12.56)	(12.51)
MKT_vol	−1.608	−1.262	−1.295	−1.303	−1.226
	(−14.11)	(−9.43)	(−9.83)	(−9.75)	(−9.16)
RI_traded_vol		−0.819	−0.827	−0.736	−0.888
		(−4.75)	(−4.88)	(−4.25)	(−5.12)
RI_sec_num			−0.125		
			(−5.08)		
RI_days_num				0.0287	
				(3.18)	
Ratio_seller					2.237
					(2.76)
R^2	0.2703	0.2921	0.3163	0.3018	0.2994
N	734	734	734	734	734

trading, because trading in a higher number of securities is identified with a more diversified knowledge of the financial instruments traded on the exchange. The average number of trading days serves as a proxy for the average frequency at which RIs who participated in trading arrive to the market. The question is whether a more diversified knowledge or a higher arrival frequency of RIs affects aggregate stock market liquidity. In the regression analysis, I also control for the daily ILS trading volume of RIs in the stock market. This variable is expected to have a positive effect on liquidity. In addition, I control for the daily standard deviation and the daily trading volume of the stock market.

Table 5 reports the result of this time-series analysis. The unit of analysis is the daily estimates of the variables mentioned above. The *t*-statistics of the coefficients are calculated using the Newey–West (Newey & West, 1987) method, with the number of lags varying according to the auto-correlation of the coefficient. In Panel A, the dependent variable is BAS (i.e., the daily average bid–ask spread of the index's stocks). Column (1) relates only to the daily standard deviation and the daily trading volume of the stock market as explanatory variables. The purpose of this analysis is to verify that the coefficients are in the expected direction. For the daily standard deviation STD_t, I calculate the TA-100 index value each minute and use it to calculate the daily standard deviation. In addition, I use

Table 6

Regressions of market returns on lagged variables. The table presents the coefficients from the time-series regressions of market returns on the respective variables. The sample period is 2012–2014. The sample is defined in Table 1. The dependent variable is the TA-100 daily stock index return (RTN). RTN(t-1) to RTN(t-5) are lagged daily index returns from period (t-1) to (t-5), respectively. NNF is the normalized daily net flows of retail investors (RIs), calculated as the daily ILS value of all RI buys minus the daily ILS value of all RI sells, divided by the daily ILS volume of the TA-100 index. NNF(t-1) to NNF(t-5) are lagged normalized daily net flows from period (t-1) to (t-5), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.038	0.043	0.020	0.030	0.034	0.020
	(1.46)	(1.63)	(0.59)	(0.66)	(0.76)	(0.57)
RTN(t-1)	0.018	0.007			0.009	0.017
	(0.48)	(0.19)			(0.25)	(0.47)
RTN(t-2)		−0.018			−0.017	
		(−0.50)			(−0.45)	
RTN(t-3)		−0.065			−0.065	
		(−1.75)			(−1.75)	
RTN(t-4)		−0.062			−0.059	
		(−1.66)			(−1.59)	
RTN(t-5)		−0.025			−0.033	
		(−0.68)			(−0.87)	
NNF(t-1)			−1.117	−1.361	−1.581	−1.111
			(−0.77)	(−0.88)	(−1.58)	(−0.77)
NNF(t-2)				0.171	0.262	
				(0.11)	(0.16)	
NNF(t-3)				−1.886	−1.756	
				(−1.17)	(−1.08)	
NNF(t-4)				3.002	3.036	
				(1.86)	(1.87)	
NNF(t-5)				−0.331	−0.485	
				(−0.21)	(−0.31)	
R^2	0.0003	0.0092	0.0008	0.0066	0.0159	0.0011
N	733	729	733	729	729	733

the log of the daily trading volume. Indeed, as expected, higher standard deviation (trading volume) increases (decreases) aggregate stock market liquidity.

Columns (2)–(4) of Panel A present additional explanatory variables that relate to the characteristics of RIs as a group. Column (2) relates to the daily trading volume of RIs and its effect on the market's bid–ask spread using the variable RI_traded_vol. As expected, this relation is negative and significant, with a coefficient of −0.036 and a *t*-stat of −4.98. That is, an increase of 1% in the daily trading volume of RIs decreases the market's bid–ask spread by 0.036% on average. Column (3), in addition to the RI trading volume, relates to the average of the annual number of securities that RIs who participated on trading day *t* traded in. As noted above, this variable serves as a proxy for financial knowledge, because trading in a higher number of securities on the exchange is identified with more diversified investment in financial instruments. As expected, the coefficient of this variable is negative and significant, with a value (*t*-stat) of −0.009 (−9.35). That is, on average, if RIs trade in one more security, then the market's BAS decreases by approximately one basis point. Column (4) relates to the average of the number of trading days that the RIs traded on during the year. This variable is calculated daily according to the RIs who participated on trading day *t*. This variable, which proxies for the frequency with which RIs trade in the market, is also expected to have a negative sign. However, the results show that it is statistically insignificant (a *t*-stat of 1.32). This indicates that, on average, a higher arrival frequency of RIs to the market has no impact on the market's bid–ask spread.

