Limit Orders and Volatility in a Hybrid Market: The Island ECN

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Comments welcome

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All errors are our own responsibility.

Limit Orders and Volatility in a Hybrid Market: The Island ECN Abstract

This paper presents a cross-sectional empirical investigation of the relations between volatility and various measures of activity on the Island ECN, an Alternative Trading System for US equities that is organized as an electronic limit order book. We find that higher volatility is generally associated with

- a lower proportion of limit orders in the incoming order flow,
- a higher probability of limit order execution, and
- shorter expected time to execution.

We find weaker evidence that higher volatility is associated with lower depth in the book. In addition, we find that Island's market share for a given firm is positively related to the overall level of Nasdaq trading in the firm, and document substantial use of hidden limit orders (for which the submitter has opted to forgo display of the order). Finally, over one quarter of the limit orders submitted to Island are canceled (unexecuted) within two seconds or less. The extensive use of these "fleeting" orders is at odds with the view that limit order traders (like dealers) are patient providers of liquidity.

1. Introduction

The electronic limit order book has emerged as the most common form of security market organization worldwide. By choosing a market or limit order and selecting a limit price, a market participant enjoys access to a range of strategies that trade off execution certainty against expected execution price. When the market has many participants, the collection of unexecuted limit orders (the book) may constitute a continuous source of liquidity, diminishing the role of professional intermediaries and maximizing direct interaction of the market's users. The factors that influence a trader's order choice and the aggregate properties of the limit order book are therefore of great interest.

For a market organized as an electronic limit order book, the volatility of the traded security stands out as a very important determinant of market activity. To illuminate the connections between volatility and investor choice of strategy in such a market, the present paper undertakes a cross-sectional empirical analysis of the trading process on the Island ECN, an electronic limit order book for U.S. equities.

Previous studies have identified four volatility effects that we summarily describe as mechanistic, winner's curse, market order certainty, and equilibrium. Briefly, the mechanistic effect refers to the negative relation between volatility and the expected first passage time of a diffusion process (the security price) to a barrier (the limit price). Higher volatility thus increases the probability of execution within a given time window and decreases the expected time to execution. The winner's curse refers to adverse changes in security value conditional on order execution. This cost is positively related to volatility and causes traders to submit less aggressive orders. The market order certainty effect arises from the premium placed by risk-averse traders on a definite outcome. Higher volatility generally increases the dispersion of wealth outcomes for any given limit order strategy. A market order therefore becomes relatively more attractive.

The mechanistic, winner's curse, and market order certainty effects described above influence an individual's order choice, holding invariant the order strategies of other traders. Equilibrium considerations broadly suggest the possibility of offsetting influences. For example, a direct effect that implies a shift in favor of limit orders also implies fewer market orders. The execution rate drops, which militates against the usage of limit orders. In Foucault (1999) an increase in volatility causes limit order traders to set prices less aggressively (the winner's curse). This increases the relative cost of market orders, making them less attractive, and leads to a reduction in their usage. We describe the associated increase in the proportion of limit orders in the incoming order flow and the reduction in the limit order execution rate as the equilibrium effect.

Island's market share falls far short of dominating overall Nasdaq activity. This affects our analysis in two ways. First, some of the above predictions derive from models in which the electronic book constitutes the entire market. In applying these models to a hybrid market, we are extending the implications of these models beyond their original formal scope. Second, Island's small market share helps justify the assumption that overall price determination and overall Nasdaq trading activity are exogenous with respect to measures of Island activity. It therefore lessens concerns about reverse causality in our econometric specifications.

We use a cross-sectional approach to analyze the effects of volatility in a limit order book market since it is more reasonable to examine the implications for the book of "true value" volatility, which derives from asset fundamentals, using a cross-sectional rather than a time-series specification. We examine three types of measures of Island activity. First, we analyze the flow of orders through Island: the proportion of limit orders in the order flow (the reminder are market orders), and the proportion of limit orders that are filled (the remainder are canceled or expire). Second, we examine average depths in the book that can be viewed as Island's supply and demand curves. Third, we conduct duration analyses of Island's execution times.

We then investigate the relation between Island's measures and a range of volatility measures: total, permanent, systematic, unsystematic and trade-driven. We generally find that across all measures, higher volatility is associated with:

- a lower proportion of limit orders in the incoming order flow,
- a higher probability of limit order execution, and

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• shorter expected time to execution.

The association between book depth and volatility is significant mostly for the tradedriven volatility proxy, where it is negative. The depth result is consistent with the winner's curse. The limit order proportion result is consistent with the market order certainty effect. The execution rate and time to execution results are consistent with the mechanistic effect. The limit order proportion and execution rate findings are not consistent with the equilibrium effect.

Like many other electronic markets, Island permits undisclosed (also called hidden, invisible, or "iceberg") orders. Our data support a partial characterization of such orders. We also examine an issue that is of particular interest to understanding the electronic limit order book, the phenomenon of "fleeting" limit orders, i.e., orders that are canceled almost immediately after submission. These constitute a substantial portion of the order flow, belying the usual characterization of limit order traders as patient suppliers of liquidity. Finally, we look at Island's market share and how it relates to volatility and investor measures, and we document the presence of Island at the inside quote on Nasdaq.

The paper is organized as follows. In the next section, we review prior studies. Section 3 describes the Island system. Sample construction and data sources are discussed in Section 4. Section 5 discusses the econometric specifications. Results are presented in Section 6. Section 7 documents the importance on the Island system of hidden and "fleeting" limit orders. Section 8 provides an analysis of Island's market share. A summary concludes the paper in Section 9.

2. Literature survey

The large and growing importance of electronic limit order book systems in many securities markets has engendered much interest. In the following survey, we concentrate initially on the theoretical literature, with the purpose of illuminating volatility effects on order submission and execution rates, depths in the limit order book, and execution durations. We then highlight prior empirical work related to our analysis.

a. Theoretical considerations

Mechanistic effects

Lo, MacKinlay, and Zhang (2002) investigate a simple model in which the stock price (or log price) is modeled as a Brownian motion diffusion process. A limit order placed away from the current market price is executed when the limit price barrier is hit. If the diffusion has zero drift and variance per unit time σ^2 , then the probability of an execution in any finite time increases with σ and converges to one (certainty) as time approaches infinity. Thus, assuming that traders prefer a lower expected execution time, increased volatility should make a given limit order more attractive.

The winner's curse

The winner's curse refers to adverse changes in the agent's wealth conditional on execution of the limit order. For a limit buyer these outcomes are characterized by a price decline below the limit price; for a short seller, price appreciation above the limit price. The winner's curse may be caused by asymmetric information. Copeland and Galai (1983) note that in posting a bid or offer, a market maker essentially writes an option. If the order is hit by an informed trader, the option has been exercised in the money. This effect figures prominently in the models of Glosten and Milgrom (1985) Easley and O'Hara (1987), and Glosten (1994), among others. In general, the spread (or alternatively the permanent price impact of a trade) in a sequential trade model with private information can be decomposed into an information multiplier times the stock's volatility (see, for example, Easley, O'Hara, and Saar (2001)). In Foucault (1999), the winner's curse arises from agents who receive public information and act promptly to hit a limit order before it can be withdrawn. In all of these models, the winner's curse increases with volatility. The limit order trader (the writer of the option) will therefore post a less aggressive price. This will cause lower cumulative depth in the book at all prices.¹

¹ Hasbrouck (1991) develops a variance decomposition procedure to isolate trade-driven volatility that may correspond better to the permanent price effects due to trading on

Market order certainty

The analyses cited in the previous section model limit order submitters as riskneutral. Cohen et al. (1981) (CMSW) consider a risk-averse agent choosing between a limit and a market order. In the buyer's problem, the prevailing ask quote follows a compound Poisson process: jump occurrences follow a Poisson process, and the jumps themselves are i.i.d. zero-mean random variables. Within any finite time, the execution probability of a buy limit order increases as the limit price approaches the ask from below. Importantly, though, as long as the intensity is finite, this execution probability does not converge to unity. With risk-aversion, this induces a discontinuity in expected utility at the ask. A market order dominates limit orders priced within some finite distance of the ask.

CMSW do not provide explicit volatility results.² It is possible to construct simple models to examine the effect of risk aversion on the strategies of traders who need to acquire a position in the stock and can trade only once. When the state space is discrete and traders have exponential utility, we can find numerical examples where an increase in volatility induces the traders to shift from a limit order strategy to a market order.³ The intuition is that volatility increases the dispersion of wealth outcomes from using a limit order. A risk-averse trader therefore may opt for the sure outcome associated with a market order over the risky payoff associated with a limit order. We term this effect as it applies to the individual trader the market order certainty effect.

private information. We therefore use the trade-driven volatility component in the empirical analysis as one of our volatility measures.

² Volatility effects in the CMSW model are complex. For the compound Poisson process, the price volatility per unit time depends positively on both the Poisson arrival intensity and the jump variance. An increase in either parameter increases the execution probability of a given limit order (the mechanistic effect). A large increase in jump variance coupled with a small drop in the arrival intensity, however, might reduce the execution probability of a limit order even though total price variance increases. It is not possible, therefore, to establish any unambiguous volatility results.

³ We are not aware, however, of any paper that modeled this effect in detail and investigated the conditions under which the examples we find can be generalized.

Equilibrium effects

The mechanistic effect, the winner's curse, and market order certainty arise in formulating an individual's order submission strategy, holding constant the actions of others. Equilibrium considerations suggest indirect, induced and possibly offsetting effects. CMSW note that an essential determinant of a limit order's execution likelihood is the arrival rate of counterparty market orders. Since market orders originate from traders who have opted to use them in preference to limit orders, any effect that induces traders to shift to limit orders, ceteris paribus, necessarily decreases the usage of market orders in equilibrium, driving down the likelihood of execution, and offsetting the initial shift.

Foucault (1999) provides a dynamic equilibrium model that demonstrates the effects on the incoming order mix of the winner's curse problem. For a given limit order in his model, volatility increases the cost of being picked off (the winner's curse). Limit orders are therefore priced less aggressively. The resulting increase in the bid-ask spread increases the cost of a market order, so fewer market orders are used. In equilibrium, increased volatility results in a higher proportion of limit orders in the incoming order flow. These are priced less aggressively, and have lower execution probabilities.⁴

⁴ Other theoretical work that examines the role of limit orders in markets include Angel (1994) and Harris (1998) who implement numerical solutions to individual order strategy models, Chakravarty and Holden (1995) who show that informed traders may use limit orders to undercut the dealer's quotes, Seppi (1997) and Rock (1990) who consider the interplay between the book and a strategic dealer, and Parlour and Seppi (2001) who examine competition between one trading venue organized as a pure electronic book and one constituted as a book/dealer hybrid. Besides Foucault (1999), dynamic equilibrium in a limit order book market is investigated in Parlour (1998) and Foucault, Kadan, and Kandel (2001). In these models, traders' optimal strategies are conditioned on conjectures of other traders' optimal strategies. To make the analyses tractable, traders' problems and strategies are constrained (e.g., they do not possess private information and are limited to one action in the market). Domowitz and Wang (1994) examine the behavior of a limit order market in which orders arrive at various price levels with Poisson intensities that are partially endogenous. The book in this model, however, generally achieves a stationary limiting distribution, which is incompatible with a diffusion process for the fundamental asset value. Accordingly, volatility in this framework derives solely from disturbances that are transitory (such as bid-ask bounce).

b. Empirical studies

Economic logic suggests that since limit orders forgo immediate execution, they should realize a cost advantage (on average) relative to market orders. Harris and Hasbrouck (1996) find this to be the case in a sample of NYSE orders. Investigating simulated strategies imposed on actual data, Handa and Schwartz (1996) find that when the costs of nonexecution are ignored (an assumption applicable to patient traders), the returns to limit orders are positive.

Chung, Van Ness, and Van Ness (1999) find that bid and ask quotes on the NYSE frequently represent the book instead of the specialist's interest. Harris and Panchapagesan (1999) conclude that the state of the book is informative, in the sense of predicting future short-term (though not long-term) price movements.

A number of studies examine various features of markets organized primarily as consolidated limit order books. Sandas (2001) estimates a specification derived from Glosten (1994). His results suggest that the book on the Swedish Stock Exchange provides less liquidity than would be predicted on the basis of the information in the order flow. For incoming buy orders, for example, the supply curve is too steep relative to the price revisions that these orders ultimately cause.

