Journal of Corporate Finance 35 (2015) 120–135

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Does individual investor trading impact firm valuation?

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ARTICLE INFO

Article history:
Received 2 June 2013
Received in revised form 30 July 2015
Accepted 1 August 2015
Available online 9 August 2015

JEL classification:
G14
G32

Keywords:
Individual investor trading
Firm valuation
Granger causality
Information production
Bid-ask spread

ABSTRACT

Motivated by recent evidence of informed trading by individual investors (Kaniel et al., 2012; Kelley and Tetlock, 2013; Wang and Zhang, 2015), we posit that individual investor trading enhances firm performance. Consistent with the conjecture, we find that individual investor trading positively impacts firm value. The results are robust to inclusion of year, industry and firm fixed effects, alternative model specifications, a control for endogeneity, Granger causality test, matched sample analysis and subsample analyses. The positive effect of individual investor trading on firm value is stronger for firms with higher information production and stocks with higher spread, consistent with the information and spread channel mechanism. Our results suggest that trading by individual investors enhances firm value by improving stock price informativeness and reducing spread.

1. Introduction

The role of individual investor trading in financial markets is a subject of widespread interests. However, the relevant evidence is far from converging. Some studies indicate that individual investors are subject to fads and psychological biases (Odean, 1998; Barber and Odean, 2000; Kumar, 2009; Han and Kumar, 2013), are uninformed noise traders (e.g., Kumar and Lee, 2006; Barber et al., 2009a, 2009b; Ng and Wu, 2010), and their trading activity adds volatility to stock prices (Foucault et al., 2011).

However, there is also a strong literature that points to the collective rationality of individual's in the marketplace and to the informativeness of individual investor trading.[2] Forsythe et al. (1992) find that a sufficient number of traders in Iowa Political Stock Market were free of judgment bias. Jackson (2003) finds trades of individuals predict future market returns on the Australian Stock Exchange. Kaniel et al. (2012) find that aggregate individual investor trading predicts abnormal returns on and after earnings announcement dates, and about half of the post earnings announcement abnormal returns can be attributed to private information. Kelley and Tetlock (2013) find that retail investors' orders convey fundamental information and the aggregated decisions of retail traders contribute to market efficiency. In particular, they offer two potential channels for reconciling the recent findings of informed individual investor trading with prior studies. First, the individual investor trading data used in previous research may not be representative. Second, the aggregate skill of individual investors may have improved over time. Evans (2010) finds that retail trading increases stock price accuracy. Wang and Zhang (2015) investigate the effect of individual investor trading on stock market liquidity and find that individual investor trading improves stock liquidity through reducing information asymmetry. These studies suggest that

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[2] Surowiekci (2004) provides an excellent overview of the literature.

http://dx.doi.org/10.1016/j.jcorpfin.2015.08.001

although not every individual investor has precise information, information revealed by collective individual investors trading can be relatively precise and valuable.

This study aims to examine role of individual investor trading by analyzing the NYSE ReTrac End of Day (EOD) database, which summarizes daily retail trading activities for each stock listed and traded on NYSE from March 2004 to December 2011, with the research design being different from previous literature in that we examine aggregate effect of individual investor trading on firm valuation. We find strong evidence that daily aggregate individual investor trading in each stock has a positive impact on firm valuation. The result is remarkably robust to alternative model specifications, the inclusion of year, industry, firm fixed effects, a control for endogenous individual investor trading using two-stage least square regressions, and the use of alternative measures of firm valuation. Granger causality tests and nearest neighbor matching analyses suggest a causal effect of individual investor trading on firm valuation.

We then explore the information channel through which individual investor trading affects firm value.[3] Our conjecture is that individual investor trading enhances firm value by improving stock price informativeness. If our conjecture is true, the effect of individual investor trading on firm value should be stronger when individual investors are more likely to have additional information and their aggregated trading is more informative. Dow et al. (2011) suggest more information production in financial market about good firms than about bad firms. Thus individual investors are more likely to have private information about good firms, and by incorporating their private information into stock price through trading, their trades should have stronger effect on value of good firms. Consistent with the information production hypothesis, we find that the effect of individual investor trading on firm value is stronger for good firms that have higher Tobin's q or return on assets.

The improvement in price informativeness induced by individual investor trading should reduce information asymmetry and spread, leading to higher firm value. To test the spread channel, we first perform nearest neighbor matching analyses of relative spread to see how individual investor trading affects spread. We examine change in relative spread of stocks of otherwise very similar firms with high and low individual investor trading, and find that individual investor trading have a negative effect on change in spread. Moreover, if the spread channel works, we would expect the effect of individual investor trading on firm value to be stronger for high spread stocks. Consistent with this expectation, we find that individual investor trading has a significantly positive effect on market-to-book ratio for high spread stocks, but no significant effect for low spread stocks.

This study makes several contributions to the literature. First, this study contributes to the individual investor trading literature by using of a direct NYSE retail trading data from the most recent time periods. The majority of previous studies on individual investor trading use data from brokerage firms that only cover a small set of individual investors (see, for examples, Barber and Odean, 2000; Barber and Odean, 2008; Graham and Kumar, 2006; Ivkovic and Weisbenner, 2005; Kumar and Lee, 2006), or examine non-US retail trading data (Barber et al., 2009a, 2009b), or rely on individual investor trading proxies such as small trade size (Lee and Radhakrishna, 2000; Barber et al., 2009a, 2009b; Han and Kumar, 2013) or odd-lot trading. However, there are problems associated with the data sources that may produce biased results. A small group of retail investors of certain brokerage firms may not be a representative sample in terms of trading skills and information sources (Kelley and Tetlock, 2013). Using trade size or odd-lot trading as individual investor trading proxies suffer from important limitations and can bias results, especially for recent years.[4]

Next, our study contributes to the ongoing debate on whether individual investor trading is informative. Literature on individual investor trading has long treated individual investors as irrational or noise traders and focused on whether individual investors lose by trading (for example, Kumar and Lee, 2006; Barber et al., 2009a, 2009b). Recent studies provide evidence of price informativeness of trading by individual investors, and suggest that individual investors may possess valuable private information (Evans, 2010; Jackson, 2003; Kaniel et al., 2012; Kelley and Tetlock, 2013; Wang and Zhang, 2015). Our study extends this line of literature by providing evidence that is consistent with informative trading by individual investors.

Finally, our study is also related to the literature at the intersection of market microstructure and corporate finance, especially on relation between financial market and firm fundamentals. Financial markets not only reflect firm fundamentals, but also *affect* firm fundamentals. Baker et al. (2003), Luo (2005), and Chen et al. (2007) provide evidence that market prices affect firms' investments via managerial learning and/or the firm's access to new capital. Roll et al. (2009) study the effect of options trading on firm value and show that corporate investment in firms with greater options trading is more sensitive to stock prices. Fang et al. (2009) find that stock market liquidity positively impact firm performance through increasing the information content of market prices and of performance-sensitive managerial compensation. Our study contributes to this line of literature by showing that trading by individual investors affects firm performance and it makes its impact through improving stock price informativeness.

The rest of the paper proceeds as follows. Section 2 develops hypotheses. Section 3 describes the sample, data sources and variable measurements. Section 4 presents the empirical results, and Section 5 concludes.

[3] The increased stock price informativeness may positively affect firm value. Foucault and Gehrig (2008) show that cross-listed firms obtain more precise information from the stock market and make better investment decisions. Roll et al. (2009) find that the effect of option trading activity on firm valuation occurs by way of its impact on price informativeness. Fang et al. (2009) show that stock market liquidity positively impacts firm value through increasing the information content of market prices and of performance-sensitive managerial compensation contracts. Therefore, by improving stock price informativeness, aggregated trading by individual investors should have a positive effect on firm value.

[4] As discussed in several recent studies (e.g., Barber, Odean, and Zhu, 2009; Han and Kumar, 2013), the introduction of decimalization in 2001 and wide use of computerized trading algorithms by institutional investors for order splitting (Hvidkjaer, 2008) have led to a dramatic decrease in the average trade size, implying that trade size would not be an effective proxy for trades by individual investor after 2000. Therefore, these studies restrict their sample periods before 2000. Secondly, the problem with using odd-lot trading data as a proxy for individual investor trading is that many individual investors trade in round lots (Dhar et al., 2004), and O'Hara et al. (2014) show that odd lots are increasingly used in algorithmic and high-frequency trading. Thus odd-lot trading is not a good proxy for individual investor trading, especially for recent years.

2. Hypotheses

Our main hypothesis is that daily aggregate individual investor trading positively impacts firm value. Recent literature (e.g., Kaniel et al., 2012; Kelley and Tetlock, 2013; Wang and Zhang, 2015) suggests that at aggregated level, trades by individual investors may be informative. Thus stocks subject to more individual investor trading should have greater price informativeness. Literature has provided both theoretical and empirical evidence that stock price informativeness has positive impact on firm value. Highly informative stock prices may enable firms to allocate resources more efficiently, make better investment decisions and design more efficient managerial compensation contracts (Subrahmanyam and Titman, 1999; Holmstrom and Tirole, 1993), all of which lead to increased firm value. Foucault and Gehrig (2008) find that cross-listed firms make better investment decisions because of more precise price information obtained from the stock market. Fang et al. (2009) show that higher information flow due to higher stock liquidity increases information content of performance-sensitive managerial compensation contracts, which in turn, enhances firm performance. Roll et al. (2009) find that option trading enhances firm valuation by positively impacting price informativeness.