I perform several robustness tests for these results. First, as an explanatory variable, I use the log of BAS, which yields similar results to those that appear in Table 5. Moreover, rather than examine the entire stock exchange, I calculate the variables of RI characteristics for the TA-100 index and use them as explanatory variables (for example, instead of calculating the average number of securities that RIs traded on the TASE, I calculate the average number of securities that RIs traded on the TA-100). The results remain qualitatively similar in all cases.

Panel B of Table 5 presents a similar analysis to the one that appears in Panel A. The only difference is that the independent variable is Amihud's (2002) measure ILLIQ. Overall, the results in Panel B are similar to those in Panel A. That is, both stock and RI characteristics have a significant effect on this price impact proxy of the stock market.

Overall, the results show that aggregate stock market liquidity is affected not only by the daily trading of RIs but also by the type of RIs who arrive to the market. If these RIs are more experienced in trading in a variety of securities, their contribution to the liquidity in the market will be higher. A further inquiry in this direction may assist regulators, policymakers, and market designers to better enhance the trading motives for direct RI trading in stock markets. A possible avenue in this respect is investing in financial literacy, which has been documented to have a positive impact on investor diversification (Abreu & Mendes, 2010; Mouna & Jarboui, 2015).

5.2. The effect of retail investors' buys vs. Sells

The literature provides evidence that trading activity of buyers has different characteristics relative to trading activity of sellers. This evidence relates to all types of traders in the market and not just to RIs. Brennan et al. (2012) show that the liquidity premium in equities arises mainly from the sell order side in the cross-section of stocks. Ranaldo (2004) and Kalay et al. (2004) present empirical evidence suggesting that buy orders tend to be more information-motivated than sell orders, and Saar (2001) presents a theoretical model that explains the permanent price impact asymmetry between buyer-initiated and seller-initiated block trades. With respect to RIs, Barber and Odean (2000) show different execution costs (denoted there as "spread") for retail buyers and retail sellers (see Table 1 in their paper).

Following this line of literature, I examine whether RIs tend to trade at different levels of liquidity in their trading activity as buyers and sellers, using the variable $Ratio\_seller_t$. This variable measures the daily proportion of RIs trading as sellers relative to their total trading activity. The results, presented in column (5) of Panels A and B of Table 5, show that the coefficient of $Ratio\_seller_t$ is positive and significant, indicating that RIs tend to act as sellers when the market's bid–ask spread or when ILLIQ is higher. With respect to the bid–ask spread as the independent variable, the value of the coefficient, 0.134, indicates that a 1% increase in the ratio of RIs as sellers in the market increases the spread by a value of 0.134, on average. With respect to the ILLIQ as the independent variable, the value of the coefficient, 2.23, indicates that a 1% increase in the ratio of RIs as sellers in the market increases the ILLIQ by a value of 2.23, on average. Thus, RIs act as sellers even when the liquidity in the market is lower, but as buyers they demand higher liquidity.

A possible reason for the difference between sellers and buyers is that because of the limitations/costs of short selling, it is easier to act upon positive information, which drives the buy side, than upon negative information, which drives the sell side. Hence, RIs face more informed trading when they are sellers. An additional possible explanation is that sellers might need more immediate execution than buyers. Therefore, they are willing to act at higher spreads.

6. Do retail investors distort future prices at the aggregate stock market level?

The potential downside of RI trading is the price noise that RIs might induce in the market (Foucault, Sraer, & Thesmar, 2011). It is possible that RIs' net trading activity (buys minus sells, hereafter "flows") pushes prices from their fundamental levels. Detecting price noise is based on the relation between flows and *subsequent* returns. This is because a distortive effect should influence *future* prices.

To examine this question, I consider the daily returns of the TA-100 index, denoted as RTN_t. I also consider the normalized net flow of each day. This is the ILS value of all buys made by RIs minus the ILS value of all sells made by RIs divided by the daily ILS volume of all TA-100 stocks, denoted by NNF_t (normalized net flow). Table 6 reports the results, where the TA-100 returns (RTN_t) are regressed on lags of NNF, lags of RTN, and lags of both NNF and RTN. The results indicate that TA-100 returns are not related to the lags of NNF (alone or with the lags of RTN). A formal Granger causality test for NNF causing RTN is based on an *F*-test for an unrestricted model (regression 6) vs. a restricted model (regression (1)). The result is very insignificant: *p*-value of 0.23. Overall, these results show that aggregate RI trading does not distort future prices at the aggregate stock market level.[15]

7. Summary

This paper examines the contribution of the group of RIs with low trading volume to aggregate stock market liquidity using a unique database of the TASE that enables me to proxy these investors.