Other studies characterize the incoming order mix. A positive relation between the prevailing spread and the probability that an incoming order is a limit order is found on the Paris Bourse (Biais, Hillion, and Spatt (1995)), the Toronto Stock Exchange (Griffiths et al. (2000)), and for an anonymous Nasdaq wholesaler (Smith (2000)). These findings are consistent with the theoretical considerations.

The evidence on volatility shocks is mixed. Ahn, Bae, and Chan (2001) examine transitory volatility on the Hong Kong Stock Exchange. They measure volatility over 15minute intervals and find that depth on the book rises subsequent to a volatility shock. On the other hand, Coppejans, Domowitz, and Madhavan (2001) estimate a vector autoregression model for Swedish (OMX) stock index futures. They find that a volatility shock reduces depth. Goldstein and Kavajecz (2000) note that during extreme market conditions in October 1997 (when NYSE circuit breakers were triggered), book depth declined dramatically. Although some of these studies employ cross-sectional variables, they generally investigate variation over time.⁵ The present paper employs a cross-sectional (across firms) perspective, which is particularly appropriate for investigating how an attribute of a firm such as "true value" volatility is related to the behavior of the book.

Time, in the formal analyses of limit orders, is primarily a notional construct. It typically indexes the sequence of agents' moves, rather than the passage of real ("wall clock") time.⁶ It is nevertheless clear that in actual trading situations, real time may play a more distinctive role, due to institutional features (such as regular trading hours), decision cycles or monitoring costs that are measured in clock time. In limit order analyses, real time effects have been studied using duration models to characterize the time-to-fill or time-to-cancel of an order (Lo, MacKinlay, and Zhang (2002) and Cho and Nelling (2000)). If time were important solely as a volatility scale factor, a duration model would have a simple form: an accelerated failure time representation with volatility (per unit time) as the only important determinant. We look at this issue by empirically investigating the relation between duration and volatility.

Finally, there is a literature that looks at U.S. ECNs: Huang (2002) investigates the contribution of ECNs to price discovery for the ten most actively traded NASDAQ stocks; Simaan, Weaver, and Whitcomb (1998) examine the behavior of market makers and ECNs following the tick size change to sixteenths; Conrad, Johnson, and Wahal (2001) examine institutional trading costs on ECNs and crossing systems; and Barclay, Hendershott, and McCormick (2001) compare execution costs between ECNs and market makers.

⁵ Griffiths et al. (2000) examine firm size as a determinant of order aggressiveness. In similar specifications, Smith (2000) includes price and volatility.

⁶ The distinction between real time and event or "informational" time is a recurring theme in studies of financial markets (see Clark (1973) and Russell and Engle (1998), for example).

3. The Island ECN: Background and trading protocol

The Island ECN was founded in 1996 and began operating on January 1997, becoming one of the two largest ECNs in the market today in terms of both share volume and number of trades (the other major ECN is Instinet).⁷ In terms of market share, about 11% of the trades in Nasdaq stocks were executed on Island during our sample period (the last quarter of 1999), representing close to 6% of Nasdaq's volume. The disparity between the market share in terms of trades and share volume testifies to the small size of most Island trades. In addition, Island's market share is not the same for all stocks, and seems to be higher for a small number of very active stocks. The market share of the average stock in our sample (that is comprised of the top 300 Nasdaq firms by market capitalization) is 6.23% in terms of trades and 3.52% in terms of share volume.

Island operates a pure agency market. The system is active (i.e., orders can be submitted and trades can take place) from 7:00 in the morning to 8:00 in the evening.⁸ Island accepts only priced limit orders. Market orders as such are not accepted. A trader who seeks immediate execution must submit an order at a limit price that meets or crosses the best opposing price (a marketable limit order). Each time a limit order is received and the book contains a matching order, the limit order is immediately executed. If there is no matching order, the limit order is placed in the book until a matching order is received or the limit order is canceled. All outstanding limit orders in the book expire at 8:00 in the evening.

All orders are matched based on strict price-time priority without regard to the number of shares in the order. The Island display is anonymous—the identities of the investor or the broker are not visible—with only the price and the number of shares made available to the market. Island's top orders are also represented in the Nasdaq quote montage, and are therefore incorporated into the National Best Bid/Offer (NBBO)

⁷ In US securities law, an ECN (Electronic Communications Network) is a medium for disseminating ("publishing") quotes (U.S. Securities and Exchange Commission (1996)). Because it offers executions, Island is also classified as an Alternative Trading System (ATS, US Securities and Exchange Commission (1998)).

⁸ During our sample period, Island ran a continuous session from 8:00 a.m. to 8:00 p.m.

display. At the trader's discretion, however, display may be limited to Island subscribers or suppressed entirely. In neither of these cases is the order incorporated into the Nasdaq montage or the NBBO.

Since Nasdaq forbids locking or crossing their market, subscriber-only orders are a convenient way of attempting to buy or sell a stock outside the Nasdaq quote without violating Nasdaq rules.⁹ The display requirements of SEC's Regulation ATS dictate that if an ECN executes more than five percent of the total volume in a given stock during four out of the last six months, then the ECN is large enough that it should be required to display all its visible orders to the public marketplace. Island does not accept subscriberonly orders in the list of stocks that are subject to the ATS display requirements. This regulation does not apply to invisible orders because they are not seen on the Island book.

A subscriber can also specify the minimum number of shares of an order that can be executed. This feature is primarily aimed at subscribers who do not want to get odd-lot executions. However, orders that specify a minimum number of shares that is higher than 100 are not reflected in Island's quote on Nasdaq. An order that either specifies a minimum number of shares or is invisible has a lower priority than an order that is not restricted in these two ways. The lower priority means that if an order with a restriction is entered before an unrestricted order at the same price, the unrestricted order will execute first (i.e., restricted orders lose time priority).

An Island subscriber can submit limit orders without charge. If a limit order sits in the book and is subsequently executed by an incoming order, it is considered to have added liquidity to the book, and the subscriber receives a 0.1 cent rebate per executed share. The incoming order that removed liquidity from the Island book is charged 0.25

⁹ Island operates solely as an agency market that automatically executes matching buy and sell interest, irrespective of quotes displayed by other market participants. Hence, routing an order to Island does not guarantee receiving the best price in the market. Island maintains that it is the subscriber's responsibility to ensure best execution for their transactions by selecting the appropriate market venue. Also, subscribers bare sole responsibility to complying with Nasdaq's short sale rule, as Island does not check orders or executions to ensure compliance with the rule. The Island system is programmed to comply with the SEC short sale rule for NYSE-listed securities.

cent per executed share.¹⁰ While Island subscribers pay a fee for getting a data feed that allows complete construction of the book in real time, anyone with an Internet browser can observe the top 15 orders on each side of the book (for any stock) on Island's web site.

4. Sample and data

a. Sample construction and descriptive statistics

The sample was drawn from all Nasdaq National Market common stocks with data in the CRSP database from October 1 to December 31, 1999.¹¹ The sample is the 300 largest firms based on equity market capitalization as of September 30, 1999.¹²

Table 1 presents summary statistics. The smallest firm has an average market capitalization over the sample period of 824 million dollars, while the median firm is just over 3 billion dollars and the largest firm is close to 495 billion dollars. The sample also spans a range of trading activity and price levels. The most active firm has a daily average of 28,654 trades, while the median firm has about 1,066 trades on an average day, and the least actively traded firm in the sample has (on average) only 16 trades per day. Average daily CRSP closing prices range from \$8.40 to \$326.58, with a median of \$45.66. To provide a sense of the cross-sectional characteristics of the variables, we report means for subsamples constructed by ranking on market capitalization, average number of daily trades and standard deviation of daily returns, σ_r .

¹⁰ The rebate and charge for executed shares were changed to 0.11 cent and 0.19 cent, respectively, on March 1, 2002.

¹¹ The Nasdaq Stock Market is comprised of two separate market categories—Nasdaq National Market (NNM) and Nasdaq SmallCap Market (SCM). The two market categories differ mainly with respect to the listing requirements (but also with respect to a few details of trading protocol). The NNM has stricter listing requirements and generally includes larger firms.

¹² We also required that firms do not have more than one series of common stocks traded. Two firms (Associated Group Inc. and Molex Inc.) were excluded from the sample on this basis. We also excluded Comair Holdings Inc., which was in the process of being acquired by Delta Air Lines during the sample period.

b. Island data and statistics

The Island data we use are identical to those supplied in real time to Island subscribers. These data comprise time-sequenced messages that completely describe the history of trade and book activity. The process may be summarized as follows. When an arriving order can be matched (in whole or part) against an existing order in the book, the system sends an Order Execution message. If all or part of the order can't be matched, the system sends an Add Order [to the book] message. An Add Order message contains the direction (buy or sell), number of shares, limit price, a display condition (normal, subscriber-only, or invisible), and a unique identification number. If and when the order is executed, this number is reported in the Order Execution message. When an existing order is canceled or modified (in size), the system generates a Cancel Order message. The book, excepting the invisible orders, may be constructed by cumulating these messages from the start of the day onwards. Although the arrival time and quantity of an invisible order are never made available, the execution of an invisible order is signaled by a special trade message. In the rare event that a previous trade report was in error, the system sends a Broken Trade message.

Table 2 presents summary statistics on the number and sizes of orders that arrive to Island. We only consider data from the regular trading session of the Nasdaq Stock Market (from 9:30 a.m. to 4:00 p.m.). This was done to ensure that we are looking at the Island system only when it is part of a much larger market and captures a relatively small fraction of the order flow and not when it is one of a handful of venues for trading during pre-opening and after-market hours. The average number of daily limit orders increases with market capitalization (in the ranked group means), average daily trades, and σ_r . The average size of limit orders on Island is 572 shares, testifying to the retail nature of trading on the system. The average size decreases slightly across capitalization and average trade subsamples, which may suggest that retail activity is more concentrated in the largest, most active Nasdaq stocks.

Island does not accept unpriced orders. We therefore consider orders priced so as to receive immediate execution to be market orders. Table 2 shows that market orders

tend to be smaller than limit orders, with a mean of only 335 shares. As with limit orders, the average size decreases with market capitalization and trading activity.

Nasdaq and Island trading activity is illustrated in Figure 1. For both Nasdaq and Island, activity is concentrated in the higher market capitalization stocks. Figure 2 describes Island's orders in our sample stocks across market capitalization deciles. Limit orders outnumber market orders. Most limit orders are priced away from (less aggressively than) Island's quote.

c. Constructed Island variables

The observable variables that are closest to their counterparts in the theoretical models are the number of limit orders submitted (as a proportion of the total, limit and market orders), and their execution proportions. It is also interesting and useful to characterize the aggressiveness of the limit orders. Accordingly, we examine the number of limit orders priced at Island's quote or better, e.g., buy orders priced at Island's bid or better, and those less aggressive orders priced behind Island's quote. We also compute similar statistics based on the number of shares in the orders.

Table 3 presents summary statistics on the submission proportions. First note that most of the orders submitted are limit orders: a median of 82% (by number of orders), and 89% (by number of shares). In the ranked subsample means these proportions decrease with capitalization, average number of trades, and σ_r . This behavior also characterizes the more aggressive limit orders (priced at or better than Island's quote). The reverse is true, however, for the less aggressive limit orders. That is, in stocks with higher capitalization, average number of trades, or σ_r , traders tend to submit less aggressive limit orders. Proportions defined in terms of shares behave in a similar fashion.

Table 3 also presents summary statistics for execution proportions. It is worth emphasizing that execution proportions cannot simply be defined as the ratio of market orders to limit orders due to differences in size (limit orders are larger on average than market orders). We are able to follow each limit order that enters the system and therefore can produce an exact characterization of the execution proportion of orders. The mean execution rate is 18% (by orders) and 13% (by shares). In the subgroup means, the execution rates increase with market capitalization, average number of trades, and σ_r . Surprisingly, execution rates for more aggressive orders (those priced at the quote or better) are generally *lower* than the execution rates for less aggressive orders (behind the quote). There are a number of considerations that could potentially account for this, notably strategic order management. In particular, many of the more aggressive orders are canceled after one or two seconds, thus depriving them of the chance for execution. We discuss this behavior more extensively in Section 7.