Moreover, the enhanced price informativeness induced by daily aggregate individual investor trading should reduce information asymmetry, increase stock liquidity, and reduce spread.[5] Both theoretical and empirical studies have shown that liquidity should be priced by the market. Higher liquidity results in lower expected return (e.g., Amihud and Mendelson, 1986; Acharya and Pedersen, 2005), and thus, higher current stock price and greater firm value.

Therefore, if individual investor trading is informative and improves stock price informativeness and liquidity, it should have a positive effect on firm value. This leads to the first and main hypothesis.

H1. All else equal, firms whose stocks are more heavily traded by individual investors have higher value.

We then examine the information channel through which individual investor trading affects firm value. We do not test whether individual investor trading enhances stock price informativeness, but instead, we develop a testable hypotheses implied by the information mechanism. If trading by individual investors increases firm value by improving stock price informativeness, the effect of individual investor trading on firm value should be stronger when the overall information production is higher, and thus, individual investors are more likely to possess private information. Dow et al. (2011) suggest that there will be more information production about investment opportunities that have strong fundamentals. This implies more information production about good firms than about bad firms. So we next test the following information production hypothesis.

H2. The positive effect of individual investor trading on firm value is stronger for good firms than for bad firms.

We further test the spread channel. The enhanced price informativeness induced by individual investor trading should reduce information asymmetry and thus spread, leading to higher firm value. Therefore, we would expect that individual investor trading has a negative impact on spread of stocks, and the effect of individual investor trading on firm value to be stronger for higher spread stocks. This leads to the following spread channel hypotheses.

H3a. Individual investor trading has a negative impact on spread of stocks.

H3b. The positive effect of individual investor trading on firm value is stronger for stocks with higher spread.

3. Data

3.1. Sample selection

Our individual investor trading data is from the NYSE ReTrac EOD database between March 15, 2004 and December 31, 2011. ReTrac database contains daily executed trades of all NYSE-listed stocks made by individual investors that are executed on NYSE. It tracks all trades that are made from individual accounts with account type designation "I" (individual investors) and summarizes the daily trading share volume and number of trades made by individual investors for each stock.[6]

We obtain firm financial data from Compustat database, stock return, spread and total trading volume data from the Center for Research in Security Prices (CRSP), institutional ownership data from Thomson Reuters 13(f) institutional holdings database, and analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) database. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. Since we aggregate daily individual investor trading activities over firms' fiscal years, and a firm must have at least one year of individual trading data to be included in our sample, the earliest fiscal year end in our sample is March 2005. Our final sample has 8645 firm-fiscal year observations.

[5] Diamond and Verrecchia (1991) develop a model showing that reduced information asymmetry by disclosing public information increases stock liquidity. Bartov and Bodnar (1996) provide empirical evidence that is consistent with high information asymmetry firms reducing informational asymmetries and increasing liquidity through improved disclosure by switching to more informative accounting methods. Roulstone (2003) finds that analyst following reduces information asymmetry and improves market liquidity.

[6] Kaniel et al. (2008) and Kanielet al. (2012) use the same database from NYSE from a different sample period (2000 to 2003) to study the relation between individual investor trading and stock return. Evans (2010) uses the NYSE ReTrac EOD data for a short sample period (April 2005 to August 2006) to study the effect of individual investor trading on stock price informativeness. The data used in our study covers a longer and more recent sample period. Using of this comprehensive and real individual investor trading data allows us to make more reliable inferences.

3.2. Variable construction

We use market-to-book ratio of equity (M/B) to measure firm value.[7] The main measures of individual investor trading intensity are individual trading volume ratio, IndVolRatio, and individual trading turnover, IndTurnover. For each firm in our sample, daily individual investor trading share volume and total trading volume are aggregated over each fiscal year. IndVolRatio is computed as the ratio of individual investor trading volume to total trading volume, both over the fiscal year, and IndTurnover is defined as the ratio of individual investor trading volume over the fiscal year to number of shares outstanding at the beginning of the fiscal year.[8] To account for non-normality concerns, we use natural logarithm of the two measures, Log(IndVolRatio) and Log(IndTurnover), in our analyses.

A wide range of control variables are included in our analysis. We control for spread, turnover, stock return, and idiosyncratic volatility to capture factors from stock market that may affect firm performance. Spread is logarithm of relative spread, defined as bid-ask spread divided by middle point of bid-ask. Turnover is the total trading share volume over a firm's fiscal year divided by the number of shares outstanding at the beginning of the fiscal year, and its natural logarithm, Log(Turnover) is used in analysis. Stock return is measured over a firm's fiscal year. Idiosyncratic volatility is the standard deviation of the residuals from fitting daily returns from the fiscal year to the four-factor model (the Fama and French (1993) three factors plus the momentum factor). We also control for several firm characteristics. Return on assets is net income divided by the book value of assets. Capital expenditure is capital expenditures divided by book value of assets. Firm size is measured by Log(Total Assets), the natural logarithm of book value of assets. Leverage is measured by long-term debt divided by book value of assets. EPS Growth is three-year growth rate of earnings per share and is included in regressions to control for growth prospect. Institutional ownership is the fraction of shares outstanding held by institutions that file quarterly 13-f reports at the end of the previous fiscal year. Analyst coverage is measured by Log(1 + #Analysts), the natural logarithm of one plus the number of analysts following a firm during the fiscal year. Dividend dummy is an indicator variable for whether the firm pays a dividend during the fiscal year. SP500 dummy is an indicator variable for whether the firm is included in the S&P 500 during the fiscal year. Industries are defined using Fama and French 48 industry classification.

3.3. Summary statistics

Table 1 presents summary statistics for main variables in our sample. The mean value of M/B is about 2.7, and for a typical stock over a typical year, individual investor trading volume represents 1.3% of total trading volume, and the turnover made by individual investors is about 0.03, with the total turnover of 2.8. While the overall magnitude of individual investor trading is small, considering that a significant part of the non-individual trading is high-frequency trading (HFT),[9] which is deemed uninformed, the percentage of individual investor trading would be higher once the uninformed HFT is removed.[10]

4. Empirical results

4.1. Firm fixed effect panel regressions

This section examines the effect of daily aggregate individual investor trading on firm value measured by the market-to-book ratio of equity, M/B. We regress M/B on intensity of individual investor trading, measured by Log(IndVolRatio) or Log(IndTurnover), while controlling for a set of variables related to stock market and firm characteristics. Although we control for a variety of variables, it is still possible that some unobservable firm characteristics may affect intensity of trading by individual investors and also correlate with firm performance. In other words, an endogeneity problem due to omitted variables could induce biased results. Therefore we conduct firm fixed effect panel regressions to account for the endogeneity concern. Year and industry fixed effects are also included.

We begin our analysis with a regression of M/B on control variable only, with no individual investor trading measure included. As shown in the first column of Table 2, most of the control variables have significant effects on M/B. Models 2 and 3 of Table 2 are the baseline specifications, where the individual investor trading measures are the independent variable of interest. The coefficients on Log(IndVolRatio) and Log(IndTurnover) are all positive and significant, suggesting that firms whose stocks are more heavily traded by individual investors have higher firm value, consistent with the main hypothesis H1.

Compared to model 1, the results on the control variables remain largely unchanged in models 2 and 3. As expected, spread is significantly and negatively related to firm value, consistent with lower spread stock having lower expected return and higher value. Stock return has a significantly positive effect on firm value. Return on assets and capital expenditure also have significant positive

[7] M/B is computed as market value of equity divided by book value of equity. Our results are qualitatively the same when Tobin'q is used to measure firm value.

[8] Our results are qualitatively the same when we measure the intensity of individual investor trading by absolute value of trading volume or number of trades made by individual investors.

[9] High-frequency trading (HFT) and computerized trading have grown rapidly over the last decade. HFT firms typically trade hundreds or thousands of times per day for their own account, with a typical holding period measured in seconds or minutes. Evidence in current literature on impact of HFT on market quality is mixed. HFT may create excess volatility and destabilize market (e.g., Kirilenkoet al., 2011), but improve market liquidity (e.g., Hendershott et al., 2011, Hasbrouck and Saar, 2013, Jarnecic and Snape, 2014). See Chordia et al. (2013), and Goldstein et al. (2014) for recent reviews of HFT and computerized trading.

[10] Note that during our sample period, 2005 to 2011, HFT and algorithmic trading represent up to 70% of all U.S. equity trading volume (see Goldstein et al., 2014, Hendershott et al., 2011, and "Times Topics: High-Frequency Trading", The New York Times, December 20, 2012), and these low-latency trading activities are generally uninformed. Then, after removing HFT trading, the average ratio of individual trading to total potential informed trading is higher, and estimated to be 1.3/30, or about 4.3%. Considering that some of the other potential informed trading is index trading which is uninformed about the stock, the individual trading percentage might be even higher. Most ETFs track an index such as the S&P 500 or the Russell 3000, and ETF trading account for about 10% to 20% of total trading volume (Sullivan and Xiong (2012)). For index stocks, assuming 15% of total trading volume is from ETF trading, the individual trading percentage can be as large as 8.7% (1.3/(100-70-15) = 8.7%).

