Information Contents of Trade and Quote Imbalances, and the Hypothesis of Reverse Liquidity: Evidence from a Fully Automated Exchange

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Abstract

In this paper, we study the information contents of imbalances in trades and quotes emanated from an exchange resembling the one envisioned by Black (1971). We find dollar volume is more informative than number in measuring daily trading and quoting activities. Our measure of quote imbalance permits an investigation on the information asymmetry between market and limit orders. In case illegal insider trading does not occur regularly, we present a hypothesis of reverse liquidity as an alternative interpretation for our empirical findings. It could be that market-order traders charge an implicit liquidity premium for fulfilling the contrarian trading demand of limit-order traders. We suspect proprietary traders are filling the vacuum created by the absence of designated market makers and they provide reverse liquidity through their active trading.

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1. Introduction

Although trading activity is generally considered to be informative, its measurement is still contentious in the literature. For example, Jones et al. (1994) show that the positive relation of volume with price moves is due to the number of trades and not the transaction size. They conclude that size has no information content beyond that already impounded in the number of transactions. On the contrary, Chan and Fong (2000) and Chordia et al. (2002) find that trade size is more significant in explaining the volume-volatility relation, particularly when it is used to measure the aggregate order imbalance between buyer- and seller-initiated trades. In addition, Chordia et al. (2001) and Chordia and Subrahmanyam (2004)'s papers highlight the importance of order imbalance as a measure of trading activity. Their results demonstrate that order imbalance is more valuable than volume in inferring the direction of price moves for the *next* trading day. The implication of this finding in the context of designing trading strategies that yield anomalous returns is obvious.

Strictly speaking, order imbalance makes sense only when there is a middleman to make the market by holding an inventory to accommodate temporary imbalance between buy and sell orders. For a fully automated exchange that has no designated market maker, there is no order imbalance in the sense of inventory management. However, since the founding concept of order imbalance is trade direction, one could still entertain order imbalance for trades executed by a computer. A market order that hits a limit order[1] at the ask price could be considered as buyer-initiated, and seller-initiated trades are those executed at bid prices. The imbalance in trades initiated by market orders is then computed analogously as the difference between those that hit the ask and those that hit the bid.

[1]Limit orders are permitted in most if not all major stock exchanges. Four of the largest stock exchanges in the world, namely, the NYSE, Nasdaq and their associated ECN's, Tokyo Stock Exchange and London Stock Exchange all allow traders to place limit orders. The study of limit orders is gaining momentum recently. For example, Bias et al. (1995)'s empirical analysis of Paris Bourse reveals a pattern of more limit orders when spreads are wide and more market orders when spreads are narrow. Empirical tests by Handa and Schwartz (1996) suggest that placing a network of buy and sell limit orders around the current price is profitable in 1988. Using the TORQ database, Harris and Hasbrouck (1996) find limit orders placed at or better than the prevailing quote are superior than market orders on the NYSE. Ahn et al. (2001) find that transitory volatility and market depth are dynamically related for the Stock Exchange of Hong Kong. They infer that limit-order traders enter the market and place orders when liquidity is needed. Lo et al. (2002) develop an econometric model based on survival analysis and report that execution times are sensitive to limit price but not order size. Theoretical models of limit and market orders include Glosten (1994), Chakravarty and Holden (1995), Seppi (1997), Foucault (1999), Dupont (2000) and Suominen (2001).

Much research has been devoted to unveiling the relation between stock price changes and trading activity on the NYSE and Nasdaq where there are specialists and broker-dealers respectively to make the market. On an electronic exchange where the matching of orders is fully automated, it is not obvious whether volume traded contains more information than the number of transactions in driving stock prices. Furthermore, in the absence of designated market makers, it is also important to measure the information content of order imbalance that affects daily returns.

In addition to order imbalance, we quantify the imbalance in the supply and demand of limit orders by defining the depth difference as the prevailing bid size less the ask size in dollars immediately before a trade. The quote direction is positive for bid and negative for ask because bid limit orders seek to buy while ask limit orders attempt to sell. For presentation clarity, we employ the term "trade imbalance" to refer to the usual notion of order imbalance, and "quote imbalance" to the depth difference and other quantities determined primarily by quotes. These two terms are meant to highlight the duality of market and limit orders in initiating trades and quotes, respectively. An understanding of trade and quote imbalances will have implications on order placement strategies when stock exchanges are fully automated.

We purchased a unique tick-by-tick data set from the Singapore Exchange Securities Trading to examine the information contents of trade and quote imbalances[2] on a fully automated exchange. Our empirical research makes three contributions to the literature. First, we find that dollar volume is more informative than the number of trades in measuring the trade imbalance. Second, we demonstrate that the quote imbalance in dollars is also reflected in daily returns. This quantity provides additional insights on the information dichotomy between market- and limit-order traders. Interestingly, its relation with returns is found to be negative, suggesting either the existence of asymmetric information, or a situation of *reverse* liquidity where market orders provide liquidity to limit orders. We suspect proprietary traders are playing the role of market makers through their active participation in the market that results in reverse liquidity. Finally, we document for the first time a negative autocorrelation for the day-to-day changes in

[2]We focus on the information content of imbalances rather than volume because the latter is fairly well studied as seen from the empirical literature such as Gallant et al. (1992), Campbell et al. (1993), Conrad et al. (1994), Lo and Wang (2000), Lee and Swaminathan (2000), Chakravarty (2001) and Llorente et al. (2002), just to name a few after Karpoff (1987)'s survey.

quote imbalance, which may be attributed to the stalking of equilibrium price by the midpoint of prevailing quotes when the underlying depth difference between the bid and ask reflects a latent imbalance in supply and demand.

Many empirical papers have investigated trades and quotes originated from exchanges without designated market makers. The growing literature includes Lehmann and Modest (1994) who examine data time stamped to the nearest minute from the Tokyo Stock Exchange (TSE) for all stocks on the First Section over 26 months. Bias et al. (1995)'s Paris Bourse sample is 40 stocks over 19 trading days. Hamao and Hasbrouck (1995) study three TSE stocks over 59 trading days. In Brown et al. (1997), 20 most actively traded stocks on the Australian Stock Exchange over a period of two years are the objects of study. Grinblatt and Keloharju (2000) focus on 16 largest Finnish stocks over 502 trading days. Ahn et al. (2001)'s paper is based on 12-month data of 33 liquid stocks provided by the Stock Exchange of Hong Kong. Linnainmaa (2003)'s analysis uses 30 largest stocks traded on the Helsinki Stock Exchange over 622 trading days. Kalay et al. (2003) obtain data from the Tel Aviv Stock Exchange with 105 stocks over 167 trading days to estimate the supply and demand elasticity.

Our research differs from these earlier papers in a number of ways. Firstly, while most authors tend to focus on stocks with high trading and quoting activities, we cover also less liquid stocks, as a more comprehensive sample demonstrates the robustness of research findings better. In fact, our sample size of 447 stocks is second to Lehmann and Modest (1994), and our sample period of 290 days is reasonably lengthy for studying the daily information contents of trades and quotes. Secondly, our focus on daily return as a dependent variable allows the potential gains or losses from using limit orders to be inferred directly. As a comparison, Ahn et al. (2001) investigate the intra-day relation between the depth and volatility. But evidence that suggests some gains or losses from using limit orders over market orders is not examined. Moreover, their depth is computed differently as the number of outstanding limit orders at the end of 15-minute interval, whereas our daily quote imbalance in dollars is the aggregate of irregularly sampled bid or ask sizes whenever a transaction occurs. Our data are time stamped to the nearest second while theirs are half a minute. Thirdly, most authors tend to rely on insider information story or adverse selection problem confronting risk-averse market makers to motivate their empirical works, and to count on limit orders to provide liquidity. We complement information asymmetry hypothesis by exploring the possibility of proprietary traders as day traders, who provide liquidity in a reverse fashion when they use mainly market orders to move the price, and to open and close their positions quickly with a profit.

This paper presents a case for asymmetric information and the hypothesis of reverse liquidity as follows. In Section 2, we provide a description of the trading environment. Section 3 describes our unique data set in detail. We document the empirical analysis and offer some possible explanations in Section 4. A few potential shortcomings are discussed in Section 5. Section 6 summarizes our main findings.

2. Trading Environment of the Singapore Exchange

To develop an intuitive grasp on the information dynamics reflected in both market and limit orders, it is crucial to understand the underlying market architecture and trading rules. Our data are from the Singapore Exchange (SGX), which is a merged entity of the former Stock Exchange of Singapore and the Singapore International Monetary Exchange (SIMEX). Unlike U.S. and other larger countries where order flows are inevitably fragmented across multiple exchanges, the Singapore Exchange Securities Trading (SGX-ST) is the only stock exchange in Singapore. As at end of March, 2003, the order-driven SGX-ST is ranked 24th among the 48 members of the World Federation of Exchanges in terms of market capitalization denominated in U.S. dollars, which is twice larger than the American Stock Exchange (http://www.world-exchanges.org/publications/EQU1103.XLS).

In a nutshell, the SGX-ST operates an exchange system much like an Electronic Communication Network (ECN). The main features of the trading environment are the types of orders allowed, minimum tick sizes, insider trading laws and enforcement, as well as proprietary traders.

2.1. Order-Driven Market

Trading of all shares, warrants, debentures, exchange-traded funds, real-estate investment trusts and other securities can only be carried out via SGX's Central Limit Order Book (CLOB) system.

The screen-based CLOB computer system maintains an order book and matches buy and sell orders automatically. There are neither exchange-appointed market makers nor floor traders to work the orders. Under this centralized system, quote and trade records are synchronized in such a way that allows the trade sign to be *observed* directly. The best bid and ask prices with the accompanied posted depths in the book are broadcast to the public free of charge. However, the entire depth in the securities book is observable real-time if traders subscribe to streaming data services.

To place an order, every trader must have an account with a SGX-ST member company[3], which is a brokerage firm. An order routed to the CLOB takes one of the following four forms:

- Market order
- Limit order
- Amendment order
- Withdrawal order

A trade occurs only when a market order enters the CLOB system and matches the limit order in price. A market order can consume a few limit orders if the required volume is large. Conversely, a large limit order becomes partially fulfilled when the volume of a matching market order is less than its size. Unmatched limit orders at the end of the day are purged from the CLOB. An amendment order reduces the volume but not the price, while the withdrawal order is equivalent to an amendment that reduces the order volume to zero. The best bid price is determined by limit orders with the highest price, and the best ask price by limit orders with the lowest price. For limit orders with the same best bid or ask prices, the computer system determines the execution priority by the time of order entry.

For order-driven markets, the trade direction is determined by the market order. On the SGX-ST, the transaction price can only be the prevailing bid and ask prices, since there is no specialist

[3]There were 23 member companies during our sample period from the beginning of October 2002 to the end of November 2003. Brokers who deal as pure agents for their firms' clients are called dealers in Singapore. They are the employees of brokerage houses. Those who also trade on their own accounts are called remisiers. They are self-employed. Both groups of personnel are the trading representatives of member companies.

or dealer to work the order. The price grid is determined by the minimum tick sizes described below. More importantly, the trades and quotes are time stamped, reported and recorded on the same platform. These aspects of SGX-ST's market design enables the trade direction to be observed unambiguously.

2.2. Minimum Tick Sizes

Under Bye-Law 2 of the SGX, five minimum tick sizes that depend on the price level are stipulated. The step-wise increment of minimum tick size with the price level constrains the possible range of quoted spread in percent. For example, the minimum tick size is S$0.005 for stock price between S$0.005 to S$0.995. A trader who buys a penny stock at the bid price of S$0.005 and sells it at the ask price of S$0.01 will gain as much as 100%. At the other end of this price range, a trader who buys shares at S$1 and sells them at S$0.995 will lose 0.5% on the bid-ask spread. The five minimum tick sizes are displayed in Table 1 along with the five corresponding ranges of bid-ask spread in percent. Obviously, penny stocks have higher relative spreads.

2.3. Insider Trading Legislation, Disclosure and Enforcement

Regulations on insider trading and information disclosure are stringent in Singapore. Arguments for the economic importance of insider trading laws and disclosure of price-sensitive information have been presented by Bhattacharya and Spiegel (1991) and Spiegel and Subrahmanyam (2000).

In October 2001, the Securities and Futures Act (2001) was legislated to make it conducive for prosecutors to nail down persons or institutions involved in insider trading. Any persons who trade securities, futures and options contracts on stocks and stock indices while possessing price-sensitive information, whether they are connected to the company involved or not, will be prosecuted if their activities are exposed. The onus of proof is on the defendants to deny that there was insider trading. The prosecutors need not prove that the defendants are connected to the company involved.