The second type of analysis we provide is that of depth in the book. To summarize the book supply function, we compute for each firm at the end of each fiveminute interval the dollar depth at all prices at or better than the National Best Offer plus $\frac{1}{8}$, and the incremental dollar depths in the intervals (NBO + $\frac{1}{8}$, NBO + $\frac{3}{4}$], (NBO + $\frac{3}{4}$, NBO + 2], and (NBO + 2, ∞). The means (for each firm, across time) are used as dependent variables in cross-sectional regressions. On the bid side of the book, we aggregate over the intervals (∞ , National Best Bid – $\frac{1}{8}$], (NBB – $\frac{1}{8}$, NBB – $\frac{3}{4}$], (NBB – $\frac{3}{4}$, NBB – 2], and (NBB – 2, 0).

Table 4 presents cross-firm summary statistics for the depth variables. The patterns across market capitalization-ranked groups and trade-ranked groups conform to expectations. Larger and more actively traded firms have deeper books. Within the standard deviation-ranked groups, however, depth is not monotonic. Bid depth is generally smaller than ask depth.

The third Island characteristic investigated in this paper is the timing of order events, and in particular the (elapsed) times between an order's submission and its first execution. Figure 3 depicts "failure" functions for executions and cancellations. Intuitively, the failure function is the cumulative probability of event occurrence. In applying the (standard) Kaplan-Meier correction, cancellation is treated as censoring in the execution estimation, and execution is treated as censoring in the cancellation estimation. The time scale is nonlinear (to show detail for shorter times).

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The cumulative execution probability rises fairly slowly, reaching approximately 70% at two hours. The function is almost certainly biased upwards. The standard framework assumes that the censoring process is independent of the event process. In the present case, this is tantamount to assuming that a limit order that is canceled has the same probability of execution (going forward) as an order that isn't canceled. It is violated, for example, if traders are more likely to cancel limit orders when the price has moved away after submission.

The cumulative cancellation probability exhibits two notable features. Most strikingly, a large number of limit orders are canceled very shortly after their submission. Roughly 25% have been canceled after two seconds, and about 40% after ten seconds.¹³ This is inconsistent with the traditional view of a limit order as providing ongoing liquidity. We describe limit orders canceled shortly after execution as "fleeting", and discuss them in Section 7. The second interesting feature is the existence of two relatively sharp jumps in the cancellation function, at exactly three and five minutes. The Island protocol allows traders to specify a time-in-force for the order. Apparently three and five minutes are frequent choices.

d. Volatility measures

The literature surveyed above suggests a central role for volatility. Different models, however, use the term to characterize different concepts. We consequently employ multiple measures in the empirical analysis. Table 5 presents summary statistics for these measures.

The first volatility measure is simply the return standard deviation, introduced above as σ_r . A sensible refinement of this variable involves differentiation between systematic and unsystematic volatility. This distinction may be important for the usual reason (in many asset pricing models, only the systematic risk is priced). In the present

¹³ Like the execution probability function, the cancellation function is biased upwards, but since price movements over ten seconds tend to be small, the bias at this end of the time scale is likely to be small.

situation, however, systematic volatility may also proxy for trading risk that is relatively easy to hedge. An indexed portfolio manager who needs to invest in stocks, for example, might initially enter into a long futures position, and then purchase the individual stocks over time (reducing the futures position commensurately).

Our measures of systematic and unsystematic risk are based on the market model:

$$r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it} \,, \tag{1}$$

where r_{Mt} is the CRSP value-weighted portfolio return. The specification is estimated using three prior years of daily data (from October 1, 1996 to September 30, 1999). Data limitations restricted these estimations to 211 firms. Our proxy for the systematic risk for firm *i* is $\beta_i \sigma_M$; unsystematic risk is $\sigma(e_{it})$.

The volatility measures discussed to this point are derived from transaction prices. They therefore impound trading-induced price movements, such as bid-ask bounce. Noting this, Foucault (1999) suggests that long-run volatility (estimated using the Hasbrouck (1991) procedure) is the preferred measure. From intraday TAQ data aggregated at a one-minute frequency, we estimate a vector autoregression (VAR).¹⁴ The VAR estimates may be transformed to yield the variance of the random-walk component of the security price, σ_w^2 . We use the standard deviation per minute, σ_w , scaled up by a factor of $\sqrt{6.5 \times 60}$ to reflect volatility over a 6.5-hour trading day.

Table 5 shows that the estimated mean of σ_w is lower than that of σ_r in the total sample and all subsample groupings. There are two likely explanations for this. First, σ_r includes the overnight period, while σ_w does not. Second, σ_w has been purged of transient volatility.

¹⁴ The details of the procedures are as follows. All variables are one-minute timeaggregates: r_t is the change in the logarithm of the NBBO midpoint at the close of the minute; x_t is the sum of the trade volume, wherein each trade volume is signed by reference to the midpoint of the quote immediately preceding the trade; $Sign(x_t)$ is +1 if $x_t>0$; -1 if $x_t<0$; and, 0 if $x_t=0$. $x_t^{1/2}$ is the sum of the signed square-roots of the trade volumes. The VAR comprises the variables { r_t , $Sign(x_t)$, x_t , $x_t^{1/2}$ }, with first and second lags included. The model allows contemporaneous effects running from the trade variables to returns.

The VAR also supports a decomposition of the random-walk variance: $\sigma_w^2 = \sigma_{w,r}^2 + \sigma_{w,x}^2$, where the two terms on the right derive respectively from return innovations and signed trade innovations. We employ $\sigma_{w,x}$, which reflects the contribution to permanent changes in the security price that can be attributed to new trade information. Panel A of Table 5 reports summary statistics for these measures. On average, about one-quarter of the random-walk volatility is due to signed trades. The volatility measures are positively correlated (Table 5, Panel B). The correlations within the set { σ_r , σ_w , $\sigma_{w,x}$ } are generally stronger than those involving $\beta_i \sigma_M$ or $\sigma(e_{it})$.

5. Specifications

Corresponding to the three sorts of Island variables (execution and submission proportions, depths, and times to execution), this study estimates three types of crosssectional specifications. Each specification features a linear regression in which the regressors are the firm-specific variables. This commonality facilitates the presentation and discussion of results. The actual statistical models and their underlying assumptions are varied.

For the analyses of submission proportions, execution proportions and depths, we first construct a summary measure for each firm, and then use these summary measures in cross-sectional regressions. For submission and execution proportions, we use the logit transformation, $f(x) = \log[x/(1-x)]$ for 0 < x < 1, to deal with the restricted range. Observations for which the proportion was zero or one were deleted. For the depth analyses, we compute the mean dollar depths for each firm in each of four price groups (relative to the NBBO) for buys and sells. These are then used as dependent variables in the regression specifications. It is important to note that these procedures effectively weight all firms equally. All regressions are estimated using OLS with White's heteroskedasticity-consistent standard errors.¹⁵

¹⁵ For regression specifications (except the duration models), we also used two-stage Least Trimmed Squares (see Rousseeuw and Leroy (1987)) to examine whether our results are affected by outliers. The results were almost identical to the OLS results, and are therefore omitted from the presentation in the paper.

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Time to execution is analyzed using an accelerated failure time duration model, wherein the logarithm of the duration is modeled as a linear function of the explanatory variables. Like Lo, MacKinlay, and Zhang (2002), we estimate a duration model for execution in which cancellation is treated as an independent censoring process. The duration analysis conducted in one step, i.e., without first constructing summary measures at the firm level. The data here consist of individual orders, up to 2,000 for each firm, uniformly drawn from among all of the firm's orders. To maintain equal-firm weighting, we use the following procedure. Denote by n_i the number of observations (limit orders) for firm *i*. Since $n_i < 2,000$ for some firms, we weight each observation by $1/n_i$.¹⁶

In addition to the volatility measures, each specification includes a standard set of three control variables: the log of the average market capitalization, the average price per share, and the log of the median daily turnover. Among other things, capitalization may be related to investor characteristics and frequency of information events. The average price is included to pick up discreteness effects in the price grid. Median turnover is intended to control for the market-wide "normal" level of trading in the stock. The median is used instead of the mean in order to have a measure of the typical trading intensity in a stock that is less sensitive to information shocks.

Many of the variables we seek to model (e.g., limit order execution rates), as well as many of our explanatory variables (such as turnover) are derived from trading data over the same sample period. This raises the possibility of simultaneity (causal effects running from the modeled variable to the explanatory variables) or correlated

¹⁶ The quality of fit in the accelerated failure time models (as judged by the QQ plots) was similar to that found by Lo, MacKinlay, and Zhang (2002). Although the overall fit was good, residuals for individual firms often deviated noticeably from the model assumptions. Following Lo et al., we also estimated proportional hazards specifications, which are based on less restrictive assumptions. The proportional hazards estimates are qualitatively similar to those from the accelerated failure time model. We present the latter, however, because they are easier to interpret. We also attempted duration analyses for cancellations (treating execution as the exogenous censoring process). The estimated specifications generally exhibited poor fit and instability.

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measurement errors. Our modeled variables, however, are derived solely from Island data, while the explanatory variables are computed using all Nasdaq trading activity and Nasdaq-wide prices. Since Island accounts for a relatively small portion of overall Nasdaq activity, problems stemming from reverse causality or correlated measurement errors are likely to be small. We provide additional evidence on this point in Section 8. We also estimated specifications in which the explanatory variables (market capitalization, turnover, average price, and σ_r) were estimated over the three months prior to the start of the main sample. The results were essentially similar to those reported here, and are therefore omitted from the presentation.

6. Results

Table 6 reports estimations in which the Island variables are modeled as functions of the control variables and daily transaction price volatility, σ_r , using the specifications described in the last section. To help gauge the economic significance of σ_r for a representative firm, the table reports the predicted value of the dependent variable for a representative firm (when the explanatory variables are set to their respective sample means) and the predicted value when σ_r is increased by one standard deviation. These predicted values are reported as proportions for the logistic regression specifications. For execution duration, the predicted values are the median durations implied by the model.¹⁷

We find that higher volatility is associated with a lower overall limit order submission proportion. For the representative firm, a one standard deviation increase in σ_r decreases this proportion from about 87% to 82%. This is consistent with the market order certainty effect. The shift to market orders increases the execution proportion of the remaining limit orders from 13% to 18% for the representative firm.¹⁸ This result is

¹⁷ Since depth specifications are estimated using OLS, the "before" values replicate the sample means reported in Table 4. The logistic transformation used in the order proportion regressions, however, leads to a small discrepancy between the "before" values and the sample means reported in Table 3.

¹⁸ Cohen et al. (1981) and Angel (1994) predict that the execution probabilities of limit orders are increasing in the rate of order flow arrival. We tested his prediction using the total number of limit and market orders as a proxy for the rate of arrival of orders. Since

consistent with the mechanistic effect discussed in section 2. In the depth regressions, the volatility coefficients are negative, but significant only for bid depth within ¹/₈ of the NBB.

Higher volatility is associated with a higher proportion of limit orders priced behind Island's quote. This implies a reduction in aggressiveness that is consistent with the winner's curse. The equilibrium effect of Foucault (1999), however, further maintains that this increases the cost of market orders, leading to fewer market orders and lower execution rates for limit orders. The results for submission and execution proportions are not consistent with this prediction.

Time to execution is negatively associated with volatility. For the representative firm, increasing σ_r by one standard deviation decreases the median execution time from 1,452 seconds (approximately 24 minutes) to 1,057 seconds (about 18 minutes). This is consistent with the mechanistic effect.

Table 7 reports estimations based on the implicit random-walk volatility measure, σ_w . The results are similar to those discussed above for σ_r . This is noteworthy because the two measures are conceptually and operationally quite distinct. First, σ_w is estimated using one-minute observations, while σ_r is estimated for daily returns. Second, and more importantly, σ_r is a total volatility measure that encompasses transient price components, while the σ_w in principle does not. As Handa and Schwartz (1996) note, limit order traders benefit from transient liquidity pressures. That these two measures play similar roles suggests that volatility effects do not arise solely from transient price movements.

To further explore volatility effects, we next consider specifications in which systematic and unsystematic risk are differentiated. The estimates, reported in Table 8 and Table 9, do not suggest that the distinction is an important one. In most

this measure is highly correlated with capitalization and turnover, we used as controls only average price and σ_r . The results were supportive of the prediction: all measures of execution proportions were increasing in the arrival rate of orders and were highly statistically significant.

