Three Essays on the Market Microstructure of the Saudi Stock Market

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ABSTRACT

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Using data sets on orders, order packages, quotes, trades and market-limit orders, we investigate several aspects of the microstructure of the Saudi Stock Market (SSM) under the computerized trading system, ESIS (Electronic Securities Information System). We study the interaction between the order book and order flow, limit order execution, trading by limit versus market orders, order performance, and the information content of newly submitted orders. Our findings provide new evidence for several issues, and have important implications for the design of the trading mechanism on the SSM.

Although the SSM has a distinct structure, the intraday patterns in its order book and flow are surprisingly similar to those found in other markets with different structures. The average relative inside spread is large compared to other markets, mainly due to a relatively high tick size. Tick size is an important determinant of the inside spreads for low priced stocks. While immediacy is available nearly all the time, market liquidity, as commonly measured by width and depth, is relatively low on the SSM. Limit orders that are priced reasonably, on average, have a short duration before being executed, and have a high probability of subsequent execution.

The analysis of market versus limit order trading on the SSM significantly supports the spread effect predicted by order driven market models. The probability of placing a market order increases as the spread decreases. When the order imbalance

increases in favor of the other side of the market, traders are more likely to submit market orders. The performance of orders predicts limit orders placed at the quote, or when the spread is wide, perform best, and that limit orders are subject to a winner's curse.

The assessment of the information content of orders implies the presence of a very large quantity of asymmetric information on the SSM. As predicted by the asymmetric information models, we find that larger and more aggressive orders are more informative. Like many previous empirical studies, information-based trading is higher for less active stocks.

Generally, our findings indicate that liquidity on the SSM, which is sustained by limit order trading, is at risk because of a high level of information trading. Thus, we propose several measures that are expected to increase the level of participation by limit order traders in this market.

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ABBREVIATIONS

CTU	The Central Trading Unit
ESIS	The Electronic Securities Information System
ESISFAST	The ESIS Fully Automated Share Transfer
NASD	The National Association of Securities Dealers
NCFEI	The National Center for Financial and Economic Information
NYSE	The New York Stock Exchange
OTC	Over-the-counter
SAIF	The Saudi Arabian Investment Fund
SAMA	The Saudi Arabian Monetary Agency
SCD	The Share Control Division
SSM	The Saudi Stock Market
SSRC	The Saudi Share Registration Company

The Essays: An Overview

This thesis consists of three essays on the market microstructure of the Saudi Stock Market (SSM) which uses the computerized trading system known as the Electronic Securities Information System (ESIS). The essays are empirical examinations of individual, but closely related topics, that use the same data set. The research examines the behavior of prices and market participants on the SSM to understand better the placement of orders and their effect on liquidity and price formation. The findings have direct implications for the design of the trading mechanism employed on the SSM.

The thesis is unique in several aspects. First, the SSM, which is described in detail in the first essay, is a pure order-driven market with no central exchange, regulated brokers or market makers, and it is closed to foreign portfolio investments.

Second, the unique data set provided by Saudi Arabian Monetary Agency (SAMA) includes all orders for listed stocks submitted during the period from 31 October 1996 to 14 January 1997. Since the market is an order driven market, the order data set allows for the construction of the complete limit order book. The data set also has information that allows for the identification of market and limit orders, and for the generation of additional data sets used in all the essays.

Third, the study is believed to be the first on the market microstructure of the SSM. We provide evidence on several issues related to the interaction between the order book and order flow, patterns in trading activities, performance of market and limit orders, and their information contents. Thus, the thesis adds to the existing empirical literature on order driven markets.

Finally, the thesis examines a number of new issues associated with order driven markets. We examine the probability of executing a limit order on the SSM, test various hypotheses regarding the probability of placing a market order, and investigate the information content of different types of orders that are classified by their size and aggressiveness.

The first essay is a preliminary analysis of the order book, and of order flow and execution on the SSM, in order to examine the trading and liquidity characteristics of equities on the SSM. The current microstructure of the SSM under the ESIS is described, and order and other generated data sets are used to examine the patterns in the order book and the placement of new orders and the interaction between the two. We characterize the order book using summary statistics on the relative spread between adjacent quotes, volumes at these quotes, tick sizes, and availability of immediacy. Also, we examine the intraday patterns in the book variables such as the relative inside spread and quote midpoint. The conditional frequency of different types of orders and trades is used to analyze the determinants of order flow. We condition our analysis using order direction, order aggressiveness, state of the book, and time of the day. Our findings then are compared with earlier studies to determine whether certain patterns identified in these other studies can be generalized to other trading structures. We use order duration and logit regressions to examine the probability of executing a limit order on the SSM conditional on order direction, size, aggressiveness, and other variables. The issue is important because the provision of liquidity on the SSM relies entirely upon limit orders, whose placement depends largely on execution probability.

In the second essay, limit versus market order trading on the SSM is analyzed. We clarify the nature of the tradeoff between market and limit orders, and review prior research on order placement in a pure order-driven market. In these models, a trader chooses to trade using a market order rather than a limit order if his expected utility from placing a market order exceeds that from placing a limit order. Although these models differ in their assumptions, they all predict a positive relationship between the inside spread and the probability of submitting a limit order. Because we can identify market and limit orders for our data set and know the nature of the trader's choice problem in our market, we interpret the data using a *Random Utility Model*. The problem is approached statistically using a logit model. We use the extra information in our data set to test a number of predictions. Specifically, we examine the relationship between the probability of placing a market order and sets of variables related to the state of the book (including the inside spread), trader, order, and the last event type (whether the previous order is a market or limit, buy or sell order). We also examine how the orders resulting from the trader's decision perform in the market using two measures suggested in the literature.

In the third essay, the dynamic behavior of orders and stock prices is examined in order to assess the information content of newly submitted orders on the SSM. Our market provides a favorable environment for studying the extent of asymmetric information. The primary statistical technique employed is the Vector Autoregressive

(VAR) model. While previous studies primarily used VAR specifications that include only trade (market order) variables, our data set allows us to expand the specification to include limit orders which are already in the information set of market participants. Beyond the order size effect, the new specification allows us to investigate the information content of orders with different levels of aggressiveness. We also examine the cross-stock and cross-time differences in the order informativeness measures.

Following the three essays, the major findings are summarized and their policy implications discussed.

Essay 1

A Preliminary Analysis of the Order Book, and Order Flow and Execution

1. Introduction

The recent availability of order, quote, and transaction data from stock markets around the world has stimulated research on intraday stock market phenomena. Intraday patterns identified in the data of U.S. and other developed countries include the persistent U-shaped patterns in returns, number of shares traded, volumes, bid-ask spreads, and volatility.[1] For the U.S. markets, these include studies by Wood, McInish and Ord (1985), Jain and Joh (1988), McInish and Wood (1991,1992), Brock and Kleidon (1992), Gerety and Mulherin (1992), Foster and Viswanathan (1993) and Chan, Chung and Johnson (1995). McInish and Wood (1990) report similar results for the Toronto Stock Exchange

[1] U-shaped patterns refer to the heavy activity on financial markets during the beginning and the end of the trading day, and the relatively light activity over the middle of the day [Admati and Pfleiderer (1988)].

and Lehmann and Modest (1994) find U-shaped patterns in trading for the Tokyo Stock Exchange.

Biais, Hillion, and Spatt (1995) began a new phase in empirical examinations of market microstructure by studying intraday patterns on the Paris Bourse. The trading system for this market, unlike the world's major stock markets, is centralized, computerized, and relies solely on the electronic limit order book. The study provides new evidence on patterns in the order book, order flow, and the interaction between them. Niemeyer and Sandås (1995), Hedvall and Niemeyer (1996), Niemeyer and Sandås (1996) and Hedvall, Niemeyer and Rosenqvist (1997) report similar results on the dynamics of order flow and the characteristics of the order book for the stock markets in Stockholm and Helsinki.

In this essay, we study the Saudi Stock Market (SSM) which uses a computerized trading mechanism known as ESIS (Electronic Securities Information System). While the SSM has many similarities with other order-driven markets, it has several unique characteristics. In particular, it has no central exchange, regulated brokers or market makers, it is closed to foreign portfolio investments, its electronic order book is not fully visible to the traders, and its tick size is constant.

The purpose of the essay is two-fold: The first objective is to describe the current microstructure of the SSM under ESIS in order to assess the importance of different design features of the SSM. The second objective is to examine the trading and liquidity characteristics of equities on the market. Order and transaction data are used to examine the patterns in the order book and the placement of new orders in order to determine whether certain patterns identified in earlier studies can be generalized to other trading structures.

The literature on market microstructure often discusses liquidity measures such as width, depth, resiliency, and immediacy that have more relevance for market order traders. Our unique data set allows us to examine liquidity measures that are relevant for limit order traders, the only suppliers of liquidity on the SSM. Using order duration and logit regression, we present new evidence on the probability of executing a limit order on the SSM.

The remainder of the essay is structured as follows. Section 2 presents a brief review of the history of trading on the SSM followed by a detailed description of the current trading system. The data sets are described in section 3. Sections 4 and 5 analyze the limit order book and order flow respectively. Section 6 presents and analyzes the empirical findings on limit order execution. Section 7 concludes the essay.

2. Description of the Saudi Stock Market

2.1 A Brief History of Trading on the SSM [2]

The SSM is relatively new compared to the stock markets in the developed countries. In 1954, *the Arab Cement Company*, was the first company to go public. Five

[2] More on the history of the SSM is found in Seznec (1987), Abdul-Hadi (1988), Malaikah (1990), Willson (1991), Butler and Malaikah (1992), and al-Dukhail (1996).

primary flotations occurred by the end of the 1950s. During the 1960s, the government played an important role in encouraging broader ownership by privatizing part of the state utilities such as the electric companies, and by guaranteeing fixed dividends to investors. The largest increase (19) in the number of publicly traded companies occurred during the period 1976-1980, which corresponded to a period of economic prosperity in the country. By the end of 1984, 50 companies traded in the market which was completely unregulated by the government. About 80 unofficial stockbrokers who had no license, capital or credential requirements informally processed buy-and-sell orders for investors.

The *Souk Al-Manakh*[3] crisis in Kuwait in 1982 motivated the Saudi government to take regulatory action to avoid the kind of speculation that had occurred in Kuwaiti's unofficial market. The new regulations transferred share trading, which occurred in the over-the-counter (OTC) market, from the hands of the brokers to the banks. In 1985, the

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[3] *Souk Al-Manakh* is an unofficial market, which began trading shares of Kuwaiti and other Gulf-based companies next to the official Kuwaiti exchange. In August 1982, the official Kuwaiti stock market fell 21% in value and the unofficial market fell about 60%. The crash was caused by the use of post-dated cheques to purchase shares in non-listed and non-Kuwaiti companies not listed on the official Kuwaiti exchange. The use of post-dated cheques allowed buyers to buy shares with no down payment, and defer payments for up to three years in the future. Shares bought with post-dated cheques were sold at a substantial premium, which investors expected to meet from share appreciation. When share prices dropped in May, 1982, many traders were no longer able to meet their payments, and defaults rapidly climbed. According to official estimates, more than $95.5 billion ($17 billion in the official market and $76 billion in the unofficial market) was lost in the crash. The market collapse and ensuing economic and financial crises are referred to as The *Souk Al-Manakh* crisis [Butler and Malaikah (1992)].

Saudi Share Registration Company (SSRC) was jointly formed by twelve Saudi banks to coordinate buy and sell orders between bank branches and to serve as a clearing system for executed trades.

Due to the new regulations, banks installed share departments at some of their branches. Buyers who wanted to purchase shares of a given stock, first had to go to the branch and fill out a detailed order form. The bank then checked its own listing of traders for a seller. If none was identified, the bank then contacted other banks, a time-consuming procedure made by telephone or telex. Under this system, transactions for shares of the same company occurred at different banks at substantially different prices. Because of low volume and lack of coordination between the SSRC banks, a delay of several days or weeks often occurred before orders were filled. Several other restrictions resulted in lengthy delays. Banks could neither hold positions in stocks nor break up large blocks of shares to accommodate buyers.

Since the banks were unable to provide liquidity to the market by buying and selling stocks for their own account, a group of active investors became unofficial market makers. They posted their own bid and ask prices, and traded for their own and others' accounts. These unregulated investors ultimately traded through the banks, and their trades were then reported to the SSRC clearing system.

The second major development in trading on the SSM post-market-regulation was the establishment of an electronic trading system known as ESIS in 1990.[4] Under ESIS,

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[4] This is described in more detail in the next section of the essay.

all buy-and-sell orders placed at individuals banks are transferred to a central system at the Saudi Arabian Monetary Agency (SAMA) for matching on an equitable basis. ESIS also provides accurate information on outstanding orders, bid-and-ask prices, and other relevant statistics. The annual trading statistics for the SSM, as reported in Table 1, suggests a positive effect from the introduction of this computerized system due to the elimination of market fragmentation, and trading and reporting delays.

The SSM has several characteristics that differentiate it from other stock markets in the world. The market has no trading floor and no separate independent regulatory agency. Currently, trading on the SSM is regulated by three agencies: Ministry of Finance and National Economy, Ministry of Commerce, and SAMA (the central bank in Saudi Arabia).[5] There are no regulated brokers or market makers, and trades are executed through the twelve commercial banks which cannot hold positions in stocks.[6]

The Saudi market is the largest in the Arab countries in terms of market capitalization. At the end of 1996, 71 companies were traded in 6 different sectors (see Table 2). This represents a market value of US$ 41 billion,[7] and accounts for 46% of Arab stock market capitalization. However, the SSM is relatively small and thin by

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[5] Ministry of Commerce regulates the Initial Public Offerings (IPO) and information disclosure, and The Share Control Division (SCD) under the jurisdiction of SAMA handles day-to-day securities trading including operating and maintaining ESIS. Members from the Ministry of Finance are on the Supervisory Committee for Share Trading that has the authority to impose new regulations in the market.

[6] In 1992, SAMA allowed banks to manage open-ended mutual funds for public investors. However, the banks are still not allowed to invest directly or indirectly, through the mutual funds, in Saudi stocks.

[7] The Saudi Riyal (SR) has been pegged to the US$ at rate of US$ 1= SR 3.75 since June 1, 1986.

international standards. At the end of 1996, the market value was 30% of GDP, and the annual value of shares traded was about 15% of total market capitalization. Average daily turnover equals US$ 22 million. One reason for market thinness is ownership structure. Government and foreign sectors, who rarely trade their holdings of companies shares, hold a large percentage of the market available shares (46% in 1996). Even among the shares available for trade, large blocks are concentrated in the hand of investors who are less likely to sell their holdings because they do not wish to lose their board representation or voting influence.

IPOs on the SSM are tightly regulated both in terms of initial share price (usually SR 100) and the size of the share blocks that can be sold. Since government policy is tilted towards shareholders, offerings are usually grossly oversubscribed. Most companies which go public in Saudi Arabia are newly established corporations with no operating history and large capital requirements.

Although forward trading, buying on margin and the acceptance of post-dated cheques to settle current transactions are prohibited. the market is highly volatile. Fluctuations in the all-market index of the National Center for Financial and Economic Information (NCFEI Index)[8] during the period from February 1985 to June 1997 are evident from Figure 1. The market low was 63 in September 1986, and the high was 234 in April 1992 after the end of Gulf War II.

[8] The NCFEI index is capitalization-weighted with a base value of 100, and a base date of February 28, 1985.

Only Saudi companies are listed on the market, and ownership of these companies is limited to Saudi nationals with few exceptions.[9] The potential for insider trading is significant because no mechanism exists to prevent insiders from buying and selling company shares based on inside information. Not all companies have complied with quarterly disclosure demands required by SAMA for continued listing and no accounting standards apply to all companies.[10]

2.1 The Structure of the SSM under ESIS [11]

Since regulating the market, all trading activities are confined to the twelve Saudi banks. [12] After the startup of ESIS in August 1990, the banks established twelve Central Trading Units (CTU) in Riyadh where all the regulatory bodies are located. All of the CTUs are connected to the central system at SAMA. The CTU in each bank and other designated branches in various parts of the country that are connected to the CTU

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[9] In April 1997, SAMA allowed foreign ownership of Saudi stocks through the Saudi Arabian Investment Fund (SAIF), a closed-end mutual fund listed on the London Stock Exchange and managed by the Saudi American Bank.

[10] The information disclosure law set by the Ministry of Commerce requires all companies to report their audited annual balance sheets and income statements to the public, while SCD requires them to report their quarterly financial statements within two months from the end of the quarter.