Conduct outside Singapore in relation to activities that concern securities and futures contracts listed or traded on the SGX-ST is also covered under the Act. Furthermore, the Act enhances the timeliness of information disclosure to the public. Beginning from the pre-IPO, continuous disclosure of material information by listed companies is mandatory under the Act. Substantial shareholders, which include company directors and entities with direct plus deemed interests exceeding 5%, are also legally obligated to notify the SGX directly of their transactions within two days. Moreover, false or reckless take-over announcements are criminal offences. The penalties for such criminal offences are a fine not exceeding a quarter million Singapore dollars[4] or imprisonment for a term not exceeding seven years or both (Attorney-General's Chambers (2001)).

To support their enforcement activities, SGX has put in place market surveillance systems to detect irregular trading such as unusual price and volume movements. SGX may require the listed company to announce whether it knew why there might be abnormal trading or inform the public of any material information that might reasonably be expected to affect the trading volume and price significantly. SGX may initiate an investigation of alleged misconduct by member companies, their directors, employees and trading representatives upon receiving a complaint, or of its own accord. Disciplinary actions taken against broker-dealers for violating the regulations in SGX's Rules and Bye-Laws (2001) are published and archived on the official web site of SGX, www.sgx.com.

2.4. Proprietary Traders

Another noteworthy aspect of the trading environment in Singapore is that almost every brokerage house has a number of proprietary traders who occupy trading desks with specialized terminals that grant them access to the entire limit order book, as well as direct entry of their orders to the SGX-ST. They do not need to pay commission for their trades but are expected to trade actively in the market as principals, either on their own accounts or brokerage firms' accounts. In addition, their brokerage firms may grant them credit, which can amount to millions of Singapore dollars.

[4] One U.S. dollar was about 1.7 to 1.8 Singapore dollars during our sample period.

For the credit and trading facilities provided, as much as 40 to 50 percent of the gains realized by these house traders will go to their brokerage firms. Any realized losses, however, are borne by the traders themselves. These proprietary traders usually close their positions within a day, although the settlement of trades operates at the T+3 cycle. Through contra accounting, only realized gains or losses are effected without the actual transfers of principal sums. Obviously, any proprietary traders who make sizable losses will have to discontinue their business. Therefore, they have every reason to prowl the market and make a kill for their survival on each trading day. With superior information access and more agile order submission strategies, they earn their living by moving prices up and down through a combination of market and limit orders. From the bid-ask spread, they obtain their rewards for providing liquidity to passive mutual fund managers and retail investors.

Notwithstanding the fact that proprietary traders have access to financial news services and may be better informed than retail investors, they are not company insiders and usually they do not trade on insider information. In light of tough insider trading laws and enforcement, the risk is too high for doing so. Instead, they behave more like speculative "noise" traders. Some industry sources[5] believe as much as 50 to 70 percent of total daily volume is churned out by proprietary traders, especially after the brokerage industry was liberalized in 2000.

In short, these proprietary traders may be considered as some sort of "market makers," though they have no obligation whatsoever to maintain an orderly market. Every proprietary trader is looking after her own interest but this selfish behavior contributes to the general welfare of the stock market as far as liquidity is concerned. Nevertheless, the issues of fairness and possible price manipulation remain. To deter manipulative trading activities, the SGX revised the trading rules and spelled out the misconduct more explicitly in Chapter 13 of the SGX Securities Trading Rules (2003). The relevant section on market manipulation and false market is re-produced in the Appendix. It is quite telling how some market players are trying to manipulate the market through multiple-party collaboration, signalling by limit orders, successive one-sided market orders and other tactics.

[5] Business Times, November 27, 2003 Editorial: Reducing conflicts of interest.

3. Data

The data used in this paper were purchased from the SGX-ST through a third-party data vendor. Our data are daily merged files of signed trades and best quotes with a resolution of one second. The entire depth of the securities book, however, is not available. Neither does each record contain information regarding the identity of trader.

But our tick-by-tick data fulfill two important requirements. Firstly, to unambiguously examine the information content of trade imbalance, it is crucial to have transaction records with trading direction provided. Secondly, to study the relation of quote imbalances with returns, it is indispensable to have quote updates whose time stamps are based on the same clock used for trade reporting. Thanks to the CLOB system, trade and quote records satisfying these two specifications are available from the SGX-ST[6].

The sample period is from October 4, 2002 to November 28, 2003, a total of 13 months with 290 trading days. This sample period is not by choice; it is determined solely by data availability. During this period, the stock market experienced rough patches of sluggish economy with rising unemployment. A general trend of the market is a downward drift from October 2002 to March 2003, and an upward movement from mid March to November 2003.

Having described the sample period, we turn to the choice of sample stocks. To be included in the sample, the firm must not be a new listing, as typically the trading activity of an IPO is abnormally high in the first few weeks. We checked the listing date of each firm to ensure that none is within two months before the beginning of our sample period. In other words, all firms

[6] In contrast, the widely used TAQ database from the NYSE has the problem of unsynchronized timing and reporting of trades and quotes. This problem leads to ambiguities in the identification of prevailing quotes. To solve this problem, Lee and Ready (1991) suggest a five-second rule for synchronizing trades with quotes. Obviously this rule is heuristic at best. Odders-White (2000) find that the standard Lee and Ready (1991) algorithm misclassifies or simply cannot classify transactions at the quotes' midpoint and transactions in large or actively traded stocks most frequently. In addition, small transactions at the quotes and large transactions inside the spread are also prone to error, which is systematically biased against seller-initiated trades. In addition, Peterson and Sirri (2003) report that on average, estimates of execution costs overstate trading costs by up to 17% when the benchmark quotes are incorrect. Thus, it seems that the synchronization problem is quite severe. Empirical research on imbalance cannot be done rigorously without observing the trade direction. There is always this nagging concern about the direction bias in the errors and the proportion of trades that cannot be signed and thus discarded from the sample. It is not impossible that the contradicting conclusions drawn by earlier empirical papers with regards to the number of transaction versus trade size are consequent upon the limitations of the signing algorithm and data used.

in the sample are at least two months well into their respective first days of trading. We also exclude securities that are delisted and those that have only 30 transactions or less during the entire sample period.

Other than these filters, we do not exclude penny stocks and stocks with negative book values. These stocks are illiquid; they do not have trades on each trading day. Altogether, there are 447 stocks in our sample. These stocks constitute well over 95% of the entire market capitalization in Singapore. Considering the fact that there are 508 locally listed companies as at the end of first quarter of 2003, our sample is representative of both liquid and illiquid stocks traded on the SGX-ST. The descriptive statistics for our sample are documented in Table 2. Data on the market capitalization and prices are taken from the official web site of SGX, which are dated as at March 31, 2003. Median market capitalization is 47.4 million Singapore dollars while the median price per share is S$0.19. The numbers of shares outstanding, equity and book values, are provided by the data vendor. As evident from the table, the ranges of these statistics are rather wide, which bear witness to the highly representative nature of our sample.

To obtain some descriptive statistics for the trading and quoting activities, we first compute the relevant numbers for each sample stock over the sample period. The cross-sectional average, standard deviation, minimum, median and maximum values are then computed and displayed in Table 2. The cross-sectional average number of trades at the bid price is 17.5 per day, while the number of trades at the ask price is 18.9 per day. On the daily basis, the average number of bid updates is 40.6 against 38.3 for ask updates. The liquidity level before a trade takes place can also be computed from the data. On average, the daily aggregate volume is 39 million shares at the bid and 38 million shares at the ask. In dollars, it is 20.75 million against 20.31 million. Overall, we see a large variation in these statistics, which testify again our sample is an assortment of both liquid and illiquid stocks.

As mentioned above, the number and dollar volume of signed trades are computed on a daily basis for each sample stock i. With these quantities, we define the following measures for trading activity on each trading day t:

- $\mathrm{TIN}_{i,t}$: Number of buyer-initiated trades less the number of seller-initiated trades

- $\mathrm{TID}_{i,t}$: Buyer-initiated dollars paid less the seller-initiated dollars received

These two quantities are the same as order imbalances measured in numbers and in dollars respectively. Dollar volume is more convenient than volume because it is invariant whenever there is a stock split.

Since depth is generated by limit orders, it is also of interest to investigate quoting activity and direction. For this purpose, we consider the buying and selling interests signalled by limit orders and define

- $\mathrm{QIN}_{i,t}$: Number of bid updates less the number of ask updates
- $\mathrm{QID}_{i,t}$: Aggregate depth difference measured in dollars, i.e., the daily net value of bid limit orders less ask limit orders prior to transactions

The quote update imbalance $\mathrm{QIN}_{i,t}$ is computed regardless of whether there are transactions. It provides a daily summary of quotes' dynamics in numbers. The aggregate depth difference, however, is computed only if there are transactions. The quote imbalance measure $\mathrm{QID}_{i,t}$ indicates the daily net amount of imbalance in buy and sell limit orders just before market orders arrive. Put differently, the imbalance signals to market watchers the net beliefs of limit-order traders over a day. When $\mathrm{QID}_{i,t}$ is positive (negative), it means that in dollars, more limit-order traders think that the bid (ask) price is a good price to buy (sell), which coincides with the latent demand being higher (lower) than supply.

4. Empirical Analysis

This section reports our empirical findings on the efficacy of number versus dollar volume in measuring trading and quoting activities. Since we are into order placement strategies, we compare limit orders with market orders from the standpoint of daily returns. Though speculative, notions of information asymmetry and reverse liquidity provision are offered for interpreting the results. We also attempt an analysis on the relation between quote imbalance and the disparity between the midpoint of quotes and the conditional expected value of equilibrium price.

4.1. Daily Returns, Trade and Quote Imbalances

To marginalize microstructure effects, we use the closing midquotes to compute the daily return $r_{i,t}$ of sample stock i on day t as follows:

$$r_{i,t} = \frac{\text{Difference in Closing Midquotes of Stock } i \text{ on Day } t \text{ and Day } t-1}{\text{Stock } i\text{'s Closing Midquote on Day } t-1}\,. \tag{1}$$

The closing midquote is half the sum of non-zero bid and ask prices last updated before the trading session ends with at least a transaction. More precisely, if there is no transaction or one of the quote prices is zero, $r_{i,t}$ is not computable and the time series will have a gap or a missing observation on day t. Any dividend payout is added to the difference when t coincides with the ex dividend day.

To control for the market-wide effects, we consider the daily return $r_{m,t}$ of the Straits Times Index (STI), which is the benchmark index of the Singapore stock market. It comprises 45 stocks, which are selected based on their market capitalization and dollar volume. All component stocks are weighted by free float, that is, the percentage of a company's shares not in the hands of controlling or strategic shareholders.

In addition, we also control for a measure of market breadth B_t defined as

$$B_t = \frac{\text{Number of Stocks with Positive } r_{i,t} - \text{Number of Stocks with Negative } r_{i,t}}{\text{Number of Stocks with Positive } r_{i,t} + \text{Number of Stocks with Negative } r_{i,t}}\,. \tag{2}$$

Although the correlation between these two market-wide factors is 0.802, the motivation for using B_t is to echo the "market sentiment" not captured in the STI. The introduction of these two market-wide factors is to alleviate the correlation between a pair of stocks, and to control for news that has an impact on the whole market.

Not all the 447 sample stocks had trading every day during the sample period. To perform a balanced seemingly unrelated regression (SUR), we take a subsample of 63 stocks that had transactions on all the 290 days. Information regarding these stocks is in Table 3. It is noteworthy that most of the stocks are less than three Singapore dollars per share. The motivation for running SUR is to deal with the fact that the innovation $u_{i,t}$ in the cross-sectional regression is such that for any pair of sample stocks i and j, the covariance $E[u_{i,t}\, u_{j,t}]$ may still be non-zero despite the two market-wide controls.

With the market-adjusted return[7] being $R_{i,t} \equiv r_{i,t} - r_{m,t}$, each of the 63 subsample stocks has 289 observations from 290 trading days. We point out that using the quotes' midpoint does not necessarily remove the serial correlation in daily returns completely. While the market returns $r_{m,t}$ and majority of the market-adjusted returns $R_{i,t}$ have insignificant AR(1) components, price discreteness and asynchronous quotes may still induce some degree of autocorrelation in some of the stocks. Thus, we first obtain the time series of residuals $\varepsilon_{i,t}$ from the following regression,

$$R_{i,t} = a_i + \rho_i\, R_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

for each of the 63 stocks before running SUR with a_i and ρ_i being the parameters. We are after the residuals $\varepsilon_{i,t}$ only and the two parameters are not used subsequently.