Table 1
Summary statistics.
The table reports summary statistics for the sample. M/B is the market-to-book ratio of equity defined as the ratio of market value of equity to book value of equity. IndVolRatio is individual investor trading volume ratio, defined as the ratio of individual investor trading volume to total trading volume measured over firm *i*'s fiscal year. Log(IndVolRatio) is the natural logarithm of IndVolRatio. IndTurnover is individual investor trading turnover, defined as the ratio of individual trading volume over firm *i*'s fiscal year to the number of shares outstanding at the beginning of the fiscal year. Log(IndTurnover) is the natural logarithm of IndTurnover. Turnover is total turnover, defined as the total trading volume over firm *i*'s fiscal year divided by the number of shares outstanding at the beginning of the fiscal year. Log(Turnover) is the natural logarithm of Turnover. Spread is logarithm of relative spread, defined as bid-ask spread divided by middle point of bid-ask. Stock return is the stock return measured over firm *i*'s fiscal year. Return on assets is net income divided by the book value of assets. Capital expenditure is capital expenditures divided by book value of assets. Log(Total Assets) is the natural logarithm of book value of assets. Long term debt is long-term debt divided by book value of assets. Idiosyncratic volatility is the standard deviation of the residuals from the Fama and French (1993) three factors plus the momentum factor, where daily returns from the fiscal year are used to estimate the model. Institutional ownership is the fraction of shares outstanding held by institutions that file quarterly 13-f reports at the end of the previous fiscal year. Log(1 + #Analysts) is the natural logarithm of one plus the number of analysts following firm *i* during fiscal year *t*. EPS Growth is three-year growth rate of earnings per share. Dividend dummy is an indicator variable for whether the firm pays a dividend. SP500 dummy is an indicator variable for whether the firm is included in the S&P 500. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample.

Variable	Mean	Std. Dev.	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
(1) M/B	2.703	2.713	0.683	1.311	1.938	3.031	7.121
(2) IndVolRatio	0.013	0.018	0.001	0.003	0.007	0.016	0.045
(3) Log(IndVolRatio)	−4.979	1.113	−6.680	−5.876	−5.017	−4.136	−3.105
(4) IndTurnover	0.029	0.038	0.002	0.007	0.016	0.034	0.104
(5) Log(IndTurnover)	−4.165	1.134	−6.015	−5.015	−4.149	−3.369	−2.266
(6) Turnover	2.800	2.027	0.791	1.494	2.241	3.454	6.744
(7) Log(Turnover)	0.816	0.654	−0.234	0.402	0.807	1.239	1.909
(8) Spread	−7.049	1.033	−8.545	−7.807	−7.144	−6.420	−5.209
(9) Stock Return	0.114	0.706	−0.580	−0.162	0.071	0.293	0.843
(10) Return on Assets	0.124	0.091	0.009	0.078	0.118	0.167	0.266
(11) Capital Expenditure	0.050	0.062	0.001	0.014	0.032	0.062	0.162
(12) Log(Total Assets)	8.275	1.559	6.139	7.119	8.059	9.179	11.003
(13) Leverage	0.218	0.162	0.000	0.090	0.202	0.317	0.518
(14) Idiosyncratic Volatility	0.020	0.017	0.008	0.013	0.017	0.024	0.043
(15) Institutional Ownership	0.762	0.192	0.379	0.660	0.798	0.907	1.000
(16) Log(1 + #Analysts)	2.432	0.705	1.099	2.079	2.485	2.944	3.401
(17) EPS Growth	0.598	14.118	−2.545	−0.353	0.145	0.798	4.375
(18) Dividend Dummy	0.636	0.481	0.000	0.000	1.000	1.000	1.000
(19) SP500 Dummy	0.334	0.472	0.000	0.000	0.000	1.000	1.000

coefficients, suggesting that more profitable firms and firms with more growth opportunities have higher value. Log(Total Assets) has a significant negative coefficient in all specifications, indicating that smaller firms have better performance. Significant positive coefficients on Leverage, are consistent with a debt tax shield effect (e.g., Modigliani and Miller, 1963; Graham, 2000; Kemsley and Nissim, 2002) and/or a debt disciplinary effect (e.g., Jensen, 1986; Gul and Tsui, 1997). Idiosyncratic volatility has a significantly negative effect on firm value, consistent with the literature arguing that idiosyncratic volatility is positively priced, and higher idiosyncratic volatility leads to higher expected return and lower stock price. Analyst coverage has a significant positive coefficient, suggesting that analysts may tend to cover growth stocks rather than value stocks or analyst coverage may create attention and lead to higher market-to-book equity ratios.

The effects of individual investor trading on firm value are also economically significant. For examples, one standard deviation increase in Log(IndVolRatio) would lead to an increase in M/B by 0.13 ($0.119 \times 1.113 = 0.13$), which is about 4.8% of the sample mean of M/B ($0.13/2.703 = 4.8\%$); similarly, one standard deviation increase in Log(IndTurnover) would result in an increase in M/B by 0.15 ($0.129 \times 1.134 = 0.15$), which is about 5.5% of the sample mean of M/B ($0.15/2.703 = 5.5\%$).[11]

The overall results of the firm fixed effect panel regressions reveal a significantly positive effect of individual investor trading on firm value, supporting our main hypothesis (H1). The effect is also strongly economically significant.

4.2. First-difference panel regressions

In the previous section, we employ firm fixed effect panel regression to establish the main finding and account for endogeneity due to unobserved firm-specific characteristics. But firm fixed effect regression is only efficient when unobservables are constant over time. When unobservables are not constant over time, the residuals can be serially correlated, and fixed effect models are not efficient. In such cases, a better approach is the first-difference regression model, in which the transformed residuals are serially uncorrelated. With first differences of variables, we can estimate first-difference panel regression models, which allow us to control for time-varying unobserved firm-specific characteristics. In addition, it has long been recognized that regressions involving economic variables in

[11] Standard deviations of Log(IndVolRatio) and Log(IndTurnover) are 1.113 and 1.134, respectively. Sample mean of M/B is 2.703.

Table 2
Firm fixed effect panel regression results.
The table reports estimates of firm fixed effect panel regressions. The dependent variable is market to book ratio of equity (M/B). The independent variables include Log(IndVolRatio) or Log(IndTurnover), total turnover, spread, stock return, return on assets, capital expenditure, natural logarithm of total assets, leverage, idiosyncratic volatility, institutional ownership, Log(1 + #Analysts), EPS growth, dividend dummy, SP500 dummy, year dummies, industry dummies, and firm dummies. The industry classifications are defined by Fama and French (1997). Coefficients on year, industry, and firm fixed effects are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. See Table 1 for variable definitions. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Log(IndVolRatio)		0.119**	
		(2.11)	
Log(IndTurnover)			0.129**
			(2.29)
Log(Turnover)	−0.009	−0.014	−0.142
	(−0.11)	(−0.17)	(−1.59)
Spread	−0.071***	−0.072***	−0.072***
	(−3.09)	(−3.16)	(−3.17)
Stock Return	0.435***	0.431***	0.431***
	(4.11)	(4.11)	(4.12)
Return on Assets	4.638***	4.640***	4.646***
	(8.47)	(8.47)	(8.47)
Capital Expenditure	1.924**	1.903**	1.906**
	(2.07)	(2.05)	(2.05)
Log(Total Assets)	−1.429***	−1.422***	−1.421***
	(−7.80)	(−7.77)	(−7.76)
Leverage	5.443***	5.422***	5.421***
	(8.26)	(8.25)	(8.24)
Idiosyncratic Volatility	−14.857***	−16.137***	−16.286***
	(−2.61)	(−2.75)	(−2.78)
Institutional Ownership	−0.284	−0.189	−0.180
	(−0.94)	(−0.62)	(−0.59)
Log(1 + #Analysts)	0.206*	0.220**	0.221**
	(1.96)	(2.09)	(2.10)
EPS Growth	0.001	0.001	0.001
	(0.59)	(0.57)	(0.56)
Dividend Dummy	−0.093	−0.082	−0.081
	(−0.71)	(−0.63)	(−0.62)
SP500 Dummy	0.029	0.042	0.041
	(0.13)	(0.18)	(0.18)
Year Dummy	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes
Nobs	7293	7293	7293
Adj R^2	0.211	0.262	0.262

levels can be misleading, while spurious correlations are less likely to occur with variables in first difference. In this section, we perform an analysis using first-difference panel regressions.

The results of first-difference panel regressions are shown in Table 3. The dependent variable is change in M/B from the last fiscal year, and all independent variables are also in first difference format. The coefficients on the changes of individual investor trading measures are positive and significant at 1% level, implying that greater increases in individual investor trading intensity are associated with greater increases in firm value, consistent with the results in the previous section. The results provide additional evidence to support the hypothesis that individual investor trading has significantly positive impact on firm value.

4.3. Endogeneity and causality

4.3.1. Two-stage least square regressions

In the previous two sections we conduct firm fixed effect panel regressions and first-difference panel regressions, which account for endogeneity due to unobserved firm-specific characteristics that are constant over time or time-varying. However, if the time-varying unobservables do not have a linear trend, both firm fixed effect and first difference models are not efficient. Endogeneity could also occur due to simultaneity if individual investor trading activity and firm performance can affect each other. Individual investors may choose to trade stocks of high-performance firms because either individual investors prefer to hold high value stocks or such firms attract more media coverage and hence more attention from individual investors. To address these endogeneity concerns, we next carry out two-stage least square (2SLS) regressions.