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specifications, the signs of the coefficients of these variables are identical to those reported for the total volatility measures. The effects are, however, statistically weaker.

Table 10 presents the results for the trade-related volatility measure $\sigma_{w,x}$. This variable appears to behave in these specifications in much the same manner as σ_r or σ_w . The coefficients of $\sigma_{w,x}$ in the depth regressions, however, are uniformly negative and statistically significant.

In summary, the pattern of effects is generally consistent across a range of volatility proxies. The mechanistic effect predicts that higher volatility is associated with lower time to execution, and higher execution proportions, relations supported by the empirical analysis. The book depth result (primarily for trade-related volatility) is consistent with the winner's curse. The data also exhibit a negative relation between volatility and the proportion of limit orders (relative to market orders). This is consistent with the market order certainty effect. Both the negative relation between volatility and the proportion of limit orders and the positive relation between volatility and execution proportions are inconsistent with the equilibrium effect.

7. Hidden and fleeting orders

Limit orders are sometimes viewed as supplying liquidity in a manner similar to (and competing with) dealer quotes. This analogy presumes that limit orders are relatively visible and persistent, like the bids and offers of a dealer who is maintaining a market presence. In fact, many limit orders are hidden, and so (unlike dealers' quotes) do not advertise available prices. Furthermore, while a dealer usually maintains an ongoing market presence to attract counterparties, many limit orders are cancelled almost immediately. This section discusses such orders.

a. Hidden orders

The Island trading protocol allows traders to designate that an order not be displayed. The no-display option is a common feature of electronic book systems. In Island (and most of these systems), the hidden quantities lose priority to visible quantities at the same price. From a market design viewpoint, they are thought to encourage traders to supply liquidity when they might be reluctant to disclose the full size of the amount sought.

Our data report executions of hidden orders, but not submissions or cancellations. Our estimates can only suggest, therefore, a lower limit to the usage of these orders. These are reported in Table 11. Executed hidden orders constitute only about 3% of submitted limit orders (defined as submissions of visible limit orders and executed hidden orders), and about 2% by share amounts. They account, however, for almost 12% of all order executions and executed shares. This suggests a more significant presence.

b. Fleeting orders

We have noted that a large number of orders submitted to Island are canceled almost immediately. We term limit orders canceled within two seconds of their submission "fleeting". Table 11 reports summary statistics. On average in the full sample, fleeting orders constitute 27.7% of all visible orders and 32.5% relative to shares in all visible orders. In the subgroup means, relative usage declines modestly with capitalization, average trades and σ_r . Table 12 presents summary statistics on the pricing of these orders. Fleeting orders are primarily submitted at prices that better Island's preexisting bid or ask.

There are several possible explanations for the use of fleeting limit orders. One possibility is that Island receives these orders from automated order routing systems, which act as intelligent agents for customer orders. The strategies used by these systems frequently involve successive attempts to achieve execution at different market centers. For example, if Archipelago receives a marketable order at a time when Island's limit order book posts the best prices, Archipelago routes the order (or part of it) to Island for execution. If the order sent to Island fails to execute, say because the Island prices are no

longer available, Archipelago essentially cancels the Island order and submits one to another market center.¹⁹

Searching for the best prices in the market may take time, and therefore the ability to cancel orders very quickly on Island (say by specifying a very short time-in-force for the order) is very important. Sophisticated systems can also create synthetic order types that take advantage of the ability to submit and cancel orders quickly. For example, Archipelago has a Now Order type that is matched against its book or routed for execution to a select group of market participants that have direct connections to Archipelago and can accept immediate-or-cancel orders. REDIBook has a special Limit Sweep Order that, when submitted to REDIBook, generates multiple orders seeking immediate execution that are routed to ECNs and market makers at multiple prices between the NBBO and the limit price. These examples suggest that many of the limit orders generated by these systems are directed at removing liquidity from the market, rather than supplying it.²⁰

Another possible reason for a fleeting limit order is that the submitter wants to fish for hidden orders that better the opposing quote. A buyer, for example, might submit an order priced just short of the ask quote, hoping to trade against any hidden sell orders. Here as well a fleeting limit order represents a liquidity demander, rather than a supplier. Smart order routing systems may also submit limit orders in an attempt to uncover hidden limit orders. The distinction we make here is that such practices may be carried out by a human trader rather than a computer system.

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¹⁹ The function performed by an order routing system is essentially one of brokerage (as opposed to market making). Many of the systems, however, are implemented by the ECNs themselves or by brokers with close ties to ECNs. Archipelago and REDIBook, for example, incorporate order routing functions into their interfaces. These systems are sometimes generically referred to as smart order routing technology (SORT) systems. Both Smart Order Routing Technology and SORT, however, are service marks of MarketXT.

²⁰ In light of the ambiguity in classifying fleeting limit orders into liquidity demanding or supplying, we repeated the analysis of submission and execution proportions without fleeting limit orders. The results were qualitatively similar to those presented and discussed in Section 6.

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The question then arises as to why the buyer's order in the above example needs to be visible, even briefly. A hidden order would accomplish the same thing without revealing the buyer's interest. Our data cannot characterize the extent of such practices. The fact that many of the fleeting orders are visible, though, suggests that finding hidden sellers is not the only motive, and that the brief display serves some purpose. The display might signal tentative buying interest to prospective sellers, without going so far as to provide them with a firm option.

Another potential explanation for fleeting limit orders is a manipulative tactic known as "spoofing". To manipulate, a trader places a visible order in the opposite direction of the trade that is genuinely desired. For example, a seller might post a small buy order priced above the current bid, in hopes of convincing other buyers to match or outbid. If this occurs, the trader can sell into this (higher) price. It is necessary here that the order be visible. The practice resembles "shilling" by an auction seller, but there are some significant differences. In the stock market, the manipulator runs the risk that the spurious bid will be hit by some other seller, increasing the manipulator's long position. On the other hand, the Nasdaq market includes one group of buyers who are compelled to match the manipulator's spurious bid: dealers whose order preferencing arrangements require them to execute the preferenced order flow at the best prevailing price. This might make the manipulative strategy an appealing one. Both the NASD and SEC are conducting investigations and maintaining surveillance, however, against such practices (see Connor (2000)). The possibility of detection and prosecution is significant, and for this reason we doubt that such tactics lie behind the bulk of the fleeting orders.

8. Island's market presence

Island is only one venue in a broader market that comprises other ECNs and traditional dealers. In this section we examine the relative share of Island activity, and firm and investor characteristics to which it is related.

Table 13 presents summary statistics on Island's market share. For the average firm in our sample, Island's market share is roughly 6.2% by trades and 3.5% by volume.

In the ranked subgroups, this share increases with capitalization, the number of average trades, and σ_r . Figure 4 presents a log/log plot of a firm's average daily share volume for Island vs. that for all of Nasdaq. The slope of the log/log best fit line is 1.7, which suggests that within the sample Island trades rise as the 1.7th power of Nasdaq trades. In other words, Island's share increases for more active stocks.

The estimates in Table 13 suggest that Island's market share is larger for more volatile stocks. In cross-sectional regression analyses, this was confirmed in the presence of the control variables (capitalization, price and turnover) for all of our volatility proxies.

The positive relation between market share and volatility may reflect several mechanisms. The growth in ECN trading volume has been attributed in the popular press to increased day trading. While we have no direct evidence on this, our market share estimates are positively correlated with odd-lot trading volume (a measure of retail activity) and negatively correlated with institutional ownership.²¹ There is also evidence that day traders prefer volatile stocks. (Several popular how-to guides cite high volatility as a requirement for a stock to be an attractive candidate for day-trading.) This is also consistent with our evidence.

An alternative measure of Island's impact is the extent to which Island sets or matches the market price (the NBBO). Table 14 shows that on average Island matched the best bid roughly 20% of the time and the best offer roughly 19% of the time. Much less frequently, however, was Island alone at the bid or the ask (4% of the time). Only 0.2% of the time was Island alone at both the bid and ask. The market share and quoting

²¹ We also estimated the full set of specifications described in Section 5 where the regressors included either the percentage of institutional holdings from the Value Line Investment Survey (as a proxy for institutional trading) or the average number of odd lot trades provided to us by the NASD's Economic Research (a proxy for retail trading). The coefficient of institutional holdings is positive for the submission proportions of all limit orders and also that of limit orders priced at the quote or better, but negative for the proportion priced behind the quote. The odd-lot coefficients are generally of the opposite sign, though of lower significance. These estimates suggest that while institutions are relatively heavy users of limit orders, they are less likely to provide depth away from the market.

figures suggest that Island does not dominate trading in these stocks. This supports our empirical presumption that market variables used as explanatory variables are exogenous to our analysis.

9. Conclusions

The analysis in this paper focuses on the cross-sectional relationships between volatility and measures of trading activity on the Island ECN, an electronic limit order book.

We find that higher volatility is associated with lower time to execution. This is consistent with a mechanistic effect predicted by a simple barrier/diffusion model of limit order behavior. For the trade-related volatility measure, we find a negative relation between depth and volatility. This result is consistent with the winner's curse. Higher volatility is also associated with a lower proportion of limit orders in the incoming flow. This is consistent with the market order certainty effect, but not with the equilibrium modeled in Foucault (1999).

Where might the equilibrium model break down? The model features a winner's curse whereby higher volatility leads to a wider bid-ask spread. This increases the cost of market orders. Foucault's traders are risk neutral, and the cost increase unambiguously leads to a decrease in the usage of market orders. If traders are risk-averse, however, the certainty afforded by a market order becomes more desirable. It is also likely that higher volatility leads to higher costs of order monitoring and management, decreasing the desirability of limit order strategies. These factors may offset the cost of the higher spread, leading to the increased proportion of market orders.²²

Island offers limit order submitters a "no display" option. Submissions of such hidden orders are not reflected in our data set. Executions of hidden orders are noted, however, and these suggest substantial usage of these orders (roughly twelve percent of

²² Since Island is just a small fraction of the market, we do not test the winner's curse effect on spreads. However, the results we document with respect to Island's depth are consistent with the winner's curse effect being rather weak.

all executions). Furthermore, many limit orders are canceled almost immediately after they are submitted. We term orders canceled in two seconds or less "fleeting". These constitute 27.7% of all limit order submissions. Fleeting orders can arise from trading practices of smart order routing systems, or from human traders probing for hidden orders, communicating tentative trading interest, or implementing a manipulative "spoofing" strategy.

Island's market share varies considerably across firms, and is positively related to overall Nasdaq activity in the stock. Thus, while Nasdaq activity is concentrated in firms that are larger (by market value), the concentration of Island's trading is even more pronounced.

These results suggest several directions for subsequent research. First, the concentration of Island's activity in larger firms raises concerns about the viability of the electronic limit order book as the primary mechanism for low-capitalization or low-activity firms. The importance of this issue for public policy warrants further examination.

Second, in many economic models limit orders are characterized as being widely visible and persistent, much like dealer quotes. Furthermore, regulatory initiatives such as the SEC's Order Handling Rules focus on protecting the rights of limit order traders against dealers. From this perspective, limit orders compete with, and are therefore in some sense equivalent to, dealer quotes as sources of liquidity. Many of the Island limit orders, however, are hidden, and many are canceled almost immediately after submission. These orders are quite different, therefore, from dealer quotes. Economic analysis of such orders and the strategies that rely on them constitute another worthwhile research direction.

Finally, the analysis in this paper is cross-sectional, attempting to relate firmspecific characteristics to average attributes of Island activity. There is also, however, substantial dynamic variation in activity. The depth (available liquidity) on Island's book, for example, is highly variable over time. We are in the process of exploring the nature of this variation and the manner in which the limit order book adjusts to market shocks.