A key object of our study is to ascertain the explanatory power of trade and quote imbalances, as well as to gain an insight on using number versus dollar volume in measuring the activity. Hence, the market-and-AR(1)-adjusted return $\varepsilon_{i,t}$ is regressed on the market breadth B_t and an explanatory variable EXV as follows:

$$\varepsilon_{i,t} = b_0 + b_1 B_t + b_2\, \mathbf{sln}(\mathrm{EXV}_{i,t}) + u_{i,t}\,, \tag{4}$$

where EXV is either TIN, TID, QIN or QID. In this specification, b_0, b_1 and b_2 are the parameters to be estimated and their statistical significance inferred. Since these variables are of different orders of magnitude and can also be negative, we have applied a signed version[8] of natural logarithm defined as

$$\mathbf{sln}(x) = \begin{cases} \mathbf{sign}(x) \ln\left(|x|\right) & \text{if } |x| > 0\,, \\ 0 & \text{otherwise}\,. \end{cases} \tag{5}$$

[7] Similar analysis is performed without adjusting for the market returns. We find in the subsequent regressions that the statistical inferences for the estimates remain intact.

[8] Engle and Lange (2001) propose an unsigned version of trade imbalance in log levels. It is different from our signed $\mathrm{sln}(\mathrm{TIN}_{i,t})$ or $\mathrm{sln}(\mathrm{TID}_{i,t})$.

Market microstructure theory (O'Hara (1995)) requires TIN or TID to convey information asymmetry. The notion of intra-day price momentum also suggests that b_2 should be positive for these two explanatory variables. Intuitively, when market orders keep hitting the ask prices, the stock price will rise, which implies that when both TIN and TID are positive, daily return is inevitably positive.

We also run OLS regressions with the 63 time series of market-adjusted returns treated as panel data. We use τ to index the pooled series. The regression is run in the following sequence. First, the pooled series is rid of its AR(1) component by the following regression[9]:

$$R_\tau = a + \rho\, R_{\tau-1} + \varepsilon_\tau\,, \tag{6}$$

The residual ε_τ with 18,206 observations is the dependent variable in the following specification:

$$\varepsilon_\tau = b_0 + b_1 B_\tau + b_2\, \mathrm{sln}\big(\mathrm{EXV}_\tau\big) + u_\tau\,. \tag{7}$$

Table 4 contains the regression statistics for SUR and OLS regressions without correction, as well as Newey-West (1987) corrections with different lags. For the SUR, the coefficient estimates shown in the table are the means of the 63 samples, while the t-statistics are computed as $\sqrt{63} \times$ mean/standard deviation, in analogy to Fama and MacBeth (1973)'s method.

After controlling for the market factors $r_{m,t}$ and B_t, regression results show that trade imbalance measured in numbers, TIN, is not significant. When measured in dollars, however, the trade imbalance TID is so significantly positive that the market breadth B_t as a control becomes weakly significant. The adjusted value of R^2 is 10.6%, which suggests that TID accounts for about 10% of the variation in returns. This set of results demonstrates that the imbalance in trading activity should be measured in dollars rather than in numbers, at least for this subsample of 63 stocks with continuous trading throughout our 13-month sample period.

Remarkably, all the coefficients estimated with SUR and with OLS are rather close. For example, the estimate for TID's coefficient is 0.00052 under SUR while the value is 0.00057

[9] Regression results are similar when we first remove the AR(1) component from the time series of daily returns for each stock before pooling them together.

under OLS. Not only is this coefficient statistically significant, it is also economically significant. The mean of the absolute value of $\mathrm{sln}(\mathrm{TID})$ is 12.4, which suggests that it accounts for 67 basis points of daily returns on average. With the cross-sectional mean of the absolute daily returns being 151 basis points, it implies that about 44% of the information content of price moves is in the TID alone for this subsample.

Turning to the quote imbalance, we find that the loadings on QIN and QID are both negative and statistically significant. Intriguingly, the estimated value of -0.00053 from SUR is quite the same as that from OLS for the imbalance in quote updates (QIN). The quote imbalance measured in dollars (QID) has compatible coefficients from SUR and OLS. Its absolute value of between 0.00012 to 0.00015 suggests that $\mathrm{sln}(\mathrm{QID})$, whose mean absolute value is 14.8 for our subsample, accounts for about 20 basis points of daily returns on average. This is not an insignificant contribution. In other words, everything else being equal, if the dollar value of limit orders bidding to buy is higher than that offering to sell, daily adjusted returns tend to *decline* by 20 basis points on average for this subsample.

This outcome may appear counter-intuitive from the standpoint of supply and demand. A positive QID implies the aggregate dollar value of limit orders at the ask prior to transactions is smaller than that at the bid, which corresponds to a situation in which less shares are on sales than sought for. Since supply is less than demand, one would expect the stock price to rise and the daily return to be positive. However, the significantly negative coefficient of QID suggests the very opposite. Despite the smaller amount of limit orders at the ask, the daily return will tend to be negative rather than positive.

This negative relation between returns and quote imbalances measured in dollars provides a direct evidence that limit-order traders are contrarian. Put differently, their opinions are not shared by traders who use market orders to transact. Aggregated over a day, our data suggest that if the dollar value of limit orders at the ask is smaller than that at the bid, then the market orders will tend to hit the bid more than the ask. It follows that the stock price is more likely to decline. We shall endeavor to explain these results in Section 4.3 after we are convinced that this outcome is robust.

4.2. Robustness Tests with Entire Sample

To ensure that the results reported above are not peculiar to just this subsample of 63 stocks, we perform additional tests using the whole sample. First, we sort all the sample stocks based on market capitalization. Five subsamples are formed. The first quintile comprises 91 stocks with the smallest market capitalizations. The other four quintiles has 89 stocks each.

Also intended as a robustness check, we consider the following specification for each of the five subsamples:

$$\begin{aligned} \varepsilon_\tau \;=\; & b_0 + b_1\, B_\tau \\ & + b_2\, \mathbf{sln}(\text{TIN}_\tau) + b_3\, \mathbf{sln}(\text{TID}_\tau) + b_4\, \mathbf{sln}(\text{QIN}_\tau) + b_5\, \mathbf{sln}(\text{QID}_\tau) + u_\tau\,. \end{aligned} \tag{8}$$

Regressing the residual ε_τ (market-and-AR(1)-adjusted daily return) on all the contemporaneous explanatory variables allows us to examine the contribution of each variable relative to others. As before, the index τ is used for the pooled series. The results are documented in Table 5.

We report the OLS statistics with no correction for standard errors and another set with Newey-West corrections. We run Newey-West procedures with different lags up to 5,000 lags. It appears that after 1,500 lags, changes in the t-statistics are small and do not alter the inferences.

Intriguingly, based on the corrected t-statistics, only the coefficients of TID and QID are statistically significant, and consistently of the same positive and negative signs respectively across five quintiles. Notably for TIN, it is statistically significant for the fifth quintile of the largest 89 firms only. But the sign of its coefficient is negative, which is incongruent with the role of TIN as a measure of information asymmetry in the literature. Our results thus indicate that as a measure of imbalance in trading activity, TID is more reliable than TIN. Similarly, QID is more robust than QIN in measuring the imbalance in quoting activity.

We also observe that the magnitude of QID's coefficient appears to decrease with the market capitalization, especially from 0.00028 for the second quintile to 0.00010 for the fifth quintile. The coefficient of TID decreases with market capitalization as well. This is anticipated because larger firms tend to attract more trades and thus sln(TID) is typically larger. Consequently, the coefficients are smaller so that the returns are not overtly larger than those in other subsamples.

We also sort the stocks according to their book-to-market ratios. Eight stocks in our sample have negative book values. They are excluded from this test[10], but not in other tests. As a result, every quintile now has 87 stocks. The regression statistics are shown in Table 6. For this test, we witness again that both TID and QID are statistically significant. While TIN is not significant at the 5% level, the QIN is significantly positive. Another observation is that the dispersion in the estimated coefficients of QID is smaller than the corresponding ones in Table 5.

However, QID is no longer as significant when we arrange the observations according to the five price levels stated in Table 1. As shown in Table 7, only in the first two categories — smaller than S$1 and from S$1 to S$2.99 — do we obtain statistically significant QID. On the contrary, we find TIN is significantly negative except for penny stocks, underscoring once again the problem with measuring trade imbalance in numbers.

Finally, we pool all observations for the entire sample stocks together, perform the same ritual of removing any AR(1) component from the pooled series. Though computationally intensive, we run an OLS regression with Newey-West correction using 1,500 lags. The following is obtained:

$$\begin{aligned}\varepsilon_\tau &= 0.00049 + 0.00465 B_\tau \\ &\quad -0.00023\,\mathrm{sln}(\mathrm{TIN}_\tau) + 0.00089\,\mathrm{sln}(\mathrm{TID}_\tau) \\ &\quad +0.00077\,\mathrm{sln}(\mathrm{QIN}_\tau) - 0.00014\,\mathrm{sln}(\mathrm{QID}_\tau)\,. \end{aligned} \tag{9}$$

The adjusted R^2 is 5.78% and the Durbin-Watson statistic for u_τ, 2.0086. From the corrected t-statistics of 3.1, 5.7, -1.5, 33.8, 6.9 and -10.7 for the coefficients b_0 of the intercept to b_5 of QID, we infer that all are statistically significant except the coefficient of TIN.

It is easy to understand why TIN may be insignificant whereas TID is positively significant. As an illustration, suppose there are ten buyer-initiated trades with the trade size being one lot each, and the combined trade size of ten lots does not deplete the prevailing depth at the ask.

[10]Assuming that stocks with high book-to-market ratios are financially distressed firms, we include the eight stocks with negative book values in the first quintile and check whether the statistics vary drastically. They do not.

We further suppose that subsequently a seller-initiated trade of a hundred lots hits the bid and depletes its depth. The midquote shifts lower as a result of this trade. In this instance, while TIN is $+9$, TID is -90 lots times the original midquote. Clearly, the midquote is moved in the direction of TID rather than TIN.

The results of cross-correlation analysis documented in Section 4.4 are consistent with this intuitive explanation. This is because if every market order has about the same size, then TIN and TID will be highly correlated. But our data apparently suggest otherwise; their correlation is only 0.55. Overall, our results indicate that even if TIN is measured with no error, it is still an unreliable gauge of information asymmetry. This does not imply, however, that TIN has no information at all. Our analysis seeks to understand the impacts of trade and quote imbalances on daily returns, not volatility. Since volatility is high if trading frequency is high, and frequency is inversely related to the number of trades, it follows that the number of trades may be informative from the perspective of price fluctuation. Therefore, we do not see our conclusion as contradictory to Jones et al. (1994) whose focus is on volatility.

4.3. Negative Relation between QID and Returns: Information Asymmetry and Reverse Liquidity

There are at least two explanations for the seemingly paradoxical outcome of a negative relation between daily returns and quote imbalance in dollars, QID, which is the daily aggregate of depth differences prior to transactions. We consider the case for which QID is negative. Arguments for the opposite case of positive QID follow conversely.

First, in the presence of information asymmetry with market-order traders assumed to know more than limit-order traders, this outcome is inevitable. After all, market orders are active while limit orders are passive. If there are no market orders, no trade will occur even if there are many limit orders at the best bid and ask prices. It is the market order that moves prices in its trade direction. When market orders keep hitting the ask, daily return will be positive. Traders who use market orders to buy either know that even at the ask price, the stock is still undervalued as they expect the stock price to move higher than the current ask price. Other informed and momentum traders also join in the race to buy up the shares by using market orders to hit the next ask price. Thus, although the aggregate value of the limit orders at the ask price is larger than that at the bid price, informed traders will still use market orders to buy at the ask price.

On the other hand, traders who sell with limit orders do not know that the stock is undervalued. More crucially, if they do not have time to monitor the market closely and stand ready to adjust their limit orders, the unexpected arrival of news will make them especially vulnerable to the sudden change in stock valuation not in their favor. Either they get the winners's curse, or their limit orders will not be fulfilled.

Therefore, in conjunction with the fact that the coefficient of TID is positive, there is evidence to suggest that market-order traders typically know more than limit-order traders. Our result is consistent with the extant hypothesis that limit orders are used mostly by uninformed traders. This hypothesis is upheld in Linnainmaa (2003)'s study that uses high-frequency data from the Helsinki Stock Exchange.

If information asymmetry is the only cause, then it appears that limit-order traders are either dumb or irrational. On daily average, they lose by 17 basis points for the entire sample. Why then submit limit orders that may lose 17 basis points while market orders stand a chance of gaining 91 basis points on daily average for the whole sample?

Thus, a second explanation that requires a change of mindset is called for. Most market microstructure researchers deem limit orders as providing liquidity and market orders as taking liquidity. It may well be the other way round. We consider the possibility of a reverse situation where market orders provide liquidity to limit orders. We call it the reverse liquidity hypothesis.

To enunciate this reverse liquidity hypothesis as an alternative yet complementary explanation, let us recall the main feature of a limit order. Traders who do not need trade execution immediacy but are willing to bear the risk of not fulfilling their orders can use limit orders to specify the prices at which they are ready to transact. The main benefit of limit orders is that traders stand a chance to trade at a favorable price within the range of price fluctuation. For example, discretionary liquidity traders may just want to liquidate their shares for cash at what they think is a better price. If they are not desperate to liquidate immediately, the ask price is better than the bid price and so they place a limit order at the ask. Conversely, if they want to accumulate the shares, they will submit a limit order at the bid.

