

Noise trading and the price formation process[☆]

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Abstract

This study proposes the dispersion in daily net initiated order flow across brokers as a proxy for the level of noise trading in a stock, and applies this proxy to test some basic implications of market microstructure theory. We use data from the Australian Stock Exchange, a computerized limit order market where price, quantity, and broker identity for each incoming order are shown on broker screens. We find daily movements in our noise measure are positively associated with trading volume and market depth, and negatively related to the bid-ask spread. We find monthly movements in our noise measure are negatively associated with the probability of informed trading, and positively correlated with the arrival rate of uninformed traders. We also find the sensitivity of stock prices to net initiated order flow decreases in the level of noise trading. In addition we find that, after controlling for noise trading, the sensitivity of stock prices to net initiated order flow is significantly greater on Mondays. These empirical results consistently support the implications of various models of market microstructure, suggesting that our proxy provides useful information as a daily measure of noise trading.

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1. Introduction

Microstructure models that assume asymmetric information typically analyze how market makers learn from observing order flow, and how the market maker's learning affects the evolution of prices. These theoretical models incorporate asymmetric information by distinguishing between informed and uninformed (liquidity, or noise) traders. They predict that prices are directly related to net initiated order flow, and that prices are less sensitive to net initiated

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order flow when there is more noise trading.¹ These models also predict that greater noise trading should generally be associated with more liquidity (i.e., higher market volume and depth, and smaller spreads), and that this liquidity should be diminished on Mondays if discretionary liquidity traders tend to avoid trading after the accumulation of private information over the weekend.² In line with these theoretical predictions, empirical research consistently shows that prices are positively related to the sign and size of trades.³ There is also limited empirical support for the implication that greater noise trading is associated with more liquidity.⁴

This study empirically analyzes how the level of noise trading affects market liquidity and the sensitivity of stock prices to net initiated order flow. Such analysis requires a proxy for the level of noise trading in a given stock. We propose such a proxy from data available on the Australian Stock Exchange (ASX), a computerized limit order market where price, quantity, and broker identity for each incoming order are shown on broker screens.⁵ From these trade data in each stock, we first compute the daily net initiated order flow through different brokers. We then argue the standard deviation of daily net initiated order flow across brokers reveals the level of noise trading for a given stock on a given day. Since noise traders can be expected to trade randomly through different brokers, an increase in the level (dispersion) of noise trading will translate into an increase in the dispersion of net initiated order flow across the brokers through which they trade, suggesting the merit of this measure as a proxy for the level of overall noise trading.⁶

This paper thus extends the literature by developing a novel empirical measure of the daily level of noise trading in a stock, and by using this measure to test several major predictions of microstructure models. The main empirical results in this paper include the following. First, increases in our daily measure of noise trading are associated with increased market liquidity (greater trading volume, market depth, and higher arrival rate of uninformed investors, as well as lower spreads and lower PINs). Second, the sensitivity of stock prices to aggregate net initiated order flow decreases in our measure of noise variance, supporting a major tenet of the asymmetric information models discussed above. This result is robust to different definitions of order flow dispersion, as well as to various specifications of the relation between stock prices and net initiated order flow. Finally, consistent with Foster and Viswanathan (1990), we find that on Mondays the level of noise trading is relatively low, while the sensitivity of prices to net initiated order flow (after controlling for the level of noise trading) is relatively high. Our empirical results thus consistently support and corroborate the theoretical predictions of basic microstructure models, suggesting the potential value of our noise trading proxy to shed additional light on a diverse array of related microstructure issues involving information asymmetry.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 describes the sample selection, data and institutional details of the ASX. Section 4 discusses our noise measure, and presents evidence on the association between noise trading and several measures of liquidity. Section 5 provides evidence on how noise trading affects the sensitivity of stock prices to net initiated order flow. The final section summarizes and concludes.

2. Literature review

Asymmetric information microstructure models have developed along two lines. One strand of literature follows the sequential trading model approach of Glosten and Milgrom (1985). Assuming that the market maker sets ‘regret free’ prices, the bid price is the expected value of the asset given that a potentially informed trader wants to sell, and the ask price is the expected value given that a potentially informed trader wants to buy. Given that the market maker sets regret

¹ By more noise trading, we mean greater dispersion in net initiated order flow across uninformed traders. See, for example, Easley and O’Hara (1987), Glosten and Milgrom (1985), and Kyle (1985).

² See Foster and Viswanathan (1990).

³ See, for example, Breen et al. (2002), Brennan and Subrahmanyam (1996), Easley, Kiefer, and O’Hara (1997), Foster and Viswanathan (1993), Glosten and Harris (1988), Hasbrouck (1991), Huang and Stoll (1997), and Stoll (2000).

⁴ See Green and Smart (1999) and Lee et al. (1993).

⁵ Data on broker identity are also observable on a number of other exchanges around the world. For example, on the Paris Bourse member firms can observe the entire limit order book and broker identity (see Venkataraman and Kumar, 2001). Broker identity is also displayed on the Hong Kong Stock Exchange (see Ahn et al., 2001). Several other studies also use data that describe the identities of brokers involved in the trade, including Reiss and Werner (1998, 2005) for the London Stock Exchange, and Dvorak (2005) for the Jakarta Stock Exchange.

⁶ One possible concern regarding the usefulness of this proxy is that daily net initiated order flow through brokers necessarily contains the order flow initiated by informed as well as uninformed traders. We return to this issue in Section 4, where we discuss our measure of the level of noise trading in more detail.

free prices, bid-ask spreads are narrower the higher the likelihood of dealing with an uninformed trader. This result implies that an increase in noise trading reduces the sensitivity of prices to net initiated order flow.⁷

A second strand of literature builds on the batch trading strategic model proposed by Kyle (1985). In Kyle-type models, the market maker learns from the net imbalance of buys and sells and adjusts prices accordingly. In these models, if there is an increase in the level (dispersion) of noise trading, the informed can camouflage his trading more effectively, and thus increases his order size. At the same time, however, the increase in noise trading leads the market maker to adjust prices by a smaller amount per unit of net order flow. As a result, despite the increase in net initiated order flow associated with greater informed trading, the expected price change is the same because the price impact of net initiated order flow has declined with greater noise trading. The key result for this study is that, for Kyle-type models as well as sequential trading models, an increase in noise trading leads the market maker to change prices by a smaller amount per unit of net initiated order flow, and thus reduces the sensitivity of prices to net initiated order flow.⁸

This paper is closely related to the work of Easley et al. (1997). Using trade data, they estimate the probability of information-based trading (PIN) specific to a given stock over a 30-day sample period, based on the number of buyer-initiated and seller-initiated trades. We instead estimate a *daily* measure of noise trading, based on dispersion in net initiated order flow across brokers on a given day. This measure enables assessment of how day-to-day changes in noise trading affect the sensitivity of prices to net initiated order flow for individual stocks.⁹

This paper is also related to Hasbrouck (1991), who shows that trades occurring when the spread is narrow have a relatively smaller permanent impact on quotes than those occurring when the spread is wide. This result suggests the market is deeper when the level of information asymmetry, proxied by the spread, is lower. We address the related question of whether our noise measure provides incremental information in explaining daily variation in the price impact of net order flow, beyond that provided by other liquidity measures such as the spread, depth, or trading volume.

Finally, Dufour and Engle (2000) test the model in Easley and O'Hara (1992) and find prices are more sensitive to order flow in periods of high trading activity. They attribute their finding to a higher proportion of informed traders in relatively active markets, but they are unable to directly test this hypothesis. Our paper proposes a proxy that enables a direct test of the relation between the relative trading activity of uninformed traders and the sensitivity of prices to net initiated order flow.

3. Institutional features of ASX, sample selection and data

3.1. Institutional features of the ASX

The Australian Stock Exchange (ASX) uses a fully automated open limit order book known as Stock Exchange Automated Trading System (SEATS). Monday through Friday, SEATS opens at 10 a.m. with a call auction and closes at 4 p.m. There are no designated market makers on the ASX. After the open, trading occurs when incoming buy or sell orders match outstanding limit orders. Order matching in SEATS is based on price priority and then time priority. Participating brokers enter orders (as agents or principals) through networked terminals in their offices. They can cancel or amend their orders almost instantaneously. The SEATS trading system allows brokers to observe order details such as price, volume, and broker identity. All other market participants observe only the price and quantity of orders, not broker identity. Note that, with respect to broker identity, this institutional arrangement is similar to a floor based trading system like the NYSE, where floor brokers can observe the identity of other floor brokers but clients cannot.

⁷ The market maker's perception of the level of uninformed trading relative to informed trading manifests itself in various ways in sequential trading models. An increase in the level of noise trading may influence the number of trades (Glosten and Milgrom, 1985), or the proportion of small trades relative to large trades (Easley and O'Hara, 1987), or the time interval between trades (Easley and O'Hara, 1992; Easley et al., 1997). These models demonstrate that, under a variety of conditions, greater uninformed trading reduces the sensitivity of prices to net initiated order flow.

⁸ Examples of Kyle-type models that bear this result include Admati and Pfleiderer (1988), Brown and Zhang (1997), Foster and Viswanathan (1990), Holden and Subrahmanyam (1992), Spiegel and Subrahmanyam (1992), and Subrahmanyam (1991).

⁹ The methodology in Easley et al. (1997) is used to explain several information-based regularities for cross-sections of stocks. For example, Easley, Kiefer, O'Hara, and Paperman (1996b) use the cross-sectional variation in PIN to explain differences in spreads for active and infrequently-traded stocks. Easley, Kiefer, and O'Hara (1996a) investigate whether orders executed in different markets have a different probability of being motivated by information. Finally, Easley et al. (2002) analyze how information-based trading affects asset returns. We examine the association between our proxy for noise trading and the PIN measure of Easley et al. (1997) in Section 4.2.4.

Most stock prices in Australia are in the range of 10 cents to 10 dollars per share. The minimum tick for these stocks is 1 cent. On-market trading (through SEATS) accounts for 70% of total volume, with annual turnover for the year ended June 30, 1994 around Australian \$128 billion. Off-market trading is comprised of trades in excess of 1 million dollars, and is not allowed to take place outside the best bid-ask spread on-market, unless it first satisfies demand/supply at the better market prices.

3.2. Sample selection and descriptive statistics

The data used in this study are drawn from the ASX microstructure databases maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA), which contain detailed information for all orders submitted to SEATS. Each order includes a sequence number that enables the exact timing of orders to be identified. The direction of trade initiation can thus be determined with great accuracy, as the sequence of quotes and trades is exactly known and trades cannot occur inside the spread (in contrast with floor trading environments, such as the NYSE). If a trade takes place at the ask, it is initiated by a buyer; if a trade occurs at the bid, it is initiated by a seller. At any point in time the best ask is given by the lowest sell limit order in the limit order book, and the best bid is given by the highest buy limit order in the book. Further details on this database can be found in Aitken and Frino (1996).

