EFA
Eastern Finance Association

The Financial Review 35 (2000) 125–146

The Financial Review

Informed and Uninformed Trading in an Electronic, Order-Driven Environment

Paul Brockman
Dennis Y. Chung*

Hong Kong Polytechnic University

Abstract

The purpose of our study is to investigate the trading behavior of informed and uninformed investors in a screen-based, order-driven environment. As more and more exchanges conduct trading through electronic limit-order books, it is increasingly important to analyze consequent trading behavior and its impact on the liquidity provision process. We examine one of the largest electronic, order-driven markets in the world, the Stock Exchange of Hong Kong. Our findings show that the interaction of informed and uninformed traders plays a significant role in determining corporate liquidity.

Keywords: informed trading, uninformed trading, electronic markets

JEL Classification: G15

1. Introduction

The purpose of our study is to investigate the trading behavior of informed and uninformed investors in a screen-based, order-driven trading environment. The use of electronic limit-order books and automated order matching has grown rapidly in recent years due to technological improvements and financial market deregulation. Electronic screen-based trading using (transparent) public limit-order books is gain-

**Corresponding author*: Hong Kong Polytechnic University, Department of Accountancy, Hung Hom, Hong Kong; Phone: (852) 2766-7056, Fax: (852) 2330-9845, E-mail: acdchung@inet.polyu.edu.hk.

The authors wish to thank the two anonymous referees and seminar participants at the July 1999 Conference of the Accounting Association of Australia and New Zealand for helpful comments. The work described in this paper was supported by a research grant from the Hong Kong Polytechnic University (Project No. G-S962).

ing a greater share of worldwide securities trading. Many of the newly emerging equity and derivative markets have adopted electronic, order-driven systems, and some of the more mature and well-established exchanges are in the process of initiating or broadening such trading. The OM Stockholm Exchange, London International Financial Futures Exchange, Marche a Terme International de France, Sydney Futures Exchange, and Deutsche Börse AG have recently announced intentions to increase the role of electronic screen-based trading and/or upgrade electronic trading platforms. Nasdaq has recently proposed the introduction of a ''market-wide, automatic matching limit-order system'' in an effort to increase efficiency and transparency, and the Chicago futures exchanges (Chicago Board of Trade and Chicago Mercantile Exchange) are experiencing increasing challenges to their floor-based trading systems.

As more exchanges move from floor-based to screen-based platforms, it becomes more important to understand the roles of informed and uninformed traders and their impact on liquidity provision in these electronic market microstructures. Market transparency, or the ability of market participants to observe trade-relevant information, is enhanced under screen-based trading because market participants can observe the public limit-order book in real time. In addition, many of the automated markets, such as the Stock Exchange of Hong Kong (SEHK), operate order-driven systems without designated market makers or liquidity suppliers of last resort. To date, very little is known about the impact of such a trading environment on informed and uninformed trading behavior.[1]

The issue of market transparency has attracted considerable attention in the past several years because ''the information available in the trading process can affect the strategies of market participants'' (O'Hara, 1995, p. 252). Madhavan (1995) develops a theoretical framework in which greater disclosure of trade price information causes prices to be more informative and less volatile. However, from the dealer's perspective, Lyons (1996) shows that full transparency might not be optimal because it reduces the dealer's ability to share risk with outside investors. In a later study, Madhavan (1996) also argues that increased order flow disclosure can lead to higher liquidity costs since the effective bid-ask spread is expected to widen in a transparent market.

Pagano and Röell's (1996) theoretical model shows that greater transparency will generally lower the trading costs of uninformed traders. We note that ''transparency'' is a multidimensional term. It can be defined in terms of

(1) the time period in which trade-relevant information is disclosed (e.g., pre-trade versus post-trade),
(2) the range of trade-relevant information disclosed (e.g., price, volume, spread, depth, order flow, identity of order submitter), and

[1] Subsequent to the acceptance of this paper, we became aware of a concurrent study by Brown, Thompson, and Walsh (1999) that investigates informed and uninformed trading on the Australian Stock Exchange.

(3) to whom the trade-relevant information is disclosed (e.g., exchange members, dealers, floor traders, institutional and individual investors).

In this paper, a transparent market refers to one in which order flow (i.e., demand and supply schedules implied by public limit orders), transaction prices and volumes, and broker identities are publicly available in real time. Although the current study does not attempt to resolve the optimal transparency issue, it does provide some empirical evidence on the relation between corporate liquidity (i.e., both spreads and depths) and informed/uninformed trading when order flow is highly transparent.

A second feature of many automated markets is the use of order-driven, as opposed to quote-driven, trading mechanisms. In quote-driven systems, designated market-makers supply liquidity by continuously quoting the bid and ask prices and the number of shares at which they are willing to trade. Investors demand liquidity through the submission of market orders that are subsequently matched against the market-makers' bid or ask prices (and depths).[2] In order-driven systems, public limit orders provide liquidity to the market and establish the bid-ask spread and depth. There is no obligation or duty on the part of any market participant to submit such limit orders.

Madhavan (1992) shows theoretically that equilibrium in an order-driven market is at least as robust as that of a quote-driven market. However, the order-driven framework is more susceptible to the so-called "free option" problem in which a limit order to buy (sell) a fixed number of shares at a predetermined price is equivalent to writing a free put (call) option. Handa and Schwartz (1996) show that market participants with well-balanced portfolios could profit from the placement of a network of limit buy and sell orders. In this case, the granting of free options is an operating expense and part of the economic costs of supplying immediacy to the market.

It is important to identify and understand the variables that affect liquidity because of the close connection between corporate liquidity and cost of capital (Amihud and Mendelson, 1986). Recent empirical evidence confirms that a corporation's required rate of return is significantly related to various liquidity proxies, such as amortized spreads (Chalmers and Kadlec, 1998), turnover rates (Datar, Naik, and Radcliffe, 1998), and adverse selection costs (Brennan and Subrahmanyam, 1996). To date, there is no empirical evidence on the liquidity effects of informed and uninformed trading in order-driven market microstructures.