- Ahn, H.-J., Bae, K.-H., Chan, K., 2001. Limit orders, depth and volatility: Evidence from then Stock Exchange of Hong Kong. Journal of Finance 56, 767-788.
- Angel, J. J., 1994. Limit versus market orders. Unpublished working paper. School of Business Administration, Georgetown University.
- Barclay, M. J., Hendershott, T., McCormick, D. T., 2001. Electronic communications networks and market quality. Unpublished working paper. University of Rochester.
- Biais, B., Hillion, P., Spatt, C., 1995. An empirical analysis of the limit order book and the order flow in the Paris Bourse. Journal of Finance 50, 1655-1689.
- Chakravarty, S., Holden, C. W., 1995. An integrated model of market and limit orders. Journal of Financial Intermediation 4, 213-241.
- Cho, J.-W., Nelling, E., 2000. The probability of limit order execution. Financial Analysts Journal 56, 28-33.
- Chung, K. H., Van Ness, B. F., Van Ness, R. A., 1999. Limit orders and the bid-ask spread. Journal of Financial Economics 53, 255-287.
- Clark, P. K., 1973. A subordinated stochastic process model with finite variance for speculative prices. Econometrica 41.
- Cohen, K. J., Maier, S. F., Schwartz, R. A., Whitcomb, D. K., 1981. Transaction costs, order placement strategy, and existence of the bid-ask spread. Journal of Political Economy 89, 287-305.
- Connor, John. 28 February 2000. No joke: NASD plans crackdown on "spoofing," placing and canceling a quote to spark a move. *Wall Street Journal*.
- Conrad, J., Johnson, K. M., Wahal, S., 2001. Alternative trading systems. Unpublished working paper. University of North Carolina, Kenan-Flagler Business School.
- Copeland, T., Galai, D., 1983. Information effects and the bid-ask spread. Journal of Finance 38, 1457-1469.
- Coppejans, M., Domowitz, I., Madhavan, A., 2001. Liquidity in an automated auction. Unpublished working paper. Department of Economics, Duke University.

- Domowitz, I., Wang, J., 1994. Auctions as algorithms. Journal of Economic Dynamics and Control 18, 29-60.
- Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69-90.
- Easley, D., O'Hara, M., Saar, G., 2001. How stock splits affect trading: A microstructure approach. Journal of Financial and Quantitative Analysis 36, 25-51.
- Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market. Journal of Financial Markets 2, 99-134.
- Foucault, T., Kadan, O., Kandel, E., 2001. Limit order book as a market for liquidity. Unpublished working paper. HEC School of Management.
- Glosten, L. R., 1994. Is the electronic open limit order book inevitable? Journal of Finance 49, 1127-61.
- Glosten, L. R., Milgrom, P. R., 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71-100.
- Goldstein, M. A., Kavajecz, K. A., 2000. Liquidity provision during circuit breakers and extreme market movements. Unpublished working paper. Department of Finance, Wharton School, University of Pennsylvania.
- Griffiths, M. D., Smith, B. F., Turnbull, D. A. S., White, R. W., 2000. The costs and determinants of order aggressiveness. Journal of Financial Economics 56, 65-88.
- Handa, P., Schwartz, R. A., 1996. Limit order trading. Journal of Finance 51, 1835-1861.
- Harris, L., 1998. Optimal dynamic order submission strategies in some stylized trading problems. Financial Markets, Institutions and Instruments 7.
- Harris, L. E., Hasbrouck, J., 1996. Market vs. limit orders: the SuperDOT evidence on order submission strategy. Journal of Financial and Quantitative Analysis 31, 213-31.
- Harris, L. E., Panchapagesan, V., 1999. The information content of the limit order book:
 Evidence from NYSE specialist actions. Unpublished working paper. Marshall
 School of Business, University of Southern California.
- Hasbrouck, J., 1991. The summary informativeness of stock trades: An econometric analysis. Review of Financial Studies 4, 571-95.

Huang, R. D., 2002. The quality of ECN and market maker quotes. Journal of Finance 57.

- Lo, A. W., MacKinlay, A. C., Zhang, J., 2002. Econometric models of limit order execution. Journal of Financial Economics, Forthcoming.
- Parlour, C., 1998. Price dynamics in limit order markets. Review of Financial Studies 11, 789-816.
- Parlour, C. A., Seppi, D. J., 2001. Liquidity-based competition for order flow. Unpublished working paper. Graduate School of Industrial Administration, Carnegie Mellon University.
- Rock, K., 1990. The specialist's order book and price anomalies. Unpublished working paper. Graduate School of Business, Harvard University.
- Rousseeuw, P. J., Leroy, A. M., 1987. Robust Regression and Outlier Detection. John Wiley & Sons, New York.
- Russell, J. R., Engle, R. F., 1998. Econometric analysis of discrete-valued irregularlyspaced financial transactions data using a new Autoregressive Conditional Multinomial model. Unpublished working paper. University of Chicago, Graduate School of Business.
- Sandas, P., 2001. Adverse selection and competitive market making: evidence from a pure limit order book. Review of Financial Studies 14, 705-734.
- Seppi, D. J., 1997. Liquidity provision with limit orders and a strategic specialist. Review of Financial Studies 10, 103-150.
- Simaan, Y., Weaver, D. G., Whitcomb, D. K., 1998. The quotation behavior of ECN's and Nasdaq market makers. Unpublished working paper. Zicklin School of Business, Baruch College.
- Smith, J. W., 2000. Market vs. limit order submission behavior at a Nasdaq market maker. Unpublished working paper. NASD Economic Research.
- U.S. Securities and Exchange Commission. 1996. Order execution obligations. Release No. 34-37619A.
- US Securities and Exchange Commission. 1998. *Regulation of exchanges and alterative trading systems*. Release No. 34-40760.

Table 1. Summary statistics

The table presents summary statistics (across firms) over the 64 trading days in the fourth quarter of 1999. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999). Capitalization, market price, and trading volume are taken from CRSP; σ_r is the standard deviation of daily CRSP returns; and spreads are derived from Nastraq.

		Avg equity			Avg daily	Median	Average		
		mkt. cap.	Avg daily	σ_r (daily	volume	daily	price	Spread	Spread (% of
		(\$MM)	trades	return)	(1,000 shares)	turnover	(\$/share)	(\$/share)	quote midpt)
	Mean	10,205	2,677	0.0436	1,873	1.288	63.03	0.2563	0.46
	Median	3,081	1,066	0.0433	877	1.107	49.82	0.1871	0.44
Total	SD	38,104	4,413	0.0169	3,504	0.946	45.66	0.2180	0.25
Sample	Min	824	16	0.0018	7	0.028	8.40	0.0520	0.07
	Max	494,932	28,654	0.1083	30,073	5.208	326.58	1.9103	2.79
	Nobs	300	300	300	300	300	300	300	300
Means for	Low	1,500	654	0.0386	549	0.952	39.16	0.2520	0.63
mkt. cap.	Medium	3,169	1,474	0.0470	1,051	1.322	58.26	0.2757	0.49
groups	High	25,947	5,904	0.0452	4,017	1.590	91.67	0.2413	0.28
Means for	Low	1,953	326	0.0326	314	0.541	41.84	0.2730	0.63
trade	Medium	3,772	1,202	0.0491	933	1.257	62.19	0.2849	0.48
groups	High	24,891	6,504	0.0491	4,371	2.066	85.06	0.2109	0.28
Means for	Low	18,100	2,290	0.0257	2,038	0.565	44.20	0.1989	0.49
	Medium	7,304	2,548	0.0429	1,872	1.424	63.11	0.2162	0.41
o_r groups	High	5,212	3,193	0.0622	1,708	1.874	81.79	0.3538	0.49

Table 2. Island summary statistics

The table presents summary statistics (across firms) over the 64 trading days in the fourth quarter of 1999. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999). On the Island system, all orders carry a limit price. Market orders are defined as orders that are matched upon arrival (and so never appear in the book).

		Avg daily	Avg size of	Avg daily	Avg size of	Avg daily	Avg size of	Avg daily no.	Avg market	Avg daily
		no. of limit	limit order	no. of	cancelation	no. of filled	limit order	of market	order size	no. of odd-
		orders	(shares)	cancelations	(shares)	limit orders	fill (shares)	orders	(shares)	lot trades
	Mean	965.9	572.4	672.0	617.7	275.7	389.7	339.9	335.0	57.7
	Median	285.3	585.2	221.0	627.3	51.1	380.1	60.7	329.3	7.6
Total	SD	1,764.8	158.1	1,144.6	157.5	602.5	133.9	760.7	110.2	153.2
Sample	Min	3.9	214.1	2.7	241.9	0.0	148.8	0.0	123.3	0.0
	Max	11,992.4	985.3	6,963.5	1,032.0	4,726.7	931.8	6,123.6	742.7	1,498.7
	Nobs	300	300	300	300	300	299	300	299	300
Means for	Low	157.7	612.5	119.3	644.6	34.0	414.9	40.5	363.5	6.4
mkt. cap.	Medium	461.3	567.5	337.7	613.9	113.7	379.9	136.8	329.2	19.5
groups	High	2,278.6	537.2	1,558.9	594.6	679.3	374.5	842.4	312.5	147.3
Means for	Low	67.1	631.5	58.4	653.1	7.7	423.1	8.6	377.5	1.0
trade	Medium	332.5	553.3	257.2	599.5	69.5	372.2	80.7	322.1	12.2
groups	High	2,498.0	532.5	1,700.3	600.4	749.8	374.1	930.4	305.8	159.9
Means for	Low	680.0	668.1	488.9	694.0	177.9	463.2	229.8	404.5	30.5
	Medium	913.6	592.6	659.9	644.1	239.1	403.6	289.6	344.7	44.2
o_r groups	High	1,304.0	456.6	867.1	515.0	410.0	303.0	500.4	256.5	98.4

Table 3. Submission and execution proportions (percentages) for Island limit orders

The table presents summary statistics (across firms) over the 64 trading days in the fourth quarter of 1999 for visible (non-hidden) Island limit orders. The firm sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999). All data are tabulated from Island order data and the Nastraq database. The order sample is all visible (non-hidden) limit orders entered into the Island system between 9:30 a.m. and 4:00 p.m.

					Limit c	order subn	nissions						
		Limit c	order subr	nissions	(shares)) relative t	to shares	Limit	order exe	cution	Limit	order exe	ecution
		relati	ve to all c	orders:	i	n all order	S:]	proportion	IS	prop	ortions (sl	hares)
			Price re	elative to		Price re	lative to		Price re	lative to		Price relative to	
			Island's	quote at		Island's	quote at		Island's quote at			Island's	quote at
			subm	nission	submission			submission			submission		
		All	At or		All	At or		All	At or		All	At or	
		prices	better	Away	prices	better	Away	prices	better	Away	prices	better	Away
	Mean	84.3%	53.8%	30.5%	90.3%	58.5%	31.8%	16.0%	15.4%	17.8%	11.1%	10.3%	13.1%
	Median	83.4	49.2	34.0	90.1	55.7	33.8	17.2	15.2	19.4	11.0	9.7	13.7
Total	SD	7.8	25.0	17.6	5.1	23.9	19.3	8.2	8.6	7.7	6.3	6.3	6.4
Sample	Min	66.3	13.4	0.0	76.3	15.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	100.0	100.0	59.1	100.0	100.0	66.7	34.7	38.9	33.5	31.0	33.7	31.8
	Nobs	300	300	300	300	300	300	300	300	298	300	300	298
Means for	Low	88.9%	69.4%	19.4%	93.1%	73.7%	19.4%	11.3%	10.5%	13.8%	7.7%	6.9%	10.3%
mkt. cap.	Medium	84.0	53.8	30.2	90.1	58.9	31.2	16.4	15.6	18.6	11.3	10.2	13.7
groups	High	80.1	38.3	41.9	87.7	42.9	44.7	20.3	20.3	21.0	14.3	13.7	15.3
Means for	: Low	92.3	80.9	11.4	95.3	84.3	11.1	7.6	7.0	10.6	5.0	4.5	8.0
trade	Medium	83.6	51.6	32.0	89.8	57.4	32.4	16.9	15.6	18.9	11.5	10.1	13.8
groups	High	77.1	29.0	48.2	85.7	33.9	51.9	23.5	23.7	23.8	16.8	16.1	17.5
Means for	Low	90.8	75.6	15.2	94.2	78.4	15.8	9.1	9.1	11.1	6.5	6.4	8.6
	Medium	83.0	48.4	34.5	89.4	53.6	35.8	17.4	16.3	19.4	12.0	10.8	14.2
o_r groups	High	79.2	37.4	41.8	87.2	43.5	43.8	21.5	20.9	22.7	14.9	13.6	16.5

Table 4. Depth summary statistics

The table presents summary statistics (across firms) over the 64 trading days in the fourth quarter of 1999 for visible (non-hidden) Island limit orders. The firm sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999). The order sample is all visible (non-hidden) limit orders entered into the Island system that are not matched upon arrival. For firm *i* and five-minute interval *t*, we compute the dollar value of all sell orders priced at the National Best Offer + ½ or below, and the sell orders in the intervals (NBO + ½, NBO + 3/4], (NBO + 3/4, NBO + 2], and (NBO + 2, ∞). On the bid side of the book, we aggregate over the intervals (∞ , National Best Bid - ½], (NBB - 3/4], (NBB - 3/4, NBB - 2], and (NBB - 2, 0). For firm *i*, we then compute the means (across time) of the depths. The table reports summary statistics on these firm means. The units are \$1,000.