It is important to note, however, that traders who use limit orders are pursuing contrarian trading strategies. A sell limit order is executed only if the stock price advances to its ask price and beyond. Conversely, a buy limit order is fulfilled only if the stock price moves down to its bid price. If the price continues its downward momentum, limit-order traders will make a loss and suffer the winners' curse. Under the reverse liquidity hypothesis, the dual to this contrarian behavior is the remuneration exacted by market-order traders for making the trades happen. The potential loss of limit-order traders represents this implicit transaction cost. From the complementary perspective of option, limit-order traders are underwriting a free call option at the ask price and put option at the bid price for the market-order traders, so as to entice them to trade and thereby provide reverse liquidity. When these options are exercised by market-order traders, limit-order traders will lose 17 basis points immediately on average.

A possible scenario of reverse liquidity hypothesis involves proprietary traders in the brokerage houses. They trade every day for their living by buying up the shares and then selling them later in the day. Depending on the market conditions, they may short-sell first and buy back later. Any block positions outstanding at the end of trading session can be neutralized through a married deal upstairs whenever counter-parties are available. Such married deal is legal under the current bye-laws of SGX-ST.

As seen from Table 7, the statistics for penny stocks in Panel A show significantly negative QID. Since penny stocks have much larger relative spreads compared to other stocks, a bounce between the bid and ask can be as high as 4.1% on average in our sample. Therefore, there is incentive for discretionary liquidity traders to use limit orders if they can afford to wait for a better price, which is the lower bid price if they buy and the higher ask price should they want to sell. For proprietary traders, the larger relative spreads are attractive too as they need to move the quotes by just a tick to earn about 4% on average for these stocks. Therefore, when these house traders implicitly band together and use market orders to move the price, it is not implausible that market orders may at times provide liquidity to limit orders.

4.4. Autocorrelations and Cross-correlations

In Chordia and Subrahmanyam (2004), discretionary liquidity traders split their transactions over days to reduce the price impact. They demonstrate that this behavior will result in trade imbalance exhibiting autocorrelation.

In light of their theory, we compute the autocorrelations for TIN and TID up to 20 lags for our sample. The pooled technique is again employed. For completeness, we also estimate the autocorrelation functions for QIN and QID. Figure 1 displays the results. Intriguingly, these four quantities all exhibit persistent behaviors at the 5% level. The trade imbalance in dollars, nonetheless, is not as persistent as the other three. Moreover, the first-lag coefficient for TID is smaller compared to others, which are in excess of 0.2.

In Figure 2, six cross-correlation functions are plotted. TIN is found to correlate positively with the other three measures of imbalance: 0.55 with TID, 0.2 with QIN and 0.3 with QID. It is easy to understand why the two measures of trade imbalance are correlated. Somewhat surprising though, is the not so weak relation of TIN with QIN, and with QID especially. In contrast, TID is weakly related to QIN and QID, being of the order of -0.04 and 0.06 respectively. The positive correlation between the two measures of quote imbalance, QIN and QID, is remarkably low as well.

Also notable in Panel B is that TIN lags QIN by one day with a coefficient of 0.15. Put it the other way round, one could reasonably forecast next day TIN with today's QIN. Another interesting feature in Panel D is that TID leads QIN by a day with a coefficient close to -0.08. Thus, if the trade imbalance in dollars is positive today, the following day's quote imbalance in numbers is more likely to be negative. Since QIN can explain daily returns, at least for our subsample of 63 stocks as seen in Table 4, one may be tempted to use these relations to generate anomalous returns. However, these relations are rather strenuous as the R^2 values are small. Using the autocorrelations of trade and quote imbalances instead is perhaps more promising. Whether the net gain, if any, is still not negligible after deducting the transaction costs remains to be seen in future research.

4.5. Are there Inventory-Managing Market Makers on SGX-ST?

Chordia and Subrahmanyam (2004) also develop a model of risk-averse market makers who dynamically accommodate autocorrelated trade imbalances created by discretionary liquidity traders' strategies of order splitting. Their model predicts that conditional on the contemporaneous and lagged trade imbalances, the coefficient of contemporaneous trade imbalance is positive while it is negative for lagged trade imbalance when both are used to explain daily returns in an exchange with designated market makers. Empirically, they find evidence that supports this prediction for NYSE stocks. Since the SGX-ST has no designated market maker, one would not expect to find this relation of lagged trade imbalance with returns to be significant after controlling for the contemporaneous trade imbalance. To test this null hypothesis, we run the following regression:

$$\begin{aligned} \varepsilon_{i,t} &= c_{0,i} + c_{1,i}\,\mathrm{sln}\big(\mathrm{TID}_{i,t}\big) + c_{2,i}\,\mathrm{sln}\big(\mathrm{TID}_{i,t-1}\big) \\ &\quad + c_{3,i}\,\mathrm{sln}\big(\mathrm{TID}_{i,t-2}\big) + c_{4,i}\,\mathrm{sln}\big(\mathrm{TID}_{i,t-3}\big) + c_{5,i}\,\mathrm{sln}\big(\mathrm{TID}_{i,t-4}\big) + e_{i,t}\,. \end{aligned} \tag{10}$$

We pool the 447 time series and run the OLS regression with Newey-West correction using 1,500 lags. Panel A of Table 8 shows that contemporaneous $\mathrm{TID}_{i,t}$ is significant and positive, a result that reinforces the inferences in earlier subsections. Intriguingly, however, we find the trade imbalance at one lag is positively significant, which is contrary to Chordia and Subrahmanyam (2004)'s conclusion. But our results do not necessarily imply that their theory is flawed. The market designs of NYSE and SGX-ST being fundamentally different, one would not expect the relation between the daily returns and lagged trade imbalance, after controlling for the contemporaneous trade imbalance, to be the same. Moreover, since a key component of their theory is market maker managing the inventory, our results may well be an indirect affirmation. In other words, if their model is correct, then there should not be a positive $c_{i,t}$ and a negative $c_{i,t-1}$ in an exchange with no designated marker maker. This is indeed the case in our findings. The coefficients of TID at one lag are not negative for all the size-sorted subsamples.

We have alluded to the possibility of proprietary traders acting as market makers, especially in the context of reverse liquidity hypothesis as revealed by the properties of quote imbalance.

In the same breath, we have also indicated that most proprietary traders usually do not hold inventory overnight. Even if they do, they will probably use the upstair mechanism to close their positions through married deal. Hence, our proprietary traders do not make markets in the same manner as in Chordia and Subrahmanyam (2004).

What is puzzling, nonetheless, is the positive significance of TID at one lag. In the absence of a theoretical model, we can offer only the momentum effect of trade imbalance as a possible explanation. Intuitively, one could view it as momentum traders attempting to catch up with the first movers, who may be insiders, informed institutional traders, or proprietary traders. But as discussed in Section 2.3, with the somewhat draconian insider trading laws being enforced, the probability would likely be low for transactions in our sample that involved insiders or connected persons exploiting their privileged information.

For completeness, we also consider an analogous specification with TID in equation (10) replaced by QID. The results are presented in Panel B. Consistent with our earlier documentation, we see that the contemporaneous coefficients of QID are negatively significant across the five quintiles except the first quintile of smallest firms. Since the smallest firms attract the least trading activity, a weakly negative coefficient of contemporaneous QID does not necessarily nullify the possibility of adverse selection or reverse liquidity hypothesis. It does indicate, however, that QID is less robust than TID. Also notable in Panel B is that the coefficients of QID across five quintiles at one lag are positively significant, which is rather surprising. Thus, with the exception of the first quintile, it seems that there is a parallel to Chordia and Subrahmanyam (2004) but in the reverse sense with QID's contemporaneous coefficient being of opposite sign from its coefficient at one-lag. It could be that the market over-react to the information content of quote imbalance and thus the sign reverses a day later.

Regardless of what the plausible explanations may be, the positive coefficients of TID and QID at one lag are interesting features of the trades and quotes recorded in the CLOB of the SGX-ST. If these features are also present in other ECN-like exchanges, then a theoretical model of automated exchanges with no designated market maker ought to consider and explain these empirical regularities.

4.6. Implications of Quote Imbalance

To better understand the information impact of quote imbalance, we postulate a relation between the quote imbalance qid_t with the price difference between the conditional mean of the equilibrium price m_t and the midquote p_t as follows:

$$\text{qid}_t = \Big(E\big[m_t\big|\Psi_{t-1}\big] - p_t\Big)\ell + \nu_t\,. \tag{11}$$

Here, ℓ is a parameter, Ψ_{t-1} the information set and ν_t the innovation at time t. All the quantities in equation (11) are in the logarithmic levels, e.g. $\text{qid}_t \equiv \text{sln}\big(\text{QID}_t\big)$. For ease of description, the index i of individual stock is omitted. When not all the limit orders are cleared, the conditional expected value of the equilibrium price $E\big[m_t\big|\Psi_{t-1}\big]$ may not equal the midquote p_t owing to the quote imbalance qid_t that reflects the transitory disparity in the demand for liquidity by limit-order traders. In the unlikely event that $\text{qid}_t = 0$ on day t when all limit orders are matched with market orders or when the bid and ask depths are equal, then the midquote p_t coincides with the conditional mean of the equilibrium price, which is not observable.

If we further assume that the equilibrium price is a martingale, namely, $E\big[m_t\big|\Psi_{t-1}\big] = m_{t-1}$, then

$$\text{qid}_t = (m_{t-1} - p_t)\ell + \nu_t\,. \tag{12}$$

Accordingly,

$$\Delta\text{qid}_t = \big(\Delta m_{t-1} - \Delta p_t\big)\ell + \Delta\nu_t \tag{13}$$

with Δ being the time differencing operator, e.g., $\Delta p_t \equiv p_t - p_{t-1}$. From the independence of $\Delta\nu_t$ with Δp_t , Δp_{t-1} , Δm_{t-1} , Δm_{t-2} and $\Delta\nu_{t-1}$, we obtain

$$\text{Cov}\big[\Delta\text{qid}_t\,,\,\Delta\text{qid}_{t-1}\big] = \ell^2\,\text{Cov}\big[\Delta m_{t-1} - \Delta p_t\,,\,\Delta m_{t-2} - \Delta p_{t-1}\big]\,. \tag{14}$$

The assumption that m_t is a martingale implies that $\text{Cov}\big[\Delta m_{t-1}\,,\Delta m_{t-2}\big] = 0$, which leads to

$$\begin{aligned}\text{Cov}\big[\Delta\text{qid}_t\,,\,\Delta\text{qid}_{t-1}\big] \;&=\; -\ell^2\,\text{Cov}\big[\Delta m_{t-1}\,,\,\Delta p_{t-1}\big] \\ &\quad +\ell^2\,\text{Cov}\big[\Delta p_t\,,\,\Delta p_{t-1}\big] - \ell^2\,\text{Cov}\big[\Delta p_t\,,\,\Delta m_{t-2}\big]\,.\end{aligned} \tag{15}$$

Moreover, the non-contemporaneous covariance of Δp_t with Δm_{t-2} is also expected to vanish. These considerations imply that

$$\mathrm{Cov}\big[\Delta \mathrm{qid}_t\,,\,\Delta \mathrm{qid}_{t-1}\big] = -\ell^2\,\mathrm{Cov}\big[\Delta m_{t-1}\,,\,\Delta p_{t-1}\big] + \ell^2\,\mathrm{Cov}\big[\Delta p_t\,,\,\Delta p_{t-1}\big]\,. \tag{16}$$

One would expect the midquote change Δp_{t-1} to relate positively with the contemporaneous Δm_{t-1} when the market is reasonably efficient. If the autocorrelation of the midquote change is negative, equivalently, $\mathrm{Cov}\big[\Delta p_t\,,\,\Delta p_{t-1}\big]$ is strictly negative, a necessary implication of quote imbalance is

$$\mathrm{Cov}\big[\Delta \mathrm{qid}_t\,,\,\Delta \mathrm{qid}_{t-1}\big] < 0\,. \tag{17}$$

In any case, one would expect the contemporaneous covariance between Δm_{t-1} and Δp_{t-1} to be larger than the lagged covariance between Δp_t and Δp_{t-1} in magnitude. Even if $\mathrm{Cov}\big[\Delta p_t\,,\,\Delta p_{t-1}\big]$ is not negative, it probably will not overturn the negativity of $\mathrm{Cov}\big[\Delta \mathrm{qid}_t\,,\,\Delta \mathrm{qid}_{t-1}\big]$.

To verify, we compute the autocorrelation of $\Delta \mathrm{qid}_t$ for every stock. More than 98% of our sample stocks have negatively significant serial correlation at the 5% level. At the 10% level, all are significant. The range of correlation coefficient is from −0.884 to −0.115, with the average and median being −0.456 and −0.460, respectively.