We use the trading model developed in Easley, Keifer, O'Hara, and Paperman (1996) to estimate the probability of an information event, the probability of bad news given the occurrence of an information event, the order arrival rates of informed and uninformed traders, and the probability that any given trade is information-

[2] Depending on the exchange, public limit orders can also compete with the bid and ask prices of the designated market maker.

based. The Easley, Keifer, O'Hara, and Paperman (1996) model is applicable to any market structure that includes both market-making and informed and uninformed trading. Although there are no market makers with an affirmative obligation to trade in an order-driven environment, de facto market-makers on the SEHK are likely to provide liquidity in much the same fashion as "scalpers" on floor-based futures exchanges.[3]

Easley, Keifer, O'Hara, and Paperman (1996) parameter estimates, combined with additional trade-related data, allow us to determine whether limit-order traders behave like designated dealers/specialists (i.e., widening spreads/reducing depths) when confronted with the possibility of trading against informed investors. This research can help exchange officials when deciding which firms to trade on what platforms. For example, the SEHK is currently considering a "second board" for newly listed, small-capitalization firms. Whether such firms require the attention of a designated dealer or should be traded on an order-driven platform is an open issue. By analyzing Easley, Keifer, O'Hara, and Paperman (1996) parameter estimates across volume-sorted deciles, we provide useful inputs on this, and similar decisions.

Our findings, based on over seven million observations from the SEHK, show that the probability of experiencing an information event is directly related to trading activity (i.e., dollar volume), and that the probability that the information event signals bad news is inversely related to trading activity. Actively traded firms attract more informed and uninformed traders, and have a lower probability that any given trade is information based. Even after controlling for variations in price, volume, and variance, the regression results confirm that the probability of an informed trade plays a significant role in the liquidity provision process. When the probability of informed trading is high, spreads are wide and depths are small, which reduces corporate liquidity.[4]

Our findings contribute to the literature by providing estimates and an analysis of Easley, Keifer, O'Hara, and Paperman (1996) parameters in an order-driven environment. The results suggest that liquidity provision on the SEHK is determined by the same set of variables as on dealer-based markets. Limit order traders widen spreads for stocks associated with relatively high probabilities of informed trading in a manner comparable to that of a NYSE specialist. An additional contribution

---

[3] Although not investigated in this paper, the trading behavior of de facto market-makers is an interesting topic for future research. Handa and Schwartz (1996) provide some preliminary evidence on the profitability of such limit-order trading.

[4] The Easley, Keifer, O'Hara, and Paperman model is designed to capture the salient features of the trading behavior of informed and uninformed traders. Although the model produces an estimate for the probability of an informed trade, which may be related to the notion of adverse selection, it is important to note that this model does not decompose the bid-ask spread or estimate any of its individual components. Decomposition models, on the other hand, are designed to partition the bid-ask spread into its various components such as order processing, inventory holding, and adverse selection. See Brockman and Chung (1999a) for decomposition results in an order-driven environment.

of this paper is the use of depths to show a direct connection between the probability of informed trading and company depth. Our results show that as limit-order traders attempt to protect themselves from the effects of asymmetric information, corporate liquidity is significantly affected through depth reductions (in addition to spread increases). A direct implication is that since changes in depths magnify the impact of changes in spreads, liquidity costs attributable to informed trading are larger than previously documented.

The paper is organized as follows. Section 2 examines the market microstructure of the SEHK's fully automated, order-driven market and describes the intraday data set. Section 3 provides general background on the trading model. Section 4 presents the empirical findings and analyzes their implications, and Section 5 concludes.

2. SEHK market microstructure and data

The SEHK is a thoroughly continuous (i.e., no opening-call market), order-driven market. Because of its simplicity and transparency, the Exchange offers an ideal setting in which to analyze informed and uninformed trading behavior. Although other exchanges have some order-driven features, most use a hybrid form of trading mechanisms (e.g., the NYSE and Amex). The SEHK, on the other hand, is about as pure an order-driven market as can be obtained. There are no designated dealers (specialists), no designated order processors (*saitori*), no switching from call to continuous markets, no inter- or intraday price limits, no trading halts, no "hidden orders," and no mandatory versus nonmandatory quotation periods. All order flow, whether originating from informed or uninformed traders, must be displayed on computer terminals viewable by on- and off-Exchange investors.

Order entry and execution on the SEHK begins when a trader submits a limit order, and limit orders are the only order type permitted on the Exchange (i.e., there are no market orders, at least in name). A buy limit order must give the bid price and number of shares to be purchased. A sell limit order must provide the ask price and number of shares to be sold. The limit order is entered into the Automatic Order Matching and Execution System, which prioritizes it first by price and then by time. Although order sizes are posted for each bid or ask price level, trade size is not a priority in execution. Bid prices are arranged in priority from highest to lowest, and ask prices are arranged from lowest to highest. The difference between the lowest ask price and the highest bid price represents the bid-ask spread. If a buyer (seller) requires an immediate fill (i.e., equivalent to a market order), then he will submit a limit bid (ask) price that is high (low) enough to touch the lowest (highest) posted ask (bid) price.

Trade depth, at the inside spread, is a function of the number of shares available at the lowest ask and highest bid prices. The number of shares available at the highest bid price represents the number of shares that a seller can sell without inducing a price decrease. The number of shares available at the lowest ask price represents the number of shares that a buyer can purchase without inducing a price increase. Actual and potential traders are able to observe bid (ask) prices and depths, and the buying (selling) broker's identity. Exchange members observe this trading information on both floor-based and remote trading terminals, and non-Exchange members access the same information through (real-time) data providers.

These market features create a trading system that is considerably more transparent than previously researched markets such as NYSE, Amex, and Nasdaq. Exactly how such a transparent (electronic) market microstructure affects the behavior of informed and uninformed traders is not known and can only be addressed through additional empirical analysis.

We obtain our data set from the SEHK's Research and Planning Division. The data set includes intraday data for 645 companies covering the period from May 1, 1996–August 29, 1997.[5] The full sample represents all firms that traded over our sample period. We compile bid (ask) prices and depths, transaction prices, and volumes at thirty-second intervals throughout the trading day which includes a morning session from 10:00 to 12:30 and an afternoon session from 2:30 to 3:55. We eliminate from the full sample companies with incomplete trading information over the 16-month period (i.e., initial public offerings and delistings). This reduces the sample to 532 firms and a total of 7,420,801 observations. We then partition the 532 firms into decile portfolios based on dollar volume with the first (tenth) decile corresponding to the smallest (largest) dollar volume.[6]

3. A model of informed trading

The Easley, Keifer, O'Hara, and Paperman (1996) model (and its variants) is designed to capture the salient features of the trading process in which informed traders submit buy and sell orders conditional on the occurrence of a private information event and the observation of its good-versus-bad news content.[7] Uninformed traders are unaware of private information events and therefore do not observe the good-versus-bad news content (i.e., uninformed order flow is independent of private information).