[11] The information in this subsection comes mainly from SAMA (1992), market touring, and interviews with officials at SAMA.

[12] The regulations also permit share trading through share registration departments of companies. However, the number of transactions usually handled by these departments is very small, and these transactions are usually for reasons not related to market conditions such as transferring ownership between members of the same family.

(ESISNET branches) are the only places where buy and sell orders can be entered directly into ESIS.

Trading lasts for four hours per day, divided into two daily sessions for Saturday through Wednesday, and for one two-hour session on Thursday. Table 3 summarizes trading hours and trading days. During the morning and evening periods no trading occurs, but *wasata*[13] can add and maintain order packages and orders that were entered through their CTU or ESISNET branches. Sell and buy orders are generated from the incoming sell and buy order packages. An order package can have none, one or many firm orders, all within the existing order package parameters of quantity, price and validity period.[14] Order packages entered into the system may be valid for a period from 1 to 12 days.[15]

In the five-minute opening period, all firm buy and sell orders participate in a *call market*.[16] Orders are executed at an equilibrium price calculated to be the best possible price to execute the maximum number of shares available in the market at the open. This

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[13] The *wasata* are neither brokers nor dealers. They are order clerks whose assigned job is merely to receive and verify orders from public traders at the CTU, and then enter these orders into the system.

[14] In ESIS terms, order packages are called orders, and orders are called quotes. These definitions differ from those usually used in the literature. Order in the literature usually refers to order with a firm quote that leads instantly to a bid or ask if it is a limit order, or to a trade if it is a market order. The firm quotes (as defined by the ESIS) are more like orders as usually defined in the literature. In the market, generating a firm quote is the same as placing an order. To be consistent with the literature, orders are referred to as order packages, and quotes are referred to as orders.

[15] Before May 28, 1994, the validity period was either 1, 5 or 10 days. Subsequently, the validity period became 1, 6 or 12 days. From October 1, 1994, the validity period was allowed to be any period from 1 to 12 days.

[16] In a call market, orders for a stock are batched over time and executed at a particular point in time.

is followed by a *continuous auction market*, where marketable orders by public investors are transacted with the limit orders of other public investors.[17] In the post-trading period, trades are routed to settlement, trading statistics are printed, and no order package or order can be added or maintained.

Only limit orders with a specified price and firm quantity are permitted. Firm orders are eligible for execution during the opening and continuous trading periods according to price-then-time priority rules. An investor can adjust order prices and their quantities, change a firm order to on-hold, or cancel his order at any time.[18] With each change, the order loses its time priority. When adjusted, the order price must be within its order package quantity and price limit. Aggressive sell (buy) orders can walk down (up) the limit order book.[19] When an order is partially executed, any unexecuted balance is automatically placed in a new order at the same price and with the same execution priority as the original order. The order package can be executed fully or partially

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[17] Limit order is an order for a specific quantity and a specific price for a given period of time. For a limit buy (sell) order, the price is below (above) the current ask (bid). Marketable limit order is a limit order with a limit price at or better than the prevailing counterparty quote. For a marketable buy (sell) order, the price must equal or better the current ask (bid). Notice that the standard market order (order to buy or sell a given quantity for immediate execution at the current market price, without specifying it) is not accepted by the system. Since marketable and market orders are essentially similar, we use the term market order when referring to marketable orders in the remainder of the essay.

[18] All or part of an order package can be put "on-hold" or returned back to the market at any time. "On-hold" orders are out of the market, have no price or time priority, and they do not become automatically firm after executing all or part of the outstanding firm quantity in the order package.

[19] The limit order book ('the order book') is the collection of all quotes generated from all firm limit orders arrayed in descending prices for bids and in ascending prices for asks.

through more than one transaction at different times, with different orders, and maybe, with different prices.

To reduce adverse selection problems, the system has some negotiation capability beside the automatic routing and execution.[20] A transaction with large value (usually SR ½ million [US$133.333] or more) has to be executed outside the system under SAMA supervision. After execution, the *put-through* transaction is immediately reported to the market. Bought-in (or sold-out) trades to close a defaulted delivery (or purchase) are handled as a *put-through* between the original buyer and seller. The parties to *put-through* transactions have no obligation to clear the limit orders in between.

The minimum price variation, or tick size, for all stocks in the market is SR 1 (≈ 27 cents). This constant tick size implies a decreasing minimum relative spread as price increases. Stocks priced at SR 50 or less have a minimum spread of 2% or more, and it is less than 0.5% for stocks priced over SR 200. At the end of June 1996, only 20 stocks had prices exceeding SR 200.

During continuous trading periods, firm orders must be priced within +/- 10% of the opening price of the given trading period. If no opening price exists for that period, the opening price defaults to the previous day's closing price. However, occasionally SAMA can allow the price to exceed the present fluctuation limit provided the new prices are reasonably justified by the earnings or prospects of the company. Also, a potential

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[20] Adverse selection problem exists if some traders have superior information and cannot be identified. In this situation, the unformed traders lose on average to informed traders. Without uncertainty, the uninformed traders would trade with each other and not trade with the informed at all.

execution of two orders from the same CTU should be delayed for 15 minutes if there are no orders from other CTUs for the same stock. Two orders cannot be matched and executed (crossed) if they belong to the same trader. The rationale behind these regulations is to prevent one or more investors from creating a false market in a given security. Each potential execution of an order of an inactive security not traded for 20 consecutive days must be delayed for 20 minutes before it is executed against the best quote in the market.

The commissions for the executed portions of the orders, which are charged on each side of the trade, are calculated as in Table 4. A minimum commission of SR 25 is charged for any transaction in the first slice. The commission is distributed in two parts: 95% to the banks, and 5% to the SSRC for settlement and transfer services.

The electronic limit order book is not fully visible to investors since information is displayed publicly in an aggregate format (i.e. only the best quote with all quantities available at that quote). The status of the best quotes and quantities is updated (almost instantaneously) on bank screens each time an order arrives, is cancelled, or executed. Public investors can view the price, quantity, and time of last trade. The terminals and big screens where traders can monitor the market are only available in the CTUs and ESISNET branches of the banks. In the early releases of ESIS, only the *wasata* in the CTUs could view the best five bids and asks, and valued bank customers could easily learn this information by calling their bank's CTU. To prevent this type of unfair access to market information and related front-running problems, SAMA on October 1, 1994 restricted both the *wasata* in the CTUs and the public to viewing only the best two bids and asks. The *wasata* still have more information about the order book since they know the details of every order placed through their CTU or ESISNET branches connected to it, including the identification of investors, the price and quantities of firm and on-hold orders, and the type of ownership document for sell orders. Details of every order are only observable to surveillance officials. This level of transparency on the SSM hides all firm orders associated with best quotes beyond the second. Unlike on-hold orders, hidden orders have price and time priority and can be revealed to the market or executed at any time. For example, a firm order to buy with a third best bid is hidden but becomes visible when all the quantity at the first best quote is executed. The order can also be executed while it is hidden by an aggressive market sell order.

Only the *wasata* in the CTUs have the right to enter orders directly into the system. Investors in the SSM consist of public investors and bank phone customers. The latter group of customers have an agreement with the banks to change the price and firm quantity of their submitted orders at any time simply by calling their Bank's CTU. As a result, they are less affected than other public traders by the free trading option associated with limit orders since they can change the condition of their orders very quickly before they are "picked off" when new public information arrives.[21] This group of traders includes the institutional investors (e.g. mutual funds), informed traders who trade

[21] As Stoll (1992) explains, a limit order provides the rest of the market with a free option. The trader who places a buy (sell) limit order has written a free put (call) option to the market. For example, suppose the trader submits a buy limit order at $100. If public information causes the share price to fall below $100, this put option will be exercised and the trader will lose if he did not adjust the limit price.

because they have private information, and many technical traders who have trading and not fundamental information.

Because they conduct research, institutional investors are supposedly more informed than public investors with regard to the underlying economic values of the stock companies. However, they are much less informed than insiders who can trade freely in the market. Consequently, both public and institutional traders can be classified as liquidity traders whose trading arises either from the need to smooth consumption over time or for risk adjustment.

The date and time of transfer of beneficial ownership for each transaction is the date and time of execution in the system. Transaction confirmation slips are usually printed at CTUs and ESISNET branches and distributed to the clients after each trading session. Following the second trading session, transactions are routed for settlement. Under ESIS, share ownership is transferred through SSRC.[22] The settlement date depends on the type of ownership document. *Ishaar*, which can be retained in the system for future sale or printed and given to the investor, are delivered the next morning,[23] while certificates take from two days to one week or more to be delivered. *Ishaar* takes less

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[22] Under ESIS, the major role of SSRC is to keep up-to-date records of shareholding in stock companies and to issue *ishaar*.

[23] On March 19, 1994, SAMA reduced *ishaar* delivery date to one day instead of two. Starting from October 1, 1994, *ishaar* was allowed to be issued in the same branch where the order was submitted. Since September 1995, the buyer can know the type of ownership document immediately after executing his buy order. The latest version of ESIS released in June 1997 allows real time settlement for *ishaar* (i.e. execution and settlement times are the same).

time because it can be handled electronically through ESIS Fully Automated Share Transfer (ESISFAST), while the new certificate has to be issued from the company's share registration department. The goal is to abolish all existing share certificates. Because of the difference in settlement dates, and to prevent the creation of two markets for every security, the type of ownership document is not visible to market participants pre transaction.

3. The Data Sets

The data set, which was provided by SAMA, consists of intraday data on firm orders for all stocks listed on the market for 65 trading days (October 31, 1996 to January 14, 1997). Four of the 71 stocks were excluded due to an absence of orders, three stocks were excluded because they have no transactions, and eight stocks were excluded because they have a small number of transactions. The final data set includes 267,517 orders. For each order, the data set reports security ID, the date and time of creation, buy-sell indicator, limit price, quantity, and date and time when the order was terminated. The data set also includes the ID of each order package that generates the order, and an ID for the order itself. The order package data set can be easily constructed from the order data set because it includes the ID of the package. Our data set has 86,425 order packages.[24]

Given the information in the order data set, we also construct a third data set containing the end-of-minute best five quotes on both sides of the market for all 13,955

[24] Chan and Lakonishok (1995) use the trading package terminology to describe the trader's successive purchases of a stock. The correspondence between their definition of trade package and an ex ante order is approximate, while our order package is exactly the real ex ante order.

minutes of trading. Subsequently, references to quotes (bids and asks) are reserved for this data set. We use the date and time of termination, price and quantity of orders in conjunction with published *daily statistics* to identify the order that was part of a transaction (trade data set). The number of transactions in our sample is 84,382. Table 5 presents some summary statistics for each of the data sets.

Panel A in Table 5 reports the summary statistics for the order data set. Limit orders account for 71% percent of the orders in the sample. Buy and sell orders are almost equal for most stocks. Most orders (63%) are executed. Buy order sizes are slightly larger than sell order sizes for most stocks. Based on Panel B, most of the order packages are to sell. However, the package size and the number of orders per package are always larger for buy order packages. Execution rates are similar and evolve around 0.5. Based on Panel C, the public limit order trader supplies immediacy to the market nearly all the time with an average inside spread equal to SR 2.24. Panel D reports the summary statistics for the transaction data set which includes all market orders, the limit orders executed against them, and the limit orders executed against each other during the call market at the opening. Because two orders constitute each trade, the number of observations in this data set are twice the number of transactions as conventionally reported. Less than 10% of the trades occur during the opening period, and a very small percentage (0.015%) of trades are executed outside of the system (in the so-called upstairs market). The average returns are positive since the market rose over the sample period, as is apparent from Figure 1.

4. Descriptive Statistics about the Order Book

The order book collects all limit orders at any given point of time. Orders come into the book throughout the day at the time they are submitted to the market, and are removed from the book as they are executed, cancelled, or expired. This section presents and discusses various descriptive statistics concerning the order book.

4.1 Relative Spreads and Depths in the Order Book

From the orders data set, we know when the orders are entered and are removed from the book. Using this information, we extract the five best quotes and their associated depths at the end of each minute during the sample period.[25] Although our subsequent analyses are based on the five best quotes, it is important to remember that market participants only observe the first two best quotes.

Table 6 reports the cross-sectional statistics of the time series means of relative spreads between adjacent quotes in the book, and average volumes at all levels for the 56 stocks in the sample. Based on Panel A , the average (median) relative inside spread is 1.79% (1.6%) which is high compared to other markets.[26] Angel (1997) uses data on the bid-ask spread for major market indices for fifteen countries and finds that the median relative spread equals 0.65%. The relative tick size, as is shown in the next section, is the major contributing factor to this high relative spread. The relative inside spread is larger

[25] The depth is the number of shares offered or demanded at a given bid or ask.

[26] The inside spread is the difference between the first best ask ($A1$) and the first best bid ($B1$). The relative inside spread is the inside spread divided by quote midpoint: $2\frac{A1-B1}{A1+B1}$.

than all other relative spreads on either side of the book. The other relative spreads are moderately constant. In contrast, the average numbers of shares at the first best quote are small (and the smallest on the ask side), are the largest at the second best quote, and decrease beyond the second quotes.[27] Based on the test results reported in Panel C, the hypotheses that all relative spreads and all depths are equal are rejected, but not rejected when we exclude the inside relative spread, and the depth at the second quotes.[28] On average, depths and relative spreads are larger on the bid side.

Our results lie somewhat between those of Biais, Hillion, and Spatt (1994) and Niemeyer and Sandås (1995). Using data from the Paris Bourse, Biais *et al.* find that the order book is slightly concave, with an inside spread more than twice as large as the difference between the other levels of the book (which is similar to our results). They also find that the volumes offered or demanded at the first best quotes are smaller than the volumes further away from the best levels. In contrast, Niemeyer and Sandås find that the order book on the Stockholm Stock Exchange is convex. Spreads are wider further away from the inside spread, and volumes larger close to the inside spread. In fact, they find as we do that the average volumes at the second best quote are the largest. As Figure 2

[27] The number of orders contributing to each quote (not reported) also has the same pattern as the volumes. Namely, they exhibit an inverted U-shape: largest at the second best quotes, and smaller for the others quotes.

[28] The test is conducted using dummy variable regressions of the form $y = b_1 d_1 + \ldots + b_p d_p$, where y is the relative inside spread (or the depth) for all stocks after we stack all observations; d_i, $i=1,\ldots,p$, is a dummy equal to one if the observation y belongs to the book level i; p equals 9 for relative spread tests and 10 for the depth tests. We perform the reported equality tests using different sets of linear restrictions.

shows, the slope of the order book in our market does not depart strongly from linearity.[29] It is slightly concave near the second quote and convex thereafter. One possible interpretation for this shape is that the adverse selection problem is more pronounced closer to the inside spread. This leads to a higher inside spread, and smaller volumes at the first best quotes. Since all of the five best quotes are available to market participants on the Paris Bourse, and only the best two on the SSM, the contradiction between our results and those of Biais *et al.* may be due to the difference in the information available, which can affect the strategies of market participants. However, our data does not allow us to determine how the volume would be distributed for a different information structure.

Because the relative inside spread is larger and the depth lower, market liquidity as usually measured by width and depth is relatively low.[30] Market order traders can buy or sell a large number of shares but only at high transaction costs.

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[29] As in the limit order model of Glosten (1994), the execution of a trade against the book in the SSM occurs in a discriminatory fashion. Large trades that execute against several limit orders at different prices will have two prices: marginal and average prices. Glosten denotes the marginal price function of the limit order book by $R'(q)$. For q positive (negative), $R'(q)$ is the ask (bid) price paid for the last share in a purchase (sale) of q shares. The plot of price changes for trades of different sizes (as in Figure 2) is an approximation of the slope of the book, $R'(q)$.

[30] Four dimensions are often associated with liquidity in the market microstructure literature: width, depth, immediacy and resiliency. According to Harris (1990), width refers to the spread for a given number of shares, depth refers to the number of shares that can be traded at given quotes, immediacy refers to how quickly trades of a given size can be done at a given cost, and resiliency refers to how quickly prices revert to former levels after they change in response to large order flow imbalance initiated by uninformed traders. Overall, a market is liquid if traders can quickly buy or sell large numbers of shares when they want at a low transaction cost.