Sample selection begins with trade data from January 1991 through December 1994, for the hundred most actively traded stocks on the ASX. Our proxy for noise trading relies on dispersion in net initiated order flow across brokers. The validity of this proxy requires a reasonable number of brokers to be active for every stock, during each interval of observation. We use one trading day as our time interval of measurement. A shorter intraday interval would allow assessment of intraday dynamics of noise trading, net order flow, and price changes. However, for some sample stocks a shorter intraday interval reduces the average number of brokers who trade every interval to unacceptably low levels. Our choice of a daily time interval is thus dictated by the need for a minimum number of brokers to be active during each interval, for every stock in the sample.¹⁰ We include only days in which at least four brokers participated in the trading that day. In addition, we omit stocks with fewer than 800 such trading days, out of a possible 1012 trading days over the four-year sample period. Finally, given these screening criteria, we provide results for the sixty stocks with the greatest average daily trading volume over the sample period.¹¹

For every trading day, for each stock, we have the opening and closing prices and the net initiated dollar volume per broker. Since the focus in this study is on the sensitivity of stock returns to net initiated order flow during the trading day, we measure the daily return, R_{it} , as the log of the closing price over the opening price.

Net initiated order flow per broker, NIOF_{bit} , is defined as the dollar value of purchases minus the dollar value of sales initiated by broker b for stock i during day t . We use data on net trading activity per broker for the top 30 brokers (brokers are ranked by on-market dollar turnover in 1993, where each broker had to exist as a separate entity throughout our sample period). Data for the roughly fifty remaining brokers are aggregated and included as a separate category, labeled broker r . Given these data on daily net initiated order flow per broker (NIOF_{bit}), we define aggregate net initiated order flow for stock i on day t as follows:

$$\text{NIOF}_{it} = \sum_{b=1}^{30} \text{NIOF}_{bit} + \text{NIOF}_{rit}.$$

Table 1 provides descriptive statistics for this and several other relevant variables employed in the analysis. For our sample of stocks over the period, 1991–1994, the daily return ranges from –33.4% to 21.7%, with an average of 0.05%. Daily turnover ranges from 1100 dollars to 21.5 million dollars, with an average just over 600,000 dollars.¹² In addition, daily aggregate net initiated volume ranges from approximately –7.8 million dollars to +11 million dollars, with an average close to zero (approximately 13 thousand dollars). The average price of our sample stocks is 4.45

¹⁰ See Easley et al. (1997), Stoll (2000) and Evans and Lyons (2002) for other studies that use daily intervals. See also Breen et al. (2002, pp. 18–19). for a further discussion of this tradeoff.

¹¹ The sample size (number of trading days) for each of the sixty stocks in our final sample is provided in Table 3, Panel A. Trading in our sample stocks accounts for approximately 70% of total turnover on the ASX. Results are robust across the entire sample of 100 stocks. Alternative screening criteria do not alter the conclusions.

¹² Note that all price and volume data are measured in Australian dollars. The volume data are based on on-market trades after the opening.

Table 1
Descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
Daily return (%)	0.05	1.52	−33.4	21.7
Total trading volume ^a	616.4	823.1	1.1	21,483
Total net initiated order flow ^a	12.6	267.4	−7,857	11,137
PRICE	4.45	4.10	0.18	30.66
SPREAD (%)	1.9	2.2	0	53
MARKETCAP ^b	3.59	5.77	0.24	40.65
BROKERS	12.1	5.5	4	30

This table provides summary statistics on daily data from January 1991 through December 1994, across the sixty most actively traded stocks on the Australian Stock Exchange (ASX) that display broad broker coverage. All statistics are calculated across all stocks and days. In total there are 57,298 observations. The daily return for stock i on day t (R_{it}) is calculated as the log of the closing price over the log of the opening price; Total trading volume ($TOTTRAD_{it}$) is the sum of buyer-initiated plus seller-initiated dollar volume for stock i on day t ; Net initiated order flow ($NIOF_{it}$) is the total dollar value of all buyer-initiated trades minus the dollar value of all seller-initiated trades for stock i on day t . PRICE is the closing price. SPREAD is based on the best quotes in the limit order book, and is calculated as the simple average across all intraday observations where a change in the best quotes in the book was reported. Market capitalization (MARKETCAP) is the numbers of shares outstanding times the (unadjusted) share price at the end of the day. BROKERS is the number of different brokers involved in transactions in a stock on a day.

^a Thousands of dollars.

^b Billions of dollars.

Australian dollars, and the average bid-ask spread is 1.9%. The market capitalization ranges from 24 million to 40.7 billion Australian dollars. Finally, about 12 different brokers participate in trading our sample stocks on the average day.

4. A new proxy for noise trading

In this section we first motivate our measure of noise trading based on the dispersion in daily net initiated order flow across brokers. We then provide empirical evidence on the relation between several measures of liquidity and our measure for the daily level of noise trading.

4.1. A new proxy for noise trading: theory

We consider several alternative measures to proxy for the level of noise trading, all of which focus on dispersion in net initiated order flow across brokers. This focus merits justification and elaboration. First consider our emphasis on net *initiated* orders as opposed to, for example, net trading across brokers (which would include net initiated and net uninitiated order flow across brokers). The emphasis on initiated order flow is based on the common assumption that informed traders are likely to initiate trades (see, for example, [Glosten and Milgrom, 1985](#)).¹³ Therefore, the ability of informed traders to camouflage their trading will depend on dispersion in the order flow initiated by noise traders. A useful proxy for the level of noise trading thus requires consideration of initiated order flow.

Second, consider our emphasis on dispersion in net initiated order flow across *brokers*. This emphasis is based on the reasoning that, if noise traders trade randomly through different brokers, an increase in the dispersion of net initiated order flow across noise traders (i.e., the level of noise trading) will translate into an increase in dispersion of net initiated order flow across the brokers through which they trade. To elaborate on this reasoning, ignore for the moment the presence of informed traders. Then, to measure noise variance, one would ideally observe the actual net initiated order flow of all N noise traders on day t $\{u_{jt}; j = 1, \dots, N\}$. If, for simplicity, we assumed the $\{u_{jt}\}$ were iid with mean zero and variance σ_t^2 (for example, see [Kyle, 1985](#); [O'Hara, 1997](#)), the true variance of net initiated order flow across all noise traders on day t would be $N\sigma_t^2$. The sample variance across the $\{u_{jt}\}$ would then offer a consistent estimate of σ_t^2 , which is proportional to the variance across all noise traders ($N\sigma_t^2$).

¹³ Traders that initiate a transaction demand liquidity and are willing to pay a liquidity premium in order to obtain immediate order execution.

Since we do not observe the actual activity of noise traders themselves $\{u_{jt}\}$, we instead take advantage of available data on daily net initiated order flow for the B brokers through which the noise traders trade, $\{u_{bt}; b=1, \dots, B\}$. If we assume each broker has equal market share (i.e., N/B noise traders trade through each broker), then the $\{u_{bt}\}$ represent aggregated measures of daily net initiated order flow across B different groups of N/B noise traders, which are iid with mean zero and variance, $(N/B)\sigma_t^2$. Given these assumptions, the sample variance across the B observations on daily net initiated order flow per broker provides a consistent estimate of $(N/B)\sigma_t^2$, which is also proportional to the variance of daily net initiated order flow across noise traders, $N\sigma_t^2$. This result establishes the potential merit of dispersion in net initiated order flow across brokers as a proxy for noise trading. However, this discussion ignores the presence of informed traders and differences in market share across brokers.

Differences in market share across brokers can be dealt with by standardizing each broker's time series of daily net initiated order flow, before considering the cross-sectional variation in net initiated order flow across brokers on a given day. Brokers with a larger market share have greater expected total variation in their order flow over time. To account for such differences across brokers, we divide each time series on daily net initiated order flow per broker (NIOF_{bit}) by the standard deviation of that broker's NIOF_{bit} over time.

Finally, consider the presence of informed traders. We argue that information-based trading does not emasculate the usefulness of this broker-based proxy for noise trading. Informed traders are expected to break up their trades in order to camouflage their trading (in the spirit of Kyle (1985)), and they have incentive to spread their trading across brokers in proportion to each brokers' market share (as in Roell, 1990).¹⁴ In this fashion, informed traders should attempt to mimic the random dispersion of noise traders across brokers, so that the order flow through individual brokers does not convey their private information beyond that revealed in aggregate net order flow. If informed trading is spread across brokers in this manner, it should alter each broker's net initiated order flow in proportion to that broker's market share.

If informed trading is spread across brokers in proportion to each broker's market share, then informed trading should affect this measure of standardized NIOF_{bit} in a neutral way across brokers. As a result, the B observations on standardized NIOF_{bit} on a given day still enable consistent estimation of the dispersion in net initiated order flow across brokers, $(N/B)\sigma_t^2$, which remains proportional to the dispersion across noise traders, $N\sigma_t^2$. In this light, we proxy the dispersion in order flow across noise traders on a given day with the standard deviation across the B observations on standardized net initiated order flow per broker.

The validity of this proxy for noise trading depends on the condition that informed traders spread their trading across brokers in accord with brokers' market share (as in Roell, 1990). If informed traders do not split their orders across brokers, but instead place large orders through individual brokers, such behavior would reduce the usefulness of our measure of dispersion in noise trading.¹⁵ On the other hand, such behavior by informed traders would also make it more difficult for our proxy to reveal the robust negative relation with the sensitivity of stock prices to net order flow that is documented in this study.

To see this result, suppose that informed traders receive substantive new value-relevant information on a given day. This information arrival should increase the sensitivity of stock prices to net order flow (see Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Further, suppose informed traders do not split their orders, but instead concentrate their increased informed trading in one or a few brokers. This behavior would result in an increase in the standard deviation of net initiated order flow across brokers. The increase in informed trading combined with the tendency to not split trades should thus be associated with, both, an increase in the sensitivity of stock prices to net initiated order flow and the standard deviation of net order flow across brokers. Such behavior over time would make it more difficult for our proxy to detect the inverse relation between noise trading and the sensitivity of stock prices to net initiated order flow that is hypothesized in the asymmetric information microstructure models discussed above. Our empirical results indicate overwhelming evidence that our proxy for noise trading is negatively associated with the sensitivity of stock prices to net order flow. The robustness of these empirical results thus provides indirect evidence for the validity of our proxy as a measure of noise trading.

¹⁴ See Cornell and Sirri (1992) for evidence that insiders split trades across brokers to hide their trades. Barclay and Warner (1993) also report evidence consistent with informed traders breaking up their trades.