This asymmetric information model and its variants have been used to determine the probability of informed trading in high-versus-low-volume stocks (Easley, Keifer, O'Hara, and Paperman, 1996), to extract the information content of trade

[5] Because of an internal clock misalignment in the original data capturing process, we make minor adjustments to the time-of-day for the first eight months of the sample period. These adjustments are made based on information provided by SEHK's Research and Planning officials and verified by our program filters.

[6] We select dollar volume because the Easley, Keifer, O'Hara, and Paperman (1996) model is a trade-based model. Additional testing, using volume deciles and market capitalization deciles (all available on request), produces very similar results.

[7] Although all versions of the Easley, Keifer, O'Hara, and Paperman (1996) model are based on the same underlying trade process, this section specifically describes the recent Easley, O'Hara, and Paperman (1998) version.

size and test various market microstructure models (Easley, Keifer, and O'Hara, 1997a,1997b), to analyze the effect of analysts' following on the level of informed and uninformed trading (Easley, O'Hara, and Paperman, 1998), and to examine whether informed traders prefer to trade in the stock or options market (Easley, O'Hara, and Srinivas, 1998).

More specifically, the model provides a method for estimating the probability of a private information event (α), the probability of negative news given the occurrence of a private information event (δ), the order arrival rate of informed traders (μ), and the order arrival rate of uninformed traders (ε). At the beginning of every trading day, nature selects whether an information event occurs (with probability α) or not (with probability 1-α). On noninformation days, only uninformed traders participate in the market, and buy order arrivals (with arrival rate ε) equal sell order arrivals (with arrival rate ε). On private-information event days, both informed and uninformed traders enter the market. If the information event represents bad news (with probability δ), then both informed and uniformed traders will issue sell orders (with arrival rate μ+ε), but only uninformed traders will submit buy orders (with arrival rate ε). If the information event represents good news (with probability 1-δ), then both informed and uniformed traders will issue buy orders (with arrival rate μ+ε), but only uninformed traders will submit sell orders (with arrival rate ε).

The arrival of buys (B) and sells (S) within the trading day is modeled as a combined Poisson process. In total, three such processes are specified (i.e., one for each information structure, corresponding to a non-event day, a bad-news day, and a good-news day). The probabilities of observing buys and sells on a non-event day, a bad news day, and a good-news day, respectively, are given by

$$e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} \tag{1}$$

$$e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\varepsilon+\mu)}\frac{(\varepsilon+\mu)^S}{S!} \tag{2}$$

$$e^{-(\varepsilon+\mu)}\frac{(\varepsilon+\mu)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} \tag{3}$$

As mentioned above, the probability of a non-event day is 1-α, the probability of a bad-news day is $\alpha\delta$, and the probability of a good-news day is α(1-δ).

Combining these probabilities with the Poisson processes in Equations (1), (2), and (3) yields the following likelihood function:

$$L((B,S)\mid\alpha,\delta,\varepsilon,\mu) = (1-\alpha)\,e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} + (\alpha\delta)\,e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^S}{S!} + \alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} \tag{4}$$

We obtain parameter estimates for the probability of a private information event (α), the probability of negative news given the occurrence of a private information event (δ), the order arrival of informed traders (μ), and the order arrival of uninformed traders (ε) by maximizing the likelihood function:

$$L(D \mid \alpha, \delta, \varepsilon, \mu) = \prod_{i=1}^{N} L(\alpha, \delta, \varepsilon, \mu \mid B_i, S_i) \tag{5}$$

The data set, D, requires only the number of buys (B) and sells (S) compiled on a daily basis over a total of N days. The overall derivation assumes that B and S are independent across trading days. This assumption is consistent with an informationally efficient market that fully impounds news events by the close of the trading day. Recall that information events occur at the beginning of the trading day. In addition, Easley, Keifer, and O'Hara (1997a) provide empirical evidence that supports the independence assumption.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 1 presents summary statistics for the combined sample of 532 companies covering the sample period of 330 trading days, along with summary statistics for the first, fourth, seventh, and tenth dollar-volume decile portfolios. Reported values refer only to the ordinary shares (i.e., no convertibles, preferred stock, or warrants) of the respective firms.

The average Hong Kong company's market capitalization, price, and daily trading volume is $6,069,920,000, $6.137, and 5,257,287 shares, respectively.[8] Average daily dollar volume per company is $16,686,136. The typical Hong Kong company is traded during 84.83% of all trading days, 33.68% of all five-minute intervals, and 9.03% of all 30-second intervals. These numbers confirm that the SEHK is a relatively large and actively traded stock market. It typically ranks between the top six to eight stock exchanges in the world by market capitalization, and second in Asia behind Japan.

Average absolute bid-ask spreads (i.e., ask price minus bid price) are $0.06444 and average relative bid-ask spreads (i.e., absolute bid-ask spread divided by the bid-ask midpoint) are 0.02021, representing approximately 2% of the stock's price. Depth, a second dimension of liquidity, can be measured either as the number of shares at the highest bid price plus the number of shares at the lowest ask price, or as the number of shares at the highest bid and lowest ask price times their respective prices. The first measure is referred to as volume depth, and the second is dollar

[8] All $ values refer to Hong Kong dollars. The Hong Kong dollar is officially pegged at 7.8 per U.S. dollar, and remained very close to this rate during the period under investigation.

depth. Both measures show that the average Hong Kong stock is relatively liquid, with a volume depth of 693,588 shares and dollar depth of $1,318,737.

The first, fourth, seventh, and tenth decile results suggest that dollar volume provides a meaningful partitioning criterion since considerable cross-sectional variation is revealed across other variables as well (e.g., price, market capitalization, spreads, depths). Average market capitalizations, volumes, active trading intervals, and dollar depths monotonically increase from the first to the tenth deciles, and relative bid-ask spreads monotonically decrease. The comparatively large average price for the first decile portfolio ($8.118) indicates there are inactive firms with relatively high prices. This result is also consistent with the large average absolute spread ($0.16785) associated with the same decile. Previous research (e.g., Benston and Hagerman, 1974; Brockman and Chung, 1998) shows that absolute spreads are an increasing function of stock prices, and relative spreads are a decreasing function.

Finally, we note that there is considerable variation in liquidity measures across deciles. Without designated market makers, the order-driven trading mechanism produces an average relative spread of only 0.00809 and an average dollar depth of $7,724,626 for the high-dollar-volume portfolio compared to 0.03943 and $189,723, respectively, for the low-dollar-volume portfolio.