As instruments, we use the first and second lags of measures of individual investor trading (Log(IndVolRatio) or Log(IndTurnover)) and the average value of measures of individual investor trading for two firms in the same industry and with

Table 3
First difference panel regression results.
This table reports estimates of first difference panel regressions. The dependent variable is change in market to book ratio of equity (M/B) from previous to current fiscal year. The independent variables are changes (Δ) in Log(IndVolRatio) or Log(IndTurnover), total turnover, spread stock return, return on assets, capital expenditure, natural logarithm of total assets, long term debt, idiosyncratic volatility, institutional ownership, Log(1 + #Analysts), EPS growth dividend dummy, and SP500 dummy from previous to current fiscal year. The year dummies and industry dummies are included, but their coefficients are not reported. The industry classifications are defined by Fama and French (1997). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. See Table 1 for variable definitions. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

	(1)	(2)
ΔLog(IndVolRatio)	0.186***	
	(3.45)	
ΔLog(IndTurnover)		0.199***
		(3.68)
ΔLog(Turnover)	−0.002	−0.198*
	(−0.02)	(−1.76)
ΔSpread	−0.016	−0.016
	(−0.74)	(−0.74)
ΔStock Return	0.401***	0.401***
	(3.76)	(3.77)
ΔReturn on Assets	2.222***	2.229***
	(3.64)	(3.65)
ΔCapital Expenditure	0.282	0.283
	(0.35)	(0.35)
ΔLog(Total Assets)	−1.634***	−1.634***
	(−6.72)	(−6.72)
ΔLeverage	4.624***	4.626***
	(6.95)	(6.95)
ΔIdiosyncratic Volatility	−17.556**	−17.703**
	(−2.48)	(−2.51)
ΔInstitutional Ownership	0.104	0.108
	(0.37)	(0.39)
ΔLog(1 + #Analyst)	0.149	0.149
	(1.56)	(1.56)
ΔEPS Growth	−0.001	−0.001
	(−0.91)	(−0.92)
ΔDividend Dummy	0.095	0.097
	(0.69)	(0.70)
ΔSP500 Dummy	0.010	0.006
	(0.06)	(0.03)
Year Dummy	Yes	Yes
Industry Dummy	Yes	Yes
Nobs	5741	5741
Adj R^2	0.172	0.172

closest size (measured by total assets).[12] These instrumental variables are believed to be correlated with current measures of individual investor trading but uncorrelated or much less correlated with current firm performance. Using lagged individual investor trading as instruments also helps mitigate concerns that an unobservable is correlated with both individual investor trading and firm value for the same year but changes over time so that it cannot be controlled by including firm fixed effects. In the first-stage regressions, a measure of individual investor trading is regressed on its instruments as well as all control variables in the baseline specifications as in Table 2. The second-stage regression is the same as the baseline specification except for the measures of individual investor trading being replaced by their predicted values from the first-stage regressions.

Table 4 reports results of 2SLS regressions. In the first-stage regressions, for both measures of individual investor trading, Log(IndVoRatio) and Log(IndTurnover), all instruments have highly significant coefficients and the R-squares are as high as above 70%, indicating high predictive power of the instruments. Hansen's *J* test statistics are insignificant with large *p*-values, suggesting that the instruments are uncorrelated with the errors of the second equation. Therefore, our instruments are correlated with measures of individual investor trading but uncorrelated with firm value, and hence are valid. In the second-stage regressions, the coefficients on the predicted values of the measures of individual investor trading are positive and significant at 1% level, consistent with a positive effect of individual investor trading on firm value.

4.3.2. Granger causality

We have shown a positive effect of daily aggregate individual investor trading on firm value, and we next establish the causality from individual investor trading to firm value. We hypothesize that individual investor trading enhances firm value by improving stock price informativeness, but reverse causality may exist if individual investors choose to trade stocks of high-performance

[12] Similar results are obtained when sales is used to measure firm size.

Table 4
Two-stage least square (2sls) regression results.
The table reports two-stage least square regression results. In the first-stage regressions, the measure of individual investor trading, Log(IndVolRatio) (Panel A) or Log(IndTurnover) (Panel B) is regressed on its first and second lags, an instrumental variable, IV_Log(IndVolRatio) (Panel A) or IV_Log(IndTurnover) (Panel B), and all control variables that included in the baseline specification (Table 2). In the second-stage regressions, M/B is regressed on the predicted value of Log(IndVolRatio) (Panel A) or Log(IndTurnover) (Panel B) and all control variables. Year and industry dummies are included but their coefficients are not reported. Pred_Log(IndVolRatio) and Pred_Log(IndTurnover) are the predicted values of Log(IndVolRatio) and Log(IndTurnover), respectively. Log(IndVolRatio)$_{t=1}$ and Log(IndVolRatio)$_{t=2}$ are the first and second lags of Log(IndVolRatio), and Log(IndTurnover)$_{t=1}$ and Log(IndTurnover)$_{t=2}$ are the first and second lags of Log(IndTurnover). For firm *i*, IV_Log(IndVolRatio) and IV_Log(IndTurnover) are the average value of Log(IndVolRatio) and Log(IndTurnover), respectively, of two firms in the same industry as firm i with the closed sizes measured by total assets. If firm *i* is the largest (smallest) firm in its industry, the second largest (smallest) firm in its industry is selected to compute IV_IndVolume and IV_IndTrade. The industry classifications are defined by Fama and French (1997). See Table 1 for definitions of other variables. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. *p*-values of Hansen J tests are reported. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

	Panel A: Log(IndVolRatio)		Panel B: Log(IndTurnover)	
	First-stage Log(IndVolRatio)	Second-stage M/B	First-stage Log(IndTurnover)	Second-stage M/B
Pred_Log(IndVolRatio)		0.303***		
		(5.75)		
Log(IndVolRatio)$_{t-1}$	0.544***			
	(34.44)			
Log(IndVolRatio)$_{t-2}$	0.035**			
	(2.47)			
IV_Log(IndVolRatio)	0.217***			
	(17.65)			
Pred_Log(IndTurnover)				0.297***
				(5.31)
Log(IndTurnover)$_{t-1}$			0.515***	
			(33.49)	
Log(IndTurnover)$_{t-2}$			0.066***	
			(4.60)	
IV_Log(IndTurnover)			0.212***	
			(18.89)	
Log(Turnover)	−0.008	−0.135	0.522***	−0.432***
	(−0.46)	(−1.47)	(22.81)	(−4.08)
Spread	−0.058***	−0.188***	−0.085***	−0.191***
	(−5.97)	(−4.75)	(−8.47)	(−4.84)
Stock Return	0.074***	0.414***	0.035**	0.412***
	(3.03)	(3.25)	(2.30)	(3.22)
Return on Assets	−0.267***	9.525***	−0.078	9.539***
	(−2.97)	(12.44)	(−0.74)	(12.42)
Capital Expenditure	0.145	−1.613*	0.408**	−1.507
	(1.02)	(−1.68)	(2.48)	(−1.55)
Log(Total Assets)	−0.012	−0.314***	0.005	−0.314***
	(−1.51)	(−6.86)	(0.56)	(−6.81)
Leverage	0.074	3.198***	0.056	3.251***
	(1.47)	(8.31)	(0.96)	(8.39)
Idiosyncratic Volatility	3.739***	−4.209	6.897***	−4.356
	(3.72)	(−0.77)	(6.54)	(−0.80)
Institutional Ownership	−0.328***	−0.504**	−0.381***	−0.493**
	(−6.65)	(−2.07)	(−6.54)	(−2.02)
Log(1 + #Analysts)	−0.069***	0.657***	−0.138***	0.646***
	(−4.10)	(8.06)	(−6.84)	(7.95)
EPS Growth	−0.000	−0.001	−0.000	−0.001
	(−0.89)	(−1.01)	(−0.21)	(−1.08)
Dividend Dummy	−0.040**	0.004	−0.002	0.001
	(−2.36)	(0.05)	(−0.11)	(0.01)
SP500 Dummy	−0.077***	0.667***	−0.073***	0.665***
	(−3.91)	(5.77)	(−3.23)	(5.73)
Year Dummy	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes
Nobs	4562	4562	4530	4530
Adj R^2	0.726	0.337	0.756	0.338
p-value of Hansen J Test		0.310		0.816

firms. In the previous section, we perform 2SLS regressions to account for endogeneity due to simultaneity, i.e., individual investor trading activity and firm performance affect each other. In this section, we conduct Granger causality tests to further rule out the reverse causality.

To perform Granger causality tests, we first run vector autoregressions using two models. In model 1, M/B is regressed on its lagged values and lagged individual investor trading measures, as well as the control variables. Then we conduct an *F* test with the null hypothesis that coefficients of all lagged individual investor trading measures are jointly zero, or, in other words, individual investor trading dose not Granger cause firm value (M/B). In model 2, the individual investor trading measure, Log(IndVolRatio) or Log(IndTurnover), is regressed on its lagged values and lagged M/B, as well as the control variables. We then test the null hypothesis that coefficients of all lagged M/B are jointly zero, or, in other words, firm value does not Granger cause individual investor trading.[13]

The results are shown in Table 5. Panel A and Panel B report *F*-statistics and *p*-values of the *F* tests for the two individual investor trading measures, Log(IndVolRatio) and Log(IndTurnover), respectively. For each measure, F tests reject the null hypothesis that individual investor trading does not cause firm value at 1% level, and fail to reject the null hypothesis that firm value does not cause individual investor trading. The results are consistent with a causal effect of individual investor trading on firm value.