4.2 Tick Size and Price Discreteness

The SSM has one tick size of SR 1, which imposes price discreteness and forms a lower bound on the spread. The prices of the stocks in our sample range from 24 to 960 implying a minimum relative spread (or relative tick size = 1/price) between 4.21% and 0.1%. The median relative tick size is 0.9% which is relatively large compared to the median relative tick size for major stock markets. Using data for 2,517 stocks that constitute the majority of the capitalization in the world equity market, Angel (1997) finds that the median relative tick size is equal to 0.259%

Theoretically, a large tick size encourages limit order traders to provide liquidity to the market, and imposes higher transaction costs on market order traders. Given the price and time priority rules, the limit order trader has a first mover advantage only if the tick size is large enough to prevent quote matching.[31] If the tick size is small, the quote matcher obtains time precedence by submitting an order at a price slightly better than the standing quote. Thus, tick size is the maximum value of time precedence and the minimum cost that a quote matcher must pay.

Based on the summary statistics on tick size reported in Table 7, 53.8% of the inside spreads are binding (the inside spread equals one tick), 22.5% equal two ticks, and 23.8% equal three or more ticks. Tick size is more important for lower priced stocks. The tick size is binding for 77% of the observations for stocks in the lowest price category.

[31] Quote-matchers are traders whose willingness to supply liquidity depends on the limit orders of other liquidity suppliers. Harris (1990) discusses the quote-matcher problem in detail.

and for only 26% of the stocks in the highest price category. The majority of the other spreads are binding even for highly priced stocks. The last row of Table 7 supports the assertion that large tick size encourages limit orders traders to provide liquidity to the market. The percentage of limit orders submitted to the market increases as the relative tick size increases.

4.3 Availability of Immediacy

Immediacy is available in the market when a market order can be instantaneously executed. In an order driven market as the SSM, the availability of immediacy depends upon the limit order traders. Immediacy will be unavailable if no public limit orders are present. Table 8 summarizes the percentages of time when immediacy is available at all levels of the book. The sample period has 65 morning trading sessions of 115 minutes each, and 54 evening trading sessions of 120 minutes each. This results in a grand total of 13,955 trading minutes. Despite the absence of market makers, market liquidity measured by immediacy is notably high. On average, the immediacy at the first best quotes is available for 98% of the total trading time. As expected, most active stocks have even higher percentages. The difference between the five categories becomes more evident as we move away from the first best quotes. Comparing the results in Table 8 with those in Table 6, we find that the volumes offered at the asks are smaller but last longer than the volumes demanded at the bids.

4.4 Intraday Pattern in the Order Book

In this section we examine the intraday pattern in the relative inside spread, depth and the squared quote midpoint return.[32] As shown in Figure 3, the relative inside spread decreases over the first trading session, and is fairly constant over the second. The test results reported in Panel A of Table 9 support this result. In the first session, the last trading interval has the lowest relative spread (1.74%). The regression is constructed so that the slopes represent the difference between the mean relative spread in this interval and the other intervals in the session. As constructed, the *t*-statistics are direct tests of whether any differences exist in mean relative spreads. Moving from the first to the seventh coefficient estimate finds that both the difference and significance decrease. We also reject the hypothesis that all differences are zero. In contrast, no significant patterns are identified in the second trading session.

While many studies document a U-shaped intraday pattern for the spread,[33] other studies report patters similar to that found in our market. Chan, Christie and Schultz (1995) find that NASDAQ spreads are at their highest at the open and narrow over the trading day. Similar results are reported by Chan, Chung and Johnson (1995) for the CBOE options, and by Niemeyer and Sandås (1995) and Hadvall (1995) for two order-driven markets, the Stockholm Stock Exchange and Helsinki Stock Exchange, respectively.

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[32] The quote midpoint is the average of the best bid and ask quotes.

[33] Studies which find a U-shaped pattern in the spread include Brock and Kleidon (1992), McInish and Wood (1992), Foster and Viswanathan (1993) and Lehmann and Modest (1994).

If the spread is a good proxy for transaction costs, the relative inside spread pattern together with patterns found in trading activities (see section 5.3) is not supportive of most of the models for explaining trade concentration. Admati and Pfleiderer (1988) present a model where concentration of trading may be generated at an arbitrary time of the day. Liquidity traders, particularly traders who have to trade within a given time period, pool their trades in an effort to reduce their transaction costs. Informed traders, in an attempt to hide their trading intentions, also trade at the same time. The model predicts that traded volume should be highest when transaction costs are lowest. Similarly, Brock and Kleidon (1992) conjecture that periodic market closure results in greater liquidity demand at the open and close. In response, liquidity suppliers may practice price discrimination by changing their quotes during these periods of high demand. This model implies high transaction volumes and concurrent wide spreads at both the open and close.

However, the observed spread pattern for the SSM can be explained using the model of Madhavan (1992). The high spread in the morning is due to greater uncertainty. As information asymmetries are partially resolved, traders become informed by observing the market. This leads to a decline in the spread during the day. The explanation offered by Chan, Chung and Johnson (1995) attributes such a spread pattern to the absence of specialist market power.

We use the squared midpoint quote returns as a measure of stock return volatility. As shown in Figure 3 and the regression results reported in Panel B of Table 9, volatility is at its highest during the first trading interval, followed by the last trading interval before the close.[34] Considered in isolation, this finding is consistent with the information-based model of Admati and Pfleiderer (1988), which predicts that high volume periods have more informative and hence more volatile prices.

No significant patterns are identified for the number of shares and volume for the first best quotes, probably due to high limit order duration in this market. The median duration of all limit orders is 55 minutes, whereas the median duration of non-executed limit orders placed at or within the inside spread are 202 and 154 minutes, respectively.

5. Order Flow Dynamics on the SSM

In this section, we investigate the dynamics of order flow on the SSM. We condition our analysis on order direction (buy or sell), price position, state of the book, and time of the day.

5.1 Order Flow and the Limit Price Position

We divide the orders into twelve categories based on limit price position. On the buy side, the price position of a buy order may be above the prevailing ask (aggressive market buy), at the prevailing ask (market buy), within the existing spread (limit buy within), at the prevailing bid (limit buy at), and below the prevailing bid (limit buy below). The last event is the cancellation of a previously posted limit buy. Orders on the sell side are categorized similarly. The frequency of each occurrence is documented in

[34] The U-shaped pattern in volatility is documented for other markets by Wood et al (1985), Harris (1986), McInish and Wood (1992), Foster and Viswanathan (1993), and Lehmann and Modest (1994).

the last row of Panel A in Table 10. With regard to market orders, the most frequent events are market sell and buy orders (11.48% and 13.41%, respectively). The frequency of aggressive orders is very small. On the limit order side, the most frequent events are limit orders at or away from standing quotes. The percentage of limit orders within the inside spread is relatively small. Consequently, most of the activity is at or away from the best quote.

In Table 10, the columns correspond to an event at time *t*, and the rows to events at time *t-1*. Each row reports the percent frequency of each of the twelve events conditional on the event in that row. The table supports the "*diagonal effect*" found in Biais *et al.* (1995) that the probability that a given event will occur is larger after this event has just occurred than it would be unconditionally. For example, market sell (buy) orders are most frequent after market sell (buy) orders.[35] Biais *et al.* put forward three explanations for this correlation. First, the succession of identical types of orders could reflect strategic order splitting, either to reduce the market impact of a non-informational trade, or to get the most from private information about the value of the stock. Second, if different traders are imitating each other, the cause of the correlation is the order flow itself. Finally, traders could react similarly to the same events related to a particular stock or the economy as whole.

Since our data sets do not identify traders, we cannot explicitly investigate the three hypotheses concerning individual order submission behavior. However, we know

[35] The diagonal effect is present beyond one lag. When we account for additional lags, we find similar effects.

that orders originating from the same order package certainly belong to one trader, and this allows us to infer a subset of orders belonging to the same trader. The fraction of observations where the same trader acted in two subsequent events is 28.94% of all of the order flow events.[36] To test the above hypotheses, we split the data into two subsets. The first subset contains the subsequent order flow events that are definitely initiated by the same trader. The second subset contains the subsequent events that are generated by one or different traders. If the order-splitting hypothesis is the dominant factor in explaining order flow correlation, then we should observe higher correlation in the first data subset. This is indeed the case as shown in Panel B in Table 10. The diagonal conditional percent frequencies in the same trader sub-sample are larger for most events, which indicates that the "diagonal effect" is more common in the same trader subset. Hedvall and Niemeyer (1996) use a data set from the Helsinki Stock Exchange that includes dealer identities and find, as in our market, that strategic order splitting is more common than imitation.

The diagonal effect in the case of limit orders within the best quotes, not conditional on trader identity, has been explained by the undercutting and overbidding behavior of traders competing to supply liquidity to the market [Biais *et al.* (1995)]. The results in Panel B do not support this explanation. The gradual narrowing of the spread,

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[36] Given the limited information concerning trader identification for our data set, the frequencies of subsequent order events on different sides of the market from one trader are always zeros. In reality, these frequencies may not be zero. However, the fact that market regulation does not match and execute two orders if they are generated from the same trader makes this possibility less likely. One trader can make a market in one or more stocks by posting limit orders on both sides of the market, but he cannot make a false market by executing his market orders against his limit orders.

as a result of placing quotes within the spread, comes mainly from the same trader and not from competition between different traders. However, the succession of cancellation is consistent with the explanation that traders imitate each other or react similarly to the same events.

Based on Panel A of Table 10, we find that market buys (sells) are exceptionally frequent after asks (bids) at and within the best quotes. Traders prefer to wait for more additional liquidity to be provided, and preferably at a better price, before deciding to trade. In contrast, limit orders to buy (sell) at the quotes are particularly frequent after market sell (buy) orders. Since a market sell (buy) order consumes the existing liquidity and may lead to a downward (upward) shift in the book, the observed behavior may reflect competition between limit order traders to restore liquidity. Market liquidity in term of resiliency is considerable.

Several other observations are consistent with information effects in the order process. After aggressive and market sell (buy) orders, there are often new limit sell (buy) orders placed within the quotes. Furthermore, limit buy (sell) orders placed away from the quote and cancellations on the buy (sell) side of the book are more frequent after aggressive market sell (buy) orders. The order book tends to shift downward (upward) after aggressive market sell (buy) orders. This behavior could reflect the adjustment in market expectations to the information content of these trades.[37] Biais *et al.* observe a similar effect after large trades, and attribute their observation to the information effect.

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[37] This adjustment could be transient or permanent. Evidence on the permanent price reaction to different types of orders is investigated in the third essay using time series methods.

Using χ^2 tests for the significance of the equality between the condition and unconditional probability for all stocks, we reject the hypothesis at the 1% level.

5.2 Order Flow and the State of the Order Book

Table 11 reports the probability of different types of orders and trades occurring given the previous state of the book. The state of the book is summarized by the size of the inside bid-ask spread and the depth at the first best quotes. Both the spread and depth for a given stock are defined to be large (small) when they are larger (smaller) than their respective time series medians over the sample period. Consistent with earlier theoretical and empirical findings for order flow, market orders occur more frequently when the spread is tight. Limit orders occur within the spread more frequently when the spread is large. Limit orders "offer liquidity when it is scarce" and market orders "consume it when it is plentiful" [Biais *et al.* (1995)].

Limit orders within the spread occur more frequently when the depth at the quote is large, and limit orders at the quotes are relatively more frequent when the depth is small. Given the price and time priority rules, the only way to increase the probability of execution when the depth is large (and especially when the spread is large) is to undercut or overbid the best quote. Based on χ^2 tests, we reject the null hypothesis at the 1% level of the independence between the order and trade events and the state of the book.

5.3 Order Flow and the Time of the Day

In this section, we examine the pattern of number and volume of all, limit and sell orders, and all, small and large transactions. As Figure 4 shows, the number and volume of all new orders and transactions exhibit a U-shaped pattern during each within-day session, and a W-shaped pattern over the trading day. The proportions of orders and trades submitted are largest in the morning. The proportions in the first trading interval in the second session are usually larger than the proportions at the end of day. The concentration around the open and close are like those observed in many stock markets with different microstructures.[38]

In section 4.4, we discussed models that can be used to explain this concentration. The call market also may be a contributing factor to the concentration at the opening. Since all qualifying orders are executed at a single price at the open, traders benefit from their orders being executed at a price better than their quote. Limit order traders are less affected by free option problems at the open, and lose less to informed traders if they trade during the call market. The large proportion of limit orders during the first interval of each session supports this explanation. The high level of limit orders at the end of every trading session could result from limit price adjusting.[39] Less patient traders start to

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[38] See, for example, Jain and Joh (1988), McInish and Wood (1990,1991), Gerety and Mulherin (1992), Foster and Viswanathan (1993), Biais, Hillion and Spatt (1995) and Niemeyer and Sandås (1995).

[39] Adjusting the limit order price or quantity results in the order receiving new date and time stamps. Accordingly, an order adjustment leads to two events: canceling an existing order, and submitting a new one.

adjust their price as the end of the session approaches in order to induce other traders to execute against them [Niemeyer and Sandås (1995)].

A larger proportion of small orders is executed at the opening, whereas larger proportions of large orders are executed during and at the end of the session. One possible explanation for this behavior put forward by Biais *et al.* (1995) is that small traders at the opening contribute to price discovery, while large trades tend to occur after price discovery has already occurred.

Test results for the significance of the patterns in number and volume for new orders and transactions are reported in Table 12. The pattern in the observed p-values indicates significant U-shapes. Similar unreported results are found for the pattern for limit orders, small and large trades.

6. The Analysis of Order Execution

Market liquidity can be measured by the cost of effecting a transaction at a given point of time, or by the time it takes to transact [Lippman and McCall (1986) and Amihud and Mendelson (1989)]. In our examination of the order book and order flow, various aspects of the former measure of market liquidity (such as width, depth, resiliency and the availability of immediacy) were addressed. The former measure of liquidity is more relevant to market order traders whose objective is to obtain immediacy at a low cost. The latter measure of liquidity is more relevant to limit order traders, who supply liquidity on the SSM. In a setting where limit orders provide immediacy and wait for order execution, the liquidity is measured by the expected time to execute a limit order at a given price, and more generally, by the probability of limit order execution. In this section, we examine these issues.[40]

6.1 Order Duration Given Limit Order Characteristics

The duration of an order is the length of time until the order is executed, cancelled or expired. Following Harris (1996), we measure order aggressiveness by $1\text{-}2(A\text{-}p)/(A\text{-}B)$ for buy orders and the negative of this quantity for sell orders, where A (B) denotes the first best ask (bid), and p is the limit order price. This measure assigns a value of one to market orders and less than one to limit orders. Limit orders placed at the quote have a value of -1, and the difference between the order price and the best quote on the same side increases as this value get a smaller.

Table 13 reports median durations for different types of limit orders. The median duration for all limit orders is 55.82 minutes. Duration is shorter for more aggressive orders, which is a natural outcome of the price priority rule. The difference between the durations of executed orders and non-executed orders, even those placed within the spread, is high. The median duration for non-executed orders placed within the spread is 154 minutes, while it is only 1.37 minutes for executed orders. Executed (non-executed) sell orders have shorter (longer) durations than buy orders. Given that sell orders have a smaller median size, this result explains the previous finding that volumes offered at the ask are smaller but last longer. The number of orders per package is used to measure the degree of trader activity in the market, where large numbers indicate more active traders.

[40] A trader's decision to choose to trade using a market or limit order is addressed in the second essay.

Order duration for more active traders is shorter for orders priced within the spread, and longer for orders placed at or away from the market. Active traders frequently have standing firm orders at and away form the quote either to make a market, or to seize the free option quickly. Since they also monitor the market more closely, we expect them to adjust their exposed orders more frequently than others. No systematic patterns are detected in the durations of orders with large and small sizes, or for those submitted when the inside spread is small or large.

6.2 The Probability of Executing Limit Orders

When immediacy is available during a continuous trading session, a trader can trade with certainty using a market order and not limit order. The probability of executing a limit order is always less than one. In this section, we analyze the probability of order execution using a logistic probability model. The dependent variable, y, is the execution indicator, which equals one if the order is executed and zero otherwise. The probability of execution is conditioned on a set of regressors, x, $\text{Prob}[y=1 \mid x] = \Lambda(x'b)$, where $\Lambda(.)$ is the logistic cumulative distribution function. The marginal effect of x on the probability is $\Lambda(x'b)[1-\Lambda(x'b)]\, b$. The set of regressors in x includes a constant, a direction dummy (sell=1,buy=0), an aggressiveness indicator, order size, number of orders per package, and the inside spread. We report the cross-sectional distribution of the estimate of the coefficient, b, and the marginal effect (the slope) in Table 14. The marginal effect, $\Lambda(.)$, is evaluated at the mean of the variable. The rejection rate for the null hypothesis that each b is equal to zero, which is reported in the last column, is relatively high, especially for the aggressiveness indicator.[41] The logit regression results indicate that more active traders and sell orders have higher probabilities of execution. While the market has no size priority rule, small orders have a higher probability of execution. Orders submitted when the spread is small also have a higher probability of execution, probably because a smaller spread implies a lower transaction cost. This provides a greater incentive for market order traders to execute against the existing limit orders.