4.2. Model estimation

We compile the daily number of buys (*B*) and sells (*S*) for each company during thirty-second intervals. Identification of buys and sells is generally straightforward on automated, order-driven systems because transactions can take place only at posted bid prices (sells) or posted ask prices (buys). There is no monopolistic market maker who can trade within posted spreads and, therefore, there is no need to apply Lee and Ready's (1991) midpoint rule.

Next, we use the Newton-Raphson method with a line search algorithm to obtain parameter estimates that maximize the natural log of the following likelihood function,

$$\prod_{i=1}^{330} \left[(1-\alpha)e^{-\varepsilon} \frac{\varepsilon^{B_i}}{B_i!} e^{-\varepsilon} \frac{\varepsilon^{S_i}}{S_i!} + \alpha\delta\, e^{-\varepsilon} \frac{\varepsilon^{B_i}}{B_i!} e^{-(\mu+\varepsilon)} \frac{(\mu+\varepsilon)^{S_i}}{S_i!} + \alpha(1-\delta)e^{-(\mu+\varepsilon)} \frac{(\mu+\varepsilon)^{B_i}}{B_i!} e^{-\varepsilon} \frac{\varepsilon^{S_i}}{S_i!} \right] \quad (6)$$

where 330 is the number of days in the estimation period, and B_i and S_i are the number buys and sells, respectively, during the i^{th} trading day. As in Easley, Keifer, O'Hara, and Paperman (1996), α and δ are restricted to (0,1) through a logit transformation, and μ and ε are restricted to $(0,\infty)$ through a logarithmic transformation. We determine starting values by an extensive grid search over the parameter space on a firm-by-firm basis. From the original sample of 532 firms, 521 companies

Table 1

Selected market statistics on trading activities of sample companies over the sample period from May 1, 1996–August 29, 1997

The sample comprises of the population of all companies with ordinary shares listed on the SEHK throughout the entire sample period. The sample consists of 532 firms, which are divided into ten volume deciles based on the dollar volume of the firms. We measure each company's dollar volume as the mean of the company's daily trading volume in dollars across all trading days over the sample period. Our sample period covers a total of 330 trading days. Two trading days (October 14, 1996 and December 12, 1996) are not included, because data on the bid and ask quotes were not available from the SEHK on these two particular days.

	Combined Sample	Tenth Decile Subsample	Seventh Decile Subsample	Fourth Decile Subsample	First Decile Subsample
Number of companies in sample	532	53	54	54	53
Average market capitalization per company (HK$)	$6,069,920,000	$42,661,830,000	$1,738,600,000	$1,617,700,000	$791,950,603
Average daily trading volume per company in number of shares	5,257,287	15,547,667	6,668,238	1,158,332	78,582
Average daily trading volume per company in total dollar volume (HK$)	$16,686,136	$112,416,924	$7,564,877	$1,697,279	$87,574
Average percentage of trading days (over the sample period) with one or more shares traded	84.83%	98.19%	93.46%	89.42%	40.87%
Average percentage of 5-minute intervals with one or more shares traded	33.68%	77.62%	41.15%	20.63%	2.05%
Average percentage of 30-second intervals with one or more shares traded	9.03%	31.42%	9.41%	3.20%	0.19%
Average share price in 5-minute intervals	$6.137	$20.581	$3.860	$3.411	$8.118

(continued)

Table 1 *(continued)*

Selected market statistics on trading activities of sample companies over the sample period from May 1, 1996–August 29, 1997

	Combined Sample	Tenth Decile Subsample	Seventh Decile Subsample	Fourth Decile Subsample	First Decile Subsample
Average absolute bid-ask spread in 5-minute intervals (HK$)	$0.06444	$0.07811	$0.03356	$0.04919	$0.16785
Average relative bid-ask spread in 5-minute intervals	0.02021	0.00809	0.01605	0.02031	0.03943
Average volume depth in 5-minute intervals	693,588	925,340	2,979,940	215,353	122,046
Average dollar depth in 5-minute intervals (HK$)	$1,318,737	$7,724,626	$749,149	$357,515	$189,723

generate valid maximum likelihood estimates. The results for 11 companies are considered invalid because of problems with convergence or estimates that involve corner solutions (i.e., zero or one) to within seven or more decimal places.

Table 2 reports the mean and median estimated parameters for the combined sample and for each of the dollar-volume decile portfolios. Parametric F-statistics and non-parametric Kruskal-Wallis tests show that there is significant variation (at the 0.001 level) across the decile portfolios for all mean and median parameter estimates. The mean (median) probability of an information event (α) for the combined sample is 0.2395 (0.2149), suggesting that private information is released about once a week. The high-dollar-volume firms in the tenth decile (mean=0.4800, median=0.4971) are associated with substantially more information events than are the low-dollar-volume firms in the first decile (mean=0.1145, median=0.0764). In fact, there is a consistent monotonic relation between dollar volume and the probability of an information event. This finding is consistent with the notion that greater amounts of information are generated for larger, more actively traded firms.

The mean (median) probability of a bad news event (δ) for the combined sample is 0.475 (0.47). Although bad news is not quite as likely as good news (i.e., 1-δ) overall, there is a clear pattern of low- (high-) dollar-volume firms associated with high (low) δ values. Large, actively traded firms have a higher probability of an information event, but if an event occurs, there is a lower probability that the information is bad news. Alternatively, inactive firms tend to generate fewer information events, but if an event occurs, there is a higher probability that the information contains bad news. Easley, Keifer, O'Hara, and Paperman (1996) also document a direct relation between dollar volume and α, and an inverse relation between dollar volume and δ by using NYSE data from a specialist environment.

The mean (median) order arrival rate of informed traders (μ) for the combined sample is 36.46 (36.67). The high-dollar-volume firms in the tenth decile (mean= 62.09, median=65.08) are associated with substantially more informed trading arrivals than are the low-dollar-volume firms in the first decile (mean=5.96, median= 4.34), and there is a strictly monotonic relation between dollar volume and informed trading arrivals.

We observe a similar pattern for uninformed arrival rates. The mean (median) order arrival rate of uninformed traders (ε) for the combined sample is 13.49 (9.46), and there is a strictly monotonic relation between dollar volume and uninformed trading arrivals. Mean and median ε values begin at 41.22 and 42.33, respectively, for the tenth decile and then fall steadily until reaching the first decile values of 0.25 and 0.18, respectively.