5. Potential Caveats

Naturally, our results and arguments are subject to a number of criticisms. First, an implicit assumption made in our paper is that the prevailing quotes and their depth imbalances are much more informative than the second, third and deeper quote prices and depths in the order book. One may argue that the entire securities book must be taken into account when computing QIN and QID.

The limitation in our data set prevents us from looking into the effects of quotes and depths at the deeper levels on daily returns. Nonetheless, it is more unbelievable that the prevailing quotes and depths have less information than their counterparts at the deeper levels. Furthermore, if we take it that the total depth at the bid may or may not be smaller than that at the ask whenever a trade is about to take place, then the coefficient of QID should not be significant. Since the entire depth includes the prevailing depth, it would also imply that QID is probably not significant when the depth difference is computed using only the prevailing depths for the entire sample of 447 stocks. Moreover, if price pressure from the disparity in supply and demand of limit orders is the only possibility, then the coefficient of QID should be positive rather than negative.

Whatever the case may be, the negative relation of QID with returns found in this paper need to be qualified with the warning that they are conditional on the validity of the implicit assumption made.

The second shortcoming is that the exclusion of trades and quotes five minutes outside the regular hours of SGX-ST may introduce biases. To make sure, we perform the same analysis with such observations included. Our inferences at the conventional levels of statistical significance still hold.

The third shortcoming concerns the estimation procedures used. But like Chordia and Subrahmanyam (2004), we minimize the effects of cross-sectional covariance of innovations by adjusting the returns with market returns. In addition, we have also controlled for any remaining AR(1) component, as well as the market breadth. To ensure that the t statistics are not over-rejecting the nulls, we have experimented with various estimation methods including generalized least squares, the random effects model and so on. We find that OLS with Newey-West correction is appropriate in not over-rejecting the nulls. Since OLS estimates are unbiased and consistent, and given the large number of observations when data are pooled, it is not likely that the economic significance of the estimated coefficients is compromised [11].

The fourth shortcoming is our lack of direct observations of order flows from proprietary traders. Because the SGX is adamant in protecting the confidentiality of the trader identity and in upholding transaction anonymity, we are not able to differentiate their trades and quotes from others in our data set. Nonetheless, we had opportunities to speak with representatives from three prominent brokerage houses, as well as with officials from the SGX-ST. A straw poll

[11] Further discussion of the practical merit of OLS with Newey-West correction vis-à-vis a general variance-covariance weighting matrix can be found in Section 15.4.2 of Mittelhammer et al. (2000).

was conducted with regards to the overall trading volume of proprietary traders. The range of between 50 to 70 percent of total daily volume traded for some of the stocks was the consensus.

With brokerage commissions being fully negotiable for all transactions on the SGX-ST after the brokerage industry was liberalized, coupled with the trend that more retail investors are bypassing broker-dealers by entering orders online themselves to reduce transaction fees, it is not surprising that even the trading representatives of financial institutions — brokerage houses especially — have no choice but to make a kill in the market. In Linnainmaa (2003), similar situation seems to prevail in the Helsinki Stock Exchange where institutional traders are "smarter" and use market orders more often than retail investors. In this regard, our analysis of SGX-ST is consistent with Linnainmaa (2003)'s documentation.

That said, we reiterate the caveat that we do not observe proprietary traders' transactions. Our arguments for their possible role in reverse liquidity provision are only worth considering if a rendition for the positive relation of returns with TID and a negative relation with QID is required. Similarly, like many other empirical papers that use insider trading as a motivation, it is impossible to directly observe illegal transactions by insiders or connected persons from our data. Neither are the order flows of informed traders observable.

6. Concluding Remarks

Inspired by Black (1971)'s arguments for reducing the functions performed by designated market makers, this paper examines the information contents of trade and quote imbalances for shares traded on a fully automated exchange. The main focus is on asymmetric information and liquidity, as well as the possible emergence of proprietary traders in filling the vacuum created by the absence of designated market makers.

In addition to trading activity, we introduce quoting activity as the daily aggregate difference in the dollar values of limit orders at the bid and ask immediately before transactions. This measure is particularly useful in unfolding the asymmetric information contents of limit orders and market orders.

Our study provides clear evidence that dollar volume is more informative than number in measuring trade and quote imbalances. This result is obtained after controlling for market-wide factors and microstructure effects. It is also independent of how our 447 sample stocks from the Singapore Exchange Securities Trading are grouped. Whether by market capitalization, book-to-market ratio, or price level, dollar volume is consistently informative in capturing price pressure signals, asymmetric information with price momentum and reverse liquidity provision.

When market orders and limit orders agree on the direction of price moves, in the sense that if dollar values of limit orders at the bid are larger than at the ask, stock prices tend to move up by market orders. Conversely, daily stock prices tend to decline when the selling pressure is higher. This phenomenon can be understood within the standard framework of net supply and demand pressure on prices. A higher limit order value at the bid signals demand is higher than supply, which nudges the stock price higher.

But our empirical findings are more consistent with market orders disagreeing with limit orders. Despite demand being higher than supply as reflected by the posted depth difference before a trade, the stock price moves downward instead. This phenomenon is counter-intuitive. It can nonetheless be explained by two possible hypotheses. The first hypothesis is based on asymmetric information. Traders who use market orders appear to know more about the daily stock value than those who use limit orders. Informed traders will sell down the stock price even if the size of limit orders at the bid price is larger. Inherently, limit orders are passive and contrarian; traders who have no resource to monitor and cancel their orders readily must bear the risk of winners' curse.

Given that company insiders do not trade everyday, we consider the second possibility called the reverse liquidity hypothesis. Traditionally, it is thought that limit orders provide liquidity to market orders. It could well be the reverse. At times, it is the market order that provides liquidity to the limit order. This situation can arise when proprietary traders move prices and profit from their active trading activities. They may even implicitly co-operate to sell down the price and then buy up later in the day. Such profiteering processes that provide liquidity concurrently may benefit discretionary liquidity traders who seek to accumulate shares for longterm investment or to liquidate their holdings. On average, limit order traders pay a daily rate of 17 basis points to market order traders for fulfilling their contrarian trading demand.

Since the trade and quote imbalances are found to be persistent, there may be implications of our findings on forecasting daily returns that are worth exploring in future research. Nonetheless, this paper focuses on trade imbalance and introduces quote imbalance to unfold the innards of information dynamics empirically. We also demonstrate for the first time that the *change* in quote imbalance measured in dollars is negatively auto-correlated. On average, it is -0.46 for our sample stocks. This negative autocorrelation may be attributed to the stalking of equilibrium price by the midpoint of prevailing quotes when the underlying depth difference between the bid and ask reflects a latent imbalance in supply and demand.

In summary, from the standpoint of daily returns, it is concrete that volume measured in dollars rather than in numbers is more informative in revealing the information contents of trades and quotes. Trade imbalance is definitively a positive driver of stock returns. We have also provided evidence that suggests a negative relation between quote imbalance and daily stock returns. The information asymmetry between market and limit orders, as well as the reverse liquidity hypothesis are presented to explain this negative relation.

Our study may be potentially useful for U.S. markets during pre-regular-hour sessions when most trades and quotes are not mediated by market makers, as well as for ECN-like exchanges around the world. We suspect in the vacuum of designated market makers, proprietary traders or some market participants fill the gap by their active trading. While they contribute to liquidity through their trading activities, the issues of fairness and alleged price manipulation remain. The insights obtained herein may also shed light on whether certain functions performed by a specialist or *saitori* should be automated.

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Appendix SGX Securities Trading Rules (2003)

13.8 MARKET MANIPULATION AND FALSE MARKET

13.8.1 A Trading Member or a Trading Representative must not engage in, or knowingly act with any other person in, any act or practice that will or is likely to:-

(1) create a false or misleading appearance of active trading in any securities; or

(2) lead to a false market in respect of any securities. For avoidance of doubt, a false market includes a market in which:-

(a) information is false, exaggerated or tendentious;

(b) contrived factors are in evidence, such as buyers and sellers acting in collaboration to bring about artificial market prices; or

(c) manipulative or fictitious orders, transactions or other devices have been employed.

Please refer to Practice Note 13.8.1.

13.8.2 The following factors are relevant when considering whether an act or practice may breach Rule 13.8.1:-

(1) whether the proposed transaction will be inconsistent with the history of, or recent trading in, the security;

(2) whether the proposed transaction will or may cause or contribute to a material change in the market for or the price of the security, and whether the person involved or another person with whom the first person is collaborating may directly or indirectly benefit from alterations in the market or price;

(3) whether the proposed transaction involves the placing of multiple buy and sell orders at various

prices higher or lower than the market price, or the placing of buy and sell orders which give the appearance of increased volume;

(4) whether the proposed transaction will coincide with or is likely to influence the calculation of reference prices, settlement prices and valuations;

(5) whether parties involved in the proposed transaction are connected;

(6) whether the buy and sell orders are to be entered at about the same time, for about the same price and quantity (excluding Direct Business);

(7) whether the proposed transaction will or may cause the price of the security to increase or decrease, but following which the price is likely to immediately return to about its previous level;

(8) whether a proposed bid (offer) is higher (lower) than the previous bid (offer) but is to be removed from the market before it is executed;

(9) whether the volume or size of the proposed transaction is excessive relative to reasonable expectations of the depth and liquidity of the market at the time;

(10) whether the proposed buy (sell) order is likely to trade with the entire best offer (bid) volume and part of the offer (bid) at the next price level;

(11) whether the proposed buy (sell) order forms part of a series of orders that successively and consistently increase (decrease) the price of the security; and

(12) whether there appears to be a legitimate commercial reason for the proposed transaction.

Please refer to Practice Note 13.8.1.

Table 1: **Minimum Tick Sizes and Implicit Costs of Transaction Immediacy**

Under Bye-Law 2 of the Singapore Exchange, there are five minimum tick sizes for shares traded at five different price levels. Based on the five price ranges, we compute their corresponding ranges of relative bid-ask spreads. For example, the minimum tick size is S$0.005 for stock price below S$1. A trader who buys the stock at the bid price of S$0.005 and sells it at the ask price of S$0.01 will gain as much as 100%. At the other end of this price range, a trader who buys the stock at S$1 and sells it at S$0.995 will lose 0.5% on the bid-ask spread. In general, penny stocks have much larger bid-ask spreads in percent. During our sample period, one U.S. dollar was about 1.7 to 1.8 Singapore dollars.

Share Price	**Minimum Tick Size**	**Minimum Relative Bid-Ask Spread**	**Maximum Relative Bid-Ask Spread**
Below S$1	S$0.005	0.5%	100%
S$1 to S$2.99	S$0.010	0.333%	1%
S$3 to S$4.98	S$0.020	0.4%	0.667%
S$5 to S$9.95	S$0.050	0.5%	1%
S$10 and above	S$0.100	–	1%

Table 2: **Descriptive Statistics for a Cross Section of 447 Sample Stocks**

This table presents the descriptive statistics for the sample stocks listed on the Singapore Exchange (SGX). Their dates of listing are at least two months before the sample period from October 4, 2002 to November 28, 2003. As at end of March, 2003, these stocks constitute well over 95% of the entire market capitalization in Singapore. Using the high-frequency data purchased from the SGX through a third-party financial data service provider, we compute daily number, volume and dollar volume of trades that occurred at the bid prices during the sample period for each stock. Same statistics are gathered for trades that occurred at ask prices. The numbers of bid and ask updates reflect the quoting activity. The corresponding aggregate depths capture the prevailing supply and demand of limit-order traders immediately before market orders arrive.

	Unit	**Average**	**Standard Deviation**	**Minimum**	**Median**	**Maximum**
Market Capitalization	Million S$	432.7	1,809	2.2	47.4	23,887
Shares Outstanding	Million Shares	511	1,258	9	254	17,827
Price	S$	0.715	1.774	0.005	0.19	17.8
Equity	Million S$	441.9	1,808.3	-947.9	54.4	23,324
Book	Million S$	362.7	1,629.9	-10,765	52.5	25,037
Trades at Bid	Number	17.5	32.0	0.2	7.1	384.0
	Volume in 1,000 Shares	607.3	1,156.1	0.6	204.8	13,756
	Volume in 1,000 S$	475.1	1,687.9	0.3	52.8	17,769
Trades at Ask	Number	18.9	36.4	0.2	7.2	470.6
	Volume in 1,000 Shares	646.9	1,261.7	0.6	205.0	14,946
	Volume in 1,000 S$	509.2	1,770.7	0.2	54.4	18,568
Bid Updates	Number	40.6	78.0	1.1	15.6	902.9
Ask Updates	Number	38.3	72.4	0.8	15.2	811.7
Bid Depth	Volume in 1,000 Shares	39,189	228,455	1.5	2,304.4	4,408,143
before a Trade	Volume in 1,000 S$	20,754	103,874	0.8	738.4	1,176,225
Ask Depth	Volume in 1,000 Shares	38,054	188,941	1.3	2,298.1	3,289,106
before a Trade	Volume in 1,000 S$	20,311	103,040	0.9	850.0	1,244,505

Table 3: **Subsample of 63 Stocks**

This table contains the statistics for 63 stocks that had at least one trade on each of the 290 trading days from October 4, 2002 to November 28, 2003. Their ticker symbols are shown under the column labeled by SYM. Stocks that are the components of the Straits Times Index are highlighted in bold font. Dated March 31, 2003, the information source of market capitalization is the official web site of SGX. The stock prices are the closing prices on the same date. The number of shares outstanding, earnings per share (EPS) and book value per share (BPS) are from the third-party data service provider.