Similar to the findings in the previous section, price aggressiveness has the most significant effect (positive) on the probability of execution. The mean predicted probability of execution as a function of the aggressiveness indicator is depicted in Figure 5. The figure clearly illustrates that limit orders with prices far away from the market have a very low probability of execution. The predicted probability increases, as expected, as aggressiveness increases. Overall, limit orders with "reasonable" prices are highly liquid in term of executability.

7. Concluding Remarks

In this essay, we describe and analyze the microstructure in the Saudi Stock Market (SSM) under the computerized trading system, ESIS. We analyze the order book, order flow and order execution using four rich data sets on orders, order packages, quotes and transactions. Although the SSM has a distinct structure, its intraday patterns are surprisingly similar to those found in other markets with different structures. These include U-shaped patterns in traded volume, number of transactions and volatility. Like

[41] Based on unreported results, the rejection rate for the null that the slopes are all equal to zero is nearly the same.

other order-driven markets, the SSM exhibits a U-shaped pattern in the placement of new orders.

We find that the relative inside spread is higher only at the open and declines gradually afterward on the SSM. This pattern is similar to the one observed for a number of markets without designated market makers. We find that the average relative inside spread is large compared to other markets, mainly due to a relatively high tick size. Tick size is an important determinant of the inside spreads for low priced stocks, and for all other relative spreads. As in other studies, we detect a "diagonal effect" in order flow. Strategic order splitting rather than imitation appears to be the dominant factor causing this effect.

We find that liquidity, as commonly measured by width and depth, is relatively low on the SSM. However, it is exceptionally high when measured by immediacy. We also present new evidence on other measures of market liquidity that are more relevant to order-driven markets. For example, we find that limit orders that are priced reasonably, on average, have a short duration before being executed, and have a high probability of subsequent execution.

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Table 1

Annual Trading Statistics for the SSM

Year	Number of transactions	Traded share volume	Traded Share value	Number of listed companies
1985	7,842	3.94	760	51
1986	10,833	5.26	831	53
1987	23,267	12.01	1,686	55
1988	41,960	14.64	2,037	58
1989	110,030	15.27	8,527	61
1990	85,298	16.94	3,364	63
1991	90,559	30.76	4,403	63
1992	272,075	35.20	13,699	64
1993	319,582	60.31	17,360	66
1994	357,180	152.09	24,871	69
1995	291,742	116.62	23,227	69
1996	283,759	137.83	25,327	71
1997	460,056	313.27	62,060	71

Figures in columns 2 and 3 are in millions of shares and dollars, respectively.
(*Source: SAMA, Money and Banking Statistics: 2nd Qtr. 1997*).

Table 2

Summary Statistics for the Sectors of the SSM

This table reports summary statistics for the sectors of the SSM as of the end of the second quarter, 1996. Paid-up capital is the capital that shareholders have subscribed to, and market capitalization is the number of outstanding shares multiplied by share price at the end of the second quarter, 1996.

Sector	Number of stocks	Paid-up capital	Ownership decomposition (%)			Number of Shares	Number of shareholders	Market Capitalization
			Private	Government	Foreign			
Banks	11	14,650	69.2%	11.8%	19.0%	146.5	180,141	55,329
Industry	16	14,314	47.6%	51.3%	1.0%	150.87	672,096	50,550
Cement	8	6,636	83.4%	13.1%	3.4%	76.85	92,191	14,269
Services	17	10,153	83.4%	16.6%	0.0%	122.86	349,356	12,299
Electricity	10	23,102	23.8%	76.2%	0.0%	235.714	26,999	19,672
Agriculture	9	1,884	92.6%	7.4%	0.0%	23.57	225,479	1,645
Total	71	70,739	54.0%	41.5%	4.5%	756.364	1,546,262	153,764

Figures in columns 2, 6 and 8 are in millions (Source: *Bakheet* Financial Advisors).

Table 3

Trading Hours and Trading Days on the SSM

Days	From Saturday through Wednesday		Thursday	
Time	From	To	From	To
Morning period	8:15 AM	10:00 AM	8:15 AM	10:00 AM
The first opening period	10:00 AM	10:05 AM	10:00 AM	10:05 AM
The first continuous trading session	10:05 AM	12:00 AM	10:05 AM	12:00 AM
The second opening period	4:25 PM	4:30 PM	-	-
The second continuous trading session	4:30 PM	6:30 PM	-	-
Post-trading period	6:30 PM	7:00 PM	12:00 AM	12:30 PM
Evening period	7:00 PM	8:00 PM	12:30 PM	1:30 PM

(*Source: SAMA, ESIS: Instructions to Central Trading Units*).

Table 4

The Commission Structure on the SSM

The table reports the commission structure on the SSM. The commissions are automatically calculated by the trading system for the executed portions of the Central Trading Units orders. The commissions are charged on both sides of transactions. The minimum commission is SR 25.

Slice: Value Executed in SR	Commission: % of Value Executed
1 - 10,000	0.50%
10,001 - 100,000	0.25%
100.001 - 500,000	0.15%
Over 500,000	0.10%

(*Source: SAMA, ESIS: Instructions to Central Trading Units*).

Table 5
Summary Statistics for Each of the Four Data Sets

For the 65 trading days over the period between October 31, 1996 and January 14, 1997, the first column reports various summary statistics after pooling all stocks. The other columns report the cross-sectional distribution of these statistics across the 56 stocks in the sample. All the reported statistics are mean values except for the number of observations and the percentages. The size statistics are computed using the number of shares. The large orders and put-through trades are those with volumes larger than SR 0.5 million. Immediacy is considered available when bid, ask or both are established. Inside spread is the difference between the first best ask and the first best bid. The quote midpoint returns are based on the end-of-minute quote midpoints, while trade-to-trade returns are computed using the time series of transaction prices. Depth is the number of shares offered at the best ask or demanded at the best bid. Execution rate is the number of shares that are filled divided by the total number of shares submitted as a package.

	All observations	Cross-sectional distribution across the 56 stocks					
		Mean	Min	First quartile	Median	Third quartile	Max
Panel A: Order Data Set							
Number of observations	267,517	4,777	411	1,104	3,027	6,946	26,240
Buy (%)	0.489	0.501	0.447	0.480	0.492	0.520	0.597
Limit (%)	0.712	0.738	0.674	0.713	0.726	0.771	0.831
Limit Buy (% of limit orders)	0.462	0.494	0.410	0.459	0.486	0.522	0.634
Market Buy (% of Market orders)	0.554	0.511	0.327	0.485	0.539	0.563	0.614
Executed orders (%)	0.631	0.589	0.363	0.564	0.608	0.624	0.771
Order size							
All	843.40	814.79	113.61	464.99	700.12	1,076.30	2,972.80
Buy	871.15	856.40	107.73	465.24	708.23	1,106.50	3,827.30
Sell	816.88	772.35	118.91	437.35	684.77	1,072.80	2,121.30
Large orders (%)	0.0062	0.0028	0	0	0.0013	0.0038	0.0201
Panel B: Order Package Data Set							
Number of observations	86,425	1,543	138	396	1,109	1,900	8,180
Buy (%)	0.385	0.399	0.138	0.336	0.408	0.448	0.630
Package size							
All	2,610.64	2,359.90	272.02	1,341.20	2,157.40	3,080.20	8,409.40
Buy	3,421.52	3,128.60	888.58	1,917.40	2,734.50	3,986.20	14,356.00
Sell	2,102.51	1,930.70	173.71	1,064.30	1,844.10	2,551.10	4,819.70
Orders per package							
All	3.095	2.969	2.015	2.637	2.909	3.206	4.350
Buy	3.928	3.937	2.488	3.097	3.729	4.341	8.249
Sell	2.574	2.518	1.461	2.118	2.501	2.841	3.643
Execution rate							
All	0.5711	0.548	0.343	0.516	0.546	0.590	0.793
Buy	0.5622	0.508	0.267	0.469	0.532	0.576	0.642
Sell	0.5864	0.569	0.366	0.522	0.566	0.616	0.824
Panel C: Quote Data Set							
Number of observations	778,593	13,903	11,960	13,955	13,955	13,955	13,955
Availability of Immediacy (%)							
Bid side	0.985	0.985	0.835	0.982	1.000	1.000	1.000
Ask side	0.988	0.988	0.850	0.998	1.000	1.000	1.000
Both sides	0.977	0.977	0.808	0.977	1.000	1.000	1.000
Inside spread	2.247	2.274	1.038	1.278	1.533	2.541	10.351
Quote midpoint return (x1000)	-	0.005	-0.015	0.002	0.005	0.008	0.019
Panel D: Transactions Data Set							
Number of observations	168,764	3,014	154	656	2,045	4,281	17,438
Trades at open (%)	0.088	0.110	0.031	0.053	0.077	0.145	0.345
Trade size	560.88	518.78	52.03	284.76	483.58	721.98	1,372.10
Trade-to-trade return (x1000)	-	0.114	-0.615	0.007	0.051	0.147	2.039
Put-through trades (%)	0.0015	0.001	0	0	0	0.0013	0.0104

Table 6

The Relative Spreads and Depths in the Book

Using the five best bids and asks and their associated depths, this table reports the cross-sectional distributions of the time series averages of the relative spreads between adjacent quotes, and the time series averages of the quantities offered or demanded at these quotes. The reported depth is the original number of shares divided by 100. A and B denote ask and bid, respectively. B1 is the first best bid, and A1-B1 is the relative inside spread (first best ask – first best bid) / Quote midpoint. The quote midpoint is calculated as (first best ask +first best bid)/2. Other relative spreads are defined similarly.

	Mean	Min	First Quartile	Median	Third Quartile	Max
Panel A: The Relative Spreads Between Successive Levels of the Limit Order Book (x100)						
B4-B5	1.271	0.125	0.550	1.288	1.907	4.024
B3-B4	1.297	0.134	0.554	1.205	1.813	4.232
B2-B3	1.240	0.135	0.505	1.115	1.595	4.232
B1-B2	1.193	0.140	0.472	1.057	1.563	4.346
A1-B1	**1.790**	**0.328**	**0.732**	**1.600**	**2.359**	**5.126**
A2-A1	1.281	0.164	0.534	1.246	1.720	4.232
A3-A2	1.337	0.144	0.527	1.251	1.860	4.232
A4-A3	1.412	0.143	0.558	1.393	1.968	4.472
A5-A4	1.348	0.154	0.644	1.436	1.850	3.758
Panel B: The Average Volume at Different Levels of the Limit Order Book						
B5	4,394	0	1,039	2,081	4,785	28,935
B4	5,741	473	1,604	2,711	7,294	37,238
B3	8,321	425	1,811	3,370	9,774	53,672
B2	10,319	379	1,611	3,448	12,409	73,064
B1	**5,616**	**298**	**937**	**1,910**	**7,851**	**39,539**
A1	**4,072**	**277**	**847**	**1,514**	**4,428**	**20,311**
A2	6,926	446	1,161	2,764	8,884	36,322
A3	6,374	458	1,207	2,949	9,239	34,460
A4	5,672	576	1,413	2,665	6,904	37,752
A5	4,410	0	1,261	2,443	4,933	26,807

Panel C: Test of Equality of Spreads and Depths Across Levels in the Order Book

Hypothesis	Test Statistic	Calculated	F-probability
All relative spreads are equal	F(8,492)=	1.9380	0.0526
All relative spreads excluding inside spread are equal	F(7,492)=	0.2884	0.9698
All depths are equal	F(9,550)=	2.6379	0.0054
All depths are equal excluding the depths at the second best quotes	F(7,550)=	1.3255	0.2203

Table 7

Tick Size Statistics for the SSM

This table presents statistics on tick sizes on the SSM. The statistics are computed for all 56 stocks in the sample and for five sub-samples classified by the mean of stock price during the sample period. We classify using price because the tick is constant and equal to SR 1 for all stocks, which implies that the relative tick size can be measured by the inverse of price. The tick is binding when the spread and the tick are equal. A and B denote ask and bid, respectively. B1 is the first best bid, and A1-B1 is the inside spread (first best ask – first best bid). Since the tick size is one, the spread (in ticks) is the same as the observed spread in the market. The relative inside spread is (first best ask – first best bid) / quote midpoint. Quote midpoint = (first best ask +first best bid)/2. The relative tick size is 1/quote midpoint. Limit orders is the percentage of limit orders to the total number of orders.

		Price level subsamples				
Variable	All Stocks	1 (Lowest)	2	3	4	5 (Highest)
Number of quotes at all levels (in millions)	5.688	0.913	1.111	1.120	1.255	1.164
Average quote midpoint	195.27	46.37	77.94	118.72	226.32	469.73
Binding ticks at different levels (%)						
B4-B5	0.819	0.826	0.861	0.768	0.852	0.781
B3-B4	0.843	0.880	0.880	0.818	0.871	0.780
B2-B3	0.875	0.908	0.915	0.890	0.897	0.774
B1-B2	0.884	0.954	0.939	0.868	0.899	0.761
A1-B1	**0.538**	**0.767**	**0.621**	**0.528**	**0.521**	**0.262**
A2-A1	0.837	0.935	0.885	0.817	0.872	0.680
A3-A2	0.849	0.920	0.862	0.833	0.912	0.728
A4-A3	0.827	0.901	0.841	0.834	0.886	0.695
A5-A4	0.815	0.939	0.836	0.857	0.852	0.670
Inside spreads that equal 2 ticks (%)	0.225	0.169	0.220	0.253	0.260	0.220
Inside spreads that equal 3 or more ticks (%)	0.238	0.064	0.159	0.219	0.219	0.518
Spread (in ticks)	2.278	1.336	1.825	1.965	2.193	4.196
Relative inside spread	1.79%	3.12%	2.27%	1.70%	1.02%	0.91%
Relative tick size	1.04%	2.38%	1.30%	0.87%	0.46%	0.22%
Limit order (%)	0.594	0.642	0.614	0.609	0.581	0.568

Table 8

The Availability of Immediacy at all Levels of the Book on the SSM

Using the best five quotes, this table reports the percentage of minutes when bids and asks are established for all stocks during the sample period. The table also reports these percentages for five sub-samples classified by order frequency. There are 13,955 trading minutes during the sample period. A and B denote ask and bid, respectively, and B1 is the first best bid.

		Order frequency subsamples				
Variable	All Stocks	1 (Lowest)	2	3	4	5 (Highest)
Mean number of orders	4,777	564	1,536	3,157	5,897	11,544
Immediacy (%)						
B5	0.563	0.260	0.295	0.550	0.801	**0.904**
B4	0.696	0.412	0.445	0.768	0.880	**0.968**
B3	0.838	0.602	0.709	**0.911**	**0.965**	**0.995**
B2	**0.947**	0.842	**0.941**	**0.964**	**0.986**	**1.000**
B1	**0.985**	**0.957**	**0.994**	**0.985**	**0.989**	**1.000**
A1	**0.988**	**0.954**	**0.998**	**0.988**	**1.000**	**1.000**
A2	**0.953**	0.833	**0.958**	**0.983**	**0.990**	**1.000**
A3	0.866	0.590	0.769	**0.973**	**0.988**	**1.000**
A4	0.767	0.358	0.560	**0.919**	**0.986**	**0.999**
A5	0.673	0.200	0.398	0.782	**0.980**	**0.995**

Table 9

Tests for Intraday Patterns in the Order Book for the SSM

This table reports the results from dummy variable regressions of the form $y = a + b_1 d_1 + \ldots + b_7 d_7$, where y denotes the relative inside spread (or squared quote midpoint return) during all intervals and days after all the observations are stacked; and d_i, $i=1,\ldots,7$, is a dummy variable that equals one if the observation y belongs to interval i. Seven dummy variables are used in order to avoid linear dependency among the explanatory variables. Separate regressions are performed for each trading session. The constant term represents the coefficients of the deleted dummy variable, while the other coefficients represent the difference between each of the other intervals and the omitted interval. In each regression, we delete the dummy belonging to the interval with the lowest mean. Given this setting, t-statistics based on White covariance matrix estimation provide a direct test of whether any intraday differences exist between the omitted interval and the other intervals. F-statistics show the overall significance (all differences are zero).