4.3.3. Nearest neighbor matching analysis

Having established the causal effect of daily aggregate individual investor trading on firm value and estimated the effect using panel regressions, we now estimate the causal effect using matching estimators. Matching methods estimate causal effect by comparing the outcomes of treated and control groups with similar covariate distributions, and thereby, reduce bias due to the covariates. In particular, we form two groups of firms that are as close as possible in other covariates (i.e., matching variables), one group with high individual investor trading intensity (treated group), and the other with low high individual investor trading intensity (control group), and compare their firm value. Compared with the panel regression estimator, matching estimator is less dependent on linear model assumption and singles out the effect of a particular cause.

We perform nearest neighbor matching estimation. In each year we identify firms with high (low) individual investor trading intensity as those whose individual investor trading measure falls in the top (bottom) quartile. For each firm with high individual investor trading intensity (treated firm), we find a matched firm (control firm) with low individual investor trading intensity that is in the same industry and has the closest values in matching variables to those of the treated firm. The list of matching variables consist of the control variables in Table 2 that have significant effects on firm value (M/B), including firm size, stock return, return on assets, and so on, and an additional matching variable that is either total trading volume or number of shares outstanding. We estimate the average treatment effect using the Abadie–Imbens bias-corrected matching estimator.

Table 6 reports the average treatment effect for the treated group (ATT), as well as the corresponding *Z*-statistics and *p*-value. For each of the individual investor trading measures, Log(IndVolRatio) in Panel A and Log(IndTurnover) in Panel B, and each of the two additional matching variables, the ATT is positive and significant at 1% level, suggesting that compared with similar firms with low individual investor trading intensity, firms with high individual investor trading intensity have higher firm value. The results are consistent with the finding from panel regressions and the main hypothesis that individual investor trading has a positive causal effect on firm value.

Overall results in this section provide evidence that individual investor trading has a positive causal effect on firm value, and the finding is robust to controlling for endogeneity.

4.4. Subsample analyses

In this section we perform subsample analyses to examine how the effect of daily aggregate individual investor trading on firm value depends on firm size, trading volume, and time.

After utilizing the matching estimation to control for the firm size and total trading volume, along with other covariates, and single out the effect of individual investor trading on firm value, we next conduct a subsample analysis to explore how the effect of individual investor trading on firm value varies across firms that are different in terms of firm size and trading volume. The full sample is divided into halves based on firm size or total trading volume. Big (small) firms are those with total assets above (below) its sample median of the fiscal year, and high (low) trading volume firms are those with total trading volume above (below) its sample median of the fiscal year. Four subsamples (2×2) are then formed, and firm fixed effect panel regressions are run for each subsample, with specifications the same as those in Table 2 (models 2 and 3). The coefficients and corresponding t-statistics of the two individual investor trading measures, Log(IndVolRatio) and Log(IndTurnover), are reported in Panel A of Table 7. The effect of individual investor trading on firm value is significantly positive only for subsamples of firms with high total trading volume, and is much less dependent on firm size.[14] The results suggest that individual investor trading has a significant positive impact on firm valuation only if a firm's total trading volume is relatively high. Together with the fact that our individual investor trading measures are essentially percentage of total trading volume, the results imply that sufficiently large absolute trading volume by individual investors is necessary for individual investor trading to incorporate sizable additional information into stock price, improve price informativeness, and hence, increase firm value.

We then explore how the effect of daily aggregate individual investor trading on firm value varies from year to year. We perform year-by-year cross-sectional regressions to focus on the cross-sectional relation between individual investor trading and firm value. Panel B of Table 7 reports the coefficients on Log(IndVolRatio) and Log(IndTurnover) and the corresponding t statistics from the cross-sectional regressions for each year from 2005 to 2011. The coefficients on Log(IndVolRatio) and Log(IndTurnover) are significantly positive for five of the seven years, suggesting a strong cross-sectional relation between individual investor trading and firm

[13] Considering the length of our sample period, we choose a maximum of three lags in the tests.

[14] Similar results are obtained when we create dummy variables for each subsample and run a firm fixed effect panel regression with Log(IndVolRatio) or Log(IndTurnover) interacting with the subsample dummies. The coefficients on the interaction terms involving dummies for high trading volume/big firms and high trading volume/small firms are significantly positive and are not significantly different from each other. The coefficients on the interaction terms involving dummies for low trading volume/big firms and low trading volume/smalls firm are not significant.

Table 5
Granger causality tests.
This table reports results of Granger causality tests. For each of the individual investor trading measures, Log(IndVolRatio) in Panel A and Log(IndTurnover) in Panel B, we test two null hypotheses, that individual investor trading does not cause firm value (M/B), and that firm value (M/B) does not cause individual investor trading. The corresponding *F*-statistics and *p*-value of the tests are reported.

Individual trading:	Panel A: Log(IndVolRatio)		Panel B: Log(IndTurnover)	
H_0:	Individual trading does not cause firm value	Firm value does not cause individual trading	Individual trading does not cause firm value	Firm value does not cause individual trading
F-statistics	6.82	1.51	5.63	1.78
p-value	0.00	0.20	0.00	0.15

value. The results indicate that the positive and significant effect of individual investor trading on firm value is not driven by a specific year or a few years only, but exists during majority of our sample period.

4.5. Information and spread channels

4.5.1. Information channel

Previous studies suggest that individual investor trading improves stock price infomativeness, leading to better firm performance. In this section we examine this information channel through which individual investor trading affects firm value by testing the information production hypothesis (H2).

When overall market information production is higher, individual investors are more likely to obtain valuable information and their trades are more likely to be informative at the aggregated level. If individual investor trading enhances firm value through the information channel, the effect of individual investor trading on firm value should be stronger when the overall information production is higher. Dow et al. (2011) suggest that there will be more information production about investment opportunities that have stronger fundamentals. This implies more information production about good firms than about bad firms. So H2 predicts that the effect of individual investor trading is stronger for good firms than for bad firms. We define an indicator variable “Good Firm” that takes value of one if a firm's lagged Tobin's q or return on assets (ROA) is above its sample median of the fiscal year, and zero otherwise.

As shown in Table 8, we include the interaction terms between Log(IndVolRatio) or Log(IndTurnover) and the indicator variable “Good Firm” in the firm fixed effect panel regression specifications as in models 2 and 3 of Table 2. Both year and industry fixed effects are controlled. The coefficients on Log(IndVolRatio) or Log(IndTurnover) remain positive but become insignificant, and the coefficients on Log(IndVolRatio) or Log(IndTurnover) interacting with Good Firm are significantly positive, indicating that the positive impact of individual investor trading on firm value only occurs for good firms, but not for bad firms. The results strongly suggest that effect of trading by individual investors is stronger when information production is higher, and support the information channel mechanism that individual investor trading enhances firm value by improving stock price informativeness.

4.5.2. Spread channel

The information channel mechanism suggests that individual investor trading enhances stock price informativeness, which reduces information asymmetry, increases liquidity, and reduces spread, leading to lower expected return and higher current market value and market-to-book ratio of equity. So we specifically test the spread channel mechanism that individual investor trading enhances firm value by reducing spread.

We first perform nearest neighbor matching analyses of relative spread to see how individual investor trading affects spread. Since may factors can affect spread, and some of them may be unobservable, we examine change in spread, rather than spread. We test whether individual investor trading in a stock has a significant effect on the change of its relative spread from the previous year.

Table 6
Nearest neighbor matching analysis.
This table reports results of nearest neighbor matching analysis. In each year we identify firms with high (low) individual investor trading intensity as those whose individual investor trading measure, Log(IndVolRatio) in Panel A and Log(IndTurnover) in Panel B, falls in the top (bottom) quartile. For each firm with high individual investor trading intensity (treated firm), we find a matched firm (control firm) with low individual investor trading intensity that is in the same industry and has the closest values of matching variables to those of the treated firm. Matching variables include the control variables in Table 2 that have significant effect on firm value (M/B), and an additional matching variable that is either total trading volume or number of shares outstanding. The average treatment effect for the treated group (ATT), as well as the corresponding *Z*-statistics and *p*-value are reported.