Higher arrival rates of informed and uninformed trading for large, actively traded firms are not surprising. However, these results do highlight the fact that informed and uninformed traders concentrate their trading activity in the same firms. These results are consistent with much of the strategic trading literature. These results also demonstrate that knowledge of informed or uninformed trading alone is insufficient to describe the adverse selection attributes of a firm. Since it is the relation between informed and uninformed trading that is necessary to understand a firm's level of asymmetric information, Easley, Keifer, O'Hara, and Paperman (1996) define the probability of informed trading as

$$\frac{\alpha \mu}{(\alpha \mu + 2\varepsilon)} \tag{7}$$

where α is the probability of an information event, μ is the order arrival rate of informed traders, and ε is the order arrival rate of uninformed traders. This measure uses informed and uninformed arrival rates, combined with the probability of an information event, to construct the probability that any given trade is information-based.

The last two columns in Table 2 report the mean and median probability of informed trading (*PINF*) results. The mean (median) *PINF* value for the combined sample is 0.3296 (0.2975). As we expected, there is an inverse relation between dollar volume and the probability of informed trading. Large, actively traded firms attract not only more informed trading, but also more uninformed trading. However, the net result is a lower probability that any given trade is information-based.

Smaller, inactively traded firms attract not only less informed trading, but also less uninformed trading. The net result is a higher probability that any given trade is information-based. We also note that the relation between dollar volume and PINF is not exactly monotonic. This finding suggests there are additional factors that explain why some firms are more susceptible to information-based trading than others.[9]

4.3. Cross-sectional analysis

We use cross-sectional analysis to determine whether Easley, Keifer, O'Hara, and Paperman (1996) trading parameters have a significant impact on the provision of liquidity in an automated, order-driven environment. Higher PINF values should generate wider bid-ask spreads and/or smaller depths. It is important to test both measures of liquidity because either one could magnify or offset the effect of the other. Previous research shows that liquidity is affected by cross-sectional variation in volume, volatility, and price (e.g., Benston and Hagerman, 1974; Barclay and Smith, 1988; Franz, Rao, and Tripathy, 1995; Brockman and Chung, 1998). Therefore, we use these three variables as control variables in the following regression:

$$\begin{aligned} Liquidity_i = \alpha + \beta_1\, vol_i + \beta_2\, var_i + \beta_3\, price_i + \\ \gamma\, ITraders_i + \lambda\, UTraders_i + \theta\, PINF_i + \varepsilon_i \end{aligned} \tag{8}$$

where $Liquidity_i$ is defined as either the RBA_I (relative bid-ask spread) or dollar

[9] One such potential factor, the number of analyst followings, is investigated in Easley, O'Hara, and Paperman (1998). The evidence shows that firms with high analyst followings are associated with low PINFs.

Table 2

Estimates of model parameters

We perform a maximum likelihood estimation of the Easley, Keifer, O'Hara, and Paperman (1996) trade process model for each sample firm. We use the Newton-Raphson method with the line search algorithm to obtain the parameter estimates that maximize the natural log of the likelihood function over the 330-day sample period. α, δ, μ, and ε are the Poisson process parameters that represent the probability of an information event, probability of the information being bad news, arrival rate of informed trades, and arrival rate of uninformed trades, respectively. B_i and S_i are the number of buys and the number of sells, respectively, on the i^{th} trading day. We use 30-second intervals to compile transaction and bid-ask data on all the sample firms throughout the trading days. For each interval, trades are identified as a buy if the transaction price is at the posted ask, and as a sell if the transaction price is at the posted bid. The total number of buys and the total number of sells for each of the 330 trading days are then determined for each sample firm. As in Easley, Keifer, O'Hara, and Paperman (1996), α and δ are restricted to (0,1) through a logit transform. μ and ε are restricted to $(0, \infty)$ through a logarithmic transform of the unrestricted parameters. To ensure that the global maximum is reached, we determine starting values based on an extensive grid search over the parameter space for each firm. Of the 532 sample firms, we obtain valid results for 521 companies in the maximum likelihood estimation. The probability of informed trading is a function of the estimated model parameters and is derived as $\hat{\alpha}\hat{\mu}(\hat{\alpha}\hat{\mu}+2\hat{\varepsilon})^{-1}$. We present means and medians of the estimated parameters for the reduced sample of 521 firms by the volume decile membership of the firms. We form volume deciles on the initial sample of 532 firms based on the dollar volume of the firms. We measure each company's dollar volume as the mean of the company's daily trading volume in dollars across all trading days over the sample period. Also presented are the F-statistic in one-way ANOVA for equality of means across the 10 decile subsamples (d.f. = 9, 511) and the approximated χ^2 statistic in Kruskal-Wallis test for equality of medians across the 10 decile subsamples (d.f. = 9)

$$\prod_{i=1}^{330}\left[(1-\alpha)e^{-\varepsilon}\frac{\varepsilon^{B_i}}{B_i!}e^{-\varepsilon}\frac{\varepsilon^{S_i}}{S_i!}+\alpha\delta\, e^{-\varepsilon}\frac{\varepsilon^{B_i}}{B_i!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^{S_i}}{S_i!}+\alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^{B_i}}{B_i!}e^{-\varepsilon}\frac{\varepsilon^{S_i}}{S_i!}\right]$$

(continued)

Table 2 *(continued)*

Estimates of model parameters

	Number of Firms in the Initial Sample	Number of Firms in the Reduced Sample	Estimate of Probability of Information Event α		Estimate of Information Being Bad News δ		Estimate of Arrival Rate of Informed Traders μ		Estimate of Arrival Rate of Uninformed Traders ε		Estimated Probability of Information-based Trading PINF	
			Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Combined sample	532	521	0.2395	0.2149	0.4750	0.4700	36.46	36.67	13.49	9.46	0.3296	0.2975
10^{th} decile subsample	53	53	0.4800	0.4971	0.4028	0.3947	62.09	65.08	41.22	42.33	0.2668	0.2675
9^{th} decile subsample	53	53	0.3502	0.3488	0.3918	0.3845	55.21	57.71	26.98	26.92	0.2632	0.2599
8^{th} decile subsample	53	53	0.2775	0.2761	0.4289	0.4275	50.74	51.51	20.81	21.57	0.2545	0.2402
7^{th} decile subsample	54	54	0.2454	0.2440	0.4684	0.4368	48.12	49.73	14.60	13.05	0.2886	0.2811
6^{th} decile subsample	53	53	0.2209	0.2200	0.4726	0.4736	40.30	42.73	11.29	11.22	0.2687	0.2694
5^{th} decile subsample	53	53	0.1921	0.1855	0.4753	0.4779	38.58	38.27	8.24	8.48	0.3008	0.2921
4^{th} decile subsample	54	51	0.2073	0.1846	0.4876	0.4679	26.07	27.33	5.22	4.90	0.3162	0.2959
3^{rd} decile subsample	53	50	0.1609	0.1511	0.5061	0.4984	22.75	25.18	3.16	3.24	0.3678	0.3550
2^{nd} decile subsample	53	48	0.1297	0.1294	0.5805	0.5791	11.03	9.22	0.96	0.86	0.4675	0.4557
1^{st} decile subsample	53	53	0.1145	0.0764	0.5483	0.5647	5.96	4.34	0.25	0.18	0.5169	0.4843
F-statistic				67.35*		7.28*		108.32*		219.96*		60.67*
χ^2 statistic				336.79*		62.10*		346.15*		465.51*		241.93*