Panel A: Relative Inside Spread (x100)

	First session				Second session			
No. of observations	520				432			
Omitted interval	8				1			
F(7,512)	2.302				0.0933			
P-value	0.0256				0.9986			
Interval	Coefficient	*t*-Statistic	*P*-value		Interval	Coefficient	*t*-Statistic	*P*-value
C	1.7456	86.6036	0		c	1.717	73.8843	0
1	0.0857	2.9906	0.0029		2	0.0048	0.1493	0.8814
2	0.0673	2.4501	0.0146		3	0.018	0.581	0.5616
3	0.0519	1.8634	0.063		4	0.0058	0.1908	0.8487
4	0.0438	1.5452	0.1229		5	0.0101	0.3287	0.7426
5	0.0321	1.1316	0.2583		6	0.0089	0.2926	0.7699
6	0.0187	0.654	0.5134		7	0.0114	0.3795	0.7045
7	0.0049	0.1732	0.8626		8	0.0177	0.6111	0.541

Panel B: Squared Quote Midpoint Return (x100,000)

	First session				Second session			
No. of observations	520				432			
Omitted interval	5				2			
F(7,512)	4.2354				1.0904			
P-value	0.0001				0.3683			
Interval	Coefficient	*t*-Statistic	*P*-value		Interval	Coefficient	*t*-Statistic	*P*-value
c	0.1211	5.2417	0		c	0.1279	7.8211	0
1	0.2738	6.0002	0		1	0.1051	3.4395	0.0006
2	0.0031	0.1153	0.9083		3	0.0444	1.3719	0.1708
3	0.0408	1.5114	0.1313		4	0.0516	1.0435	0.2973
4	0.0012	0.0462	0.9632		5	0.0416	1.0471	0.2957
6	0.0384	1.3627	0.1736		6	0.0274	0.9058	0.3655
7	0.0836	2.4448	0.0148		7	0.0458	1.6122	0.1077
8	0.1734	1.4003	0.162		8	0.0642	2.8834	0.0041

Table 10

Order Flow Conditional on the Position of the Last Limit Price

For all trading days and stocks, this table reports the empirical percent frequency for twelve events related to limit price position, conditional on the previous event. Aggressive (market) order is an order with price better than (equal to) the opposite prevailing quote. Limit order within (at, above or below) is the order priced within (at, away from) the inside spread. Rows correspond to events at time *t-1*, and columns correspond to events at time *t*. Each row adds up to 100 percent.

t-1 \ *t*	Aggressive MS	Aggressive MB	MS	MB	LS within	LB within	LS at	LB at	LS above	LB below	Cancel LS	Cancel LB
Panel A: All Observations												
Aggressive MS	**50.63**	0.04	3.27	1.31	**4.01**	0.87	0.44	1.18	1.26	**30.39**	0.96	5.66
Aggressive MB	0.00	**50.29**	0.96	2.37	0.49	**4.22**	1.51	0.89	**30.73**	1.96	5.88	0.70
MS	1.72	0.15	**35.46**	3.97	**8.04**	1.56	2.59	**38.22**	2.76	2.39	1.53	1.62
MB	0.06	1.86	3.25	**44.81**	2.56	**8.92**	**24.26**	3.35	3.58	2.52	3.96	0.87
LS within	0.06	0.78	6.15	**32.47**	**13.67**	2.82	7.17	6.55	14.09	8.05	5.89	2.30
LB within	0.36	0.39	**25.23**	6.25	4.01	**13.32**	5.86	8.78	11.41	15.64	5.68	3.08
LS at	0.05	0.21	3.07	**22.51**	1.91	2.38	**29.96**	5.61	13.47	7.43	11.56	1.83
LB at	0.04	0.16	**21.72**	3.77	3.14	1.96	6.75	**22.06**	11.95	12.75	7.29	8.41
LS above	0.11	3.28	4.82	6.01	3.00	2.68	8.45	7.38	**33.06**	10.40	19.89	0.91
LB below	1.17	0.46	6.68	4.77	3.21	2.63	6.02	8.88	13.14	**27.54**	1.11	24.39
Cancel LS	0.19	0.60	8.56	6.02	3.58	2.84	9.09	8.45	20.47	9.69	**27.34**	3.18
Cancel LB	0.29	0.42	8.00	5.82	3.48	3.23	8.00	11.24	14.18	24.23	3.50	**17.62**
Unconditional	0.83	1.93	11.48	13.41	3.94	3.73	11.60	12.32	14.38	11.16	**9.22**	**6.01**
Panel B: Diagonal Percent Frequency in the Sub-samples												
The same trader	86.92	88.94	73.52	77.19	43.92	51.46	22.82	30.21	33.17	30.71	18.75	17.16
Different traders	2.73	10.41	2.83	8.81	4.79	4.20	31.13	20.79	33.01	25.73	28.33	17.71

MS: Market sell, MB: Market buy, LS: Limit sell, and LB: Limit buy.

Table 11

Order Flow Conditional on the State of the Order Book

For all trading days and stocks, this table reports the empirical percent frequency for twelve events related to limit price position conditional upon the state of the book (summarized by spread and depth) one second before submitting the order. Aggressive (market) order is the order with price better than (equal to) the opposite prevailing quote. Limit order within (at, above or below) is the order priced within (at, away from) the inside spread. For each stock the spread and depth is defined to be large, if it is larger than its time-series median during the sample period.

Spread	Depth	Aggressive MS	Aggressive MB	MS	MB	LS Within	LB within	LS at	LB at	LS above	LB below	Cancel LS	Cancel LB
Large	Large	0.73	1.71	11.02	13.46	5.31	5.11	11.31	11.11	12.64	9.81	10.81	6.98
	Small	0.65	1.54	9.75	10.87	3.04	2.63	13.26	14.98	17.44	13.40	7.50	4.93
Small	Large	2.06	4.63	13.75	16.68	2.70	3.63	8.62	8.76	11.06	9.73	10.60	7.78
	Small	1.30	2.80	19.29	21.35	1.46	1.28	8.25	9.98	12.83	9.73	7.31	4.41
Unconditional		0.83	1.93	11.47	13.41	3.94	3.73	11.60	12.32	14.37	11.16	9.22	6.02

MS: Market sell, MB: Market buy, LS: Limit sell, LB: Limit buy.

Table 12

Test of the Significance of Any U-shaped Patterns in Order Flow and Transactions

This table reports the results for dummy variable regressions of the form $y = a + b_1d_1 + \ldots + b_7d_7$, where y denotes the number and volume of new orders (or transactions) during all intervals and days after all the observations are stacked. d_i, $i=1,\ldots,7$, is a dummy variable that equals one if the y observation belongs to that interval i. Seven dummy variables are used in order to avoid linear dependency among the explanatory variables. Separate regressions are performed for each trading session. The constant term represents the coefficient of the deleted dummy variable, while the other coefficients represent the difference between the other interval and the omitted interval. In each regression, the dummy belonging to the interval with the lowest mean is deleted. Given this setting, t-statistics based on White covariance matrix estimation serve as a direct test of whether any intraday differences exist between the omitted interval and the other intervals. F-statistics show the overall significance (all differences are zero).

Panel A: New Orders

Number								Volume							
First session				Second session				First session				Second session			
No. of observations	520				432				520				432		
Omitted interval	4				4				4				2		
F(7,512)	87.8149				20.3312				120.473				7.0511		
P-value	0				0				0				0		
Interval	Coefficient	t-Statistic	P-value	Interval	Coefficient	t-Statistic	P-value	Interval	Coefficient	t-Statistic	P-value	Interval	Coefficient	t-Statistic	P-value
c	217.97	25.68	0	c	217.74	13.97	0	c	178.04	22.08	0	c	183.51	16.85	0
1	368.18	13.28	0	1	144.52	6.39	0	1	414.06	15.39	0	1	107.21	5.22	0
2	19.34	1.32	0.1869	2	14.67	0.74	0.4579	2	28.33	2.20	0.0285	3	26.45	1.30	0.1942
3	21.09	1.49	0.1369	3	25.72	1.18	0.2376	3	27.60	2.16	0.0315	4	4.20	0.21	0.8325
5	5.31	0.45	0.6553	5	6.96	0.32	0.7498	5	8.67	0.72	0.4701	5	7.52	0.40	0.6919
6	18.77	1.58	0.1145	6	14.56	0.67	0.5005	6	13.75	1.10	0.2707	6	18.47	0.92	0.3587
7	23.77	1.86	0.0629	7	32.52	1.61	0.1079	7	13.06	1.01	0.3107	7	36.41	2.03	0.0431
8	98.83	6.72	0	8	173.43	7.55	0	8	46.76	3.54	0.0004	8	96.72	4.93	0

Table 12 *continued*

Panel A: Transactions															
Number								Volume							
First session				Second session				First session				Second session			
No. of observations	520.00				432				520				432		
Omitted interval	4.00				4				4				2		
F(7,512)	24.56				9.9913				5.9725				1.859		
P-value	0.00				0				0				0.0748		
Interval	Coefficient	*t*-Statistic	*P*-value	Interval	Coefficient	*t*-Statistic	*P*-value	Interval	Coefficient	*t*-Statistic	*P*-value	Interval	Coefficient	*t*-Statistic	*P*-value
c	66.94	18.43	0	c	76.59	12.05	0	c	38.14	13.86	0	c	43.75	10.58	0
1	81.57	7.54	0	1	53.94	4.96	0	1	29.71	4.18	0	1	13.84	1.81	0.0713
2	1.46	0.23	0.8155	2	5.37	0.63	0.5303	2	2.42	0.55	0.5819	2	11.33	1.45	0.1491
3	8.68	1.44	0.1505	3	7.22	0.78	0.4381	3	8.39	1.80	0.072	3	4.85	0.69	0.488
5	3.15	0.60	0.5498	5	4.11	0.45	0.6534	5	2.17	0.49	0.6242	4	3.28	0.52	0.6022
6	10.92	2.10	0.0359	6	2.26	0.26	0.798	6	8.01	1.77	0.0781	6	3.12	0.46	0.6428
7	12.58	2.27	0.0236	7	13.19	1.56	0.1198	7	5.99	1.37	0.172	7	11.43	1.71	0.0875
8	26.66	4.29	0	8	44.63	5.01	0	8	17.05	3.51	0.0005	8	22.57	3.54	0.0004

Table 13

Order Duration for Limit Orders with Various Characteristics

This table reports the median durations for different types of limit orders. The duration of an order is the length of time the order stays active (firm) in the market. The aggressiveness indicator equals 1-2(Ask-Order price)/(Ask-Bid) for buy orders, and the negative of this quantity for sell orders. Number of orders per package, size and inside spread are defined to be large if they are larger than their time series medians during the sample period. The reported medians are computed after pooling all stocks in the sample.

Order Characteristics	Aggressiveness indicator > -1	-1	-1 - -2	-2 - -3	-3 - -4	<-4	Total
Panel A: Executed Limit Orders							
Direction							
Sell	1.10	0.83	0.92	1.72	3.57	18.73	0.92
Buy	1.63	1.85	1.45	9.32	36.33	23.10	1.82
Number of orders per package							
Large	1.25	1.58	1.35	2.03	5.66	14.32	1.50
Small	1.47	0.90	0.93	2.73	15.75	27.58	1.08
Size (number of shares)							
Large	1.07	0.93	0.95	5.40	13.00	25.20	0.98
Small	1.50	1.45	1.27	1.52	3.02	12.57	1.48
Inside spread							
Large	1.32	0.92	1.42	8.33	16.50	93.87	1.18
Small	1.38	1.27	0.90	1.78	3.32	17.51	1.35
Total	1.37	1.15	1.01	2.47	7.93	20.70	1.30
Panel B: Non-executed Limit Orders							
Direction							
Sell	160.45	220.32	246.00	246.00	246.00	246.00	245.36
Buy	146.69	191.20	244.77	232.63	246.00	240.97	225.92
Number of orders per package							
Large	142.38	213.28	301.60	307.07	318.45	368.94	287.04
Small	160.43	194.85	220.43	208.83	227.38	215.78	210.23
Size (number of shares)							
Large	174.25	207.78	246.00	245.38	246.00	246.00	239.98
Small	142.24	198.93	246.00	234.93	246.00	240.25	230.57
Inside spread							
Large	202.00	230.13	246.00	246.00	246.00	246.00	246.00
Small	73.65	191.20	246.00	232.65	246.00	245.95	230.22
Total	154.00	202.67	246.00	238.37	246.00	246.00	234.83
All orders	1.62	3.77	150.12	192.64	233.53	237.49	55.82

Table 14

Logit Regression Results

This table reports the results for the logit regressions, $E[y|x] = \Lambda(x'b)$, where y is a dummy variable that is equal to one if the order executed, and zero otherwise. The set of regressors, x, includes constant, sell-buy dummy, aggressiveness indicator, number of orders per package, size, and inside spread. $\Lambda(.)$ is the logistic cumulative distribution function. The coefficient is the b estimate. The slope is the marginal effect of x on the probability of execution, as given by $\Lambda(x'b)[1-\Lambda(x'b)]\, b$, when $\Lambda(x'b)$ is evaluated at the mean of the regressors. McFadden pseudo R-squared is $1-(\ln L / \ln L_0)$, where $\ln L$ and $\ln L_0$ are the log-likelihood functions evaluated at the unrestricted and restricted estimates (all coefficients, except the constant, are zero), respectively. Price aggressiveness is measured by 1-2(Ask-Order price)/(Ask-Bid) for buy orders, and the negative of this quantity for sell orders.

	Mean		Min		First quartile		Median		Third quartile		Max		
No. of observations	3040		279		763		1919		4531		15482		
Dependent variable equals one	44.12%		23.30%		41.05%		45.08%		47.59%		67.77%		
McFadden pseudo R-squared	0.3683		0.1183		0.3053		0.3715		0.4452		0.5413		
Independent Variables	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Rejection rate
Constant	2.3911	-	1.02	-	1.827	-	2.4155	-	2.8566	-	4.1752	-	100.00%
Direction dummy	0.3176	0.0444	-0.8952	-0.1692	0.0034	0.0007	0.4286	0.0551	0.6157	0.0948	0.9705	0.1607	73.21%
Price aggressiveness	0.981	0.1505	0.3628	0.0596	0.7172	0.1067	0.8993	0.1338	1.177	0.1785	2.2309	0.4407	100.00%
No. of orders per package	0.0142	0.0025	-0.0462	-0.0073	-0.0038	-0.0006	0.0115	0.0018	0.0235	0.0033	0.1482	0.0281	62.50%
No. of shares	-0.0942	-0.0161	-0.4001	-0.094	-0.1179	-0.0181	-0.0693	-0.0108	-0.0513	-0.0073	0.0004	0.0001	96.43%
Inside spread	-0.4099	-0.0633	-1.3537	-0.188	-0.4794	-0.0828	-0.3254	-0.0527	-0.2142	-0.03	0.2318	0.0566	92.86%

The hypothesis that all the coefficients, except the constant term, are equal to zero is rejected for all the stocks using both the Likelihood Ratio and Wald tests.

Figure 1

Level of the All Market Index (NCFEI) from February 28, 1985 to June 26, 1997

This figure plots the National Center for Financial and Economic Information (NCFEI) all-market index together with the Standard and Poor composite index of 500 stocks (S&P500) after adjusting the latter to start at 100 points on February 28, 1985. Both indexes are capitalization-weighted indexes. The Saudi Riyal (SR) has been pegged to the US$ since June 1, 1986.