¹⁵ Indeed, one might mistakenly argue that the informed trader would have an incentive to increase the dispersion in order flow across brokers in order to increase the variance of noise trading (and thereby seemingly minimize the price impact of his trades). However, such an argument confuses our empirical proxy for noise trading with true noise variance (an exogenous variable). Also note that, with the exception of brokers, market participants cannot observe broker identity.

4.2. A new proxy for noise trading: empirical evidence

4.2.1. Definitions

Based on the theory in the previous section, we define our first measure of daily order flow dispersion ($STD1_{it}$) as the standard deviation of standardized net initiated order flow for stock i on day t across all 31 brokers (including broker category r). This measure accounts for differences in market share by first dividing the daily net initiated order flow for each broker ($NIOF_{bit}$) by the standard deviation of $NIOF_{bit}$ across time. $STD1_{it}$ is then calculated as the standard deviation of these standardized measures of net initiated order flow across brokers each day.

Our second measure of net initiated order flow dispersion ($STD2_{it}$) is analogous to $STD1_{it}$, but includes only the top thirty brokers (excluding all remaining brokers in category r). The third measure ($STD3_{it}$) includes all thirty-one broker categories, as in $STD1_{it}$, but employs a different standardization scheme to make the measure comparable across stocks. In this case we scale every stock's daily net initiated order flow for each broker, by the standard deviation in aggregate daily net order flow across *all* brokers. Our fourth measure ($STD4_{it}$) employs the average absolute deviation from the mean standardized net initiated order flow across the thirty-one broker categories, where the standardization scheme is applied to broker data separately, as in $STD1_{it}$ and $STD2_{it}$.

4.2.2. Descriptive statistics

Table 2 presents descriptive statistics for each of the proxies for daily variance in noise trading. These measures show considerable variation across days and across the sample of stocks. For example, $STD1$ has an average value of 0.81 across the entire sample, but ranges from near zero to 6.51 across different stocks and days. $STD3$ standardizes each broker's daily order flow by the daily standard deviation of aggregate net initiated order flow over time, for every stock, and is therefore much smaller in magnitude than $STD1$ or $STD2$. $STD4$ employs the mean absolute deviation rather than standard deviation, and ranges from 0.004 to 29.3.

4.2.3. Noise trading and daily measures of liquidity

Various models of market microstructure imply that, when market makers perceive greater informed trading and/or less uninformed trading, they are expected to increase their bid-ask spreads and decrease their depth at these quotes (Glosten and Milgrom, 1985; Kyle, 1985). Alternatively, if there is greater noise trading, total volume should rise while market makers reduce spreads and increase market depth.

There is a paucity of prior empirical research on the relation between market liquidity (spreads and depth) and the relative amounts of informed versus noise trading. One reason is the lack of a useful proxy for the relative amounts of informed trading versus noise trading that prevails in the marketplace. Two previous studies examine changes in bid-ask spreads and market depth around events that are likely to be characterized by systematic changes in the level of informed trading relative to noise trading.

Lee et al. (1993) argue that quarterly earnings announcements represent a recurring natural experiment around which informed trading systematically increases relative to noise trading. Around earnings announcements, they find

Table 2
Noise measures: descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
STD1	0.81	0.58	0.001	6.51
STD2	0.79	0.60	0.001	7.64
STD3 (*1,000,000)	7.85	11.2	0.004	285.7
STD4	1.04	1.10	0.004	29.3

This table provides summary statistics for our noise measures based on daily data from January 1991 through December 1994, across the sixty most actively traded stocks on the Australian Stock Exchange (ASX) that display broad broker coverage. Variable definitions:

$STD1_{it}$ is the standard deviation of the standardized net initiated order flow per broker for stock i on day t , across all 31 broker categories ($NIOF_{bit}$; $b=1, \dots, 30$, and all remaining brokers in category r), where standardized daily order flows per broker are obtained by dividing the daily net initiated order flow for each broker ($NIOF_{bit}$) by the standard deviation of $NIOF_{bit}$ across time;

$STD2_{it}$ is the standard deviation in $NIOF_{bit}$ across the thirty brokers ($b=1, \dots, 30$), excluding the last group of all remaining brokers ($NIOF_{rit}$), after standardizing as in $STD1_{it}$;

$STD3_{it}$ is the standard deviation in $NIOF_{bit}$ across all 31 broker categories ($b=1, \dots, 30$, and r), after first standardizing $NIOF_{bit}$ for each broker category using the standard deviation of *total* net initiated order flow per stock ($NIOF_{it}$) over time rather than its own standard deviation ($NIOF_{bit}$);

$STD4_{it}$ is the mean absolute deviation in $NIOF_{bit}$, across the 31 broker categories ($b=1, \dots, 30$, and r), after standardizing as in $STD1_{it}$ and $STD2_{it}$.

Table 3

Associations between noise trading and liquidity measures

Panel A: firm-specific correlations

This panel presents the correlations of $STD1_{it}$ with $SPREAD_{it}$, $VOLUME_{it}$, and $DEPTH_{it}$, estimated using daily data from 1991 through 1994, for each of the sixty most actively traded stocks on the Australian Stock Exchange (ASX), ranked according to average daily volume, with firm 1 (60) the lowest (highest) volume. $SPREAD_{it}$ is the average bid-ask spread across all quotes for stock i on day t divided by the standard deviation of the daily spread for stock i ; $DEPTH_{it}$ is average market depth across all quotes for stock i on day t , divided by the standard deviation of the daily depth for stock i ; $VOLUME_{it}$ is total dollar volume in stock i on day t , divided by the standard deviation of daily trading volume of stock i . P -values appear beneath each correlation (in parentheses).

Small volume firms					Medium volume firms					Large volume firms				
Firm	SPREAD	DEPTH	VOLUME	N	Firm	SPREAD	DEPTH	VOLUME	N	Firm	SPREAD	DEPTH	VOLUME	N
1	-.032 (.336)	.247 (.000)	.114 (.001)	891	21	-.074 (.018)	.420 (.000)	.372 (.000)	1012	41	-.046 (.152)	.367 (.000)	.395 (.000)	995
2	-.096 (.002)	.298 (.000)	.400 (.000)	997	22	-.058 (.073)	.302 (.000)	.343 (.000)	947	42	-.082 (.009)	.366 (.000)	.368 (.000)	1012
3	-.129 (.000)	.317 (.000)	.263 (.000)	937	23	-.014 (.669)	.360 (.000)	.352 (.000)	992	43	-.131 (.000)	.345 (.000)	.118 (.000)	1011
4	-.048 (.160)	.237 (.000)	.289 (.000)	847	24	-.003 (.933)	.298 (.000)	.083 (.009)	984	44	.004 (.892)	.241 (.000)	.377 (.000)	1012
5	-.131 (.000)	.298 (.000)	.314 (.000)	832	25	-.123 (.000)	.415 (.000)	.280 (.000)	1003	45	-.006 (.841)	.319 (.000)	.299 (.000)	1012
6	-.099 (.002)	.259 (.000)	.312 (.000)	986	26	-.072 (.023)	.290 (.000)	.372 (.000)	1009	46	-.083 (.009)	.232 (.000)	.426 (.000)	994
7	-.072 (.025)	.280 (.000)	.298 (.000)	971	27	-.088 (.006)	.261 (.000)	.379 (.000)	962	47	-.024 (.444)	.034 (.287)	.310 (.000)	1012
8	-.135 (.023)	.191 (.001)	.160 (.007)	281	28	-.168 (.000)	.329 (.000)	.383 (.000)	959	48	-.113 (.000)	.356 (.000)	.327 (.000)	1012
9	-.055 (.093)	.355 (.000)	.357 (.000)	946	29	-.074 (.032)	.269 (.000)	.465 (.000)	851	49	-.037 (.246)	.306 (.000)	.384 (.000)	1012
10	-.064 (.049)	.303 (.000)	.245 (.000)	961	30	-.069 (.029)	.232 (.000)	.176 (.000)	1011	50	-.076 (.017)	.228 (.000)	.414 (.000)	989
11	-.061 (.053)	.162 (.000)	.127 (.000)	1010	31	-.075 (.020)	.370 (.000)	.222 (.000)	969	51	-.075 (.017)	.378 (.000)	.423 (.000)	1012
12	-.097 (.002)	.381 (.000)	.357 (.000)	1009	32	-.136 (.000)	.349 (.000)	.206 (.000)	1011	52	.046 (.141)	.308 (.000)	.367 (.000)	1012
13	-.082 (.010)	.282 (.000)	.163 (.000)	987	33	-.011 (.724)	.242 (.000)	.449 (.000)	971	53	.036 (.256)	.286 (.000)	.279 (.000)	1012
14	-.156 (.000)	.383 (.000)	.220 (.000)	970	34	-.014 (.660)	.434 (.000)	.359 (.000)	1012	54	-.159 (.000)	.393 (.000)	.274 (.000)	1012
15	-.068 (.031)	.424 (.000)	.475 (.000)	1012	35	-.019 (.543)	.253 (.000)	.384 (.000)	1012	55	-.082 (.009)	.290 (.000)	.426 (.000)	1011
16	-.161 (.001)	.288 (.000)	.428 (.000)	450	36	-.015 (.636)	.126 (.000)	.218 (.000)	1012	56	.003 (.931)	.408 (.000)	.356 (.000)	1012
17	-.043 (.191)	.229 (.000)	.293 (.000)	942	37	-.102 (.001)	.402 (.000)	.407 (.000)	1011	57	-.013 (.756)	.336 (.000)	.142 (.000)	617
18	-.089 (.005)	.236 (.000)	.179 (.000)	988	38	-.103 (.001)	.323 (.000)	.255 (.000)	1008	58	.057 (.069)	.374 (.000)	.355 (.000)	1012
19	-.123 (.000)	.241 (.000)	.254 (.000)	918	39	-.108 (.001)	.188 (.000)	.093 (.003)	999	59	-.054 (.085)	.245 (.000)	.424 (.000)	1012
20	-.051 (.137)	.415 (.000)	.394 (.000)	852	40	-.099 (.002)	.326 (.000)	.231 (.000)	990	60	.002 (.937)	.331 (.000)	.372 (.000)	1012

Panel B

This panel provides the Pearson correlation coefficients of $STD1_{it}$ with three measures of liquidity: $SPREAD_{it}$, $VOLUME_{it}$, and $DEPTH_{it}$, estimated across all days from 1991 through 1994, across different subsamples of the twenty smallest, twenty medium, and twenty largest volume stocks, as well as across all sixty stocks. Next to each correlation coefficient we present (in parentheses) the P -value.