The findings reveal that RI participation in trading contributes to aggregate stock market liquidity. First, I find that RI participation in trading Granger causes stock market liquidity. After establishing causality, I find there is a positive relation between RI trading activity and stock market liquidity. Moreover, exploring the determinants of RI trading reveals that in case more diversified RIs arrive to trade in the stock market, they require, on average, a higher level of liquidity to trade. Conversely, when RIs with higher trading frequency arrive to trade, they do not require a higher level of stock market liquidity. Further, consistent with existing literature regarding liquidity at the stock level, I find that when RIs act as buyers, they require a higher level of liquidity to trade relative to their trading activity as sellers. Last, I examine the possible cost that RI trading activity may have on market quality—which is the price noise it might induce. However, I find that at the aggregate stock market level, RI trading does not create noise.

Overall, the findings highlight the positive effect that RIs have on market quality. First, the findings show that the group of RIs is not uniform and that exposing them to financial knowledge—such as diversification—can contribute to market quality. These findings carry a message for market designers, regulators, and policymakers about the importance of financial literacy that will assist to increase direct retail trading in capital markets. Second, as market-wide liquidity is an asset pricing factor, it follows that higher participation of RIs in trading may have positive effects on expected returns and firms' cost of capital. Such implications may be the subject for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

[15] I also examined Table 6 regressions using ILLIQ as the independent variable. The results (untabulated) are similar.

influence the work reported in this paper.

Appendix. – Variable definitions

Variable	Definition
BAS	The daily half bid–ask spread (BAS) in the market. For each stock, I estimate an hourly observation of half the difference between the ask price and the bid price, divided by the mid-quote, calculated at six time points each trading day, namely, on the hour from 10:00 to 16:00. Formally, the hourly observation is $\frac{Ask_{i,j,t} - Bid_{i,j,t}}{2 \cdot Mid_{i,j,t}}$, where $Mid_{i,j,t}=(Ask_{i,j,t} + Bid_{i,j,t})/2$, and $Ask_{i,j,t}$ and $Bid_{i,j,t}$ are ask and bid quotes prevailing on day *i* for stock *j* at hour *t*, respectively. This hourly observation is winsorized if the value is greater than 10% or if there is no valid bid–ask spread.$BAS_{j,t}$ of stock *j* is the average of these intra-daily observations on day *t*. The market's daily BAS is the average of $BAS_{j,t}$ across TA-100 stocks.BAS_j of stock *j* is the average of these intra-daily observations (within days and then across days).
ILLIQ	The Amihud (2002) measure, calculated as the average of the absolute value of daily return divided by the daily ILS trading volume (in millions ILS).
PROP_RI	The daily proportion of retail investor (RI) trading volume out of the total trading volume.RI daily proportion in stock *j*:$\frac{(RI\ buys\ in\ stock\ j\ +\ RI\ sales\ in\ stock\ j)/2}{stock\ j\ trading\ volume}$RI daily proportion in the stock market:$\frac{(Daily\ RI\ buys\ +\ daily\ RI\ sales)/2}{total\ market\ trading\ volume}$
STD	The daily standard deviation of the TA-100 index. Using the weights of each stock in the index, I calculate the index return each minute from 10:00 to 16:00. The index's daily standard deviation is the standard deviation of these minute returns.
MKT_vol	The log of the daily ILS trading volume of the TA-100 index. It is calculated as the sum of the daily ILS trading volume of all the stocks that are included in the index.
RI_Traded_vol	The log of the daily ILS trading volume of retail investors in the TA-100 index.
RI_sec_num	For each retail investor, I calculate the number of securities that they traded in a calendar year. Then, for each trading day, I calculate the average of this figure for all the retail investors who participated in trading.
RI_days_num	For each retail investor, I calculate the number of trading days that they participated in trading (i.e., made at least one transaction during the continuous trading phase) in a calendar year. Then, for each trading day, I calculate the average of this figure for all retail investors who participated in trading.
Ratio seller	The daily ratio of the ILS selling trading volume of retail investors relative to the sum of the daily ILS trading volume of retail investors in the TA-100 index. Formally, it equals$\frac{Daily\ RI\ sells}{Daily\ RI\ buys\ +\ daily\ RI\ sells}$
RTN	The daily return of the TA-100 index.
NNF	The daily normalized net flows of retail investors, calculated as the ILS value of all daily retail investorinvestors buys minus the daily ILS value of all retail investors sells, divided by the daily ILS volume of the TA-100 index. Formally, it equals$\frac{Daily\ RI\ buys\ -\ daily\ RI\ sells}{Daily\ trading\ volume}$

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