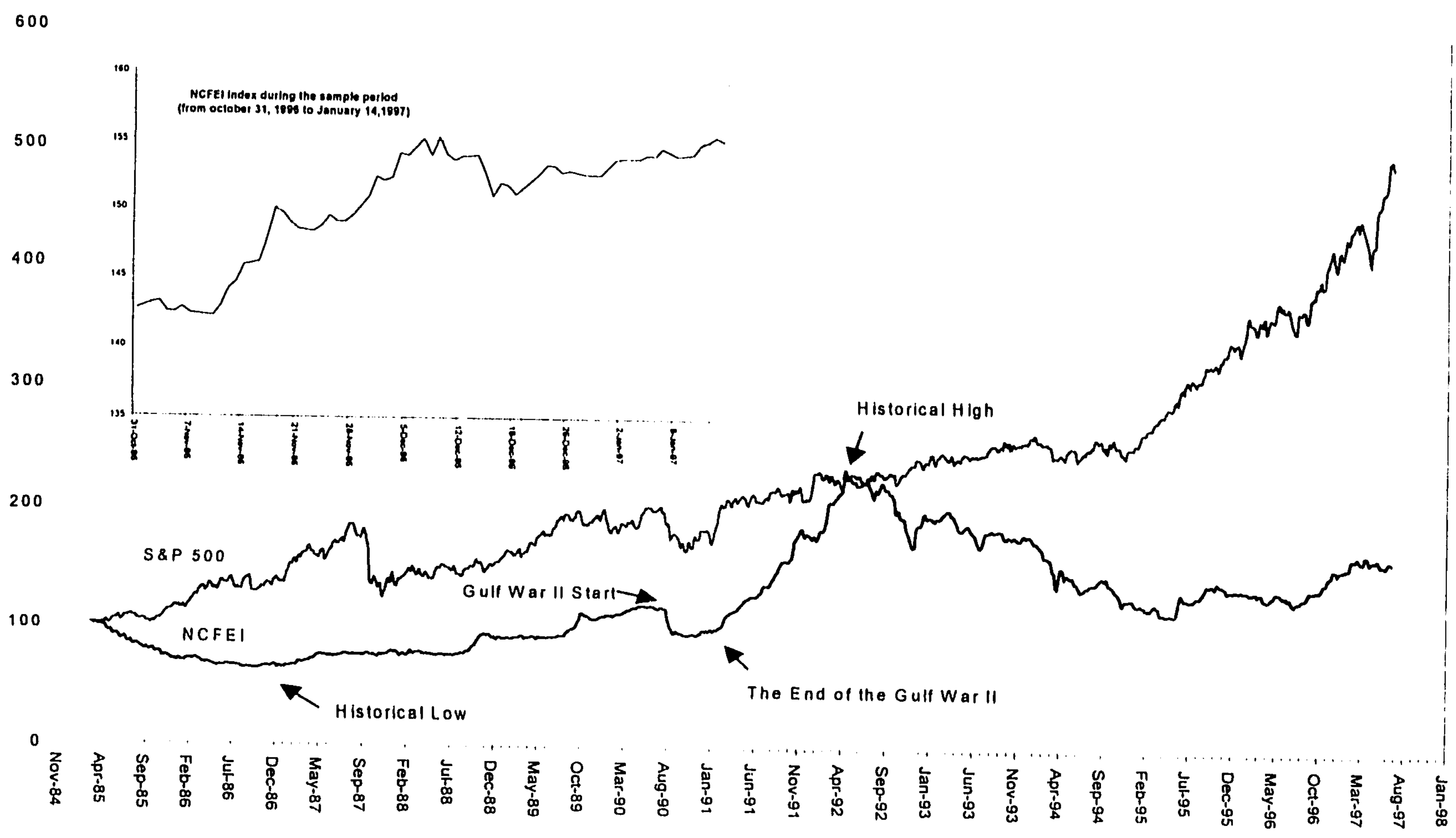


Figure 2

The Average Price Schedule on the SSM

Using the average relative spreads and depths at various levels of the order book, this figure plots the percentage changes in the transaction price relative to the quote midpoint for trades of different sizes. Negative volumes represent sell transactions.

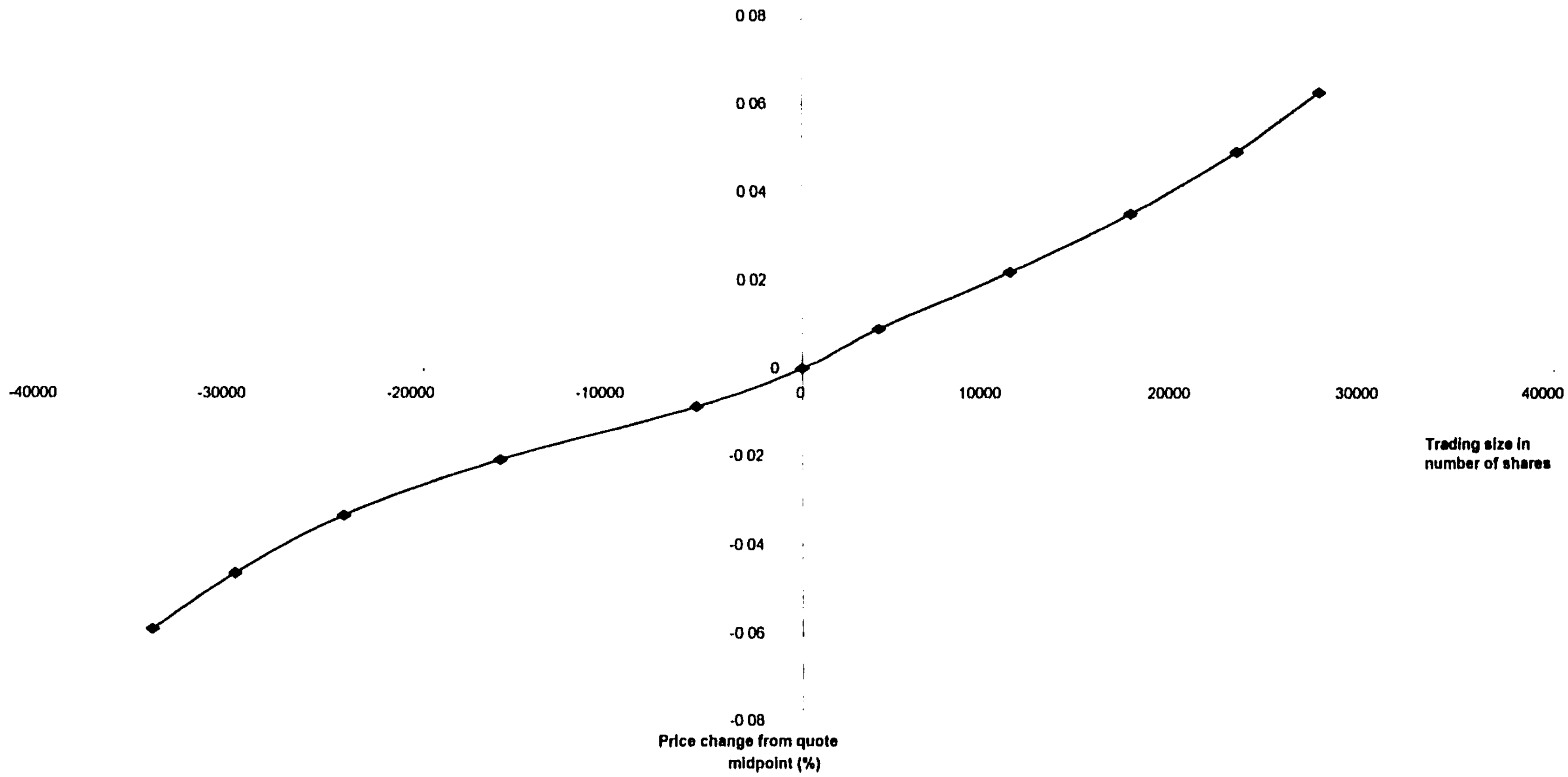


Figure 3

Intraday Patterns in the Order Book

This figure reports the intraday relative inside spreads and squared quote midpoint returns. Each trading session is divided into eight intervals, and the daily relative spread and squared midpoint return are computed for each interval for all stocks in the sample. The bars are the averages over the 65 days in the sample. The relative inside spread = (best ask – best bid) /QMP, where QMP denotes quote midpoint = (best ask + best bid) / 2. The quote midpoint return is calculated as $\log(QMP_t) - \log(QMP_{t-1})$.

Figure 3A: Intraday Relative Spread

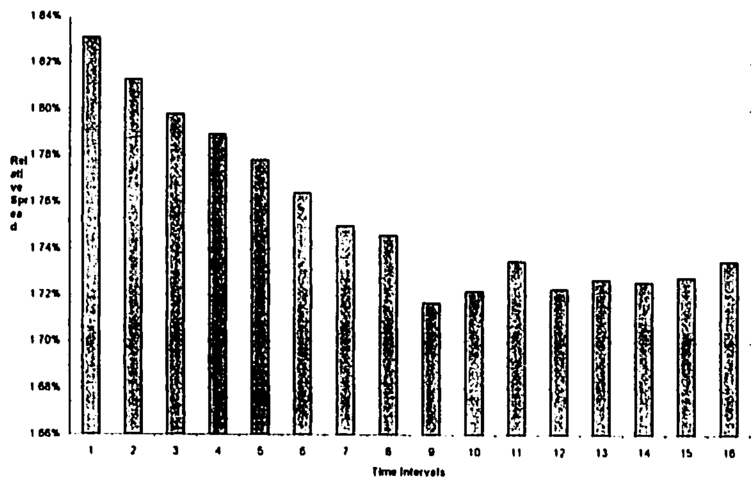


Figure 3B: Intraday Squared Return (x100,000)

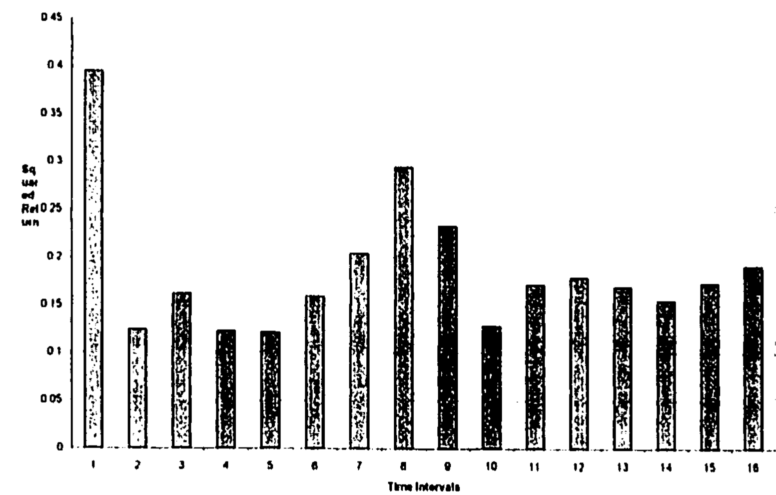


Figure 4

Intraday Patterns in the Order Flow on the SSM

The figure plots the number and volume of new orders and transactions. Each trading session is divided into eight trading intervals, and the number and volume of orders (transactions) in each interval are computed as proportions of the total daily number and volume of orders (transactions). Each bar is the average proportion across the 65 trading days in the sample. Transactions are defined to be large if they exceeded their time series median over the sample period.

Figure 4A

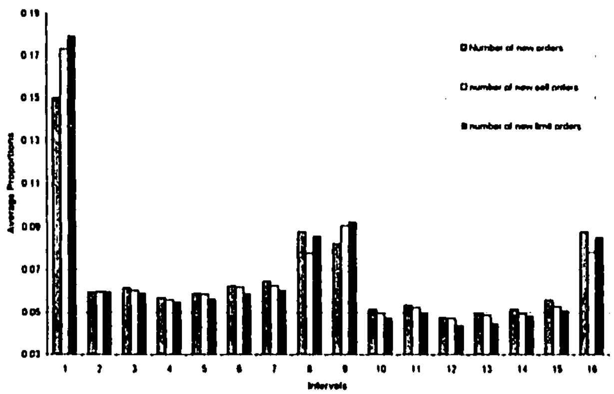


Figure 4B

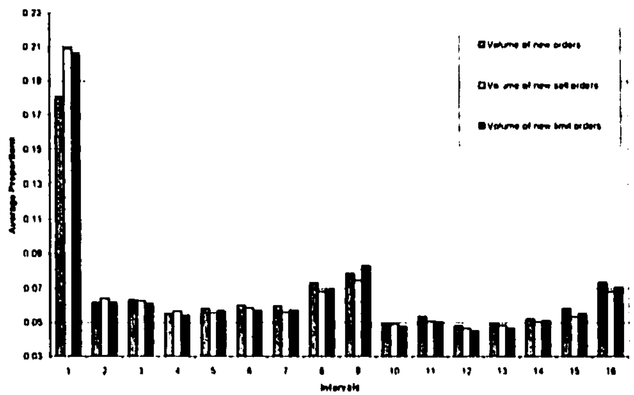


Figure 4C

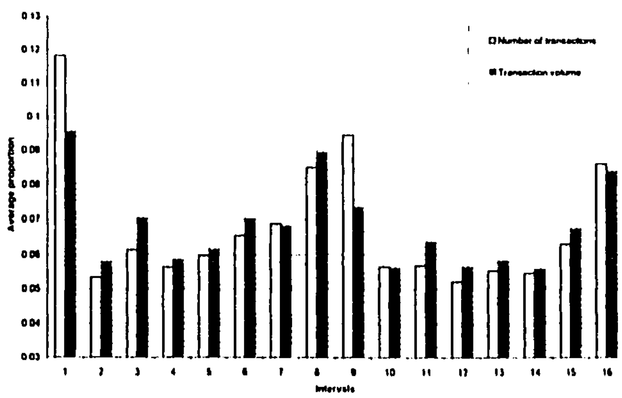


Figure 4D

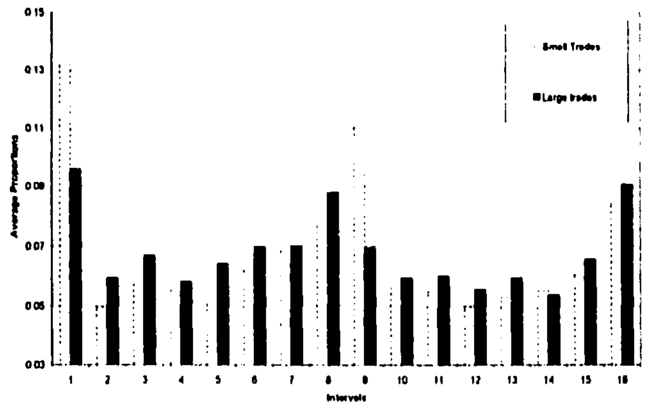
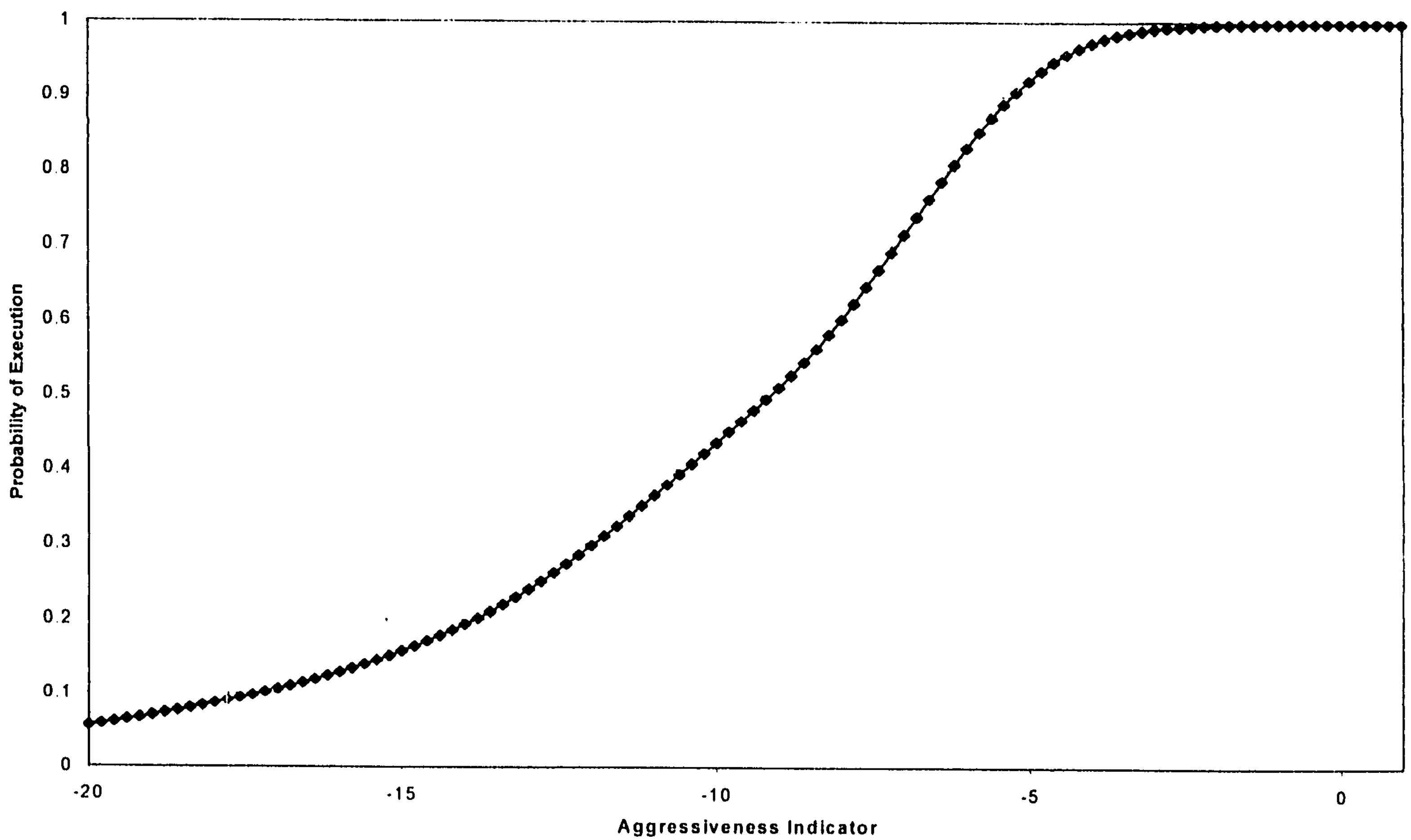


Figure 5

Order Aggressiveness and Probability of Execution

For each stock in the sample, the logit regression is run, and the predicted probability of execution is computed as the aggressiveness indicator is varied from −20 to 1 while the rest of the regressors are fixed at their mean values. The figure plots the mean of the predicted probability across all the stocks in the sample.