		Bid side d	epth within	National Bes	st Bid $-x$:	Ask side depth within National Best Offer $+ x$:				
		$x \leq \frac{1}{8}$	$\frac{1}{8} < \chi \leq \frac{3}{4}$	$3/4 < x \leq 2$	x > 2	$x \leq \frac{1}{8}$	$1/_{8} < \chi \leq 3/_{4}$	$3/_4 < x \le 2$	x > 2	
	Mean	17.0	25.3	37.5	57.8	20.2	37.2	67.9	122.3	
	Median	7.8	7.7	8.7	13.1	8.2	10.1	17.6	31.0	
Total	SD	30.5	55.7	89.0	139.9	38.3	89.9	167.4	296.5	
Sample	Min	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	Max	237.1	506.9	797.5	1,105.7	324.9	882.2	1,600.2	2,871.3	
	Nobs	300	300	300	300	300	300	300	300	
Means for	Low	4.2	6.0	7.5	10.6	4.7	8.3	13.9	25.3	
mkt. cap.	Medium	9.8	13.5	18.3	25.0	11.1	18.0	33.6	62.4	
groups	High	37.1	56.5	86.8	137.8	44.7	85.3	156.2	279.2	
Means for	Low	2.8	2.0	2.4	2.7	3.1	2.6	4.3	6.6	
trade	Medium	7.8	8.8	11.5	16.4	8.9	11.5	19.3	33.1	
groups	High	40.5	65.2	98.7	154.3	48.6	97.5	180.1	327.2	
Means for	Low	17.2	24.4	38.7	57.9	21.3	39.9	73.8	125.0	
	Medium	16.1	21.3	30.1	46.3	19.3	31.6	54.9	97.5	
o_r groups	High	17.8	30.2	43.9	69.2	19.9	40.1	75.1	144.5	

Table 5. Volatility summary statistics

The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999). σ_r is the standard deviation of the daily CRSP return. σ_w is the standard deviation of the random-walk component of the stock price; $\sigma_{w,x}$ is the standard deviation of the contribution to the random-walk component attributable to signed trades. σ_w and $\sigma_{w,x}$ are estimated using the Hasbrouck (1991) procedure applied to a vector autoregression of quote-midpoint returns and signed trades aggregated over one-minute intervals. They are scaled to reflect volatility over a 6.5 hour trading day. σ_r , σ_w , and $\sigma_{w,x}$ are estimated over the 64 trading days in the fourth quarter of 1999. $\beta_i \sigma_M$ is the standard deviation of systematic risk; $\sigma(e_{it})$ is the standard deviation of unsystematic risk. Both are based on the market model $r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it}$, where r_{Mt} is the return on the CRSP value-weighted portfolio, estimated using daily CRSP data from October 1, 1996 to September 30, 1999. The table presents summary statistics across firms.

Panel A

		σ_r	σ_w	σ _{wr}	$\beta_i \sigma_M$	$\sigma(e_{it})$
	Mean	0.0436	0.0383	0.0193	0.0133	0.0330
	Median	0.0433	0.0383	0.0197	0.0132	0.0331
Total	SD	0.0169	0.0138	0.0076	0.0050	0.0108
Sample	Min	0.0018	0.0029	0.0015	0.0025	0.0136
-	Max	0.1083	0.0890	0.0438	0.0310	0.0620
	Nobs	300	300	300	211	211
Means for	Low	0.0386	0.0346	0.0167	0.0106	0.0314
mkt. cap.	Medium	0.0470	0.0412	0.0211	0.0130	0.0348
groups	High	0.0452	0.0392	0.0202	0.0168	0.0332
Means for	Low	0.0326	0.0298	0.0142	0.0095	0.0277
trade	Medium	0.0491	0.0428	0.0221	0.0136	0.0352
groups	High	0.0491	0.0424	0.0217	0.0185	0.0380
Means for	Low	0.0257	0.0244	0.0123	0.0106	0.0251
	Medium	0.0429	0.0387	0.0199	0.0153	0.0374
o_r groups	High	0.0622	0.0519	0.0258	0.0157	0.0427
Panel B						
Correlation	ns:	σ_r	σ_w	$\sigma_{w,x}$	$eta_{i} \sigma_{M}$	$\sigma(e_{it})$
	σ_r	1				
	σ_w	0.937	1			
	$\sigma_{w,x}$	0.837	0.904	1		
	${eta}_i \sigma_M$	0.496	0.510	0.505	1	
	$\sigma(e_{it})$	0.738	0.766	0.648	0.670	1

Table 6. Island limit orders and daily return volatility

The table presents regression coefficient estimates (using the indicated specification) for submission proportions, execution proportions, depth groups on bid and ask sides (in \$1,000), and execution durations. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999) over the 64 trading days in the fourth quarter of 1999. "Logit regression" and "Linear regression" specifications are estimated across firms in the sample. The duration specifications are estimated for a sample consisting of 2,000 randomly selected limit orders for each firm, adjusted to weight all firms equally. Numbers in parentheses are coefficient estimates divided by the asymptotic standard error of estimate. The latter standard errors are heteroskedasticity-consistent in the regression and logit regression specifications (but not in the duration specifications). The last two columns of the table indicate the implied result of increasing the volatility measure by one standard deviation for the representative firm. The numbers in these columns are proportions (between zero and one) for the logistic regression specifications, depths (in \$1,000), and predicted median execution duration. σ_r is the standard deviation of the daily CRSP return.

									Predicted val dependent va when $\sigma_r =$	lue of triable
Model				Log(Avg		Log(Med.			when or	Mean +
specification	Dependent variable	Intercept	σ_r	cap)	Avg price	turnover)	No. Obs.	R^2	Mean	one s.d.
Logit	Limit subm. prop.	10.158	-20.970	-0.347	0.004	-0.486	298	0.753	0.867	0.821
regression	(all prices)	(20.44)	(-7.56)	(-17.81)	(7.42)	(-7.57)				
•	Limit subm. prop.	15.901	-34.561	-0.657	0.006	-0.774	299	0.821	0.581	0.436
	(quote or better)	(21.55)	(-8.10)	(-22.44)	(6.96)	(-8.17)				
	Limit subm. prop.	-15.205	34.834	0.584	-0.005	0.765	298	0.744	0.235	0.356
	(away)	(-16.24)	(7.71)	(15.78)	(-5.77)	(7.88)				
	Limit exec. prop.	-10.393	22.396	0.356	-0.004	0.506	298	0.754	0.134	0.184
	(all prices)	(-19.65)	(7.74)	(17.09)	(-7.35)	(7.86)				
	Limit exec. prop.	-11.401	22.098	0.400	-0.004	0.502	298	0.762	0.127	0.175
	(quote or better)	(-21.24)	(7.90)	(18.60)	(-7.24)	(8.16)				
	Limit exec. prop.	-6.568	14.652	0.204	-0.003	0.325	283	0.570	0.174	0.211
	(away)	(-14.23)	(6.71)	(10.82)	(-6.10)	(5.93)				
Linear	Bid depth at NBB $-x$	-505.619	-92.498	24.280	-0.132	4.589	300	0.626	17.035	15.468
regression	$x \leq \frac{1}{8}$	(-7.23)	(-1.81)	(7.36)	(-3.75)	(3.45)				
	Bid depth at NBB $-x$	-810.056	-107.299	38.918	-0.274	10.011	300	0.480	25.319	23.500
	$\frac{1}{8} < x \le \frac{3}{4}$	(-5.57)	(-1.04)	(5.64)	(-3.21)	(3.69)				
	Bid depth at NBB $-x$	-1,319.466	-171.815	63.112	-0.413	12.883	300	0.484	37.543	34.630
	$\frac{3}{4} < x \le 2$	(-5.48)	(-1.10)	(5.53)	(-3.17)	(3.01)				
	Bid depth at NBB $-x$	-2,018.329	-410.860	96.220	-0.411	19.550	300	0.483	57.813	50.849
	x>2	(-5.30)	(-1.64)	(5.36)	(-2.20)	(2.77)				
	Ask depth at NBO $+ x$:	-635.396	-138.010	30.516	-0.172	5.236	300	0.618	20.186	17.847
	$x \leq \frac{1}{8}$	(-6.89)	(-2.16)	(7.00)	(-3.68)	(3.20)				
	Ask depth at NBO $+ x$:	-1,354.643	-138.914	65.005	-0.545	12.711	300	0.483	37.198	34.844
	$\frac{1}{8} < x \le \frac{3}{4}$	(-5.25)	(-0.88)	(5.31)	(-3.90)	(3.03)				
	Ask depth at NBO $+ x$:	-2,499.909	-202.467	119.912	-1.037	23.713	300	0.473	67.919	64.488
	$\frac{3}{4} < x \le 2$	(-5.14)	(-0.68)	(5.20)	(-4.06)	(2.94)				
	Ask depth at NBO $+ x$:	-4,226.059	-434.660	202.743	-1.572	48.342	300	0.447	122.308	114.941
	<i>x</i> > 2	(-4.91)	(-0.81)	(4.97)	(-3.43)	(3.26)				
Duration	Time to execution	12.951	-19.470	-0.352	0.002	-0.369	91,365		1,451.7	1,056.8
		(87.02)	(-51.02)	(-57.15)	(14.53)	(-48.40)				

Table 7. Island limit orders and random-walk volatility

The table presents regression coefficient estimates (using the indicated specification) for submission proportions, execution proportions, depth groups on bid and ask sides (in \$1,000), and execution durations. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999) over the 64 trading days in the fourth quarter of 1999. "Logit regression" and "Linear regression" specifications are estimated across firms in the sample. The duration specifications are estimated for a sample consisting of 2,000 randomly selected limit orders for each firm, adjusted to weight all firms equally. Numbers in parentheses are coefficient estimates divided by the asymptotic standard error of estimate. The latter standard errors are heteroskedasticity-consistent in the regression and logit regression specifications (but not in the duration specifications). The last two columns of the table indicate the implied result of increasing the volatility measure by one standard deviation for the representative firm. The numbers in these columns are proportions (between zero and one) for the logistic regression specifications, depths (in \$1,000), and predicted median execution duration. σ_w is the standard deviation of the implicit random-walk component of the quote midpoint, estimated with one-minute data and rescaled to reflect volatility over a 6.5 hour trading day.