SYM	**Stock**	**Company Name Used by SGX**	**Firm Size Million S$**	**Shares Millions**	**Price S$**	**EPS S$**	**BPS S$**
S12	SingTel	S'PORE TELECOMMUNICATIONS LTD	23,886.6	17,827	1.47	0.0786	0.261
U11	UOB	UNITED OVERSEAS BANK LTD	16,187.5	1,572	10.7	0.6770	5.717
D05	DBS	DBS GROUP HOLDINGS LTD	13,518.2	1,555	9.15	0.6538	4.342
O04	OCBC	OVERSEA-CHINESE BANKING CORP	12,194.3	1,290	9.55	0.5167	5.445
S55	SIA	SINGAPORE AIRLINES LTD	10,658.8	1,218	9.9	0.8741	8.789
S37	SPH	SINGAPORE PRESS HOLDINGS LTD	6,520.8	370	17	1.0248	6.082
S63	ST Engg	SINGAPORE TECH ENGINEERING LTD	5,134.3	2,884	1.6	0.1147	0.496
H78	HKLand US$	HONGKONG LAND HLDGS LTD	4,452.4	2,295	1.94	-0.3597	2.160
V03	Venture	VENTURE CORPORATION LIMITED	3,396.2	240	14.9	0.7536	3.605
K02	KepCorp	KEPPEL CORPORATION LTD	3,239.3	770	4.52	0.4654	3.347
C09	CITYDEV	CITY DEVELOPMENTS LTD	2,835.6	801	3.54	0.1888	4.821
C31	Capitaland	CAPITALAND LIMITED	2,618.0	2,517	1.06	0.1153	2.366
F27	F&N	FRASER & NEAVE LIMITED	2,113.1	231	7.95	1.4446	12.148
S59	SIA Engg	SIA ENGINEERING CO LTD	1,650.7	1,000	1.61	0.2052	0.838
C27	Chartered	CHARTERED SEMICONDUCTOR MFG LTD	1,576.2	3,072	0.765	-0.2444	1.037
W08	Want WantUS$	WANT WANT HOLDINGS LIMITED	1,403.8	1,274	1.1	0.0587	0.335
S51	SembMar	SEMBCORP MARINE LTD	1,329.8	1,414	0.925	0.0651	0.663
S68	SGX	SINGAPORE EXCHANGE LIMITED	1,250.9	1,003	1.21	0.0160	0.796
S24	ST Assemb	ST ASSEMBLY TEST SERVICES LTD	1,151.0	1,154	1.32	-0.1393	0.570
P05	PFood	PEOPLE'S FOOD HOLDINGS LIMITED	1,133.3	1,164	0.755	0.1527	0.470
S30	Sp Land	SINGAPORE LAND	1,115.2	344	3.38	0.2298	7.044
U14	UOL	UNITED OVERSEAS LAND LTD	1,036.7	613	1.73	0.2631	2.769
O07	OUE	OVERSEAS UNION ENTERPRISE LTD	1,013.8	176	5.8	0.0190	7.971
U06	UIC	UNITED INDUSTRIAL CORP LTD	943.6	1,377	0.745	-0.0975	1.352
C07	C&C	CYCLE & CARRIAGE LTD	908.1	242	4.22	0.9565	4.389
A16	Allgreen	ALLGREEN PROPERTIES LTD	871.5	1,050	0.79	0.0801	1.505
C76	Creative 50	CREATIVE TECHNOLOGY LTD	858.1	55	11.7	-0.4503	9.676
K17	KepLand	KEPPEL LAND LTD	822.0	709	1.19	0.0372	2.089
R03	RafflesH	RAFFLES HOLDINGS LIMITED	790.4	2,080	0.365	0.0216	0.895
S53	SMRT	SMRT CORPORATION LTD	780.0	1,500	0.54	0.0481	0.409
B16	BIL Intl	BIL INTERNATIONAL LIMITED	567.7	1,368	0.6	-0.0793	1.120
P27	Parkway	PARKWAY HLDGS LTD	550.8	720	0.71	0.0463	0.546

Table 3, (continued)

SYM	Stock	Company Name Used by SGX	Firm Size Million S$	Shares Millions	Price S$	EPS S$	BPS S$
T05	TAC 200US$	TOTAL ACCESS COMM PUB CO LTD	426.7	474	0.9	0.1014	1.288
D06	DatacrftUS$	DATACRAFT ASIA LTD	418.0	503	0.83	-0.0321	0.333
U01	UniFood	UNITED FOOD HOLDINGS LIMITED	411.4	1,112	0.34	0.0838	0.294
C33	ChuanHup	CHUAN HUP HOLDINGS LIMITED	408.0	1,088	0.38	0.0448	0.341
600	Hyflux	HYFLUX LTD	332.6	236	1.32	0.0393	0.161
G17	Golden Agri	GOLDEN AGRI-RESOURCES LTD	314.5	2,169	0.155	0.0192	0.571
C47	ChinaAvOil	CHINA AVIATION OIL (S)CORP LTD	293.8	576	0.505	0.0698	0.256
W05	Wing Tai	WING TAI HLDGS LTD	287.7	613	0.5	0.0065	1.507
C49	Citiraya	CITIRAYA INDUSTRIES LTD	280.5	550	0.49	0.0223	0.089
L15	L-Jacob	LINDETEVES-JACOBERG LTD	227.4	288	0.84	0.0806	0.739
J10	Jaya Hldg	JAYA HOLDINGS LTD	220.4	735	0.335	0.0447	0.242
A26	AsiaFoodP	ASIA FOOD & PROPERTIES LTD	217.7	2,903	0.085	-0.0006	0.781
H34	Hotung US$	HOTUNG INVESTMENT HLDGS LTD	212.9	1,289	0.165	-0.0159	0.176
G01	GES	GES INTERNATIONAL LIMITED	203.5	714	0.295	0.0351	0.273
A11	Amtek	AMTEK ENGINEERING LTD	169.6	203	0.87	0.1589	1.056
U24	Unisteel	UNISTEEL TECHNOLOGY LTD	153.1	239	0.67	0.0698	0.247
E08	EastTech	EASTERN ASIA TECHNOLOGY LTD	148.6	302	0.545	0.0672	0.355
E18	ECS	ECS HOLDINGS LIMITED	128.1	346	0.375	0.0409	0.310
J09	JurTech	JURONG TECH IND CORP LTD	126.0	394	0.385	0.0355	0.182
S03	Seksun	SEKSUN CORPORATION LIMITED	112.0	122	0.86	0.1149	0.559
A19	Autron	AUTRON CORPORATION LIMITED	110.3	571	0.18	-0.0374	0.023
J13	JK Yaming	JK YAMING INT'L HLDGS LTD	108.6	203	0.35	0.0228	0.250
544	CSE Global	CSE SYSTEMS & ENGINEERING LTD	103.1	308	0.38	0.0392	0.060
R05	Roly	ROLY INTERNATIONAL HLDGS LTD	93.8	390	0.26	0.1064	0.208
N01	NeraTel	NERATELECOMMUNICATIONS LTD	91.8	360	0.3	0.0590	0.198
F09	FirstEng	FIRST ENGINEERING LTD	74.1	200	0.425	0.0743	0.278
I18	IPC	IPC CORPORATION LTD	74.0	2,114	0.045	-0.0007	0.065
E23	Europtron	EUROPTRONIC GROUP LTD	70.1	281	0.265	0.0242	0.187
D12	Digiland	DIGILAND INTERNATIONAL LIMITED	50.2	715	0.09	-0.0311	0.122
E05	Eastgate	EASTGATE TECHNOLOGY LTD	37.5	300	0.13	-0.0112	0.149
596	ThaiVillag	THAI VILLAGE HOLDINGS LTD	33.6	146	0.195	0.0236	0.136

Table 4: **Regression Results for a Subsample of 63 Stocks**

This table reports the estimated coefficients (Coeff) and the t statistics (t-stat) obtained under two different regression methods. The first is the balanced seemingly unrelated regression (SUR). The second is the pooled OLS regression, for which we show the t statistics with no correction under the column 0, and with Newey-West correction using different lags from 289 up to 1,445. These numbers are in multiples of individual time-series length of 289. The dependent variable is the market-and-AR(1)-adjusted daily return. The explanatory variables investigated are trade imbalance in numbers (TIN), in dollars (TID), quote imbalance in numbers (QIN), as well as in dollars (QID). Each of these four variables is used separately in the regression that includes market breadth (B) as a control. Statistically significant coefficients based on Newey-West t-statistics at 1,445 lags are indicated in bold font. For the OLS, we show the adjusted R^2 values ($\overline{R}^2$) and the Durbin-Watson statistics (DW).

	SUR		OLS								
					t-statistics with Newey-West Correction						
	Coeff	t-stat	Coeff	0	289	578	867	1,156	1,445	$\overline{R}^2$	DW
Intercept	-0.00020	-1.75	-0.00013	-0.79	-0.82	-0.82	-0.82	-0.84	-0.85	2.07%	2.003
B	**0.00720**	4.42	**0.00744**	19.59	5.66	5.06	4.79	4.51	4.32		
TIN	-0.00015	-0.91	-0.00015	-2.65	-1.05	-0.96	-0.93	-0.91	-0.89		
Intercept	0.00016	1.32	0.00024	1.47	1.16	1.12	1.1	1.12	1.14	10.6%	2.003
B	0.00192	1.37	0.00146	3.84	1.36	1.23	1.16	1.09	1.05		
TID	**0.00052**	18.45	**0.00057**	41.63	18.33	17.06	16.08	15.54	15.19		
Intercept	0.00013	1.38	0.00007	0.42	0.42	0.43	0.43	0.45	0.46	2.55%	2.012
B	**0.00672**	4.27	**0.00740**	20.01	5.46	4.88	4.57	4.28	4.07		
QIN	**-0.00053**	-5.16	**-0.00053**	-9.79	-5.48	-5.31	-5.48	-5.53	-5.41		
Intercept	**-0.00017**	-2.85	-0.00013	-0.77	-0.81	-0.82	-0.81	-0.84	-0.86	3.00%	2.006
B	**0.00661**	4.02	**0.00664**	17.91	4.92	4.39	4.09	3.83	3.64		
QID	**-0.00012**	-7.76	**-0.00015**	-13.45	-8.71	-7.86	-7.57	-7.66	-7.97		

Table 5: **Regression Results for Five Subsamples of Stocks Sorted by Market Capitalizations**

In this table, we report five sets of multiple regression results. Sample stocks are first sorted by their market capitalizations as at end of March 2003. The dependent variable is the market-and-AR(1)-adjusted daily return, ε_τ. Explanatory variables are the trade imbalance in numbers (TIN), in dollars (TID), the quote imbalance in numbers (QIN) and in dollars (QID). Every regression has market breadth (B) as a control for co-movement. The specification is

$$\begin{aligned} \varepsilon_\tau \;=\; & b_0 + b_1\, B_\tau \\ & + b_2\, \mathrm{sln}\big(\mathrm{TIN}_\tau\big) + b_3\, \mathrm{sln}\big(\mathrm{TID}_\tau\big) + b_4\, \mathrm{sln}\big(\mathrm{QIN}_\tau\big) + b_5\, \mathrm{sln}\big(\mathrm{QID}_\tau\big) + \, u_\tau\,. \end{aligned}$$

The pooled series is indexed by τ. Explanatory variables appear in signed logarithmic levels, as the function sln(x) is defined as sign$(x)\ln\big(|x|\big)$ if $|x| > 0$ and 0 otherwise. The parameters b_0, $b_1, \ldots, b_5$ are obtained from OLS procedures. The t-statistics with no correction $\big(t$-stat (n)$\big)$ and with Newey-West correction $\big($ t-stat (c) $\big)$ are shown. In addition, p values in percent for the corrected t-statistics, adjusted R^2 values $\big(\overline{R}^2\big)$ in percent as well as the Durbin-Watson statistics (DW stat) for the residuals u_τ are also tabulated. Statistically significant coefficients are indicated in bold font. Panel A has 12,686 observations pooled from stocks with the smallest market capitalizations whereas Panel E has 23,863 observations from stocks with the largest market capitalizations.