Subsample	SPREAD	DEPTH	VOLUME	N
Small	-.079 (.000)	.287 (.000)	.278 (.000)	17,788
Medium	-.067 (.000)	.303 (.000)	.301 (.000)	19,725

(continued on next page)

Table 3 (continued)

Panel B

This panel provides the Pearson correlation coefficients of $STD1_{it}$ with three measures of liquidity: $SPREAD_{it}$, $VOLUME_{it}$, and $DEPTH_{it}$, estimated across all days from 1991 through 1994, across different subsamples of the twenty smallest, twenty medium, and twenty largest volume stocks, as well as across all sixty stocks. Beneath each correlation coefficient we present (in parentheses) the P -value.

Subsample	SPREAD	DEPTH	VOLUME	N
Large	-.061 (.000)	.269 (.000)	.346 (.000)	19,785
All	-.060 (.000)	.285 (.000)	.309 (.000)	57,298

Panel C

This panel provides the Pearson correlation coefficients of $STD1_{im}$ with the probability of informed trading (PIN) and the arrival rate of uninformed traders. The last two measures are estimated for each stock for every month using the number of initiated buys and sells per day. STD_{im} is the average of daily STD_{it} for the same month and the same stock. The measures are estimated across all months from 1991 through 1994, across different subsamples of the twenty smallest, twenty medium, and twenty largest volume stocks, as well as across all sixty stocks. Next to each correlation coefficient we present (in parentheses) the P -value.

Subsample	PIN	Arrival rate uninformed	N
Small	-.030 (0.64)	.338 (.001)	870
Medium	-.075 (.001)	.365 (.001)	966
Large	-.118 (.001)	.381 (.001)	971
All	-.173 (.001)	.401 (.001)	2807

This table presents the Pearson correlation coefficients of $STD1_{it}$ with several measures of liquidity. $STD1_{it}$ is the proxy for noise variance, defined as the standard deviation of standardized net order flow for stock i on day t across all 31 brokers (including category r). We standardize by dividing daily net order flow for each broker by its own standard deviation over time.

an increase in the bid-ask spread of approximately 12% (which is statistically significant), and a decline in market depth of about 4% (which is insignificant). They interpret these findings as evidence that market makers reduce liquidity around earnings announcements when they sense an informational disadvantage, consistent with the models of [Glosten and Milgrom \(1985\)](#) and others.

[Green and Smart \(1999\)](#) examine the behavior of spreads and depth following recommendations in the Investment Dartboard column of the Wall Street Journal. They argue there is likely to be more noise trading in the subject stocks following publication of this column. They document substantial increases in abnormal trading volume in the subject stocks on the day of and the day after this column appears (days 0 and +1). They suggest this evidences an increase in the level of noise trading that is unanticipated and exogenous to the firm. Hence, this event represents the opposite experiment to that investigated in [Lee et al. \(1993\)](#). Green and Smart find a significant decrease in spreads, along with a smaller (and sometimes significant) increase in depth on days 0 and +1. They interpret this as evidence that market makers narrow quoted spreads and increase quoted depth when they perceive themselves at less of an informational disadvantage due to more noise trading, as [Glosten and Milgrom \(1985\)](#) and others predict.

We shed additional light on these issues by investigating the association between our daily proxy for noise trading ($STD1_{it}$) and three daily measures of liquidity: the average spread ($SPREAD_{it}$), average market depth ($DEPTH_{it}$), and total trading volume ($VOLUME_{it}$). Average daily spread and depth are based on the best quotes in the limit order book, where depth is defined as the sum of the number of shares offered at the best bid and the best ask. Both spread and depth are calculated as the simple average across all intraday observations where a change in the best quotes in the book was reported. To make spread, depth, and volume comparable across stocks, we standardize these variables by dividing each by the standard deviation of that variable for each firm.

Panel A of [Table 3](#) presents the correlations between our proxy for daily noise trading ($STD1$) and the average daily spread, depth, and volume, for each of the sixty stocks analyzed. Results are presented for all sample firms stratified according to average daily volume for the sample period, with firm 1 (60) the lowest (highest) volume. To the extent that larger firms have greater daily trading volume, this stratification also reflects firm size. Panel B provides the analogous correlations across subsets of the twenty smallest stocks (measured by average daily trading volume), the twenty medium-sized stocks, the twenty largest stocks, as well as across all sixty stocks.

Results in Panel A indicate that greater noise trading is consistently associated with smaller spreads, greater depth, and greater trading volume. While the positive correlations of noise trading with depth and volume are highly significant for each of the sixty stocks, the negative correlations with bid-ask spreads are not quite as robust across firms. For all

twenty small volume stocks the correlations between noise trading and spreads are negative, but just fourteen of these twenty correlations are significantly negative at the .05 level or better. Similarly, while all twenty correlations for the medium volume stocks are negative, just thirteen are significantly negative at the .05 level. Finally, just fourteen of the twenty large volume stocks are negative, and only eight of these correlations are significantly negative at the .05 level.

Panel B of Table 3 shows that the correlations between noise trading and bid-ask spreads become highly significant when measured across subsamples of the twenty small, the twenty medium, and the twenty large volume stocks, as well as across all sixty stocks. It is also interesting that these negative correlations decline in magnitude across the three subsamples as we move from small volume stocks to medium and large volume stocks. In contrast, the correlations between noise trading and trading volume become larger in magnitude across subsamples from small to large volume stocks. Together, these results are consistent with the models of Glosten and Milgrom (1985) and others, and they add to the empirical evidence provided in Lee et al. (1993) and Green and Smart (1999).

4.2.4. Noise trading and monthly measures of liquidity

We provide further evidence on the effectiveness of our measure (STD1) as a proxy for noise trading, by relating it to the probability of informed trading, PIN (see Easley et al., 1997). Based on their model, we expect a negative correlation between PIN and our noise measure.¹⁶ One potential problem with this comparison of STD1 with PIN is that the PIN not only depends on the arrival rate of informed trades, but also on the arrival of new information. Thus, our noise measure is likely to be more closely related to the arrival rate of uninformed traders, ε , in the model of Easley et al. (1997). In this light, we also relate our noise measure to the arrival rate of uninformed traders. We expect a positive correlation between our noise measure (STD1) and the arrival rate of uninformed traders (ε).

For every month, we estimate the PIN and the arrival rate of uninformed traders (ε) for each stock in our sample. Note that, unlike our noise proxy, these measures cannot be estimated on a daily basis. Thus, we first obtain a monthly measure of the level of noise trading in each stock, by averaging our daily noise measure (STD1) across all trading days in the month. Then we calculate the correlations of the monthly average of our measure of noise trading with the monthly PIN, as well as with the monthly arrival rate of uninformed traders (ε).

The results of this analysis are provided in Table 3, Panel C. As before, we report the results for each of the three groups of 20 stocks based on trading volume, and for all 60 stocks. The results show that, consistent with our expectations, our noise measure is significantly negatively correlated with the PIN. The average correlation across all months and stocks is -0.17 . Also consistent with our expectations, the average correlation between the arrival rate of uninformed traders and our noise measure is significantly positive, with an average of 0.40 . These results further support the validity of our measure (STD1) as a proxy for noise trading.

5. Noise trading and the responsiveness of stock prices to net order flow

5.1. Methodology

The empirical analogue to the relation between net initiated order flow and price changes emphasized in Kyle (1985) can be specified as follows:

$$R_{it} = \alpha + \lambda_{it} \text{NIOF}_{it} + \varepsilon_{it}. \quad (1)$$

The parameter, λ_{it} , measures the responsiveness of daily returns to aggregate net initiated order flow. The subscripts, i and t , acknowledge that Kyle's lambda varies, both, across firms (i) and time (t). Its reciprocal ($1/\lambda_{it}$) offers one measure of the depth of the market, by capturing the order flow necessary to change prices 1%. According to asymmetric information models, this measure of market liquidity (λ_{it}) is inversely related to the variance in net initiated order flow by uninformed traders. We incorporate this effect into our model by assuming a linear relation between λ_{it} and our proxy for noise variance, STD1_{it} , as follows:

$$\lambda_{it} = \gamma_{0,i} + \gamma_{1,i} \text{STD1}_{it}, \quad (2)$$

¹⁶ In the sequential trade model, the arrival rate of uninformed and informed traders is governed by independent Poisson processes. Extending the Kyle model, Foster and Viswanathan (1990) argue that uninformed traders prefer to avoid trading if they perceive a greater likelihood of trading with an informed trader.

where $\gamma_{1,i}$ is expected to be negative. Substituting Eq. (2) into Eq. (1) yields:

$$R_{it} = \alpha + \gamma_{0,i} \text{NIOF}_{it} + \gamma_{1,i} \text{NIOF}_{it} * \text{STD1}_{it} + \varepsilon_{it}. \quad (3)$$

This specification is estimated for each firm using Ordinary Least Squares (OLS) on daily data over the four years, 1991–1994.¹⁷

The model is appended to include day-of-the-week dummy variables, to incorporate possible systematic weekly patterns in returns. In addition, ten daily lagged returns are included in Eq. (3) to capture possible inertia in the time series of returns for each stock, and to ensure that the regression residuals are not autocorrelated.¹⁸

5.2. Empirical results

Table 4, Panel A presents the OLS coefficient estimates of γ_0 and γ_1 in model (3) for each firm, along with their White-adjusted t -ratios. Panel A also reports the value of λ implied by Eq (2) given the OLS estimates of γ_0 and γ_1 and the average value of STD1_{it} for each firm. Finally, the adjusted R -square and sample size for every firm's regression are also provided.

The results in Panel A indicate that γ_0 is significantly positive and γ_1 significantly negative, with λ unambiguously positive for all firms. The adjusted R -square ranges from 6% to 18% across firm regressions. These results overwhelmingly support the implications of asymmetric information microstructure models in which net initiated order flow is positively related to price changes (i.e., $\lambda > 0$), while an increase in the variance of noise trading (STD1_{it}) reduces the informativeness of aggregate net initiated order flow ($\gamma_1 < 0$).

Table 4, Panel B summarizes the results in Panel A by providing the mean OLS coefficients (γ_0 , γ_1 , and λ) across firm-specific regressions, for the three subsamples of twenty smallest, twenty medium, and twenty largest trading firms, as well as for the entire sample of sixty firms. As expected, λ decreases with an increase in firm size, indicating that smaller firms have less liquidity and market depth than larger firms. Panel B also presents the cross-sectional t -statistics for the null hypotheses that the mean coefficients (γ_0 , γ_1 , and λ) are zero, as well as the percentage of firms for which the White-adjusted t -ratio is greater than 2 for γ_0 , and less than -2 for γ_1 . Once again, these results overwhelmingly indicate that the positive relation between stock prices and net initiated order flow is attenuated by greater noise trading (i.e., $\gamma_0 > 0$, $\gamma_1 < 0$, and $\lambda > 0$).