									Predicted value dependent value $\sigma_w =$	lue of ariable
Model				Log(Avg		Log(Med.				Mean +
specification	Dependent variable	Intercept	σ_{w}	cap)	Avg price	turnover)	No. Obs.	\mathbb{R}^2	Mean	one s.d.
Logit	Limit subm. prop.	10.436	-25.472	-0.357	0.004	-0.495	298	0.753	0.867	0.821
regression	(all prices)	(20.56)	(-7.42)	(-18.52)	(7.73)	(-7.86)				
	Limit subm. prop.	16.482	-43.326	-0.677	0.006	-0.777	299	0.828	0.581	0.433
	(quote or better)	(22.07)	(-8.30)	(-23.41)	(7.17)	(-8.53)				
	Limit subm. prop.	-15.994	45.651	0.610	-0.005	0.753	298	0.762	0.235	0.365
	(away)	(-16.55)	(8.12)	(16.26)	(-6.17)	(8.31)				
	Limit exec. prop.	-10.693	27.242	0.366	-0.004	0.515	298	0.755	0.134	0.183
	(all prices)	(-19.83)	(7.60)	(17.84)	(-7.76)	(8.17)				
	Limit exec. prop.	-11.703	26.936	0.410	-0.004	0.510	298	0.763	0.127	0.174
	(quote or better)	(-21.49)	(7.81)	(19.40)	(-7.55)	(8.48)				
	Limit exec. prop.	-6.592	16.182	0.206	-0.003	0.341	283	0.547	0.174	0.207
	(away)	(-13.87)	(5.87)	(10.83)	(-6.00)	(6.10)				
Linear	Bid depth at NBB $-x$	-501.469	-140.611	24.148	-0.130	4.733	300	0.627	17.035	15.102
regression	$x \leq \frac{1}{8}$	(-7.17)	(-2.23)	(7.32)	(-3.70)	(3.57)				
	Bid depth at NBB $-x$	-806.072	-154.967	38.789	-0.272	10.122	300	0.481	25.319	23.188
	$1/_{8} < x \le 3/_{4}$	(-5.53)	(-1.25)	(5.62)	(-3.18)	(3.74)				
	Bid depth at NBB $-x$	-1,317.618	-203.690	63.042	-0.413	12.755	300	0.484	37.543	34.742
	$\frac{3}{4} < x \le 2$	(-5.46)	(-1.06)	(5.52)	(-3.15)	(3.04)				
	Bid depth at NBB $-x$	-2,017.778	-449.144	96.170	-0.414	18.982	300	0.483	57.813	51.637
	x> 2	(-5.29)	(-1.44)	(5.35)	(-2.20)	(2.76)				
	Ask depth at NBO $+ x$:	-629.075	-211.067	30.314	-0.168	5.460	300	0.620	20.186	17.284
	$x \le \frac{1}{8}$	(-6.82)	(-2.66)	(6.96)	(-3.61)	(3.35)				
	Ask depth at NBO $+ x$:	-1,343.715	-257.245	64.664	-0.539	13.245	300	0.484	37.198	33.661
	$1/_{8} < x \le 3/_{4}$	(-5.20)	(-1.38)	(5.28)	(-3.85)	(3.14)				
	Ask depth at NBO $+ x$:	-2,489.404	-321.734	119.579	-1.031	24.125	300	0.473	67.919	63.495
	$\frac{3}{4} < x \le 2$	(-5.11)	(-0.92)	(5.19)	(-4.03)	(3.01)				
	Ask depth at NBO $+ x$:	-4,221.820	-511.040	202.580	-1.572	47.988	300	0.447	122.308	115.281
	<i>x</i> >2	(-4.90)	(-0.81)	(4.96)	(-3.41)	(3.29)				
Duration	Time to execution	13.099	-23.037	-0.358	0.002	-0.381	91,365		1,466.0	1,078.4
		(86.42)	(-49.17)	(-57.52)	(15.02)	(-49.81)				

Table 8. Island limit orders and systematic volatility

The table presents regression coefficient estimates (using the indicated specification) for submission proportions, execution proportions, depth groups on bid and ask sides (in \$1,000), and execution durations. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999) over the 64 trading days in the fourth quarter of 1999. "Logit regression" and "Linear regression" specifications are estimated across firms in the sample. The duration specifications are estimated for a sample consisting of 2,000 randomly selected limit orders for each firm, adjusted to weight all firms equally. Numbers in parentheses are coefficient estimates divided by the asymptotic standard error of estimate. The latter standard errors are heteroskedasticity-consistent in the regression and logit regression specifications (but not in the duration specifications). The last two columns of the table indicate the implied result of increasing the volatility measure by one standard deviation for the representative firm. The numbers in these columns are proportions (between zero and one) for the logistic regression specifications, depths (in \$1,000), and predicted median execution duration. $\beta_i \sigma_M$ represents the systematic component of volatility. It is based on the market model $r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it}$,

where r_{Mt} is the return on the CRSP value-weighted portfolio, estimated using daily CRSP data from October 1, 1996 to September 30, 1999.

									Predicted val dependent va $\beta_i \sigma_M =$	ue of riable when
Model				Log(Avg		Log(Med.				Mean +
specification	Dependent variable	Intercept	$eta_i\sigma_M$	cap)	Avg price	turnover)	No. Obs.	\mathbf{R}^2	Mean	one s.d.
Logit	Limit subm. prop.	8.272	-23.336	-0.281	0.003	-0.638	209	0.702	0.888	0.876
regression	(all prices)	(14.81)	(-1.82)	(-8.53)	(2.86)	(-5.24)				
	Limit subm. prop.	12.270	-50.171	-0.518	0.005	-0.944	210	0.758	0.657	0.599
	(quote or better)	(14.71)	(-2.45)	(-10.71)	(2.89)	(-5.40)				
	Limit subm. prop.	-11.470	53.201	0.442	-0.005	0.974	209	0.667	0.186	0.230
	(away)	(-11.94)	(2.23)	(8.32)	(-2.59)	(5.17)				
	Limit exec. prop.	-8.379	23.754	0.285	-0.003	0.666	209	0.700	0.111	0.123
	(all prices)	(-14.29)	(1.79)	(8.31)	(-2.71)	(5.35)				
	Limit exec. prop.	-9.488	22.484	0.334	-0.003	0.649	209	0.718	0.105	0.116
	(quote or better)	(-16.50)	(1.80)	(10.05)	(-2.83)	(5.49)				
	Limit exec. prop.	-5.118	13.655	0.152	-0.002	0.414	194	0.467	0.157	0.165
	(away)	(-9.20)	(1.30)	(4.94)	(-1.59)	(3.62)				
Linear	Bid depth at NBB – x	-541.909	-105.961	25.808	-0.140	2.088	211	0.658	16.952	16.420
regression	$x \leq \frac{1}{8}$	(-6.68)	(-0.25)	(6.61)	(-2.73)	(1.37)				
	Bid depth at NBB $-x$	-823.119	436.437	38.761	-0.220	2.239	211	0.512	23.805	25.995
	$1/8 < x \le 3/4$	(-4.78)	(0.48)	(4.70)	(-1.68)	(0.72)				
	Bid depth at NBB $-x$	-1,364.150	424.722	64.142	-0.343	1.330	211	0.515	35.101	37.233
	$\frac{3}{4} < x \le 2$	(-4.78)	(0.30)	(4.69)	(-1.70)	(0.27)				
	Bid depth at NBB $-x$	-2,086.799	494.323	97.418	-0.237	-0.528	211	0.521	52.806	55.287
	x> 2	(-4.58)	(0.20)	(4.42)	(-0.84)	(-0.06)				
	Ask depth at NBO $+ x$:	-687.066	-161.240	32.701	-0.180	2.516	211	0.641	20.587	19.778
	$x \leq \frac{1}{8}$	(-6.37)	(-0.29)	(6.30)	(-2.54)	(1.28)				
	Ask depth at NBO $+ x$:	-1,400.727	725.337	66.127	-0.504	2.907	211	0.495	36.942	40.582
	$1/8 < x \le 3/4$	(-4.53)	(0.49)	(4.47)	(-2.36)	(0.56)				
	Ask depth at NBO $+ x$:	-2,574.096	1,064.053	121.634	-0.947	5.130	211	0.484	65.657	70.998
	$\frac{3}{4} < x \le 2$	(-4.38)	(0.37)	(4.30)	(-2.43)	(0.53)				
	Ask depth at NBO $+ x$:	-4,288.891	3,341.280	201.342	-1.371	5.610	211	0.462	113.378	130.148
	x> 2	(-4.14)	(0.65)	(4.04)	(-1.94)	(0.33)				
Duration	Time to execution	11.609	-30.663	-0.281	-0.001	-0.452	56,487		1,676.3	1,449.7
		(71.78)	(-14.25)	(-36.92)	(-2.38)	(-40.34)				

Table 9. Island limit orders and unsystematic volatility

The table presents regression coefficient estimates (using the indicated specification) for submission proportions, execution proportions, depth groups on bid and ask sides (in \$1,000), and execution durations. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999) over the 64 trading days in the fourth quarter of 1999. "Logit regression" and "Linear regression" specifications are estimated across firms in the sample. The duration specifications are estimated for a sample consisting of 2,000 randomly selected limit orders for each firm, adjusted to weight all firms equally. Numbers in parentheses are coefficient estimates divided by the asymptotic standard error of estimate. The latter standard errors are heteroskedasticity-consistent in the regression and logit regression specifications (but not in the duration specifications). The last two columns of the table indicate the implied result of increasing the volatility measure by one standard deviation for the representative firm. The numbers in these columns are proportions (between zero and one) for the logistic regression specifications, depths (in \$1,000), and predicted median execution duration. $\sigma(e_{it})$

represents the unsystematic component of volatility. It is based on the market model $r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it}$, where r_{Mt} is the return on the CRSP value-weighted portfolio, estimated using daily CRSP data from October 1, 1996 to September 30, 1999.

									Predicted val dependent va $\sigma(e_{it}) =$	ue of riable when
Model				Log(Avg		Log(Med.				Mean +
specification	Dependent variable	Intercept	$\sigma(e_{it})$	cap)	Avg price	turnover)	No. Obs.	\mathbb{R}^2	Mean	one s.d.
Logit	Limit subm. prop.	10.872	-25.268	-0.376	0.004	-0.513	209	0.738	0.888	0.859
regression	(all prices)	(14.25)	(-2.99)	(-15.61)	(4.46)	(-3.90)				
	Limit subm. prop.	16.954	-43.757	-0.697	0.006	-0.757	210	0.794	0.657	0.545
	(quote or better)	(13.88)	(-3.43)	(-17.47)	(4.38)	(-3.99)				
	Limit subm. prop.	-16.341	45.256	0.629	-0.006	0.787	209	0.702	0.186	0.271
	(away)	(-10.43)	(3.24)	(11.66)	(-3.99)	(3.87)				
	Limit exec. prop.	-11.152	27.205	0.386	-0.004	0.526	209	0.739	0.111	0.143
	(all prices)	(-14.08)	(3.16)	(15.24)	(-4.45)	(3.99)				
	Limit exec. prop.	-12.127	25.917	0.429	-0.004	0.516	209	0.754	0.105	0.134
	(quote or better)	(-15.83)	(3.19)	(17.17)	(-4.32)	(4.13)				
	Limit exec. prop.	-6.978	18.400	0.217	-0.002	0.302	194	0.512	0.157	0.183
	(away)	(-9.95)	(2.64)	(9.12)	(-2.78)	(2.56)				
Linear	Bid depth at NBB $-x$	-554.118	170.191	26.037	-0.144	0.359	211	0.659	16.952	18.794
regression	$x \leq \frac{1}{8}$	(-6.97)	(1.35)	(6.97)	(-2.81)	(0.25)				
	Bid depth at NBB $-x$	-872.703	485.822	40.561	-0.236	-0.240	211	0.515	23.805	29.064
	$1/_8 < x \le 3/_4$	(-5.08)	(1.85)	(5.02)	(-1.79)	(-0.09)				
	Bid depth at NBB $-x$	-1,431.572	700.592	66.421	-0.364	-2.925	211	0.518	35.101	42.685
	$\frac{3}{4} < x \le 2$	(-5.09)	(1.83)	(5.01)	(-1.81)	(-0.70)				
	Bid depth at NBB $-x$	-2,186.266	1,064.900	100.647	-0.269	-7.499	211	0.524	52.806	64.333
	x> 2	(-5.04)	(1.71)	(4.92)	(-0.97)	(-1.10)				
	Ask depth at NBO $+ x$:	-699.705	188.406	32.886	-0.184	0.456	211	0.642	20.587	22.626
	$x \leq \frac{1}{8}$	(-6.60)	(1.20)	(6.59)	(-2.60)	(0.25)				
	Ask depth at NBO $+ x$:	-1,482.633	801.474	69.105	-0.529	-1.165	211	0.498	36.942	45.618
	$1/_{8} < x \le 3/_{4}$	(-4.83)	(1.92)	(4.77)	(-2.45)	(-0.26)				
	Ask depth at NBO $+ x$:	-2,722.286	1,508.911	126.773	-0.992	-3.539	211	0.487	65.657	81.991
	$\frac{3}{4} < x \le 2$	(-4.72)	(1.96)	(4.66)	(-2.54)	(-0.42)				
	Ask depth at NBO $+ x$:	-4,596.432	2,862.998	213.148	-1.464	-6.441	211	0.465	113.378	144.370
	x> 2	(-4.49)	(2.07)	(4.42)	(-2.07)	(-0.44)				
Duration	Time to execution	15.117	-31.474	-0.414	0.001	-0.356	56,487		1,689.5	1,217.8
		(83.67)	(-34.64)	(-55.56)	(4.97)	(-32.74)				

Table 10. Island limit orders and trade-related volatility

The table presents regression coefficient estimates (using the indicated specification) for submission proportions, execution proportions, depth groups on bid and ask sides (in \$1,000), and execution durations. The sample is the largest 300 Nasdaq National Market stocks (ranked by equity capitalization on September 30, 1999) over the 64 trading days in the fourth quarter of 1999. "Logit regression" and "Linear regression" specifications are estimated across firms in the sample. The duration specifications are estimated for a sample consisting of 2,000 randomly selected limit orders for each firm, adjusted to weight all firms equally. Numbers in parentheses are coefficient estimates divided by the asymptotic standard error of estimate. The latter standard errors are heteroskedasticity-consistent in the regression and logit regression specifications (but not in the duration specifications). The last two columns of the table indicate the implied result of increasing the volatility measure by one standard deviation for the logistic regression specifications, depths (in \$1,000), and predicted median execution duration. $\sigma_{w,x}$ is the standard deviation of the contribution to the random-walk component attributable to signed trades. $\sigma_{w,x}$ is estimated using the Hasbrouck (1991) procedure applied to a vector autoregression of quote-

midpoint returns and signed trades aggregated over one-minute intervals and scaled to reflect volatility over a 6.5 hour trading day.