* Indicates statistical significance at the 0.001 level.

depth$_i$, as defined in Section 4.1, and *vol*$_i$, *var*$_i$, and *price*$_i$ are the volume, variance, and price, respectively, for the *i*th firm.

Because the Easley, Keifer, O'Hara, and Paperman (1996) model specifies that information events take place immediately prior to the opening of trading, we define RBA_i, $depth_i$, vol_i, var_i, and $price_i$ as at the first five-minute interval of the day in which a trade occurs. We then average the opening observations (by firm) across all trading days. Vol_i refers to the total volume over the opening interval. Var_i is the variance of returns over the opening interval. We calculate var_i by using one-minute continuous returns, which we obtain by taking the logarithms of bid-ask midpoint relatives one minute apart. RBA_i, $depth_i$, and $price_i$ correspond to the last recorded values in the opening five-minute interval. $ITraders_i$ (informed traders) and $UTraders_i$ (uninformed traders) represent the estimated parameter values for μ and ε, respectively, as presented in Table 2. $PINF_i$ is the probability of an informed trade, as defined in Equation (7).

Table 3 provides descriptive statistics for all variables used in regression Equation (8). Panel A presents minimum, maximum, mean, and median values for all 521 firms. Panel B gives the correlations among dependent and independent variables. Relatively high correlation coefficients among some of the independent variables suggest the potential for multicollinearity problems. A high correlation, such as that between ITraders and UTraders (i.e., 0.705), can make it difficult to distinguish the explanatory power of one variable from the other when they are both part of the same regression equation. Although estimated coefficients remain unbiased, standard errors and *t*-statistics might not be valid. However, we note that the effect of multicollinearity is to bias against finding significance in the highly correlated variable, when in fact, there is a significant relation.

In Table 4, Panel A provides the estimated coefficients for regression Equation (8) using *RBA* as the dependent variable and three combinations of independent variables.[10] We adjust all reported *t*-statistics for heteroskedasticity using White's (1980) procedure. Previous research shows that volume and price levels are inversely related to relative spreads, and variance is directly related. Consistent with these expectations, β_1 and β_3 are significantly negative across all three regressions, and β_2 is significantly positive. The adjusted R squares over 90% and the highly significant *F*-statistics show that the three regressions fit the data rather well.

We hypothesize that higher levels of uninformed trading (UTraders) will reduce spreads and that higher probabilities of informed trading (PINF) will widen spreads. The empirical results confirm these hypothesized relations. The estimated λ coefficients are significantly negative, and the θ coefficients are significantly positive, across all regressions. The impact of informed traders (ITraders) on spreads cannot be predicted ex ante because their presence increases adverse selection costs (causing

---

[10] The number of shares traded, the variance of returns, and price are always included because of their role as control variables. We test additional combinations of informed trading, uninformed trading, and probabilities of informed trading. The results are equivalent to those reported here.

Table 3

Descriptive statistics and correlation matrix of regression variables

We define the variables RBA, depth, vol, var and price as at the first 5-minute interval of the day (the opening interval) in which a trade occurs. Vol is the number of shares traded. Var is the variance of returns over the opening interval. We calculate returns on a continuously compounded basis by taking the logarithms of bid-ask midpoint relatives one minute apart. RBA is the relative bid-ask spread and is the difference between the lowest ask and the highest bid divided by the bid-ask midpoint. Depth is the dollar depth and is the total value of all shares quoted at the highest bid plus the total value of all shares quoted at the lowest ask. Price is the last recorded share price in the opening interval. We average all measures across trading days for each company over the sample period. We obtain the remaining variables, ITraders, UTraders, and PINF from the maximum likelihood estimation of the Easley, Keifer, O'Hara, and Paperman (1996) trade process model. For each firm, ITraders is the parameter estimate for μ and represents the arrival rate of informed trades. UTraders is the parameter estimate for ε and represents the arrival rate of uninformed trades. PINF is the estimated probability of information-based trading. The sample size represents the number of companies in the reduced sample with ordinary shares listed on the SEHK throughout the sample period from May 1, 1996–August 29, 1997 and valid results in the maximum likelihood estimation of the Easley, Keifer, O'Hara, and Paperman (1996) trade process model.

Panel A: Descriptive Statistics (n = 521)

Variable	Minimum	Maximum	Mean	Median
RBA	0.003	0.067	0.023	0.021
Depth (× 10^3)	49.686	42,250.189	614.754	290.741
Vol (× 10^3)	1.100	4,969.153	213.219	93.261
Var (× 10^{-6})	0.000	100.750	22.870	17.935
Price	0.038	173.523	6.006	1.761
ITraders	0.003	91.570	36.462	36.675
UTraders	0.000	62.531	13.485	9.456
PINF	0.170	1.000	0.330	0.298

Panel B: Correlation Matrix (n = 521)

	RBA	Depth	Vol	Var	Price	ITraders	UTraders
Depth	−0.252	1.000					
Vol	−0.054	0.075	1.000				
Var	0.755	−0.170	0.256	1.000			
Price	−0.366	0.653	−0.098	−0.347	1.000		
ITraders	−0.278	0.160	0.474	0.187	0.065	1.000	
UTraders	−0.573	0.365	0.367	−0.179	0.241	0.705	1.000
PINF	0.504	−0.089	−0.082	0.160	0.038	−0.472	−0.537

spreads to widen), but also adds volume-related liquidity to the market (causing spreads to narrow). Therefore, the net effect of ITraders on spreads is a purely empirical issue. According to the results in Panel A, the net effect of ITraders is to reduce spreads (i.e., estimated γ coefficients are significantly negative).