The t -statistics for the mean OLS coefficients (γ_0 , γ_1 , and λ) provided in Panel B are calculated under the assumption that the estimation error is independent across firm-specific regressions. In our sample, the average pairwise correlation across residuals in different firm-specific regressions is low, ranging from 0.001 to 0.15, with an average of 0.075. Still, this correlation is unambiguously positive, perhaps due a common firm-dependence on the market return. This correlation suggests some caution is warranted in interpreting the t -statistics of the mean OLS coefficients across firms, provided in Panel B of Table 4.

To account for one potential source of residual cross-correlation across firms, we append Eq. (3) to include the daily open-to-close return on the Australian market index. This specification leads to a drop in the average pairwise correlation across residuals to .06. The relevant regression results are summarized in Table 4, Panel C. While inclusion of the market return increases the average adjusted R -square from 11.2% to 13.6%, it has almost no impact on the remaining parameter estimates or their statistical significance. This robustness lends credence to the results provided in Panels A and B of Table 4.¹⁹

¹⁷ Note that the parameters γ_0 and γ_1 vary across firms (i). Hereafter, we suppress the firm and time subscripts on λ , γ_0 , and γ_1 for notational simplicity.

¹⁸ The Ljung-Box test has been applied to the autocorrelation function of the OLS residuals for each firm's regression, and is found to reject the white noise hypothesis no more frequently than expected by chance, at the 5% level of significance (i.e., three rejections out of sixty firm-specific regressions). Estimates of γ_0 and γ_1 are robust with respect to alternative lag lengths.

¹⁹ We have also estimated model (3) in two other ways. First, we have estimated firm-specific regressions for the sixty sample firms as a system of Seemingly Unrelated Regressions (SUR). This SUR approach is applied to the subsample of days that are common across all sixty firms. Because this subsample is substantially smaller than the sample size provided in Panel A for every firm, we elect to provide OLS results on all available days for each firm in Table 2. SUR results are robust with respect to the OLS results provided in Table 2, and are available upon request. Second, we have summarized the results across firms by estimating model (3) with pooled data. In any such pooled model it is important to allow the intercept to shift, using firm-specific dummy variables. However, Eq. (3) actually incorporates two "intercepts:" one for the price formation model (α), and another for the relation between noise variance and λ (γ_0). Firm-specific dummies in the pooled model only allow the price formation model intercept (α) to shift, resulting in misleading estimates for γ_0 and γ_1 . Firm-specific dummies can also be interacted with NIOF_{it} in the pooled model, to allow shifts in the λ intercept (γ_0), but this procedure results in sixty different estimates of λ , so there is no gain to pooling the data. In this light, we provide mean OLS estimates across different firms' regressions in Panel B, to best summarize the firm-specific results listed in Panel A. Jones et al. (1994) also provide aggregated firm-specific OLS results in this manner.

Table 4
Price changes and net order flow

Panel A: firm-specific regressions

This panel presents results of Ordinary Least Squares (OLS) applied to daily data over the four years, 1991–1994. Results are provided for all sixty firms, ranked according to average daily total volume, with firm 1 (60) the lowest (highest) volume. For each firm we present: (i) OLS estimates for γ_0 and γ_1 (times 1,000,000), (ii) their White-adjusted t -ratios (in parentheses), (iii) the value of λ implied by Eq. (2) given γ_0 and γ_1 and the average value of STD1_{it} for that firm, (iv) the adjusted R^2 , and (v) the sample size (in parentheses).

Small volume firms					Medium volume firms					Large volume firms				
Firm	γ_0 (t)	γ_1 (t)	(λ)	R^2 (N)	Firm	γ_0 (t)	γ_1 (t)	(λ)	R^2 (N)	Firm	γ_0 (t)	γ_1 (t)	(λ)	R^2 (N)
1	0.222 (8.92)	-0.059 (-6.75)	0.177	0.104 (891)	21	0.072 (8.34)	-0.022 (-4.63)	0.053	0.106 (1012)	41	0.034 (6.61)	-0.012 (-3.12)	0.024	0.087 (995)
2	0.131 (9.52)	-0.022 (-9.38)	0.113	0.095 (997)	22	0.123 (8.22)	-0.028 (-4.23)	0.102	0.176 (947)	42	0.058 (11.85)	-0.029 (-8.43)	0.033	0.169 (1012)
3	0.147 (8.24)	-0.037 (-6.00)	0.118	0.080 (937)	23	0.058 (6.95)	-0.019 (-3.81)	0.043	0.093 (992)	43	0.032 (6.50)	-0.011 (-3.42)	0.023	0.090 (1011)
4	0.264 (9.26)	-0.087 (-7.61)	0.194	0.145 (847)	24	0.033 (5.00)	-0.007 (-4.66)	0.028	0.084 (984)	44	0.034 (8.04)	-0.010 (-3.45)	0.025	0.130 (1012)
5	0.153 (6.64)	-0.044 (-3.44)	0.118	0.094 (832)	25	0.064 (9.14)	-0.021 (-7.05)	0.048	0.101 (1003)	45	0.023 (5.85)	-0.004 (-1.24)	0.020	0.121 (1012)
6	0.124 (7.19)	-0.033 (-4.53)	0.098	0.079 (987)	26	0.060 (9.04)	-0.020 (-4.58)	0.043	0.124 (1009)	46	0.030 (7.73)	-0.009 (-4.05)	0.023	0.102 (994)
7	0.144 (6.01)	-0.043 (-3.80)	0.110	0.087 (971)	27	0.083 (6.15)	-0.018 (-2.02)	0.069	0.159 (962)	47	0.022 (6.91)	-0.007 (-2.88)	0.016	0.070 (1012)
8	0.094 (5.32)	-0.018 (-2.26)	0.081	0.091 (873)	28	0.095 (9.05)	-0.029 (-6.12)	0.073	0.157 (959)	48	0.028 (8.58)	-0.012 (-4.68)	0.018	0.075 (1012)
9	0.114 (7.54)	-0.033 (-4.84)	0.088	0.078 (946)	29	0.101 (8.18)	-0.033 (-6.80)	0.077	0.114 (851)	49	0.027 (8.65)	-0.011 (-4.70)	0.017	0.119 (1012)
10	0.082 (5.33)	-0.019 (-1.73)	0.067	0.086 (961)	30	0.046 (9.90)	-0.014 (-5.94)	0.035	0.119 (1011)	50	0.027 (9.52)	-0.009 (-6.85)	0.020	0.130 (989)
11	0.132 (8.60)	-0.048 (-7.20)	0.091	0.071 (1010)	31	0.045 (8.20)	-0.017 (-4.81)	0.031	0.099 (969)	51	0.023 (8.72)	-0.007 (-4.25)	0.017	0.142 (1012)
12	0.074 (10.15)	-0.016 (-7.90)	0.062	0.111 (1009)	32	0.044 (7.99)	-0.017 (-4.59)	0.031	0.109 (1011)	52	0.020 (8.05)	-0.009 (-4.27)	0.012	0.092 (1012)
13	0.131 (8.25)	-0.044 (-6.67)	0.098	0.094 (987)	33	0.062 (8.04)	-0.023 (-6.18)	0.046	0.102 (971)	53	0.021 (10.78)	-0.007 (-4.40)	0.015	0.159 (1012)
14	0.143 (9.89)	-0.048 (-6.89)	0.105	0.138 (970)	34	0.068 (10.46)	-0.027 (-5.36)	0.044	0.175 (1012)	54	0.029 (6.96)	-0.009 (-2.85)	0.022	0.097 (1012)
15	0.093 (11.32)	-0.028 (-6.84)	0.070	0.142 (1012)	35	0.039 (9.34)	-0.015 (-5.84)	0.026	0.123 (1012)	55	0.012 (8.39)	-0.003 (-3.65)	0.010	0.109 (1011)
16	0.047 (7.51)	-0.011 (-5.70)	0.038	0.068 (981)	36	0.025 (6.30)	-0.007 (-2.29)	0.019	0.101 (1012)	56	0.020 (5.51)	-0.005 (-1.69)	0.015	0.125 (1012)
17	0.129 (10.68)	-0.047 (-8.04)	0.093	0.121 (942)	37	0.038 (9.40)	-0.012 (-6.51)	0.028	0.130 (1011)	57	0.021 (9.47)	-0.007 (-4.79)	0.015	0.143 (1012)
18	0.050 (8.11)	-0.016 (-6.01)	0.038	0.057 (988)	38	0.037 (8.05)	-0.013 (-5.79)	0.027	0.091 (1008)	58	0.018 (6.15)	-0.007 (-2.79)	0.012	0.107 (1012)
19	0.074 (7.79)	-0.020 (-4.19)	0.059	0.111 (918)	39	0.048 (8.99)	-0.016 (-5.60)	0.037	0.116 (999)	59	0.015 (10.68)	-0.006 (-6.52)	0.010	0.150 (1012)
20	0.067 (7.71)	-0.016 (-4.81)	0.055	0.077 (852)	40	0.024 (6.78)	-0.007 (-3.33)	0.019	0.113 (990)	60	0.020 (7.44)	-0.008 (-3.14)	0.013	0.165 (1012)

Panel B: cross-sectional mean estimates from Panel A

This panel provides the average OLS parameter estimates for model (3), across the firm-specific results listed in Panel A. Mean OLS results are provided for three subsamples comprised of the twenty smallest, the twenty medium, and the twenty largest trading firms, as well as for the entire sample of sixty firms. The reported mean coefficients for γ_0 , γ_1 , and λ are multiplied by 1,000,000 for ease of exposition. Next to each mean coefficient for γ_0 , γ_1 , and λ , we present (in parentheses) the cross-sectional t -statistic for the null hypothesis that the mean coefficient is zero. In addition, the Panel also reports the mean adjusted R -square and the percentage of firms for which the White-adjusted t -ratio is larger than 2 for γ_0 , and smaller than -2 for γ_1 .

Subsample	γ_0	γ_1	λ	Adjusted R^2	$t(\gamma_0) > 2$	$t(\gamma_1) < -2$
Small	0.121 (10.09)	-0.034 (-8.21)	0.094 (10.48)	0.096	100%	95%

(continued on next page)

Table 4 (continued)

Panel B: cross-sectional mean estimates from Panel A

This panel provides the average OLS parameter estimates for model (3), across the firm-specific results listed in Panel A. Mean OLS results are provided for three subsamples comprised of the twenty smallest, the twenty medium, and the twenty largest trading firms, as well as for the entire sample of sixty firms. The reported mean coefficients for γ_0 , γ_1 , and λ are multiplied by 1,000,000 for ease of exposition. Next to each mean coefficient for γ_0 , γ_1 , and λ , we present (in parentheses) the cross-sectional t -statistic for the null hypothesis that the mean coefficient is zero. In addition, the Panel also reports the mean adjusted R -square and the percentage of firms for which the White-adjusted t -ratio is larger than 2 for γ_0 , and smaller than -2 for γ_1 .