									Predicted val dependent va when $\sigma_{w,x} =$	ue of riable
						Log(Med				
Model				Log(Avg			No.			Mean +
specification	Dependent variable	Intercept	$\sigma_{\!\scriptscriptstyle W,x}$	cap)	Avg price	turnover)	Obs.	R^2	Mean	one s.d.
Logit	Limit subm. prop.	9.223	-35.526	-0.311	0.003	-0.514	298	0.709	0.867	0.833
regression	(all prices)	(19.93)	(-8.19)	(-16.40)	(3.87)	(-8.03)				
	Limit subm. prop.	14.371	-58.361	-0.599	0.004	-0.822	299	0.777	0.581	0.470
	(quote or better)	(19.95)	(-9.29)	(-19.74)	(3.30)	(-8.83)				
	Limit subm. prop.	-13.886	64.464	0.530	-0.003	0.788	298	0.715	0.235	0.334
	(away)	(-15.27)	(8.77)	(14.43)	(-2.89)	(8.23)				
	Limit exec. prop.	-9.416	38.485	0.318	-0.003	0.533	298	0.711	0.134	0.171
	(all prices)	(-19.20)	(8.31)	(15.85)	(-3.82)	(8.20)				
	Limit exec. prop.	-10.430	37.801	0.362	-0.003	0.529	298	0.720	0.127	0.163
	(quote or better)	(-20.78)	(7.95)	(17.44)	(-3.86)	(8.33)				
	Limit exec. prop.	-5.760	22.325	0.174	-0.002	0.345	283	0.506	0.174	0.199
	(away)	(-12.69)	(6.45)	(9.07)	(-2.87)	(5.84)				
Linear	Bid depth at NBB $-x$	-500.518	-381.692	24.212	-0.135	5.371	300	0.631	17.035	14.115
regression	$x \le \frac{1}{8}$	(-7.23)	(-3.45)	(7.38)	(-3.85)	(4.07)				
	Bid depth at NBB $-x$	-792.759	-726.979	38.564	-0.273	12.116	300	0.487	25.319	19.757
	$1/_8 < x \le 3/_4$	(-5.50)	(-3.34)	(5.61)	(-3.26)	(4.33)				
	Bid depth at NBB $-x$	-1,294.966	-1,084.263	62.623	-0.413	15.918	300	0.489	37.543	29.248
	$\frac{3}{4} < x \le 2$	(-5.42)	(-3.09)	(5.51)	(-3.18)	(3.65)				
	Bid depth at NBB $-x$	-1,982.436	-2,026.014	95.597	-0.419	24.420	300	0.490	57.813	42.314
	x> 2	(-5.27)	(-3.43)	(5.36)	(-2.28)	(3.41)				
	Ask depth at NBO $+ x$:	-629.342	-530.615	30.451	-0.177	6.241	300	0.624	20.186	16.127
	$x \le \frac{1}{8}$	(-6.88)	(-3.80)	(7.02)	(-3.80)	(3.89)				
	Ask depth at NBO $+ x$:	-1,327.846	-1,051.181	64.441	-0.543	15.900	300	0.488	37.198	29.157
	$1/_8 < x \le 3/_4$	(-5.17)	(-3.13)	(5.28)	(-3.90)	(3.74)				
	Ask depth at NBO $+ x$:	-2,450.961	-1,779.111	118.852	-1.030	29.400	300	0.477	67.919	54.310
	$\frac{3}{4} < x \le 2$	(-5.07)	(-2.78)	(5.17)	(-4.03)	(3.62)				
	Ask depth at NBO $+ x$:	-4,142.141	-3,290.882	200.978	-1.565	58.326	300	0.452	122.308	97.134
	<i>x</i> > 2	(-4.84)	(-2.78)	(4.94)	(-3.40)	(3.87)				
Duration	Time to execution	11.227	-26.438	-0.288	0.000	-0.322	91,365		1,535.9	1,264.1
		(76.45)	(-32.34)	(-47.75)	(1.33)	(-40.65)				

This table presents summary statistics for the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. Hidden orders are those that were entered with a "no display" qualifier. Visible orders are limit orders not so qualified, that are not matched immediately on arrival. Fleeting orders are visible limit orders that are canceled (unexecuted) within two seconds of entry.

		$\frac{\left(\text{Executions of hidden orders}\right)}{\left(\text{All visible limit orders}\right)}$	(Executed shares in hidden orders) (Shares in all visible limit orders)	$\frac{\left(\text{Executions of hidden orders}\right)}{\left(\text{All Executions}\right)}$	$\frac{\left(\begin{array}{c} \text{Executed} \\ \text{shares in} \\ \text{hidden orders} \end{array}\right)}{\left(\begin{array}{c} \text{All executed} \\ \text{shares} \end{array}\right)}$	$\frac{\left(\begin{array}{c} \text{Fleeting} \\ \text{limit orders} \end{array}\right)}{\left(\begin{array}{c} \text{All visible} \\ \text{limit orders} \end{array}\right)}$	(Shares in fleeting limit orders) (Shares in all visible limit orders)
	Mean	3.1%	1.8%	11.8%	11.8%	27.7%	32.5%
	Median	2.0	1.1	10.1	10.3	25.4	29.8
Total	SD	3.3	1.9	9.3	9.5	11.7	12.0
Sample	Min	0.0	0.0	0.0	0.0	5.9	5.8
	Max	18.2	11.7	100.0	100.0	88.4	91.5
	Nobs	300	300	299	299	300	300
Means for	Low	1.7%	1.0%	9.2%	9.2%	32.5%	36.7%
mkt. cap.	Medium	3.0	1.8	11.5	11.6	27.6	32.7
groups	High	4.7	2.7	14.6	14.5	22.9	28.1
Means for	Low	0.9	0.5	7.7	7.8	36.9	40.5
trade	Medium	3.1	1.8	12.2	12.3	25.9	31.6
groups	High	5.4	3.1	15.3	15.3	20.2	25.4
Means for	Low	0.8	0.5	6.6	6.4	34.7	37.5
	Medium	2.8	1.6	10.7	10.9	26.9	32.1
o_r groups	High	5.9	3.3	17.9	18.0	21.4	28.0

Table 12. Pricing of fleeting orders

This table presents summary statistics for the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. Fleeting orders are visible limit orders that are canceled (unexecuted) within two seconds of entry.

		Buy orders	relative to Is	sland's bid	Sell orders relative to Island's a			
		Better	At	Behind	Better	At	Behind	
	Mean	83.9%	6.7%	9.5%	85.6%	6.6%	7.9%	
	Median	88.9	5.1	5.7	87.9	5.8	5.8	
Total	SD	14.9	6.1	9.5	10.5	4.7	7.0	
Sample	Min	30.2	0.0	0.0	47.7	0.0	0.0	
	Max	100.0	33.3	48.1	100.0	28.2	40.6	
	Nobs	300	300	300	300	300	300	
Means for	Low	92.8%	3.2%	4.0%	91.7%	4.6%	3.8%	
mkt. cap.	Medium	85.8	6.1	8.1	86.4	6.4	7.3	
groups	High	73.0	10.8	16.2	78.7	8.8	12.6	
Means for	Low	96.4	1.5	2.2	94.5	3.1	2.3	
trade	Medium	87.2	5.7	7.1	86.7	6.4	6.9	
groups	High	68.0	13.0	19.1	75.5	10.1	14.4	
Means for	Low	90.4	4.0	5.6	91.0	4.6	4.4	
ivieans for	Medium	83.3	7.0	9.8	85.7	6.7	7.6	
o_r groups	High	77.9	9.2	13.0	80.0	8.3	11.7	

Table 13. Market share

		Island's market share in:		
		Trades	Volume	
	Mean	6.2%	3.5%	
	Median	5.2	2.7	
Total Sample	SD	5.0	3.5	
	Min	0.0	0.0	
	Max	23.7	20.3	
	Nobs	300	300	
Means for	Low	3.0%	1.6%	
mkt. cap.	Medium	6.0	3.2	
groups	High	9.7	5.8	
Means for	Low	1.8	0.9	
trade	Medium	5.5	2.8	
groups	High	11.3	6.9	
Means for σ_r groups	Low	2.6	1.3	
	Medium	6.6	3.5	
	High	9.6	5.7	

Summary statistics for the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999.

Table 14. Island's quotes and the National Best Bid and Offer (NBBO)

Summary statistics for the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999.

		Prop	Proportion of time Island quotes are at NBBO						
					Alone at	Alone at	Alone at		
		At ask	At bid	At both	the ask	the bid	both		
Total Sample	Mean	19.6%	18.6%	4.0%	3.9%	3.9%	0.2%		
	Median	14.5	14.4	1.3	2.9	3.0	0.1		
	SD	15.2	13.9	6.5	3.3	3.2	0.5		
	Min	0.0	0.7	0.0	0.0	0.0	0.0		
	Max	73.3	69.0	45.8	21.6	21.9	4.3		
	Nobs	300	300	300	300	300	300		
Means for	Low	10.1%	9.6%	1.0%	2.2%	2.5%	0.1%		
mkt. cap. groups	Medium	17.0	16.7	2.7	3.9	4.0	0.2		
	High	31.7	29.3	8.2	5.7	5.3	0.4		
Means for	Low	7.6	7.3	0.3	2.1	2.5	0.0		
trade groups	Medium	14.6	14.4	1.5	3.6	3.7	0.1		
	High	36.5	33.9	10.0	6.1	5.6	0.5		
Means for σ_r groups	Low	13.7	12.6	2.8	2.0	2.1	0.0		
	Medium	21.2	20.2	4.0	3.9	3.9	0.2		
	' High	23.8	22.8	5.1	5.8	5.7	0.5		

Figure 1. Number of Trades

The sample is the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. The figures is based on Island order data and the Nasdaq Nastraq database.



Figure 2. Island market and limit orders

The sample is the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. The figures is based on Island order data.

5,000 4,000 Average Daily Number 3,000 2,000 1,000 0 2 3 4 5 8 1 6 7 9 10 Mkt Cap Decile (within sample) Limit orders, quote or better] Limit orders, away Market orders

Figure 3. Executions and cancellations over time

The sample is the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. The figure plots failure functions (cumulative probabilities of occurrence) for executions and cancellations of limit orders over time, estimated with the Kaplan-Meier correction for censoring. In estimating the function for execution, cancellation was treated as equivalent to censoring. In estimating the function for cancellation, execution was treated as equivalent to censoring.



Figure 4. Nasdaq and Island Volume

The sample is the 300 largest firms in the Nasdaq National Market (ranked by equity capitalization as of September 30, 1999), over the 64 trading days in the fourth quarter of 1999. The figures presents a log/log plot of a firm's average daily volume for Island vs. that for all of Nasdaq. It is based on Island order data and the Nastraq database.