Overall, the regression results in Panel A demonstrate the robustness of the Easley, Keifer, O'Hara, and Paperman (1996) model to an automated, order-driven trading environment. The measures of informed and uninformed trading appear to be well-behaved and provide economically intuitive results. ITraders, UTraders, and PINF are statistically significant explanatory variables for cross-sectional variations in spreads, even after we control for price, volume, and variance. The relative magnitudes of the estimated coefficients are also consistent with expectations. The probability of informed trading (θ) has by far the largest impact on spreads, followed by uninformed traders (λ), and then informed traders (γ).

In Table 4, Panel B provides the estimated coefficients for regression Equation (8) using depths as the dependent variable and three combinations of independent variables. To date, no study has tested the relation between the Easley, Keifer, O'Hara, and Paperman (1996) parameters and company depth. Previous research suggests that volume and price levels are directly related to depths, and that variance is indirectly related. Consistent with these expectations, β_1 and β_3 are significantly positive across all three regressions, and β_2 is significantly negative. Again, the adjusted R squares over 85% and the highly significant F-statistics show that the three regressions fit the data rather well.

We hypothesize that higher levels of uninformed trading (UTraders) will increase depths, and that higher probabilities of an informed trade (PINF) will decrease depths. The empirical results confirm these hypothesized relations. The estimated λ coefficients are significantly positive, and the θ coefficients are significantly negative, across all regressions. For the same reasons given above, the impact of informed trading (ITraders) on depths cannot be predicted ex ante, and is therefore an empirical issue. According to the results in Panel B, the net effect of ITraders is to reduce trading depths (i.e., estimated γ coefficients are significantly negative). This finding, combined with the spread results in Panel A, means that the adverse selection costs induced by informed trading are more likely to be reflected in reduced depths than in increased spreads, *ceteris paribus*. In other words, the arrival of informed traders causes other investors to protect themselves by adjusting order submissions in terms of depths more than in terms of spreads (i.e., prices). Again, the relative magnitudes of the estimated coefficients (PINF, UTraders, then ITraders) support our expectations.

Although we must be careful in comparing Easley, Keifer, O'Hara, and Paperman (1996) results with bid-ask decomposition results, there are certain consistencies across these two model types that warrant mentioning. The direct relation between the probability of informed trading and the magnitude of the bid-ask spread is consistent with the positive relation between adverse selection and spread magnitude. The inverse relation between probability of uninformed trading and trading volume is consistent with the inverse relation between adverse selection and trading volume (Lin, Sanger, and Booth, 1995). We also note that the positive relation between probability of uninformed trading and depth is consistent with recent evidence of a positive relation between adverse selection and depth (Brockman and Chung, 1999b). Although we hesitate to push this line of comparison too far, it is at least comforting to find that two distinct models (i.e., informed/uninformed trading versus spread decomposition) produce the same overall picture of corporate liquidity.

Table 4

Cross-sectional regression of liquidity measures on informed trading and other control variables

$Liquidity_i$ for Firm i is measured by RBA_i or $depth_i$. We define the variables RBA_i, $depth_i$, vol_i, var_i and $price_i$ as at the first 5-minute interval of the day (the opening interval) in which a trade occurs. Vol_i is the number of shares traded. Var_i is the variance of returns over the opening interval. We calculate returns on a continuously compounded basis by taking the logarithms of bid-ask midpoint relatives one minute apart. RBA_i is the relative bid-ask spread and is the difference between the lowest ask and the highest bid divided by the bid-ask midpoint. $Depth_i$ is the dollar depth and is the total value of all shares quoted at the highest bid plus the total value of all shares quoted at the lowest ask. Price is the last recorded share price in the opening interval. We average all measures across trading days for each company over the sample period. We obtain the remaining variables, $ITraders_i$, $UTraders_i$, and $PINF_i$ from the maximum likelihood estimation of the Easley, Keifer, O'Hara, and Paperman (1996) trade process model. For Firm i, ITraders is the parameter estimate for μ and represents the arrival rate of informed trades. $UTraders_i$ is the parameter estimate for ε and represents the arrival rate of uninformed trades. PINF is the estimated probability of information-based trading. RBA_i, $depth_i$, vol_i, var_i, and price are transformed by taking natural logarithms. We adjust the t-statistics for heteroskedasticity, using White's (1980) procedure. The sample size represents the number of companies in the reduced sample with ordinary shares listed on the SEHK throughout the sample period from May 1, 1996–August 29, 1997 and valid results in the maximum likelihood estimation of the Easley, Keifer, O'Hara, and Paperman (1996) trade process model.

$$Liquidity_i = \alpha + \beta_1\, vol_i + \beta_2\, var_i + \beta_3\, price_i + \gamma\, ITraders_i + \lambda\, UTraders_i + \theta\, PINF_i + \varepsilon_i$$

Panel A: $Liquidity_i$ = Relative Bid-Ask Spread

Variable		Estimate of Coefficient	t-statistic	Estimate of Coefficient	t-statistic	Estimate of Coefficient	t-statistic
Intercept	α	3.5320	9.96***	3.8797	10.55***	2.7384	7.47***
Vol	β_1	–0.0324	–1.89**	–0.1807	–19.13***	–0.0525	–2.95***
Var	β_2	0.6380	20.64***	0.5711	18.55***	0.5771	19.01***
Price	β_3	–0.1169	–6.93***	–0.2383	–19.29***	–0.1484	–9.30***
ITraders	γ	–0.0029	–4.62***	–	–	–0.0014	–2.25**
UTraders	λ	–0.0162	–11.33***	–	–	–0.0121	–8.21***
PINF	θ	–	–	1.2664	12.33***	0.9174	9.01***
Overall model statistics (n = 521):							
Adjusted R^2			0.9021		0.9038		0.9263
F-statistic			F(5,515) = 959.38***		F(4,516) = 1,222.29***		F(6,514) = 1,090.63***

(continued)

Table 4 *(continued)*

Cross-sectional regression of liquidity measures on informed trading and other control variables

Panel B: $Liquidity_i = Depth_i$

Variable		Estimate of Coefficient	*t*-statistic	Estimate of Coefficient	*t*-statistic	Estimate of Coefficient	*t*-statistic
Intercept	α	2.7235	3.37***	2.5085	3.09***	2.9996	3.52***
Vol	β_1	0.5089	13.96***	0.5272	25.05***	0.5160	14.21***
Var	β_2	–0.3607	–5.80***	–0.3702	–5.55***	–0.3395	–5.15***
Price	β_3	0.5498	15.55***	0.5827	17.83***	0.5608	15.28***
ITraders	γ	–0.0027	–2.36**	–	–	–0.0032	–2.81***
UTraders	λ	0.0076	2.89***	–	–	0.0062	2.23**
PINF	θ	–	–	–0.3506	–2.00**	–0.3192	–1.70**
Overall model statistics (n = 521):							
Adjusted R^2			0.8561		0.8547		0.8571
F-statistic			$F(5,515) = 619.74$***		$F(4,516) = 765.45$***		$F(6,514) = 520.73$***

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.