Subsample	γ_0	γ_1	λ	Adjusted R^2	$t(\gamma_0) > 2$	$t(\gamma_1) < -2$
Medium	0.058 (9.97)	-0.018 (-10.85)	0.044 (9.11)	0.119	100%	100%
Large	0.026 (11.91)	-0.009 (-7.75)	0.018 (13.62)	0.119	100%	90%
All	0.068 (10.07)	-0.021 (-10.07)	0.052 (9.80)	0.112	100%	95%

Panel C: cross-sectional mean estimates, including the market return

This panel provides the cross-sectional mean OLS estimates of the relevant parameters (γ_0 , γ_1 , and λ), after appending model (3) to include the daily market return. The reported coefficients for γ_0 , γ_1 , and λ are multiplied by 1,000,000 for ease of exposition. Next to each mean coefficient for γ_0 , γ_1 , and λ we present (in parentheses) the cross-sectional t -statistic for the null hypothesis that the mean coefficient is zero. In addition, the Panel also reports the mean adjusted R -square and the percentage of firms for which the White-adjusted t -ratio is larger than 2 for γ_0 , and smaller than -2 for γ_1 .

Subsample	γ_0	γ_1	λ	Adjusted R^2	$t(\gamma_0) > 2$	$t(\gamma_1) < -2$
Small	0.112 (9.44)	-0.032 (-7.64)	0.087 (9.84)	0.113	100%	95%
Medium	0.052 (9.00)	-0.016 (-10.15)	0.040 (8.11)	0.145	100%	95%
Large	0.023 (10.94)	-0.009 (-7.11)	0.015 (12.33)	0.151	100%	90%
All	0.063 (9.54)	-0.019 (-9.50)	0.048 (9.29)	0.136	100%	93%

This table reports results of the following regression for each firm, as well as average results over three subsamples:

$$R_{it} = \alpha + \gamma_0 \text{NIOF}_{it} + \gamma_1 \text{NIOF}_{it} * \text{STD}_{it} + \varepsilon_{it},$$

with

$$\lambda = \gamma_0 + \gamma_1 \text{STD}_{it}.$$

R_{it} is the open-to-close return for stock i on day t . NIOF_{it} is net buyer-initiated volume, the dollar value of buyer-initiated trades minus seller-initiated trades for stock i during day t . STD_{it} is the proxy for noise variance, defined as the standard deviation of standardized net order flow for stock i on day t across all 31 brokers (including category r). We standardize by dividing daily net order flow for each broker by its own standard deviation over time. The model also includes day-of-the-week dummies and ten lagged returns.

5.3. Robustness checks

In this section we investigate the robustness of the results in Table 4 with respect to several variations on the variable definitions employed, as well as the specification in Eq. (3). The major empirical findings of Section 5.2 hold up to all variations; i.e., prices increase in net initiated order flow, and an increase in dispersion of net initiated order flow across brokers attenuates the responsiveness of stock prices to net initiated order flow ($\gamma_0 > 0$, $\gamma_1 < 0$, and $\lambda > 0$).

5.3.1. Alternative measures of the variance of net initiated order flow

The alternative measures of order flow variance considered here include the following:

- STD1_{it} Standard deviation in NIOF_{bit} across all thirty-one broker categories, ($b = 1, \dots, 30$, and r), after dividing daily values of NIOF_{bit} by the standard deviation of NIOF_{bit} computed over the four-year sample period;
- STD2_{it} Standard deviation in NIOF_{bit} across the thirty brokers ($b = 1, \dots, 30$), excluding the last group of all remaining brokers, NIOF_{rit} , after standardizing as in STD1_{it} ;
- STD3_{it} Standard deviation in NIOF_{bit} across all 31 broker categories ($b = 1, \dots, 30$, and r), after first standardizing NIOF_{bit} for each broker using the standard deviation of *total* net initiated order flow per stock (NIOF_{it}) over time, rather than NIOF_{bit} itself;
- STD4_{it} Average absolute deviation in NIOF_{bit} from the mean, across all 31 broker categories ($b = 1, \dots, 30$, and r), after standardizing as in STD1_{it} and STD2_{it} .

Table 5

Price changes, net initiated order flow, and the definition of noise variance

	γ_0	γ_1	λ	Adjusted R^2	$t(\gamma_0) > 2$	$t(\gamma_1) < -2$
STD1	0.068 (10.07)	-0.021 (-10.07)	0.052 (9.80)	0.112	100%	95%
STD2	0.051 (10.47)	-0.013 (-8.51)	0.041 (10.47)	0.100	100%	85%
STD3	0.059 (9.38)	-0.002 (-14.62)	0.045 (9.40)	0.102	100%	87%
STD4	0.048 (10.32)	-0.007 (-10.43)	0.047 (10.22)	0.095	100%	77%
STD5	0.0007 (10.68)	-0.0003 (-9.56)	0.0005 (10.68)	0.100	100%	75%

This table reports cross-sectional means of the OLS parameter estimates from estimating model (3) for each firm, over the entire sample of sixty firms, using five alternative definitions of noise variance (STD1_{it}–STD5_{it}).

The regression model is as follows:

$$R_{it} = \alpha + \gamma_0 \text{NIOF}_{it} + \gamma_1 \text{NIOF}_{it} * \text{STD}_{it} + \varepsilon_{it},$$

with

$$\lambda = \gamma_0 + \gamma_1 \text{STD}_{it}.$$

Variable definitions:

R_{it} is the daily open-to-close return for stock i on day t ;

NIOF_{it} is net initiated order flow for stock i during day t , defined as the total dollar value of all buyer-initiated trades minus the dollar value of all seller-initiated trades;

STD1_{it} is the standard deviation of standardized net initiated order flow per broker for stock i on day t , across all 31 broker categories (NIOF_{bit} , $b = 1, \dots, 30$, and all remaining brokers in category r), where standardization is obtained by dividing the daily net initiated order flow for each broker (NIOF_{bit}) by the standard deviation of NIOF_{bit} across time;

STD2_{it} is the standard deviation in NIOF_{bit} across the thirty brokers, $b = 1, \dots, 30$, excluding the last group of all remaining brokers (NIOF_{rit}), after standardizing as in STD1_{it};

STD3_{it} is the standard deviation in NIOF_{bit} across all 31 broker categories ($b = 1, \dots, 30$, and r), after first standardizing NIOF_{bit} for each broker category using the standard deviation of *total* net initiated order flow per stock (NIOF_{it}) over time, rather than its own standard deviation (NIOF_{bit}), as in STD1_{it} and STD2_{it};

STD4_{it} is the mean absolute deviation in NIOF_{bit} , across the 31 broker categories ($b = 1, \dots, 30$, and r), after standardizing as in STD1_{it} and STD2_{it};

STD5_{it} is the standard deviation of NNIT_{bit} across all 31 broker categories ($b = 1, \dots, 30$, and r), after first standardizing NNIT_{bit} for each broker category using the standard deviation of NNIT_{bit} over time. In the specification using STD5_{it} we replace NIOF_{it} by NNIT_{it} , defined as the number of purchases initiated by all brokers minus the number of sales initiated by all brokers, for stock i during day t .

The model (3) is appended to include day-of-the-week dummy variables and ten daily lagged returns. The appended model (3) is then estimated for each firm using Ordinary Least Squares (OLS) on daily data over the four years, 1991–1994.

The reported mean coefficients for γ_0 , γ_1 , and λ are multiplied by 1,000,000 for ease of exposition (not γ_1 using STD3). Next to each mean coefficient for γ_0 , γ_1 , and λ we present (in parentheses) the cross-sectional t -statistic for the null hypothesis that the mean coefficient is zero. In addition, the Table also reports the mean adjusted R -square and the percentage of sixty firms for which the White-adjusted t -ratio is > 2 for γ_0 , and < -2 for γ_1 .

We also replace the dollar value of net initiated order flow (NIOF_{it}) in model (3) with the net number of initiated trades, as follows (see Jones et al., 1994):

$$R_{it} = \alpha + \gamma_0 \text{NNIT}_{it} + \gamma_1 \text{NNIT}_{it} * \text{STD5}_{it} + \varepsilon_{it} \quad (4)$$

In this model, the net number of initiated trades (NNIT_{it}) is defined as the aggregation across all brokers of NNIT_{bit} , the number of purchases minus the number of sales initiated by broker b for stock i during day t . Accordingly, STD5_{it} is defined as the standard deviation of NNIT_{bit} across all 31 broker categories ($b = 1, \dots, 30$, and r), after first standardizing NNIT_{bit} for each broker using the standard deviation of NNIT_{bit} over time (STD5_{it} is analogous to STD1_{it}).

Table 5 summarizes the results from estimating models (3) and (4) for each firm with these alternative measures of noise variance, across the entire sample of sixty firms. Results include the cross-sectional mean OLS coefficients (γ_0 , γ_1 , and λ), the t -statistic testing the null hypothesis that each mean OLS coefficient is zero, the mean adjusted R -square, and the percentage of firms for which the White-adjusted t -ratio is > 2 for γ_0 and < -2 for γ_1 . Results are robust with respect to these alternative measures (i.e., $\gamma_0 > 0$, $\gamma_1 < 0$, and $\lambda > 0$) for all five definitions of noise variance.

5.3.2. The influence of firm liquidity on λ

Hasbrouck (1991) and Dufour and Engle (2000) focus on various aspects of market liquidity and the sensitivity of stock prices to net initiated order flow. Among other things, they show that trades occurring in the face of wide spreads

have a larger price impact than trades occurring when the spread is narrow. This result is consistent with the view that a higher spread indicates a higher degree of information asymmetry. It is possible that our measure of noise trading (STD_{it}) simply proxies for the liquidity of a stock on a certain day, and offers no new information regarding the sensitivity of stock prices to net order flow beyond that conveyed by other measures of liquidity, such as the spread, depth, or trading volume.

To investigate this possibility, we extend Eq. (3) to include the interaction of net initiated order flow ($NIOF_{it}$) with an alternative measure of liquidity ($LIQMEAS_{it}$), as follows:

$$R_{it} = \alpha + \gamma_0 NIOF_{it} + \gamma_1 NIOF_{it} * STD1_{it} + \gamma_2 NIOF_{it} * LIQMEAS_{it} + \varepsilon_{it}. \quad (5)$$

We test this specification by considering the three alternative daily liquidity measures analyzed earlier in Section 3: average spread, average depth, and total daily trading volume.