Individual trading	Panel A: Log(IndVolRatio)		Panel B: Log(IndTurnover)	
Additional matching variable	Total trading volume	# of shares outstanding	Total trading volume	# of shares outstanding
ATT	0.350^{***}	0.289^{***}	0.359^{***}	0.350^{***}
Z-statistics	(3.68)	(3.26)	(3.02)	(2.69)
p-value	(0.00)	(0.00)	(0.00)	(0.01)

Table 7
Subsample analyses and year-by-year regressions.
Panel A reports estimates of firm fixed effect panel regressions within subsamples based on firm size (total assets) and total trading volume. The full sample is divided into halves by firm size or total trading volume. Big (small) firms are those with total assets above (below) its sample median of the fiscal year, and high (low) trading volume firms are those with total trading volume above (below) its sample median of the fiscal year. Four subsamples (2×2) are then formed, and firm fixed effect panel regressions are run for each subsample. The dependent variable is M/B, and the regression specifications are the same as the model 2 or model 3 in Table 2, corresponding to the measure of individual investor trading of Log(IndVolRatio) or Log(IndTurnover). Only the coefficients and *t*-statistics (in parentheses) of Log(IndVolRatio) and Log(IndTurnover) are reported. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively. Panel B reports year-by-year coefficients and *t*-statistics in parentheses for Log(IndVolRatio)and Log(IndTurnover) from annual cross-sectional regressions. Industry fixed effects are included in all regressions. T-statistics in parentheses are based on standard errors adjusted for heteroskedasticity. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

Panel A Subsample analyses				
	Big Firm		Small Firm	
	Log(IndVolRatio)	Log(IndTurnover)	Log(IndVolRatio)	Log(IndTurnover)
High Trading Volume	0.270***	0.296***	0.547***	0.546***
	(2.71)	(3.01)	(2.67)	(2.64)
Low Trading Volume	−0.167	−0.158	−0.041	−0.036
	(−1.00)	(−0.98)	(−0.57)	(−0.49)
Panel B Year-by-year Regressions				
	Log(IndVolRatio)		Log(IndTurnover)	
Year	Coefficient	t-statistic	Coefficient	t-statistic
2005	0.073	(0.50)	−0.002	(−0.01)
2006	0.256**	(2.02)	0.262**	(2.07)
2007	0.061	(0.46)	0.058	(0.43)
2008	0.177*	(1.72)	0.193*	(1.67)
2009	0.228**	(2.10)	0.244**	(2.02)
2010	0.311**	(2.24)	0.295**	(2.17)
2011	0.325**	(2.14)	0.308**	(2.06)

Each year we identify firms with high (low) individual investor trading intensity as those whose individual investor trading measure, Log(IndVolRatio) or Log(IndTurnover), is above (below) the sample median of the year. For each firm with high individual investor trading intensity (treated firm), we find a matched firm (control firm) with low individual investor trading intensity that is in the same industry and has the closest values of matching variables to those of the treated firm. Matching variables include the control variables that are significant in Table 2, and an additional matching variable that is either total trading volume or number of shares outstanding. As shown in Panel A of Table 9, the average treatment effects are significantly negative, suggesting that higher individual trading stocks experience significantly smaller change in relative spread, consistent with hypothesis H3a that individual investor trading has a negative impact on spread of stocks.

Moreover, if the spread channel works, we would expect the effect of individual investor trading on firm value to be stronger for high spread stocks. We then compare high and low spread stocks to see if the spread channel does have an effect. Each year we identify high (low) spread stocks as those with relative spread above (below) the sample median of the year. We run the firm fixed effect regressions for subsamples of high and low spread stocks, and the results are shown in Panel B of Table 9. Consistent with the expectation and the hypothesis H3b, individual investor trading has a significantly positive effect on firm value for high spread stocks, but no significant effect for low spread stocks.

Overall results in this section suggest that individual investor trading positively impact firm value by enhancing stock price informativeness and reducing spread.

4.6. Robustness checks

4.6.1. Monthly measures of individual trading

In our main analyses, the individual investor trading intensity is measured by aggregating daily trading volume at annual level. Our first robustness check is to construct individual investor trading measures at monthly level and examine whether the frequency of aggregating data and running regression may have an effect on our results.

We aggregate daily individual investor trading volume at monthly level to construct Log(IndVolRatio) and (IndTurnover), and repeat the firm fixed effect regressions shown in Table 2 at monthly level.[15] The results are shown in Panel A of Table 10.[16] The coefficients on the monthly measures of Log(IndVolRatio) and (IndTurnover) are significantly positive, indicating a strong positive effect of individual investor trading on firm value at monthly level. The data aggregation frequency does not affect our results.

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[15] Control variables such as Log(Turnover), Spread, and Stock return are also constructed at monthly frequency. For other firm characteristic related control variables, such as Return on Asset, Capital Expenditure, Leverage, and so on, which cannot be constructed at monthly level, we compute them at quarterly level, and assign quarter values to each month in the corresponding quarter.

[16] Additional control variables are included in the regressions of this table, and are discussed in the later section.

Table 8
Test information channel: good firms vs. bad firms.
The table reports results of testing information production hypotheses using firm fixed effect panel regressions. The dependent variable is M/B. The independent variables include Log(IndVolRatio) in Panel A or Log(IndTurnover) in Panel B, an interaction term between Log(IndVolRatio) or Log(IndTurnover) and an indicator variable Good Firm, the indicator variable Good Firm, and the control variables in Table 2. Good Firm is an indicator variable that equals to one if the firm's lagged Tobin's q or Return on Asset (ROA) is above its sample median of the fiscal year, and zero otherwise. The industry classifications are defined by Fama and French (1997). Coefficients on year and industry fixed effects are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. See Table 1 for definitions of other variables. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

	Panel A: Log(IndVolRatio)		Panel B: Log(IndTurnover)	
	Tobin's q	ROA	Tobin's q	ROA
Log(IndVolRatio)	0.035	0.056		
	(0.62)	(0.94)		
Log(IndVolRatio)*Good Firm	0.138***	0.069***		
	(3.83)	(3.23)		
Log(IndTurnover)			0.051	0.092
			(0.90)	(1.56)
Log(IndTurnover)*Good Firm			0.132***	0.042*
			(3.40)	(1.85)
Good Firm	1.348***	0.438***	1.201***	0.261**
	(7.15)	(3.73)	(6.57)	(2.40)
Log(Turnover)	−0.068	−0.030	−0.168*	−0.148*
	(−0.87)	(−0.37)	(−1.92)	(−1.66)
Spread	−0.062***	−0.073***	−0.062***	−0.072***
	(−2.75)	(−3.23)	(−2.75)	(−3.17)
Stock Return	0.366***	0.428***	0.364***	0.429***
	(3.83)	(4.13)	(3.80)	(4.13)
Return on Assets	4.178***	4.019***	4.152***	3.956***
	(7.97)	(6.18)	(7.91)	(5.96)
Capital Expenditure	1.467	1.789*	1.532*	1.832*
	(1.63)	(1.90)	(1.69)	(1.96)
Log(Total Assets)	−1.242***	−1.373***	−1.243***	−1.387***
	(−6.81)	(−7.60)	(−6.75)	(−7.69)
Leverage	5.310***	5.490***	5.287***	5.459***
	(8.08)	(8.32)	(8.05)	(8.29)
Idiosyncratic Volatility	−12.273**	−16.348***	−11.951**	−16.195***
	(−2.12)	(−2.80)	(−2.06)	(−2.78)
Institutional Ownership	−0.160	−0.227	−0.153	−0.213
	(−0.53)	(−0.74)	(−0.50)	(−0.69)
Log(1 + #Analysts)	0.175*	0.217**	0.178*	0.224**
	(1.71)	(2.07)	(1.73)	(2.14)
EPS Growth	0.000	0.001	0.000	0.001
	(0.18)	(0.56)	(0.08)	(0.52)
Dividend Dummy	−0.094	−0.086	−0.092	−0.083
	(−0.76)	(−0.67)	(−0.74)	(−0.64)
SP500 Dummy	0.025	0.035	0.012	0.029
	(0.11)	(0.15)	(0.05)	(0.13)
Year Dummy	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes
Observations	7293	7293	7293	7293
Adjusted R^2	0.231	0.215	0.231	0.214

4.6.2. Additional control variables

Firm value may be higher just because overall market is booming and market-to-book of equity is higher across the whole market, which should induce higher individual investor trading. The high market should also induce high stock mutual fund flows, which might be correlated with individual investor trading, especially intertemporally. To mitigate the concern that our results may capture the intertemporal pressure on stock price due to mutual fund flows, we include in our analyses additional control variables that measure such intertemporal market pressure.

Firstly, since our two measures of individual investor trading, Log(IndVolRatio) and (IndTurnover), are at individual stock level, we construct the corresponding measures of market-wide individual investor trading, Log(Total_IndVolRatio), the aggregate individual trading volume ratio, and Log(Total_IndTurnover), the aggregate individual trading turnover. Since the market pressure is mainly intertemporal, the aggregate measures of individual investor trading are constructed at monthly level and included in the regressions at monthly frequency shown in Panel A of Table 10. We also include in the regressions another control variable, Annual Fund Flow, which is US Domestic Equity monthly flow,[17] to measure the intertemporal pressure on stock price due to mutual fund flows. As

[17] The US Domestic Equity monthly flow data is obtained from the ICI website at http://www.ici.org/info/flows_data_2014.xls. The data is available from 2007, so with Annual Fund Flow controlled, the sample period of the regressions in Panel A of Table 10 is from 2007 to 2011.

Table 9
Test spread channel.
Panel A reports results of nearest neighbor matching analysis of relative spread. We test whether individual investor trading in a stock has a significant effect on the change of its relative spread from the previous year. In each year we identify firms with high (low) individual investor trading intensity as those whose individual investor trading measure, Log(IndVolRatio) and Log(IndTurnover), are above (below) the sample median of the year. For each firm with high individual investor trading intensity (treated firm), we find a matched firm (control firm) with low individual investor trading intensity that is in the same industry and has the closest values of matching variables to those of the treated firm. Matching variables include the control variables that significantly affect firm value, and an additional matching variable that is either total trading volume or number of shares outstanding. The average treatment effect for the treated group (ATT), as well as the corresponding *Z*-statistics and *p*-value are reported. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively. Panel B reports firm fixed effect regression results for subsamples of high and low spread stocks. High (low) spread stocks are those with relative spread above (below) the sample median of the year. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2005 through 2011. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. See Table 1 for variable definitions. *, **, and *** indicate a significance level less than 10%, 5%, and 1%, respectively.