	Coefficient	t-stat (n)	t-stat (c)	p values in %	$\overline{R}^2$ in %	DW stat
Panel A: First quintile (smallest firms), 12,686 observations						
Intercept	-0.00023	-0.36	-0.35	72.4	6.3	2.010
B	**0.01616**	11.72	9.54	0.0		
TIN	0.00120	2.13	1.53	12.7		
TID	**0.00140**	15.57	13.81	0.0		
QIN	**0.00273**	7.53	4.12	0.0		
QID	**-0.00021**	-3.64	-2.13	3.3		
Panel B: Second quintile, 16,337 observations						
Intercept	0.00076	2.15	1.87	6.1	10.7	2.016
B	**0.01000**	12.64	7.14	0.0		
TIN	**0.00265**	8.57	5.92	0.0		
TID	**0.00105**	21.54	16.98	0.0		
QIN	**0.00173**	8.49	6.84	0.0		
QID	**-0.00028**	-8.54	-7.63	0.0		
Panel C: Third quintile, 18,463 observations						
Intercept	**0.00070**	2.53	2.28	2.3	8.4	2.010
B	**0.00430**	6.83	3.06	0.2		
TIN	**0.00128**	5.90	3.62	0.0		
TID	**0.00086**	24.09	13.23	0.0		
QIN	**0.00145**	9.98	7.34	0.0		
QID	**-0.00025**	-10.40	-7.82	0.0		
Panel D: Fourth quintile, 21,417 observations						
Intercept	0.00049	2.25	1.60	11.0	7.2	2.002
B	0.00146	2.88	0.98	32.8		
TIN	-0.00022	-1.51	-1.04	29.8		
TID	**0.00082**	31.15	29.40	0.0		
QIN	**0.00065**	6.28	4.32	0.0		
QID	**-0.00013**	-7.17	-8.37	0.0		
Panel E: Fifth quintile (largest firms), 23,863 observations						
Intercept	**0.00056**	4.50	3.40	0.1	11.4	2.028
B	**-0.00567**	-19.67	-6.73	0.0		
TIN	**-0.00086**	-14.33	-5.35	0.0		
TID	**0.00061**	49.61	13.16	0.0		
QIN	-0.00013	-2.85	-1.43	15.2		
QID	**-0.00010**	-10.11	-6.00	0.0		

Table 6: **Regression Results for Five Subsamples of Stocks Sorted by Book-to-Market Ratios**

In this table, we report five sets of multiple regression results. Sample stocks are sorted by their book-to-market ratios. Book values are from the financial data service provider, while data on market capitalization are from the Singapore Exchange. The dependent variable is the market-and-AR(1)-adjusted daily return, ε. Explanatory variables are the trade imbalance in numbers (TIN), in dollars (TID), the quote imbalance in numbers (QIN) and in dollars (QID). Every regression has market breadth (B) as a control for co-movement. The specification is

$$\begin{aligned} \varepsilon_\tau &= b_0 + b_1 B_\tau \\ &\quad + b_2 \operatorname{sln}(\mathrm{TIN}_\tau) + b_3 \operatorname{sln}(\mathrm{TID}_\tau) + b_4 \operatorname{sln}(\mathrm{QIN}_\tau) + b_5 \operatorname{sln}(\mathrm{QID}_\tau) + u_\tau \,. \end{aligned}$$

The pooled series is indexed by τ. Explanatory variables appear in signed logarithmic levels, as the function sln(x) is defined as $\mathrm{sign}(x) \ln\big(|x|\big)$ if $|x| > 0$ and 0 otherwise. The parameters b_0, $b_1, \ldots, b_5$ are obtained from OLS procedures. The t-statistics with no correction $\big($ t-stat (n) $\big)$ and with Newey-West correction $\big($ t-stat(c) $\big)$ are shown. In addition, p values in percent for the corrected t-statistics, adjusted R^2 values $\big(\overline{R}^2\big)$ in percent as well as the Durbin-Watson statistics (DW stat) for the residuals u_τ are also tabulated. Statistically significant coefficients are indicated in bold font. Panel A has 21,466 observations pooled from stocks with the highest book-to-market ratios whereas Panel E has 21,065 observations from stocks with the lowest book-to-market ratios.

	Coefficient	t-stat (n)	t-stat (c)	p values in %	$\overline{R}^2$ in %	DW stat
Panel A: First quintile (highest B/M firms), 21,466 observations						
Intercept	0.00005	0.15	0.15	88.37	4.3	2.008
B	**0.00366**	4.93	2.15	3.12		
TIN	-0.00048	-2.62	-1.88	5.99		
TID	**0.00089**	24.99	13.90	0.00		
QIN	**0.00078**	5.72	2.45	1.43		
QID	**-0.00015**	-5.90	-5.36	0.00		
Panel B: Second quintile, 17,943 observations						
Intercept	**0.00087**	2.73	2.05	4.06		
B	**0.00655**	9.00	3.80	0.01		
TIN	-0.00001	-0.06	-0.03	97.54	6.1	2.018
TID	**0.00094**	23.56	16.05	0.00		
QIN	**0.00100**	6.14	3.60	0.03		
QID	**-0.00014**	-4.97	-6.09	0.00		
Panel C: Third quintile, 16,986 observations						
Intercept	0.00039	1.50	1.44	15.02		
B	**0.00473**	7.86	3.89	0.01	7.9	2.019
TIN	0.00002	0.08	0.06	95.42		
TID	**0.00087**	27.13	24.70	0.00		
QIN	**0.00088**	6.68	4.64	0.00		
QID	**-0.00013**	-5.61	-5.09	0.00		
Panel D: Fourth quintile, 19,222 observations						
Intercept	0.00027	1.07	1.01	31.28	6.8	2.010
B	**0.00319**	5.41	2.01	4.40		
TIN	-0.00041	-2.55	-1.82	6.84		
TID	**0.00085**	28.98	23.53	0.00		
QIN	**0.00078**	6.67	3.55	0.04		
QID	**-0.00014**	-6.47	-5.58	0.00		
Panel E: Fifth quintile (lowest B/M firms), 21,065 observations						
Intercept	0.00010	0.35	0.35	73.01	4.9	2.008
B	**0.00251**	3.82	1.71	8.77		
TIN	-0.00031	-2.00	-1.48	14.00		
TID	**0.00081**	26.53	18.69	0.00		
QIN	**0.00038**	3.25	2.37	1.78		
QID	**-0.00015**	-6.72	-6.36	0.00		

Table 7: **Regression Results for Five Subsamples of Stocks Sorted by Price Levels**

In this table, we report five sets of multiple regression results. Sample stocks' observations are sorted by five price levels stipulated in Table 1. The dependent variable is the market-and-AR(1)-adjusted daily return, ε_τ. Explanatory variables are the trade imbalance in numbers (TIN), in dollars (TID), the quote imbalance in numbers (QIN) and in dollars (QID). Every regression has market breadth (B) as a control for co-movement. The specification is

$$\begin{aligned}\varepsilon_\tau &= b_0 + b_1\, B_\tau \\ &\quad + b_2 \,\mathbf{sln}\big(\mathrm{TIN}_\tau\big) + b_3 \,\mathbf{sln}\big(\mathrm{TID}_\tau\big) + b_4 \,\mathbf{sln}\big(\mathrm{QIN}_\tau\big) + b_5 \,\mathbf{sln}\big(\mathrm{QID}_\tau\big) + u_\tau \,.\end{aligned}$$

The pooled series is indexed by τ. Explanatory variables appear in signed logarithmic levels, as the function sln(x) is defined as $\mathrm{sign}(x)\ln\big(|x|\big)$ if $|x| > 0$ and 0 otherwise. The parameters b_0, $b_1, \ldots, b_5$ are obtained from OLS procedures. The t-statistics with no correction (t-stat (n)) and with Newey-West correction (t-stat(c)) are shown. In addition, p values in percent for the corrected t-statistics, adjusted R^2 values $\big(\overline{R}^2\big)$ in percent as well as the Durbin-Watson statistics (DW stat) for the residuals u_τ are also tabulated. Statistically significant coefficients are indicated in bold font.

	Coefficient	t-stat (n)	t-stat (c)	p values in %	$\overline{R}^2$ in %	DW stat
Panel A: Below S$1, 75,002 observations						
Intercept	0.00053	3.30	3.21	0.13	6.7	2.008
B	**0.00691**	18.65	12.92	0.00		
TIN	0.00020	1.74	1.23	21.99		
TID	**0.00098**	48.13	40.61	0.00		
QIN	**0.00111**	13.70	10.35	0.00		
QID	**-0.00017**	-11.81	-10.79	0.00		
Panel B: From S$1 to S$2.99, 11,999 observations						
Intercept	0.00063	3.15	3.09	0.20	9.9	2.025
B	**-0.00662**	-14.52	-11.10	0.00		
TIN	**-0.00083**	-8.06	-6.03	0.00		
TID	**0.00066**	31.68	25.87	0.00		
QIN	**-0.00021**	-2.54	-2.01	4.48		
QID	**-0.00010**	-6.21	-6.05	0.00		
Panel C: From S$3 to S$4.98, 1,735 observations						
Intercept	0.00032	0.83	0.88	37.64	13.4	2.019
B	**-0.00830**	-9.52	-8.32	0.00		
TIN	**-0.00135**	-7.22	-6.20	0.00		
TID	**0.00047**	12.86	12.17	0.00		
QIN	-0.00017	-1.14	-0.87	38.17		
QID	-0.00001	-0.27	-0.25	80.20		
Panel D: From S$5 to S$9.95, 2,098 observations						
Intercept	0.00045	1.25	1.28	20.01	13.2	2.040
B	**-0.00873**	-10.80	-10.09	0.00		
TIN	**-0.00125**	-6.61	-6.18	0.00		
TID	**0.00047**	13.70	13.44	0.00		
QIN	-0.00035	-2.38	-1.87	6.10		
QID	0.00003	1.17	1.19	23.57		
Panel E: S$10 and above, 1,932 observations						
Intercept	0.00003	0.11	0.12	90.58	17.8	2.057
B	**-0.00231**	-3.40	-2.66	0.79		
TIN	**-0.00102**	-8.89	-7.46	0.00		
TID	**0.00033**	14.44	11.97	0.00		
QIN	**-0.00041**	-4.81	-4.85	0.00		
QID	-0.00001	-0.49	-0.48	63.21		

Table 8: **Tests Motivated by Chordia and Subrahmanyam (2004)'s Model**

This table reports the OLS statistics for the following regression of market-and-AR(1)-adjusted daily returns $\varepsilon_{i,t}$:

$$\begin{aligned}\varepsilon_{i,t} \;=\; & c_{0,i} + c_{1,i}\,\mathrm{sln}\big(\mathrm{EXV}_{i,t}\big) + c_{2,i}\,\mathrm{sln}\big(\mathrm{EXV}_{i,t-1}\big) \\ & + c_{3,i}\,\mathrm{sln}\big(\mathrm{EXV}_{i,t-2}\big) + c_{4,i}\,\mathrm{sln}\big(\mathrm{EXV}_{i,t-3}\big) + c_{5,i}\,\mathrm{sln}\big(\mathrm{EXV}_{i,t-4}\big) + e_{i,t}\,.\end{aligned}$$

The explanatory variable EXV is daily trade imbalance in dollars, TID, in Panel A and quote imbalance in dollars, QID, in Panel B. The function $\mathrm{sln}(x)$ is signed logarithm of $|x|$. Following Chordia and Subrahmanyam (2004), up to four lags are specified. The stocks indexed by i are sorted on their market capitalization as at end of March 2003. The subscript t denotes trading day. In each quintile, the observations are pooled and OLS with Newey-West correction are employed to obtain the estimates (Coeff) and t statistics (t-stat). The adjusted R^2 values in percent $\left(\overline{R}^2\right)$ and Durbin-Watson statistics (DW stat) are displayed below each panel. Lag numbers are indicated in the parentheses. Statistically significant coefficients are shown in bold font.

Panel A: Regression of market-and-AR(1)-adjusted daily returns on TID and four lagged TID's.

	Smallest Firms		Second Quintile		Third Quintile		Fourth Quintile		Largest Firms	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	**0.00100**	2.77	**0.00162**	6.21	**0.00098**	3.86	**0.00055**	3.19	**0.00025**	3.48
TID (0)	**0.00169**	21.33	**0.00140**	22.67	**0.00100**	17.00	**0.00080**	23.64	**0.00045**	9.72
TID (-1)	**0.00034**	4.03	**0.00011**	2.44	**0.00009**	3.50	**0.00005**	2.29	0.00002	1.89
TID (-2)	**-0.00022**	-2.63	-0.00003	-0.64	-0.00003	-0.74	-0.00004	-1.18	-0.00002	-1.46
TID (-3)	-0.00006	-1.08	-0.00002	-0.59	0.00000	0.10	0.00000	0.24	-0.00001	-1.72
TID (-4)	**-0.00012**	-2.24	0.00004	1.49	-0.00005	-1.45	-0.00002	-1.01	-0.00002	-1.24
$\overline{R}^2$ in %	5.31		8.46		7.08		7.32		7.79	
DW stat	2.008		2.006		2.007		2.007		1.996	

Panel B: Regression of market-and-AR(1)-adjusted daily returns on QID and four lagged QID's.