Results of estimating Eq. (5) are summarized in Table 6 and include: the cross-sectional mean OLS coefficients ($\gamma_0 - \gamma_2$ and λ) across all sixty firm-specific regressions, the t -statistic testing the null hypothesis that each mean OLS coefficient is zero, the mean adjusted R -square, and the percentage of firms for which the White-adjusted t -ratio has the hypothesized sign and absolute value larger than 2.

For all three alternative liquidity measures, the mean OLS coefficient on the new interaction term (γ_2) has the expected sign. That is, on days with lower liquidity (measured by higher spreads, lower depth, or lower trading volume), order flow tends to have a larger impact on prices. Importantly, however, inclusion of these alternative liquidity measures has minimal impact on the magnitude or statistical significance of γ_1 . That is, an increase in noise trading ($STD1_{it}$) still attenuates the association between stock prices and net order flow. Furthermore, the statistical significance (i.e., the t -ratio) of the influence of each alternative liquidity measure on λ (γ_2) is low relative to the influence of $STD1_{it}$ (γ_1). These results indicate that our measure of noise trading ($STD1_{it}$) offers substantive incremental information regarding the sensitivity of stock prices to net initiated order flow, beyond that provided by commonly used liquidity measures. This outcome lends more credence to the validity of $STD1_{it}$ as a useful proxy for the level (dispersion) of noise trading.

5.4. Cross-sectional variation in the responsiveness of stock prices to order flow

It is well-documented that the cost of liquidity for a security, measured by the bid-ask spread, is a function of three factors: the security's price, trading activity, and risk (see, for example, Demsetz, 1968; Stoll, 1978; McNish and Wood, 1992). The sensitivity of a stock's price with respect to net initiated order flow (λ) is another measure of a security's cost of liquidity. Thus, we consider the influence of these same three factors on the sensitivity of stock price to net initiated order flow, by estimating the following cross-sectional regression model over our sample of sixty stocks:

$$\text{Ln}\lambda_j = \alpha + \beta_1 \text{LnPMEAN}_j + \beta_2 \text{LnTRADMEAN}_j + \beta_3 \text{LnSTDRET}_j + \varepsilon_j \quad (6)$$

where λ_j = estimated sensitivity of stock price to order flow for firm j , from Table 3;

PMEAN_j Average price of stock j over the sample period;

TRADMEAN_j Average daily trading volume for stock j over the sample period;

STDRET_j Standard deviation of daily returns for stock j over the sample period; and Ln indicates the natural logarithm.

Results are provided in Table 7. The adjusted R -square indicates a substantial portion of the cross-sectional variation in λ is associated with these three firm-specific factors. The regression coefficients indicate: (i) higher priced stocks are more sensitive to net initiated order flow ($\beta_1 > 0$), (ii) more liquid stocks are less sensitive to net initiated order flow and thus less costly to trade ($\beta_2 < 0$), and (iii) more volatile stocks are more sensitive to net initiated order flow and thus bear a higher cost of trading ($\beta_3 > 0$). These results are similar to the results for a sample of 1,421 NYSE stocks reported in Brennan and Tamarowski (2000), lending further credence to the validity of our estimates of λ , and our overall findings.

Table 6

Price changes, net initiated order flow, and alternative liquidity measures

Measure	γ_0	γ_1	γ_2	λ	Adjusted R^2
Spread	0.057 (9.28)	−0.022 (−8.92)	0.934 (5.46)	0.057	0.117
$t(\gamma_0) > 2, t(\gamma_1) < -2, t(\gamma_2) > 2,$	90%	93%	33%		
Depth	0.085 (7.49)	−0.018 (−7.31)	−0.568 ^a (−2.49)	0.059 (7.53)	0.119
$t(\gamma_0) > 2, t(\gamma_1) < -2, t(\gamma_2) < -2,$	100%	72%	58%		
Trading volume	0.076 (7.99)	−0.020 (−9.66)	−0.008 ^a (−1.27)	0.058 (7.70)	0.116
$t(\gamma_0) > 2, t(\gamma_1) < -2, t(\gamma_2) < -2,$	100%	85%	23%		

This table reports the results of the following regression model, which appends model (3) to include the interaction of net initiated order flow with an alternative liquidity measure for stock i on day t :

$$R_{it} = \alpha + \gamma_0 \text{NIOF}_{it} + \gamma_1 \text{NIOF}_{it} * \text{STD1}_{it} + \gamma_2 \text{NIOF}_{it} * \text{LIQMEAS}_{it} + \varepsilon_{it}.$$

R_{it} , NIOF_{it} , and STD1_{it} are defined as in Tables 1–3. We use three alternative measures of daily liquidity for each stock (LIQMEAS_{it}): the average spread, the average depth, and total trading volume for each stock and for every trading day. Average spread and depth are based on the best quotes in the limit order book, and are calculated as the simple average across all intraday observations where a change in the best quotes in the book was reported. OLS regressions are run for each firm. The table provides cross-sectional means of the OLS parameter estimates ($\gamma_0 - \gamma_2$, and λ), for the entire sample of sixty firms. The reported coefficients for $\gamma_0 - \gamma_2$ and λ are multiplied by 1,000,000 for ease of exposition. Next to each mean coefficient estimate for $\gamma_0 - \gamma_2$ and λ , we present the cross-sectional t -statistic for the null hypothesis that the mean coefficient is zero. In addition, the table also reports the mean adjusted R -square and the percentage of firms for which γ_0 , γ_1 , and γ_2 have the expected sign and the absolute value of the White-adjusted t -ratio is > 2 .

Note that, in this expanded model, the sensitivity of stock returns to net initiated order flow (λ) depends on both the level of noise trading (STD1_{it}) and the liquidity measure (LIQMEAS_{it}), as follows:

$$\lambda = \gamma_0 + \gamma_1 \text{STD1}_{it} + \gamma_2 \text{LIQMEAS}_{it}.$$

^a These mean OLS coefficients are multiplied by 10^{12} , and all remaining coefficients are multiplied by 10^6 , for ease of exposition.

5.5. Day-of-the-week and noise trading

Our measure of noise trading allows us to test an interesting implication of the model in Foster and Viswanathan (1990). They argue it is reasonable to assume private information is received throughout the week, while public information is received only on business days. The public information is assumed to partially reveal the private information so that informed traders have relatively more information on Mondays than other days. In reaction to this information disadvantage at the beginning of the trading week, discretionary liquidity traders tend to shift their trading from Monday to later in the week. By waiting they can learn from the trading that occurs, and from the dissemination of public information.

Table 7

Cross-sectional regression of lambda

	Parameter	t -ratio
INTERCEPT (α)	−3.177	(5.11)
$\text{LnPMEAN} (\beta_1)$	0.227	(4.01)
$\text{LnTRADMEAN} (\beta_2)$	−0.697	(−25.62)
$\text{LnSTDRET} (\beta_3)$	1.033	(7.54)
$N = 60$		
Adjusted $R^2 = .93$		

This table presents results of the following cross-sectional regression model over the sample of sixty stocks:

$$\text{Ln}\lambda_j = \alpha + \beta_1 \text{LnPMEAN}_j + \beta_2 \text{LnTRADMEAN}_j + \beta_3 \text{LnSTDRET}_j + \varepsilon_j,$$

where λ_j is the estimated sensitivity of stock price to order flow for firm j , from Panel A in Table 2; PMEAN_j is the average price of stock j over the sample period; TRADMEAN_j is the average daily total trading volume for stock j over the sample period; STDRET_j is the standard deviation of daily returns for stock j over the sample period, and Ln indicates the natural logarithm of each variable. The t -statistics are corrected for potential heteroscedasticity using the White estimator of the standard error for each OLS coefficient estimate.

Table 8

Noise trading on Monday versus the rest of the week

Panel A: average noise trading on Monday versus the rest of the week

This panel presents the average value of the four alternative proxies for the variance of noise trading on Monday versus the other days of the week.

Subsample of days	STD1 _{it}	STD2 _{it} ^a	STD3 _{it}	STD4 _{it}	VOLUME	SPREAD	DEPTH
Monday	0.746	0.727	7.248	0.99	2,632,397	.0196	48,354
Tuesday–Friday	0.827	0.806	7.991	1.05	3,303,479	.0191	51,069
Mean difference <i>t</i> -test	(13.86)	(12.82)	(6.28)	(5.12)	(11.40)	(−2.32)	(3.14)

Panel B: sensitivity of stock prices to order flow on Monday versus the rest of the week

This panel summarizes the results of the following regression model, which allows the sensitivity of stock prices to order flow (λ) to differ on Monday versus the other days of the week, while controlling for changes in noise variance (STD1) on Mondays and other days of the week:

$$R_{it} = \alpha + \beta_1 \text{NIOF}_{it} + \beta_2 \text{Monday} * \text{NIOF}_{it} + \beta_3 \text{STD1} * \text{NIOF}_{it} + \beta_4 \text{STD1} * \text{Monday} * \text{NIOF}_{it} + \varepsilon_{it},$$

where Monday is a dummy variable equal to 1 if day t is a Monday and 0 otherwise, and NIOF_{it} is as defined in Tables 1–5.

Subsample	β_1	β_2	β_3	β_4	Adjusted R^2
Small	0.073 (7.72)	0.021 (1.14)	−0.018 (−3.46)	−0.005 (−0.44)	0.072
Medium	0.037 (8.29)	0.020 (2.57)	−0.009 (−4.15)	−0.009 (−1.30)	0.096
Large	0.019 (8.75)	0.006 (1.64)	−0.006 (−3.04)	−0.002 (−0.81)	0.108
All	0.043 (9.38)	0.016 (2.35)	−0.011 (−5.32)	−0.006 (−1.23)	0.092

^a The means in this column are multiplied by 10^6 , for ease of exposition.

The hypothesized shift of noise trading away from Monday should result in two empirical phenomena that are testable in our analysis: (i) our proxies for the level of noise trading (STD1_{it}–STD4_{it}) should decline on Mondays relative to other days of the week, and (ii) the sensitivity of stock prices to net initiated order flow (λ) should increase on Mondays relative to other days in the week because, *ceteris paribus*, Mondays should have a higher proportion of informed traders. Foster and Viswanathan (1990) further argue that this latter effect should be stronger for more actively traded firms. For these firms the quality or precision of public information is higher, thus exacerbating the relative disadvantage of uninformed traders on Mondays and providing a stronger incentive to delay their trades.

Empirical evidence regarding both issues is provided in Table 8. First, Panel A presents the average value of each proxy for the variance of noise trading on Monday versus the other days of the week. In addition, the average daily trading volume, bid-ask spread, and market depth are also provided. Mean difference *t*-tests indicate that all four proxies for noise trading (STD1_{it}–STD4_{it}) are significantly lower on Monday than on the other days of the week, consistent with Foster and Viswanathan (1990). In addition, it is noteworthy that the mean values of daily trading volume, the bid-ask spread, and market depth indicate there is significantly less liquidity on Mondays relative to other days of the week.