Panel A nearest neighbor matching analysis of relative spread				
Individual trading	Log(IndVolRatio)		Log(IndTurnover)	
Additional matching variable	Total trading volume	# of shares outstanding	Total trading volume	# of shares outstanding
ATT	−0.00051***	−0.00053***	−0.00057***	−0.00061***
Z-statistics	(−2.87)	(−3.04)	(−3.06)	(−3.27)
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Panel B High vs. Low Spread Stocks				
	Log(IndVolRatio)		Log(IndTurnover)	
	High Spread	Low Spread	High Spread	Low Spread
Log(IndVolRatio)	0.174**	0.021		
	(2.23)	(0.30)		
Log(IndTurnover)			0.186**	0.014
			(2.37)	(0.21)
Log(Turnover)	0.168	−0.230*	−0.017	−0.244*
	(1.63)	(−1.90)	(−0.15)	(−1.74)
Spread	−0.051	−0.109**	−0.051	−0.109**
	(−1.06)	(−2.25)	(−1.07)	(−2.25)
Stock Return	0.289***	1.320***	0.289***	1.321***
	(3.47)	(15.71)	(3.48)	(15.70)
Return on Assets	3.565***	6.056***	3.575***	6.059***
	(4.82)	(6.33)	(4.83)	(6.33)
Capital Expenditure	1.367	3.514**	1.379	3.513**
	(1.46)	(2.18)	(1.48)	(2.18)
Log(Total Assets)	−1.646***	−1.352***	−1.644***	−1.351***
	(−5.76)	(−6.02)	(−5.76)	(−6.02)
Leverage	4.732***	6.594***	4.730***	6.595***
	(5.23)	(5.54)	(5.23)	(5.54)
Idiosyncratic Volatility	−16.161**	0.128	−16.276**	0.236
	(−2.19)	(0.02)	(−2.21)	(0.04)
Institutional Ownership	−0.440	−0.470	−0.431	−0.474
	(−0.96)	(−1.27)	(−0.94)	(−1.28)
Log(1 + #Analysts)	0.187	0.375***	0.189	0.374***
	(1.20)	(2.96)	(1.21)	(2.95)
EPS Growth	0.001	−0.000	0.001	−0.000
	(0.56)	(−0.16)	(0.53)	(−0.17)
Dividend Dummy	−0.157	0.039	−0.153	0.039
	(−0.86)	(0.22)	(−0.84)	(0.22)
SP500 Dummy	−0.064	0.033	−0.071	0.032
	(−0.17)	(0.15)	(−0.19)	(0.15)
Year Dummy	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes
Observations	3651	3642	3651	3642
Adjusted R^2	0.180	0.321	0.181	0.321

shown in Panel A of Table 10, with the additional control variables included, our results hold and individual investor trading has a significantly positive impact on firm value.

4.6.3. Effect of market condition

The year-by-year analysis shown earlier confirms that the positive impact of individual investor trading on firm value is not driven by specific years. With the monthly measures of individual investor trading, we now further explore whether the results vary at different market conditions. Specifically, we compare the results for up and down months based on return in S&P 500 index, with months with positive (negative) S&P 500 index return being up (down) months. As shown in Panel B of Table 10, in up months, individual investor trading has significantly positive impact on firm value, while in down months, the result is similar for the individual trading volume ratio measure, but insignificant for the individual trading turnover measure.

Table 10
Robustness checks.
Panel A reports firm fixed effect regressions at monthly frequency. All dependent and independent variables are computed at monthly level, and for the firm characteristic variables that do not have monthly data available, they are computed at quarterly level, and quarterly values are assigned to observations of months in the corresponding quarters. Month dummies are included. Panel B reports results of firm fixed effect regressions at monthly frequency for up and down months based on SP500 returns. Only coefficients and t-statistics of the individual investor trading measures, Log(IndVolRatio) and Log(IndTurnover) are reported. Panel C reports results of firm fixed effect regressions at monthly frequency for S&P 500 stocks and non-S&P 500 stocks. Only coefficients and t-statistics of the individual investor trading measures, Log(IndVolRatio) and Log(IndTurnover) are reported. Panel D reports results of firm fixed effect regressions at monthly frequency for NYSE stocks. Log(IndVolRatio_net) is the ratio of individual investor trading volume to the total trading volume excluding program trading volume, in logarithmic format. Only coefficients and t-statistics of the individual investor trading measures, Log(IndVolRatio) and Log(IndVolRatio_net) are reported.

Panel A				
	(1)	(2)		(3)
Log(IndVolRatio)		0.010***		
		(3.58)		
Log(IndTurnover)				0.005**
				(2.12)
Log(Total_IndVolRatio)		0.369***		
		(19.57)		
Log(Total_IndTurnover)				−0.069***
				(−7.33)
Log(Turnover)	0.042**	0.041**		0.038**
	(2.26)	(2.17)		(2.03)
Spread	−0.046***	−0.046***		−0.046***
	(−11.29)	(−11.28)		(−11.29)
Stock Return	0.089***	0.088***		0.088***
	(4.81)	(4.80)		(4.80)
Return on Assets	0.721***	0.722***		0.721***
	(7.51)	(7.52)		(7.51)
Capital Expenditure	0.736***	0.730***		0.733***
	(4.10)	(4.07)		(4.09)
Log(Total Assets)	−0.428***	−0.427***		−0.428***
	(−10.83)	(−10.83)		(−10.83)
Leverage	0.651***	0.652***		0.652***
	(7.70)	(7.72)		(7.71)
Idiosyncratic Volatility	0.239	0.199		0.221
	(0.87)	(0.74)		(0.81)
Institutional Ownership	−0.075	−0.074		−0.075
	(−1.34)	(−1.32)		(−1.35)
Log(1 + #Analysts)	0.075***	0.076***		0.076***
	(3.05)	(3.13)		(3.09)
EPS Growth	0.000	0.000*		0.000
	(1.63)	(1.65)		(1.65)
Annual Fund Flow	−0.000	0.000***		−0.000*
	(−0.21)	(4.13)		(−1.85)
Dividend Dummy	−0.012	−0.012		−0.012
	(−0.50)	(−0.49)		(−0.49)
SP500 Dummy	0.049	0.052		0.050
	(0.89)	(0.93)		(0.91)
Month Dummy	Yes	Yes		Yes
Industry Dummy	Yes	Yes		Yes
Firm Dummy	Yes	Yes		Yes
Observations	51,716	51,716		51,716
Adjusted R^2	0.323	0.324		0.324
Panel B				
Up or Down Months	Log(IndVolRatio)		Log(IndTurnover)	
	Coefficient	t-statistic	Coefficient	t-statistic
Up	0.011***	(3.73)	0.007***	(2.81)
Down	0.009***	(2.74)	0.003	(0.94)
Panel C				
	Log(IndVolRatio)		Log(IndTurnover)	
	Coefficient	t-statistic	Coefficient	t-statistic
S&P 500 Stocks	0.032***	(4.64)	0.017***	(3.21)
Non-S&P 500 Stocks	0.005	(1.55)	0.003	(1.23)
Panel D				
	Log(IndVolRatio)		Log(IndVolRatio_net)	
	Coefficient	t-statistic	Coefficient	t-statistic
NYSE Stocks	0.010***	(3.58)	0.008***	(2.70)

4.6.4. Effect of non-individual trading

As pointed out earlier, the magnitude of overall individual investor trading is small. Among the non-individual trading activities, a significant amount of them may be uninformed, such as high-frequency trading and index trading. Since individual investor trading impacts firm value through improving stock price informativeness and reducing spread, would the effect be stronger for stocks with more uninformed non-individual trading, for which information incorporation via individual investor trading may be more important? A related question is whether we need to remove the uninformed non-individual trading from the total trading volume for our measures of individual trading to better capture its information incorporation efficiency. To answer the questions, we conduct two more robustness checks.

Since more index trading is expected for S&P 500 index stocks than non-S&P 500 index stocks, we firstly compare S&P 500 index stocks and non-S&P 500 index stocks in separate regressions. As shown in Panel C of Table 10, individual investor trading has a significantly positive effect on firm value for S&P 500 stocks, and positive but insignificant effect on non-S&P 500 stocks. The results suggest a stronger effect of individual investor trading on firm value for stocks with more uninformed non-individual trading, which is consistent with the information channel.

To answer the second question, we then attempt to remove some uninformed non-individual trading to examine how that affects the magnitude of the effect of individual trading on firm value. Using a program trading data for stocks traded at NYSE, ProTrac Replay and EOD database, we remove program trading volume from the total trading volume, and compute the individual trading volume ratio relative to the total trading volume net of program trading, Log(IndVolRatio_net), in logarithmic form.[18] We compare the effects of Log(IndVolRatio_net) and Log(IndVolRatio) on firm value for NYSE stocks. As shown in Panel D of Table 10, the magnitudes of the coefficients on Log(IndVolRatio_net) and Log(IndVolRatio) are very similar. Therefore our measures of individual investor trading perform well even with the existence of significant amount of uninformed non-individual trading.

4.6.5. Alternative measures of firm value

Our results are based on market-to-book ratio of equity (M/B) as a measure of firm value. We finally check whether our results are robust to using alternative measures of firm valuations, namely, Tobin's q and return on assets, respectively.[19] Untabulated results show that our results holds when these the alternative measures of firm valuation are used.

5. Conclusion

Although finance literature traditionally views individual investors as uninformed noise traders, recent studies suggest that individual investors may possess private information and their trading collectively can be informative. More informative stock price helps firms make better investment decisions by reducing information asymmetry. Thus we conjecture that intense individual investor trading may enhance firm value through improving stock price informativeness.