	Smallest Firms		Second Quintile		Third Quintile		Fourth Quintile		Largest Firms	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	0.00002	0.08	0.00000	0.04	-0.00006	-0.92	-0.00010	-1.61	0.00003	0.77
QID (0)	-0.00005	-0.85	**-0.00011**	-3.41	**-0.00015**	-4.40	**-0.00014**	-6.52	**-0.00016**	-8.53
QID (-1)	**0.00043**	3.91	**0.00020**	4.18	**0.00012**	3.45	**0.00009**	3.74	**0.00006**	7.16
QID (-2)	0.00004	0.76	0.00003	0.75	0.00001	0.41	0.00002	1.24	0.00001	1.46
QID (-3)	-0.00002	-0.37	0.00000	0.08	0.00003	1.13	0.00003	1.65	-0.00001	-0.51
QID (-4)	-0.00003	-0.63	0.00000	0.06	0.00003	1.53	0.00000	0.29	**0.00002**	2.45
$\overline{R}^2$ in %	0.42		0.24		0.29		0.36		1.24	
DW stat	2.012		2.009		2.009		2.003		2.011	

Figure 1: **Evidence of Persistent Trading and Quoting Activities**. The autocorrelation functions of trade imbalance in numbers (TIN), in dollars (TID), as well as quote imbalance in numbers (QIN) and in dollars (QID) are estimated up to 20 lags for the whole sample. The two lines indicate two standard deviations from zero at the 5% level for the autocorrelation at one lag.

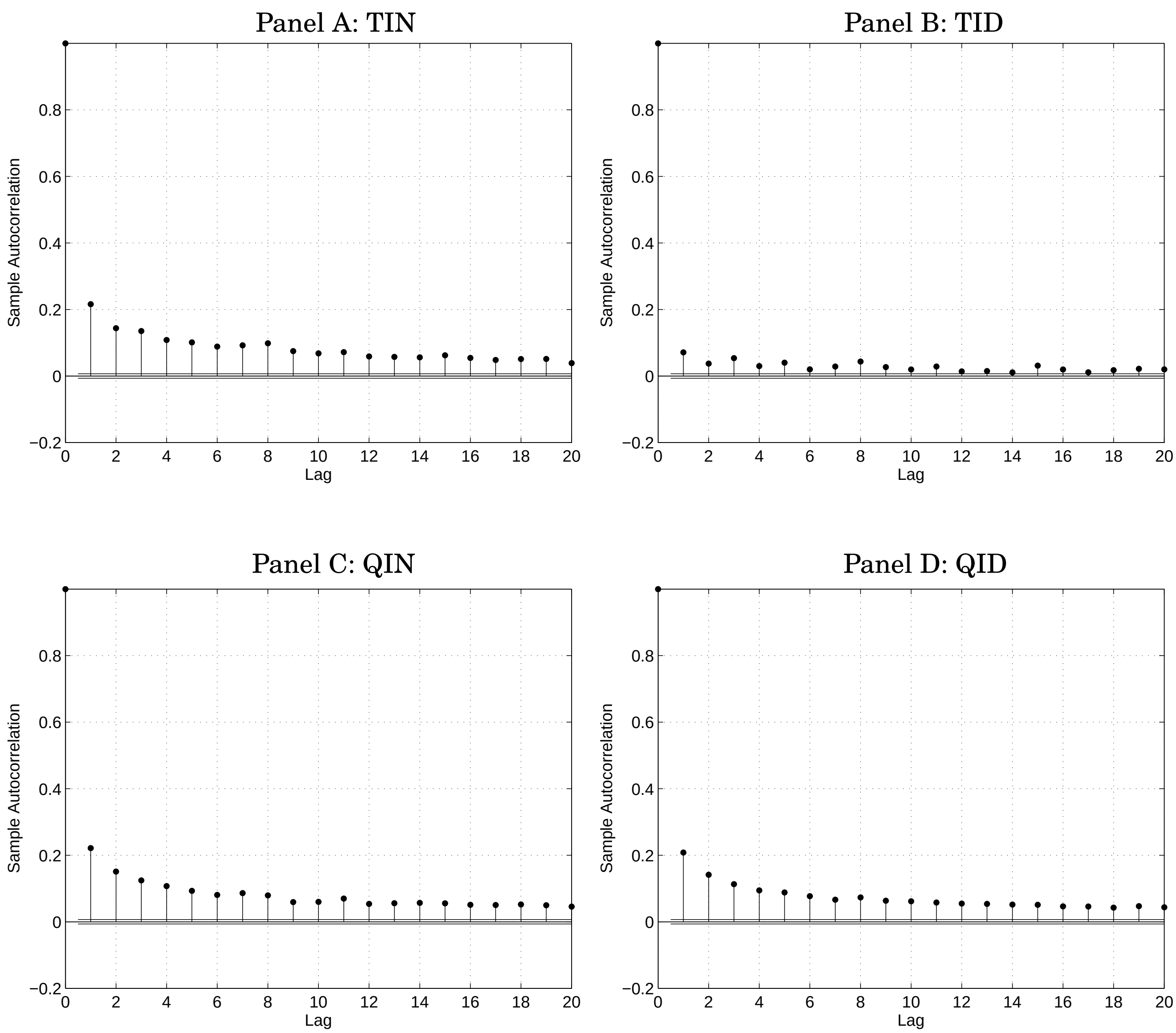
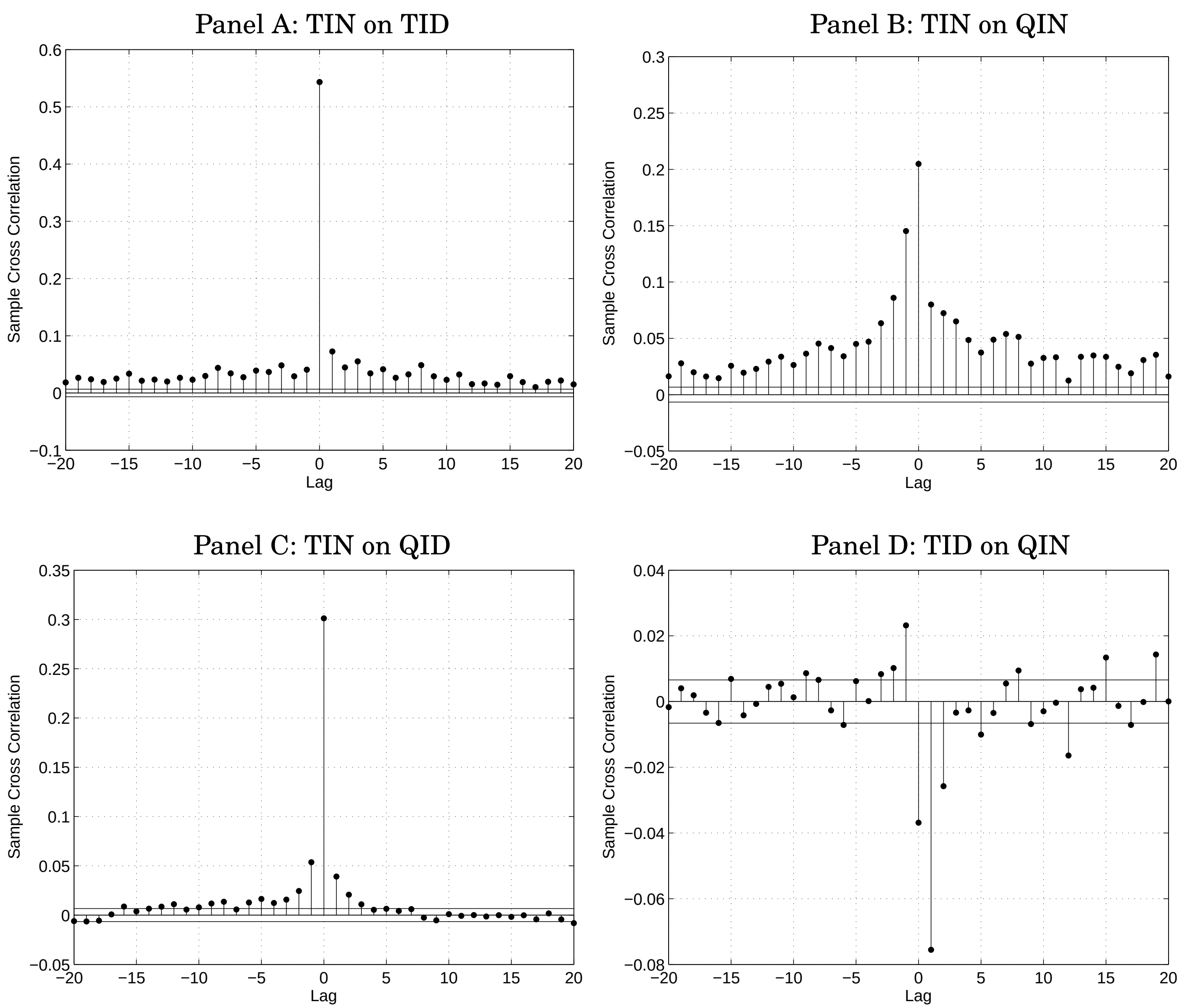
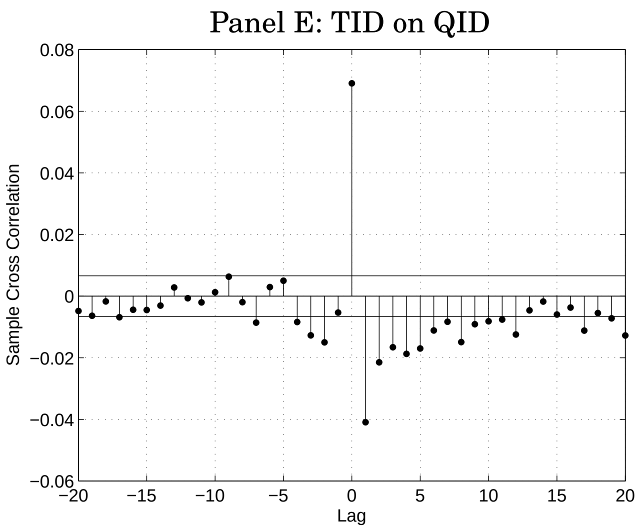
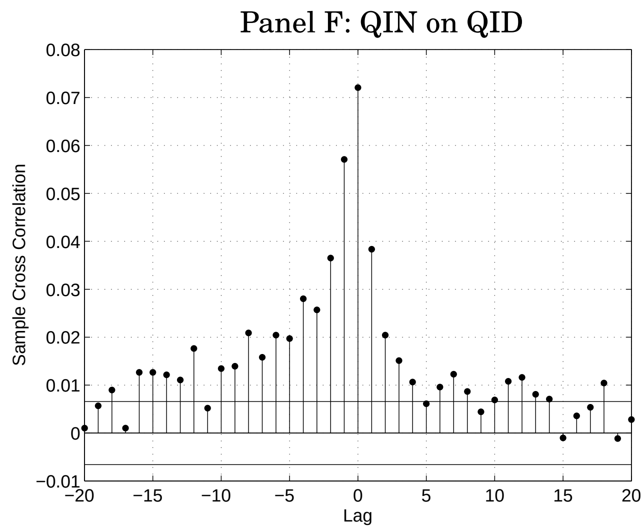


Figure 2: **Cross-correlation Functions of Trading and Quoting Activities.** The cross-correlation function of trade imbalance in numbers (TIN) on trade imbalance in dollars (TID) is shown in Panel A for the whole sample. One sees that TIN leads TID by a day with a coefficient of about 0.08, while it lags TID with a coefficient of approximately 0.05. More substantially, TIN lags the quote imbalance in numbers (QIN) by a day with a coefficient of about 0.15, as evident in Panel B. The other four cross-correlation functions are displayed in Panel C to Panel F, where QID is the quote imbalance in dollars. The two lines indicate two standard deviations from zero at the 5% level for the contemporaneous cross-correlation.




Panel E: TID on QID
Sample Cross Correlation
Lag
0.08
0.06
0.04
0.02
0
−0.02
−0.04
−0.06
−20
−15
−10
−5
0
5
10
15
20


Panel F: QIN on QID
Sample Cross Correlation
Lag
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
−0.01
−20
−15
−10
−5
0
5
10
15
20