Second, Panel B summarizes the results of the following model, which allows the price sensitivity to order flow to differ between Monday and the other days of the week, while controlling for the level of noise trading on Monday and other days of the week:

$$R_{it} = \alpha + \beta_1 \text{NIOF}(it) + \beta_2 \text{Monday} * \text{NIOF}_{it} + \beta_3 \text{STD1} * \text{NIOF}_{it} + \beta_4 \text{STD1} * \text{Monday} * \text{NIOF}_{it} + \varepsilon_{it} \quad (7)$$

where Monday is a dummy variable equal to 1 if day t is a Monday and 0 otherwise.

According to Foster and Viswanathan (1990), if the proportion of informed traders on Monday is higher than on other days, then the price impact on Monday should be larger than on other days of the week, after controlling for changes in noise trading (STD1) on Monday versus other days of the week. In other words, we expect β_2 to be positive in Eq. (7). The coefficient, β_3 , shows whether STD1 attenuates the sensitivity of stock prices to net initiated order flow on days other than Monday. The coefficient, β_4 , allows STD1 to affect this sensitivity differently on Monday.

In Panel B of Table 8, β_3 is always significantly negative, corroborating the earlier results that greater noise trading attenuates the price sensitivity to net initiated order flow on the typical trading day (other than Monday). In addition, β_4

is negative for all subsamples in Table 8, suggesting that the price sensitivity to net initiated order flow tends to be attenuated even further on Mondays (although this tendency in β_4 is not statistically significant). The most important result in Panel B is that β_2 is significantly greater than zero. This outcome implies that stock prices are more sensitive to aggregate net initiated order flow on Monday than on other days of the week (after controlling for the level of noise trading on Monday and other days). This result supports one implication of Foster and Viswanathan (1990).

It is noteworthy that the increase in price sensitivity on Monday (β_2) is not statistically significant for the subsample of small trading firms, while it is significant at better than the 10% level for medium and large trading firms, as well as for all firms. On the other hand, the differences in β_2 across the three subsamples are not statistically significant. Thus, the further implication of Foster and Viswanathan (1990) that this latter effect should be stronger for more actively traded firms is not supported by this analysis. As a result, the evidence is not conclusive that there is a smaller relative disadvantage for uninformed traders on Mondays, for less actively traded firms.

6. Summary and conclusions

Microstructure theory generally incorporates information asymmetry by distinguishing between informed and uninformed (noise, or liquidity) trading, where the level of noise trading is typically modeled as the dispersion in net order flow across noise traders. This study proposes a novel empirical proxy for the daily level of noise trading. We use daily data on net initiated order flow per broker, available from the computerized Australian Stock Exchange, to measure dispersion in net initiated order flow across brokers in each stock. This proxy for the daily level of noise trading is based on the notion that greater dispersion in net order flow across noise traders should translate into greater dispersion in net order flow across the brokers through which noise traders trade. We apply this measure to empirically analyze a number of major implications from market microstructure theory.

Throughout our battery of tests, the empirical results uniformly support and corroborate the implications of noise trading set forth in microstructure theory. First, we find increases in our daily measure of noise trading are associated with increased market liquidity (greater trading volume, market depth, higher arrival rate of uninformed investors, as well as lower spreads and lower PINs). Second, we find the sensitivity of stock prices to net initiated order flow decreases in our proxy for noise trading, supporting a basic implication of asymmetric information models. This outcome is robust to alternative ways to measure the dispersion in net initiated order flow across brokers, as well as to alternative specifications of the regression model. For example, inclusion in our model of common liquidity measures such as the spread, depth, or trading volume does not reduce the explanatory power of our proxy for noise trading. Finally, consistent with Foster and Viswanathan (1990), we find the level of noise trading is low and the sensitivity of stock prices to order flow is high on Mondays, relative to other days of the week, after controlling for changes in noise trading on Monday versus other days of the week.

In addition to the issues investigated here, microstructure theory suggests that the level of noise trading could have an important bearing on various other stylized facts that characterize behavior in financial markets, such as the positive association between volume and absolute price changes, negative serial correlation in stock price changes, and autocorrelation in volume. Furthermore, a daily measure of noise trading could also allow additional insight into the trading behavior of different market participants around information events such as earnings announcements. Empirical analysis of the role of noise trading in explaining these phenomena represents a potentially fruitful area of future inquiry.

References

- Admati, Anat R., Pfleiderer, Paul, 1988. A theory of intraday patterns: volume and price variability. *Review of Financial Studies* 1 (1), 3–40.
- Hee-Joon, Ahn, Base, Kee-Hong, Chan, Kalok, 2001. Limit orders, depth, and volatility: evidence from the Stock Exchange of Hong Kong. *Journal of Finance* 56, 767–788 (2, Apr.).
- Aitken, Michael, Frino, Alex, 1996. The accuracy of the tick test: evidence from the Australian Stock Exchange. *Journal of Banking and Finance* 20, 1715–1729 (10, Dec).
- Barclay, Michael J., Warner, Jerold B., 1993. Stealth trading and volatility: which trades move prices? *Journal of Financial Economics* 34 (3), 281–306.
- Breen, William J., Hodrick, Laurie S., Korajczyk, Robert A., 2002. Predicting equity illiquidity. *Management Science* 48, 470–483.
- Brennan, Michael J., Subrahmanyam, Avanidhar, 1996. Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41, 441–464 (3, Jul).
- Brennan, Michael J., Tamarowski, Claudia, 2000. Investor relations, liquidity and stock prices. *Journal of Applied Corporate Finance* 12, 26–37 (Winter).

- David, Brown, Zhang, Zhi Ming, 1997. Market orders and efficiency. *Journal of Finance* 52, 277–308.
- Cornell, Bradford, Sirri, Erik R., 1992. The reaction of investors and stock prices to insider trading. *Journal of Finance* 47 (3), 1031–1060.
- Demsetz, H., 1968. The costs of transaction. *Quarterly Journal of Economics* 33–53 (February).
- Dufour, Alfonso, Engle, Robert F., 2000. Time and price impact of a trade. *Journal of Finance* 55 (6), 2467–2498.
- Dvorak, Thomas, 2005. Do domestic investors have an information advantage? Evidence from Indonesia. *Journal of Finance* 60, 817–839 (2, Apr.).
- Easley, David, O'Hara, Maureen, 1987. Price, trade size, and information in securities markets. *Journal of Financial Economics* 19 (1), 69–90.
- Easley, David, O'Hara, Maureen, 1992. Time and the process of security price adjustment. *Journal of Finance* 47 (2), 577–606.
- Easley, David, Kiefer, Nicholas M., O'Hara, Maureen, 1996a. Cream-skimming or profit-sharing? The curious role of purchased order flow. *Journal of Finance* 51, 811–833 (3, Jul).
- Easley, David, Kiefer, Nicholas M., O'Hara, Maureen, Paperman, Joseph B., 1996b. Liquidity, information, and infrequently traded stocks. *Journal of Finance* 51, 1405–1436 (4, Sep).
- Easley, David, Kiefer, Nicholas M., O'Hara, Maureen, 1997. One day in the life of a very common stock. *Review of Financial Studies* 10, 805–835 (3, Fall).
- Easley, David, Hvidkjaer, Soeren, O'Hara, Maureen, 2002. Is information risk a determinant of asset returns? *Journal of Finance* 57 (5), 2185–2221.
- Evans, M., Lyons, R., 2002. Order flow and exchange rate dynamics. *Journal of Political Economy* 110, 170–180.
- Foster, F. Douglas, Viswanathan, S., 1990. A theory of the interday variations in volume, variance, and trading costs in securities markets. *Review of Financial Studies* 3 (4), 593–624.
- Foster, F. Douglas, Viswanathan, S., 1993. Variations in trading volume, return volatility, and trading costs: evidence on recent price formation models. *Journal of Finance* 48 (1), 187–212.
- Glosten, Lawrence R., Harris, Lawrence E., 1988. Estimating the components of the bid/ask spread. *Journal of Financial Economics* 21 (1), 123–142.
- Glosten, Lawrence R., Milgrom, Paul R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14 (1), 71–100.
- Green, Jason, Smart, Scott, 1999. Liquidity provision and noise trading: evidence from the 'Investment Dartboard' column. *Journal of Finance* 54, 1885–1899 (5, Oct.).
- Hasbrouck, Joel, 1991. Measuring the information content of stock trades. *Journal of Finance* 46 (1), 179–208.
- Holden, Craig, Subrahmanyam, Avanidhar, 1992. Long-lived private information and imperfect competition. *Journal of Finance* 47, 247–270.
- Huang, Roger D., Stoll, Hans R., 1997. The components of the bid-ask spread: a general approach. *Review of Financial Studies* 10 (4), 995–1034.
- Jones, C.M., Kaul, G., Lipson, M.L., 1994. Transactions, volume and volatility. *Review of Financial Studies* 7 (4), 631–651.
- Kyle, Albert S., 1985. Continuous auctions and insider trading. *Econometrica* 53 (6), 1315–1336.
- Lee, Charles M.C., Mucklow, Belinda, Ready, Mark J., 1993. Spreads, depths, and the impact of earnings information: an intraday analysis. *Review of Financial Studies* 6 (2), 345–374.
- McInish, Thomas H., Wood, Robert A., 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *Journal of Finance* 47 (2), 753–764.
- O'Hara, Maureen, 1997. *Market Microstructure Theory*. Blackwell, Malden, MA.
- Reiss, Peter C., Werner, Ingrid M., 1998. Does risk sharing motivate interdealer trading? *Journal of Finance* 53, 1657–1703 (5, Oct.).
- Reiss, Peter C., Werner, Ingrid M., 2005. Anonymity, adverse selection, and the sorting of interdealer trades. *Review of Financial Studies* 18, 599–636 (2, Summer).
- Roell, Ailsa, 1990. Dual-capacity trading and the quality of the market. *Journal of Financial Intermediation* 1 (2), 105–124.
- Spiegel, Matthew, Subrahmanyam, Avanidhar, 1992. Informed speculation and hedging in a non-competitive securities market. *Review of Financial Studies* 5, 307–329.
- Stoll, Hans R., 1978. The pricing of security dealer services: an empirical study of Nasdaq stocks. *Journal of Finance* 33 (4), 1153–1172.
- Stoll, Hans R., 2000. Friction. *Journal of Finance* 55 (4), 1479–1514.
- Subrahmanyam, Avanidhar, 1991. Risk aversion, market liquidity, and price efficiency. *Review of Financial Studies* 4, 417–441.
- Venkataraman, Kumar, 2001. Automated versus floor trading: an analysis of execution costs on the Paris and New York Stock Exchanges. *Journal of Finance* 56, 1455–1485 (Aug.).