This study examines the effect of daily aggregate individual investor trading in each stock on firm performance using a comprehensive and real retail trading data. Consistent with the conjecture, we find that daily aggregate individual investor trading has a significantly positive effect on firm value. The results are robust to different model specifications, instrumental variable regressions, Granger causality tests, matched sample analysis, subsample analyses, and alternative measures of firm valuation.

This study explores the information and spread channels through which individual investor trading affects firm value. If individual investor trading enhances firm value by improving stock price informativeness, the effect of individual investor trading on firm value should be stronger when information production level is high so that individual investors are more likely to have valuable information. Consistent with the information production hypothesis implied by the information channel mechanism, we find that the effect of individual investor trading on firm value is greater for good firms for which information production is deemed to be higher. We also find that individual investor trading has a negative impact on spread, and its effect on firm value is only significant for high spread stocks, consistent with the spread channel mechanism that individual investor trading reduces spread, leading to lower expected return and higher market value.

We conclude that individual investor trading enhances firm value, and its effect on firm value is stronger for firms that have higher information production and higher spread. The overall results are consistent with individual investor trading increasing firm value through improving stock price informativeness and reducing spread.

Acknowledgments

We would like to thank one anonymous referee, Bing Han, Jungshik Hur, Alok Kumar, Jeff Netter (the Editor), and Lilian Ng for helpful comments and suggestions. We are especially grateful to the Editor Jeff Netter for his precious encouragement in the review process. All remaining errors are our own.

[18] Program trading refers to trading strategies that usually consist of baskets of fifteen stocks or more and are executed by a computer program simultaneously, and can largely be considered as uninformed. ProTrac Replay and EOD database summarizes program trading volume for each stock listed on NYSE on each trading date. During the sample period of 2006–2011, the mean and median ratios of program trading volume to total trading volume for NYSE stocks are 46% and 37%, respectively.

[19] Please refer to Harford and Li (2007), Bhagat and Bolton (2008), Klapper and Love (2004), and Mehran (1995) for rationale of using these two variables as alternative measures of firm performance. For brevity, the regression results using the two alternative measures of firm value are not tabulated.

References

Acharya, V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. J. Financ. Econ. 77, 375–410.
Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. J. Financ. Econ. 17, 223–249.
Baker, M., Stein, J., Wurgler, J., 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. Q. J. Econ. 118, 969–1006.
Barber, B., Odean, T., 2000. Trading is hazardous to your wealth, the common stock investment performance of individual investors. J. Financ. 55, 773–806.
Barber, B., Odean, T., 2008. All that glitters, the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21, 785–818.
Barber, B., Lee, Y., Liu, Y., Odean, T., 2009a. Just how much do individual investors lose by trading. Rev. Financ. Stud. 22, 609–632.
Barber, B., Odean, T., Zhu, N., 2009b. Do retail trades move markets. Rev. Financ. Stud. 22, 151–186.
Bartov, E., Bodnar, G., 1996. Alternative accounting methods, information asymmetry and liquidity, theory and evidence. Account. Rev. 71, 397–418.
Bhagat, S., Bolton, B., 2008. Corporate governance and firm performance. J. Corp. Financ. 14, 257–273.
Chen, Q., Goldstein, I., Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. Rev. Financ. Stud. 20, 619–650.
Chordia, T., Goyal, A., Lehmann, B.N., Saar, G., 2013. High-frequency trading. J. Financ. Mark. 16, 637–645.
Dhar, R., Goetzmann, W., Shepherd, S., Zhu, N., 2004. The impact of clientele changes: evidence from stock splits. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=410104.
Diamond, D., Verrecchia, R., 1991. Disclosure, liquidity, and the cost of capital. J. Financ. 46, 1325–1359.
Dow, J., Goldstein, I., Guembel, A., 2011. Incentives for information production in markets where prices affect real investment. Working paper, London Business School.
Evans, A., 2010. Do individual investors affect share price accuracy? Some preliminary evidence. University of Michigan Law School, The John M. Olin Center for Law & Economics Working Paper Series.
Fama, E., French, K., 1993. Common risk factors in the returns on bonds and stocks. J. Financ. Econ. 33, 3–56.
Fama, E., French, K., 1997. Industry costs of equity. J. Financ. Econ. 43, 153–193.
Fang, V., Noe, T., Tice, S., 2009. Stock market liquidity and firm value. J. Financ. Econ. 94, 150–169.
Forsythe, R., Nelson, F.D., Neumann, G.R., Wright, J., 1992. anatomy of an experimental political stock market. Am. Econ. Rev. 82, 1142–1161.
Foucault, T., Gehrig, T., 2008. Stock price informativeness, cross-listings, and investment decisions. J. Financ. Econ. 88, 146–168.
Foucault, T., Sraer, D., Thesmar, D., 2011. Individual investor and volatility. J. Financ. 66, 1369–1406.
Goldstein, M.A., Kumar, P., Graves, F.C., 2014. Computerized and high-frequency trading. Financ. Rev. 49, 177–202.
Graham, J., 2000. How big are the tax benefits of debt? J. Financ. 55, 1901–1941.
Graham, J., Kumar, A., 2006. Do dividend clienteles exist? Evidence on dividend preferences of retail investors. J. Financ. 61, 1305–1336.
Gul, F., Tsui, J., 1997. A test of the free cash flow and debt monitoring hypotheses: evidence from audit pricing. J. Account. Econ. 24, 219–237.
Han, B., Kumar, A., 2013. Speculative retail trading and asset prices. J. Financ. Quant. Anal. 48, 377–404.
Harford, J., Li, K., 2007. Decoupling CEO wealth and firm performance: the case of acquiring CEOs. J. Financ. 62, 917–949.
Hasbrouck, J., Saar, G., 2013. Low-latency trading. J. Financ. Mark. 16, 646–679.
Hendershott, T., Jones, C., Menkveld, A., 2011. Does algorithmic trading improve liquidity? J. Financ. 66, 1–33.
Holmstrom, B., Tirole, J., 1993. Market liquidity and performance monitoring. J. Polit. Econ. 101, 678–709.
Hvidkjaer, S., 2008. Small trades and the cross-section of stock returns. Rev. Financ. Stud. 21, 1123–1151.
Ivkovic, Z., Weisbenner, S., 2005. Local does as local is, information content of the geography of individual investors' common stock investments. J. Financ. 60, 267–306.
Jackson, A., 2003. The aggregate behaviour of individual investors. http://ssrn.com/abstract=536942.
Jarnecic, E., Snape, M., 2014. The provision of liquidity by high—frequency participants. Financ. Rev. 49, 371–394.
Jensen, M., 1986. Agency cost of free cash flow, corporate finance, and takeovers. Am. Econ. Rev. 76, 323–329.
Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. J. Financ. 63, 273–310.
Kaniel, R., Liu, S., Saar, G., Titman, S., 2012. Individual investor trading and return patterns around earnings announcements. J. Financ. 6, 7639–7680.
Kelley, E., Tetlock, P., 2013. How wise are crowds? Insights from retail orders and stock returns. J. Financ. 68, 1229–1265.
Kemsley, D., Nissim, D., 2002. Valuation of the debt tax shield. J. Financ. 57, 2045–2073.
Kirilenko, A., Kyle, A.S., Samadi, M., Tuzun, T., 2011. The flash crash: the impact of high frequency trading on an electronic market. University of Maryland, Working paper.
Klapper, L., Love, I., 2004. Corporate governance, investor protection, and performance in emerging markets. J. Corp. Financ. 10, 703–728.
Kumar, A., 2009. Who gambles in the stock market? J. Financ. 64, 1889–1933.
Kumar, A., Lee, C., 2006. Retail investor sentiment and return comovements. J. Financ. 61, 2451–2486.
Lee, C., Radhakrishna, B., 2000. Inferring investor behavior: evidence from TORQ data. J. Financ. Mark. 3, 83–111.
Luo, Y., 2005. Do insiders learn from outsiders? Evidence from mergers and acquisitions. J. Financ. 60, 1951–1982.
Mehran, H., 1995. Executive compensation structure, ownership, and firm performance. J. Financ. Econ. 38, 163–184.
Modigliani, F., Miller, M., 1963. Corporate income taxes and the cost of capital: a correction. Am. Econ. Rev. 53, 433–443.
Ng, L., Wu, F., 2010. Peer effects in the trading decisions of individual investors. Financ. Manag. 39, 807–831.
O'Hara, M., Yao, C., Ye, M., 2014. What's not there: odd lots and market data. J. Financ. 69, 2199–2263.
Odean, T., 1998. Are investors reluctant to realize their losses? J. Financ. 53, 1775–1798.
Roll, R., Schwartz, E., Subrahmanyam, A., 2009. Options trading activity and firm valuation. J. Financ. Econ. 94, 345–360.
Roulstone, D., 2003. Analyst following and liquidity. Contemp. Account. Res. 20, 551–578.
Subrahmanyam, A., Titman, S., 1999. The going-public decision and the development of financial markets. J. Financ. 54, 1045–1082.
Sullivan, R.N., Xiong, J.X., 2012. How index trading increases market vulnerability. Financ. Anal. J. 68, 70–84.
Surowiekci, J., 2004. The Wisdom of Crowds: Why the Many are Smarter than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations. Little, Brown and Company.
Wang, Q., Zhang, J., 2015. Individual investor trading and stock liquidity. Rev. Quant. Financ. Account, Forthcoming.