Essay 2

Market vs. Limit Order Trading

on the Saudi Stock Market

1. Introduction

Market microstructure theory focuses on the modeling of price formation given a specific trading mechanism. Many microstructure models concentrate on price formation under a mechanism that involves a specific intermediary such as a dealer or a specialist (a designated market maker) as is the case on many organized exchanges. On these exchanges, market makers are granted monopoly rights to trade in one or more securities provided they supply liquidity to the market by standing ready to buy at the bid price and sell at the ask price whenever the public wishes to sell or buy. Their compensation is in the form of the bid-ask spread. Price formation in these models results from solving the monopolistic *market maker's problem* when faced with inventory and adverse selection risks.

The Saudi Stock Market (SSM) is a pure order driven market with a special trading mechanism.[1] In the absence of assigned market makers, the market is sustained by traders who voluntarily provide liquidity to the market by posting *limit orders* rather than *market orders*. Limit order traders supply liquidity to the market in much the same way as a market maker does. However, the primary objective of limit order traders is to implement their trading strategies and each limit order trader usually does not post two-sided quotes and charge the spread. Price formation, under such a structure, results from solving the *trader's problem* who can either place market or limit orders given adverse selection, non-execution, and free option risks.

The objective of this essay is to analyze trading by limit versus market orders on the SSM. Our data set allows us to identify market and limit orders, and other characteristics that are related to trader and order. We interpret the data using a *Random Utility Model*, and empirically approach the problem facing the trader in this market using a logit model. We also examine how the orders resulting from the decision by traders in this market perform by using two measures suggested in the literature.

The remainder of the essay is structured as follows. Section 2 reviews the literature. We present various models of order placement in a pure order driven market and summarize their empirical implications. In section 3, we describe the market and data set. We perform the empirical analysis and report the findings in section 4. Section 5 concludes.

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[1] The first essay describes in detail the current trading structure of the SSM.

2. Literature Review

Most of the initial models in the market microstructure literature focus on price formation in specialist markets. O'Hara (1995) provides a comprehensive discussion of these models.[2] The growing number of order driven markets has directed the literature towards models for markets with no active specialist. In these models, market prices evolve as the market orders of some traders execute against the limit orders of others. Hence, the trader's decision to trade via a market or a limit order is central to these models.[3] In the next subsections, we clarify the nature of the tradeoff facing the trader when choosing between market and limit orders, and present various models that model this choice and discuss their empirical implications. We conclude the section by using a representative model to illustrate some of the issues.

2.1 The nature of the tradeoff between market and limit orders

The problem confronting traders in these models is as follow. The trader faces a tradeoff. If he places a market order, execution is assured at the prevailing opposite quote

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[2] These models are usually classified into inventory models and information-based models. The first set of models views the trading process as a matching problem in which market makers must use prices to balance supply and demand across time. Examples of these models include Garman (1976), Stoll (1978), and Amihud and Mendelson (1980). The second group of models views the trading process as a game involving traders with asymmetric information regarding the asset's true value. Examples of these models are Bagehot (1971), Kyle (1985) and Glosten and Milgrom (1985).

[3] Other models study optimal order placement and price formation in a specialist market with limit order traders. Examples include Chakravarty and Holden (1995), and Seppi (1996). Also, there are models that examine price formation in limit order markets but do not explicitly model the choice of trading via limit or market orders. Example includes Golsten (1994), and Domowitz and Wang (1994).

(i.e. he pays an implicit price for immediacy). If he places a limit order, three alternative scenarios are possible.

- The limit order is executed during the trading window due to the presence of a liquidity trader on the other side of the market.[4] In this case the trader benefits from trading using the limit order because he saves paying the spread.

- The limit order is executed due to the presence of informed traders (adverse selection risk). A similar situation occurs if the limit order becomes mispriced because public information causes a revision in stock value (free option risk). This risk differs from adverse selection risk in the sense that it might exist even if all traders had the same information at a given point of time. In both cases, a market order "moves through" the limit order and the trader suffers from the winner's curse. This is the major source of risk associated with trading using limit orders.

- Non-execution risk occurs because the limit order may not be executed during the trading window. This may occur because the limit price is far away from the market, the stock value moves away from the limit price, or because no liquidity traders exist on the other side of the market. In all cases, a decision has to be made at the end of the trading window whether to trade at the prevailing opposite quote or to forego trading, and this decision has cost implications.

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[4] The liquidity trader is the trader who demands immediacy for reasons unrelated directly to the future payoff of the stock. Liquidity trading usually arises from the need to smooth consumption over time and for risk adjustments [Stoll (1992)].

Given these possibilities, trader choice depends critically on the probabilities of an order being executed against an informed or liquidity trader.

2.2 Prior Research

This tradeoff is the basis of the current theoretical literature on the choice between limit and market orders, and was first addressed in the early microstructure literature. Cohen, Maier, Schwartz and Whitcomb (1981) describe the basic condition which a model of order placement strategy must fulfill. They consider a trader who maximizes the expected utility of terminal wealth by choosing between a market or limit order given transaction cost and price continuity. The model establishes that transaction costs cause traders to use order placement strategies that generate a "*gravitational pull effect*", and ultimately result in a non-trivial market spread. Given transaction costs, the probability that a limit order will be executed does not rise to unity as the limit order is placed infinitesimally close to the opposite quote. Thus, in the neighborhood of the current market bid and ask, what might otherwise have been limit orders are instead submitted as market orders so as to achieve execution certainty.

Another implication of this model is that, if the spread is wide, then a trader gains from submitting a limit order. This induces traders to shift from using market orders to using limit orders. This tends to decrease the spread. However, as the spread narrows, the trader at some point prefers market to limit orders, which in turn widens the spread. For thinly traded securities, the probability of a limit order executing is low. Hence, even with a large spread, traders may prefer to submit market rather than limit orders. This trading strategy dictates that large spreads will be an equilibrium property of thinner securities.

Angel (1995) models an informed trader's choice between limit and market orders to trade a fixed number of shares, given his belief about the future stock price, the prevailing spread, the expected rate of order flow, stock volatility, and the depth of the limit order book. Unlike previous models, Angel's model accounts for the discreteness of stock prices. The model shows that although informed traders usually prefer market orders, limit orders are preferred under certain circumstances. For example, when the spread is wide, a limit order at or within the spread is worthwhile. Generally, the position of the limit price depends on market conditions and available information about the stock.

Harris (1997) solves optimal dynamic order submission strategies for trading problems faced by three stylized traders: an uninformed liquidity trader, an informed trader, and a value-motivated trader. The various trading problems are modeled as dynamic programming problems since traders often adjust their limit orders when they do not execute. Thus, the option to resubmit affects the original submission decision. The author uses numerical methods to solve the model given the parameters characterizing price volatility, spread, tick size, information dissemination rates, and execution difficulties. The results of the model are highly intuitive. Trader submit limit orders when their deadline is distant or the spread is wide, and they submit market orders when volatility is high and when information advantage is large and decays quickly. Value-motivated traders may use limit orders to position themselves to take advantage of any mean reversion that they believe is present in prices.

Foucault (1996) derives a game theoretic model of order placement and price formation in a dynamic order driven market. His model focuses on the risk of limit orders being executed at a loss when they become mispriced due to the arrival of new public information. The model explicitly solves the Markov subgame equilibrium for order choice and quotes given the trader's valuation and the state of the order book, and analyzes the welfare properties of the solution. A negative relationship exists between market order (transaction frequency) and both asset volatility and the spread. As the volatility of the asset decreases relative to the dispersion in the trader's private valuation, traders widen their spreads. As a result, traders submit fewer market orders in equilibrium.[5]

Parlour (1996) characterizes dynamic equilibrium in a market which traders optimally choose the type of order to submit, given no asymmetric information. Unlike the Foucault (1996) model, the stock's underlying value is fixed, and the limit order can be stored in a limit book for more than a single trading sub-period. This allows the model to minimize free option and adverse selection risks and focus on the time and price priority rules on the trader's decision. The model predicts that if the spread is wide, traders are more likely to submit limit orders within the spread to gain priority, and are less likely to submit market orders. The model also predicts systematic and persistent

[5] Hollifield, Miller, and Sandås (1996) empirically analyze a generalization of Foucault's model which allows orders to last over multiple periods. In their model, the optimal order strategy is characterized by a monotone function which maps the trader' valuation into the optimal order price. For example, a seller with a higher (lower) valuation will submit an order with higher (lower) price and lower (higher) probability of execution. The observed order choice in combination with a non-parametric estimate of order strategy allows the authors to derive an estimate of the distribution of traders' valuations which they use to test various hypotheses concerning the strategic order choices of traders.

patterns in transaction prices and order flow. Transactions at the quotes are conditionally autocorrelated, whereas limit orders are negatively autocorrelated.

2.3 A representative model

Handa, Schwartz and Tiwari (1997), HST (1997) henceforth, explicitly model the choice of trading strategy (market vs. limit orders) faced by an uninformed trader in a pure order driven market with asymmetric information, and study its impact on price formation. In this subsection, we present this model as a representative example for order driven market models.

The model considers a pure order driven market with one risky asset and two groups of traders. Potential buyers, with proportion k, attach high value V_h to the asset, and potential sellers, with proportion $1 - k$, attach low value V_l to the asset. The traders arrive at the market sequentially and decide to trade via a market or a limit order. The limit order exists in the limit book until the next trader arrives, after which it expires. A proportion of traders, δ, receive short-lived private information about a change in the value of the asset. The private information is either $+H$ or $-H$ with equal probability. Further, δ is assumed to be identical across types V_h and V_l.

Traders are risk neutral and expected utility maximizers. The expected utility is given by:

$$E(U) = \begin{cases} \phi (V_i - P) & \textit{from a buy order} \\ \phi (P - V_i) & \textit{from a sell order} \end{cases} \qquad i = l, h \qquad (1)$$

where ϕ is the probability of execution which equals one for a market order and less than one for a limit order. P is the execution price, which can either be the market bid (B^m), or market ask (A^m).

Given the short-lived nature of the informational advantage, the informed trader has no incentive to place a limit order. He either places a market order or does nothing. In equilibrium, the value of H is constrained so that the optimal action for this trader is to buy if he attaches V_h to the stock and receives good news, and sell if he attaches V_l to the stock and receives bad news. Otherwise he does nothing.

On the other hand, the uninformed trader (buyer or seller) can place a market order or limit order. For example, the uninformed buyer can place either a market buy order (MB) at the prevailing ask price in the market A^m, or a limit buy order (LB) at a price less than A^m. Given that the probability of execution equals one for the market order, the expected utility from placing the market order is,

$$E[U_{MB}] = V_h - A^m . \qquad (2)$$

If he places a limit order at a bid price B instead, the probability of execution depends on the type of the next trader: (1) whether he is a seller or buyer, (2) whether he is informed or not, and (3) whether he is informed with good or bad news. Hence, the current uninformed trader expects $V_h - B$ with probability $(1\text{-}k)(1\text{-}\delta)$, if the next trader is an uninformed seller, and $V_h - H - B$ with probability $(1\text{-}k)\,\delta/2$, if the next trader is an informed seller with bad news. If the next trader is an uninformed buyer or informed with good news, the order expires without execution. Normalizing the trader's utility to zero if the limit buy order expires and setting $p = \delta/2$ yields an expected utility from placing a limit order equal to,

$$E[U_{LB}] = (1-k)\,[(1-p)(V_h - B) - pH] \tag{3}$$

It follows that,

$$if \begin{cases} E[U_{MB}] \geq E[U_{LB}] & then\ he\ places\ a\ MB \\ E[U_{MB}] < E[U_{LB}] & then\ he\ places\ a\ LB \end{cases} \tag{4}$$

This implies that an optimal threshold ask price A exists such that any limit sell order (LS) with price equals to A is executed. Given (2), (3) and (4), A is given by,

$$A = V_h - (1-k)\,[(1-p)\,(V_h - B) - p\,H] \tag{5}$$

The problem of the uninformed seller yields a similar expression for the bid price:

$$B = V_l + k\,[(1-p)\,(A - V_l) - p\,H] \tag{6}$$

The equilibrium values of the market ask and bid prices $\{A^*, B^*\}$ in closed form are found by solving (5) and (6) simultaneously to get:

$$B^* = \lambda\ V_l + (1-\lambda)\ (V_h - qH) \tag{7}$$

$$A^* = \mu\ V_h + (1-\mu)\ (V_l - qH) \tag{8}$$

where $\lambda = \dfrac{1-\phi_s}{1-\phi_s\phi_b}$, $\mu = \dfrac{1-\phi_b}{1-\phi_s\phi_b}$, $q = \dfrac{p}{1-p}$, $\phi_s = k(1-p)$, $\phi_b = (1-k)(1-p)$, ϕ_s and ϕ_b being the unconditional probabilities of executing limit sell and limit buy orders respectively, and q is the probability that the counterparty was informed, conditional on observing a trade.

The equilibrium spread is given by,

$$s^{*}=A^{*}-B^{*}=\psi(V_h-V_l)+(1-\psi)qH \qquad (9)$$

where $\psi = (1-\phi_b)\lambda = (1-\phi_s)\mu$.

In this model, the size of the spread is a positive, monotonic function of the difference of opinion, $V_h - V_l$, and adverse selection (the expected loss to an informed trader), qH.

HST (1997) show that the proportion of buyers in the market, k, through ψ, affect both the spread size and its position between V_h and V_l. As Figure 1A illustrates, the spread is a concave function of k. It is maximized when $k = ½$, and minimized when $k = 0,1$. Figure 1B shows that as k increases, the spread position moves away from V_l towards V_h.

The effect of k on spread size and its position between V_h and V_l reflects the balance of relative execution probabilities for buyers and sellers. Given the definition of ϕ_s and ϕ_b, λ (μ) can be interpreted as the relative risk of non-execution to an uninformed buyer (seller) relative to the risk of non-execution to both parties. As is evident from (7) and Figure 1A, the optimal bid, B^{*}, is a weighted combination of V_l and $V_h - qH$. As k decreases, λ approaches its maximum value of unity, B^{*} approaches V_l, and the uninformed buyer's gains the most from the trade. Conversely, as k increases, λ approaches its minimum value, B^{*} approaches V_h, and the uninformed buyer's gain from trade goes to zero. The relation between k, μ and the optimal ask is symmetrical. As a result, for $k < ½$ ($k > ½$), the non-execution risk for the buyer is lower (higher) and the "*gravitational pull*" exerted by the bid (ask) dominates. For a buyer, the relative attractiveness of trading via a market order at the posted ask, or an aggressive limit order (closer to V_h) increases as k increases. This leads to a smaller spread at a higher location.

3. Market and Data Description

3.1 The Market

The market is a pure order driven market where traders can place either limit or market orders. As in the theoretical model considered in the previous section, market orders are executed with certainty at the standing opposite quote. For limit orders, the rules on price-then-time priorities are strictly enforced. The first best two quotes are available to market participants in an aggregate format (i.e. the best quote is shown with all order quantities available at that quote). Market participants also can view the price and quantity of the last trade. The tick size is constant and equal to SR 1($\approx$ 27 cents). All bids and asks must be priced within $\pm$ 10% of the opening price. Transaction fees, which are charged on each side of the trade, have a minimum of SR 25 ($\approx$ \$ 6.66), and range between 0.5% and 0.1% of trade value depending on the number of shares executed.