5. Conclusion

In this study, we investigate the trading behavior of informed and uninformed investors in a screen-based, order-driven trading environment. Although many exchanges are moving toward such markets, very little is known about the informed/uninformed behavior within these trading mechanisms. The SEHK offers an ideal setting in which to analyze such behavior because of its simplicity, size, and transparency. We use the trading model developed in Easley, Keifer, O'Hara, and Paperman (1996) to estimate the probability of an information event (α), the probability of bad news (δ) given the occurrence of an information event, the order arrival rate of informed traders (μ), the order arrival rate of uninformed traders (ε), and the probability of an informed trade (*PINF*).

Our results show that high-dollar-volume firms (relative to low-dollar-volume firms) are associated with a higher probability of experiencing an information event, but a lower probability that the event signals bad news. Although these large, actively traded firms attract more informed and uninformed traders, they are associated with a lower probability that any given trade is information-based. Regression results show that the PINF measure plays a significant role in the liquidity provision process, even after controlling for variations in price, volume, and variance. Higher PINF levels induce wider spreads and smaller depths, thereby unambiguously reducing the liquidity of the firm.

Our findings contribute to the literature in several ways. This is the first study to apply the well-established Easley, Keifer, O'Hara, and Paperman (1996) model to an automated, order-driven trading environment.[11] Besides generating comparable findings from an increasingly widespread market microstructure, the results also provide evidence on the robustness of the underlying model. Second, we use both depths and spreads to measure the impact of the probability of an informed trade on corporate liquidity. Spreads and depths react in a similar way to higher probabilities of an informed trade, thus magnifying the overall impact on corporate liquidity. And lastly, our findings have potential policy implications for security exchanges. Several exchanges, such as the London Stock Exchange (LSE), operate different trading mechanisms for different companies. Although most firms are traded in a quote-driven dealer market, the LSE has recently implemented order-driven trading for a subset of listed companies (i.e., the FTSE 100). The SEHK is also currently considering the use of dealers for a subset of its least actively traded companies. Based on the spread and depth results of this study, high versus low PINF values could provide a useful criterion for determining which firms are in need of designated market makers.

[11] As mentioned above, a concurrent study by Brown, Thompson, and Walsh (1999) also investigates informed and uninformed trading in a market without (formal) designated market makers.

References

Amihud, Y. and H. Mendelson, 1986. Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Barclay, M. and C. Smith, Jr., 1988. Corporate payout policy: Cash dividends versus open-market repurchases, *Journal of Financial Economics* 22, 61-82.

Benston, G. and R. Hagerman, 1974. Determinants of bid-ask spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353-364.

Brennan, M.J. and A. Subrahmanyam, 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Brockman, P. and D.Y. Chung, 1998. Inter- and intra-day liquidity patterns on the Stock Exchange of Hong Kong, *Journal of International Financial Markets, Institutions & Money* 8, 279-300.

Brockman, P. and D.Y. Chung, 1999a. Bid-ask spread components in an order-driven environment, *Journal of Financial Research* 22, 227-246.

Brockman, P. and D.Y. Chung, 1999b. An analysis of depth behavior in an electronic, order-driven environment, *Journal of Banking and Finance* 23, 1861-1886.

Brown, P., N. Thompson, and D. Walsh, 1999. Characteristics of the order flow through an electronic open limit order book, *Journal of International Financial Markets, Institutions & Money* 9, 335-357.

Chalmers, J.M.R. and G.B. Kadlec, 1998. An empirical examination of the amortized spread, *Journal of Financial Economics* 48, 159-188.

Datar, V.T., N.Y. Naik, and R. Radcliffe, 1998. Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203-219.

Easley, D., N. Keifer, and M. O'Hara, 1997a. One day in the life of a very common stock, *Review of Financial Studies* 10, 805-835.

Easley, D., N. Keifer, and M. O'Hara, 1997b. The information content of the trading process, *Journal of Empirical Finance* 4, 159-186.

Easley, D., N. Keifer, M. O'Hara, and J. Paperman, 1996. Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, 1405-1436.

Easley, D., M. O'Hara, and J. Paperman, 1998. Financial analysts and information-based trade, *Journal of Financial Markets* 1, 175-201.

Easley, D., M. O'Hara, and P.S. Srinivas, 1998. Option volume and stock prices: Evidence on where informed traders trade, *Journal of Finance* 53, 431-465.

Franz, D.R., R.P. Rao, and N. Tripathy, 1995. Informed trading risk and bid-ask spread changes around open market stock repurchases in the Nasdaq market, *Journal of Financial Research* 18, 311-327.

Handa, P. and R. Schwartz, 1996. Limit order trading, *Journal of Finance* 51, 1835-1861.

Lee, C. and M. Ready, 1991. Inferring direction from intraday data, *Journal of Finance* 46, 733-746.

Lin, J.-C., G. Sanger, and G.G. Booth, 1995. Trade size and components of the bid-ask spread, *Review of Financial Studies* 8, 1153-1183.

Lyons, R.K., 1996. Optimal transparency in a dealer market with an application to foreign exchange, *Journal of Financial Intermediation* 5, 225-254.

Madhavan, A., 1992. Trading mechanisms in security markets, *Journal of Finance* 47, 607-641.

Madhavan, A., 1995. Consolidation, fragmentation, and the disclosure of trading information, *Review of Financial Studies* 8, 579-603.

Madhavan, A., 1996. Security prices and market transparency, *Journal of Financial Intermediation* 5, 255-283.

O'Hara, M., 1995. *Market Microstructure Theory* (Blackwell Publishers: Oxford, U.K.).

Pagano, M. and A. Röell, 1996. Transparency and liquidity: A comparison of auction and dealer markets with informed trading, *Journal of Finance* 51, 579-611.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica* 48, 817-838.