The market has no official market makers or brokerage firms. The potential for insider trading is high because no effective mechanism to prevent insiders from trading based on inside information. A special type of traders (called bank phone customers) have an agreement with the banks to change the price and firm quantity of their submitted orders at any time simply by calling their Bank's Central Trading Unit. As a result, they are less affected than other public traders by the free trading option mentioned earlier, since they can change the condition of their orders before they are "picked off" when new public information arrives. This type of trader includes value motivated investors (e.g. mutual funds), informed traders, and many technical traders. The presence of bank phone customers and informed traders likely creates a winner's curse problem for limit order traders on the SSM. Limit order traders, however, can benefit from trading with liquidity traders in the market.

3.2 The Data Set

The data set provided by the Saudi Arabian Monetary Agency (SAMA) includes all submitted market and limit orders for 56 stocks during the period from 31 October 1996 to 14 January 1997. For each order, the data set reports security ID, the date and time of creation, sell-buy indicator, limit price, quantity, and date and time when the order was terminated. The data set also includes the ID of the order package that generates the order, and an ID for the order itself. We use the date and time of termination, and the price and quantity of orders to identify the order that was executed. The identified transaction record matches perfectly the published daily transaction statistics. Given the order data set, the state of the book can be determined at any point of time during the sample period.[6]

For the executed orders, we are able to differentiate between the market and (executed) limit orders using the orders characteristics and the order book. A market order typically has a zero duration, can only be placed during the continuous trading session, and has a price at or better than the prevailing opposite quote. We double-check our identification procedure by examining the change in the state of the book at the time

[6] The data sets and their summary statistics are described in more detail in the first essay.

of order submission. Market orders clear the book, whereas limit orders add to the book. Table 1 presents summary statistics for the data set.

Most of the analysis in this essay requires orders to be preceded by a valid bid-ask spread. A valid bid-ask spread is defined as one in which both the bid and ask prices are established and visible to market participants. Only 5.67% of orders entered during the continuous trading session fail to meet the restriction. The summary statistics for the restricted data set (not reported herein) are similar to the statistics reported in Table 1.

Table 1 reveals that buyers use market orders more often than sellers. This could be attributed to the rising market during the sample period. The NCFEI index rose 9.23%. More than half the limit orders are not executed. Size statistics show that the largest percent of market and limit orders have a size of between 100 and 500 shares. A large percentage of the orders are parts of packages. If the number of orders per package is interpreted as an indicator of trader activity, then the data suggests that less active traders usually use limit orders, and more active traders typically use market orders.

4. Empirical Analysis

In this section, we investigate empirically two issues. First, we examine the relationship between the decision to trade by market or limit orders and different sets of variables related to the state of the book and the order. Second, we investigate how the orders resulting from this decision perform using performance measures suggested by Harris and Hasbrouck (1996).

4.1 Logit Analysis

As shown above, a trader chooses to trade using a limit order rather than a market order if his expected utility from placing the limit order, U_L, exceeds that from placing a market order, U_M. Since in our data set we only observe the trader's choice, the observed indicator, y, equals one if the order is a market order and zero if it is a limit order. The observed choice reveals which one is believed to provide the greater utility, but not the unobservable utilities themselves. We also observe other variables that probably affected this decision. In particular, we observe the state of the order book before order placement (such as spread and depth) and some order characteristics (such as order size and direction).

The data on trade choices can be interpreted using the *Random Utility Model.*[7] In this model, the utility of the trader is given by.

$$U_i = V_i(x) + \varepsilon_i \quad i = M,L \tag{10}$$

where x is a set of explanatory variables which are used to explain the occurrence of market and limit orders and ε_i is the error term. The function defined in $V_i(x)$ is commonly assumed to be linear, that is, $V_i(x) = x\beta_i$ .This formulation implies that:

$$\begin{aligned}
\text{Prob}[y = 1 \mid x] &= \text{Prob}[U_M > U_L \mid x] \\
&= \text{Prob}[x\,\beta_M + \varepsilon_M - (x\,\beta_L + \varepsilon_L) > 0 \mid x] \\
&= \text{Prob}[x\,(\beta_M - \beta_L) + \varepsilon_M - \varepsilon_L > 0 \mid x] \\
&= \text{Prob}[x\beta + \varepsilon > 0 \mid x]
\end{aligned}$$

[7] Maddala (1983) and Greene (1997).

Assuming that ε has a standard (symmetric) logistic distribution with mean zero and variance one, we get the logit model: [8]

$$\text{Prob}[y = 1 \mid x] = \text{Prob}[\varepsilon > -x\beta] = \text{Prob}[\varepsilon < x\beta]$$

$$= \text{F}(x\beta) \tag{11}$$

where $F(x\beta)$ is the logistic cumulative distribution function, $e^{x\beta} / (1+e^{x\beta})$. The maximum likelihood method is used to estimate the parameter vector, β. The objective is to determine if a relationship in our data set exists between the probability of an order being a market order and a given set of explanatory variables. In interpreting the estimated model, the marginal effect of x on this probability is given by $F(x\beta)[1- F(x\beta)]\ \beta$.

In applying the logit model to this trader choice, we use the predictions from the theoretical models reviewed in section 2 about the relationship between the inside spread and the trader's decision. Although these models differ in their assumptions regarding types of traders, trading mechanisms, preferences, information structures and dynamics, the models all predict that if the spread is tight (wide), traders in a pure order driven market are more likely to submit market (limit) orders. This prediction is intuitive in that wider spreads increase the implicit cost of market orders, and increase the feasible set of limit orders within the spread. Given price and time priority rules, traders having a larger opportunity set can increase the probability of executing their limit orders simply by undercutting or overbidding the prevailing quotes. The Parlour queuing model (1996) also has strong predictions that can be tested using the same methodology. The model

[8] Assuming that ε_i has a normal distribution with mean zero and variance one produces a probit model.

ranks the probability of observing market orders conditional on whether the last event is a market or limit order to sell or to buy.

Some of the models have closed-form solutions [e.g. Equation (9)].[9] Although these solutions provide valuable insights into the economics of the microstructure of order driven markets, they are too easily rejected by the data because they impose many restrictive assumptions in order to obtain their closed-form solutions. As an example in the appendix, we provide the results of our attempt to test the prediction of the HST (1997) model using the Generalized Method of Moments (GMM). The model is rejected because the estimated parameters are inconsistent with the model for almost all of the stocks in the sample. As we constrain the parameter values to be more consistent with the model, we get higher statistical rejection rates.

In selecting the set of explanatory variables in the logit regression, we seek to capture the relation between the trader's decision and the state of the book when the decision was taken, observable order characteristics, and the type of the last event.

4.1.1 The Probability of a Market Order and Order Characteristics

The specification of the first set of explanatory variables, x, includes a constant and the following variables:

Spread: $A - B$, where A and B are the prevailing first best ask and bid at time of order entry, respectively.

Order imbalance: k for buy order and $(1-k)$ for sell order, where $k = Q_b / (Q_b + Q_s)$, and Q_s (Q_b) is the number of shares offered at A (demanded at B) at time of order entry.

[9] Angel (1995) and Focault (1996) also obtain closed form solutions.

Direction dummy:	An indicator variable that takes the value of 1 if the order was placed by a seller and 0 if it was placed by a buyer.
Order per package:	Number of orders in the package that generated the order.
Order size:	Number of shares in the order.

Table 2 presents summary statistics for these variables.

The theoretical motivation for including the spread in the set of regressors is obvious. Order imbalance, as in HST (1997) and Parlour (1996), can affect the probability of executing the limit order, and hence the trader's decision. As k increases, the models predict that the probability of executing a limit order decreases, and a market order becomes more attractive. We also include order direction (sell, buy), size, and the number of orders in the package that generate the order so that we can examine the probability of placing market orders by traders with different characteristics.

Consistent with the prediction of the theoretical models, the logit regression results reported in Table 3 indicate that the spreads have highly significant negative effects on the probability of placing a market order. As the inside spread increases by one tick, the probability of placing a market order decreases on average by 7.34%. The results also indicate that as the order imbalance k increases, the probability of placing a market order increases. Both results are consistent with the observation of Biais, Hillion and Spatt (1995) that the conditional probability that traders place limit orders (rather than market orders) is larger when the spread is larger, and the order book is thin at the same-side quote. The results show that buyers of most stocks are more likely to submit market orders. Since informed traders are more likely to submit market orders, the results may provide some support to the conjecture that buyers tend to be better informed than sellers. However, the results may be mainly due to the optimistic expectations of traders during the sample period.[10]

More active traders have a higher probability of placing a market order, and larger size orders have a lower probability of being market orders. More active traders watch the market more closely and are expected to seize opportunities using market orders. Execution difficulties for large orders may explain the size effect. Given market thinness, large market orders can only be partially executed and with high market impacts. Hence, to execute large orders with the lowest market impact, traders are more likely to use limit orders.

4.1.2 The Probability of a Market Order and the Last Event Type

The Parlour queuing model (1996) views a trader's decision solely as a queuing problem, where the decision to submit a market or limit order depends critically on the time priority rule and the thickness of both sides of the book at the time of order placement. The model's predictions (stated in *proposition* 1, *corollary* 1 and *corollary* 2) can be restated for a seller as:

$$\text{Prob}[MS|LS] \geq \text{Prob}[MS|MS] \geq \text{Prob}[MS|LB] \geq \text{Prob}[MS|MB] \tag{12}$$

[10] Oil price and government fiscal policies are two major factors affecting all other economic activity in the country. The government budget (the most important financial event in the country) is usually announced on the first of January. Due to high oil prices in 1996, traders expected good news in the budget announcement. Indeed, the SSM rose by 27.8 percent in 1997, its second best performance since it was regulated in 1984. The NCFEI Index rose to 195.89 points by year-end, from 153.10 points at the end of 1996.

Thus, the probability of observing a market sell order depends on whether the previous event is a market or limit order, to sell or to buy. Each of these four events changes the balance of book depth and the place of the trader in the queue. It alters the probability of execution of the next order, and the next trader's decision to submit a market order. For example, suppose a trader at time t submits a limit sell order. This adds to the depth at the ask. A limit sell order at the same ask price therefore has a poorer chance of execution. A seller at time $t+1$ is more inclined to submit a market order. The chance to execute a limit sell is higher if the previous event was a market sell, and even higher if it was a limit buy, and the highest if it was a market buy. Similarly, for a buyer:

$$\text{Prob}[MB|LB] \geq \text{Prob}[MB|MB] \geq \text{Prob}[MB|LS] \geq \text{Prob}[MB|MS] \qquad (13)$$

To test these predictions we split our sample into sell and buy order subsamples. We then construct four dummy variables that indicate the type of the last event and evaluate the predictions from (12) and (13) using logit regressions. The four dummies are d_i, $i = MS, MB, LS$ and LB, where $d_i = 1$, if the last event is i, and 0 otherwise.

Table 4 reports the summary statistics for the predicted probabilities conditional on each of the four events. The findings are similar for sell and buy orders. The predicted probability of a market sell (buy) conditional on the last event being a market sell (buy) is the largest whereas the predicted probability of a market sell (buy) conditional on the last event being a market buy (sell) is the smallest. The data supports the prediction that the probability of a market sell (buy) conditional on the last event being a market sell (buy) is larger than the probability of a market sell (buy) conditional on the last event being a limit buy (sell). These systematic patterns are consistent with the rankings of the last three probabilities in (12) and (13). The only prediction not supported by the data is the probability that market sell (buy) orders conditional on the last event being limit sell (buy) orders is largest. While this probability exceeds that for market sell (buy) conditional on the last event being market buy (sell), it is smaller than the other probabilities.

The queuing model abstracts from other factors that influence a trader's choice. The model precludes price competition among limit order traders by assuming a constant spread equal to one tick, and by assuming that limit price can be placed only at the quotes. Therefore, a trader who arrives in the market can either place a market order at the best quote on the other side of the market or place a limit order at the best quote on the same side of the market. The model further assumes no asymmetric information and no uncertainty regarding stock value. Therefore, the lack of support discussed above is probably contaminated by price competition and information effects, which are difficult to isolate. For example, when the spread is larger than one tick, the trader can jump the queue by placing a limit order within the spread, and a market sell after a market sell can be a result of an information effect. To be more consistent with the model, the price competition effect is better isolated by restricting the sample to include only orders placed at the quote when the spread equals one. The results for the restricted sample (not reported) do not deviate substantially from those reported in Table 4. The information effect is difficult to isolate.

4.2 Performance of Market versus Limit orders

After analyzing the trader's decision to trade using a market or limit order, it is natural to examine how the orders resulting from this decision performed in the market. Following Harris and Hasbrouck (1996), we employ two performance measures.

1. Ex Ante Performance Measure: This measure compares the execution price of an order to the opposite quote prevailing when the market received the order. This measure estimates the prospective benefit of using a limit order versus a market order that immediately executes against the prevailing opposing quote. Such a choice typically confronts a trader who is committed to trade. For an order that executes at the price, *P*, the ex ante performance measure is:

$$P^{ex\ ante} = \begin{cases} A - P & for\ a\ buy\ order \\ P - B & for\ a\ sell\ order \end{cases} \tag{14}$$

B and *A* are bid and ask quotes, respectively, prevailing at the time of order submission. For unexecuted orders, the execution price does not exist. These orders embody the real costs of a foregone trade. To avoid the selection bias that would result from dropping unexecuted limit orders from the sample, we assume, as in Harris and Hasbrouck (1996), that a cancelled or expired order is replaced by a market order at the time of cancellation or expiration. For example, a cancelled buy order is assumed to have been executed at the prevailing ask at the time of cancellation. In our order driven market, a market order can not better the opposite-side quote.[11] Hence, this performance measure will be (negative)

[11] In other markets, market orders can improve upon the existing opposite quote. The term "price improvement" is usually used to refer to this phenomenon [Knez and Ready (1996)].

zero for (aggressive) market orders. The ex ante measure is positive for executed limit orders and is generally negative for unexecuted limit orders.

2. Ex Post Performance Measure: For executed order, this measure compares the execution price of an order to the same side quote prevailing five minutes after the execution.

$$P^{ex\ post} = \begin{cases} B_5 - P & for\ a\ buy\ order \\ P - A_5 & for\ a\ sell\ order \end{cases} \tag{15}$$

B_5 and A_5 are bid and ask quotes prevailing five minutes after the execution. This ex post measure estimates the trader's retrospective loss or gain associated with the newly established position. It is appropriate for a passive trader whose only reason to trade is expected trading profits.

The sign and value of the measure depends on the movement in the same side quote after the order execution and can be positive or negative for both market and limit orders. For limit orders, a negative value for this measure reflects the adverse selection and free option costs associated with limit orders. For market orders, the measure will be zero (positive) if the order causes the other side quote to be revised to (above) the execution price, and will be negative otherwise. Therefore, positive values can be interpreted as the information impact of a market order.

Using a sample of NYSE orders, Harris and Hasbrouk (1996) analyze the performance of market and limit orders using these two measures. They find that ex ante performance of limit orders placed at or better than the prevailing quotes is better than market orders, even after imputing a penalty for unexecuted orders, and after accounting for market order price improvement. The ex post performance results indicate that limit orders are subject to adverse selection risk.[12]

Following Harris and Hasbrouk (1996), we condition our analysis of performance on the prevailing inside spread at time of order entry, order size, strategy (market, limit within the spread, limit at the quote, and limit away from the market), and direction (sell or buy). During the 65 trading day sample period, the market was rising (only 28 days with negative returns). This makes the distribution of returns for the full sample negatively skewed towards positive returns. As a result, the performance of sell orders is artificially higher. When the market is rising, sell limit orders are more likely to execute than buy limit orders placed equally far from the market. Table 5 confirms this effect. The average ex ante performance of sell (buy) orders increases (decreases) as the index return increases. Harris and Hasbrouck (1996) faced the same problem for their data set, and tackled it by basing their analysis on return-matched subsamples.[13]

Table 6 reports the number of orders and execution rate in the restricted subsamples classified by order size, direction, the prevailing spread at time of entry, and

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[12] To assess the profitability of limit orders, Handa and Schwartz (1996) conduct an experiment by replaying the transaction record of thirty Dow Jones Industrial firms, and assess the profitability of entering experimental, one-share market and limit orders. Similar to Harris and Hasbrouk (1996), if the limit order does not execute in the trading window, the stock is purchased at the opening price on the next day. The empirical results suggest that trading using limit orders dominates trading via market orders for market participants with relatively well balanced portfolios, and that placing a network of buy and sell limit orders as a pure trading strategy is profitable.

[13] They match all days with negative open-to-close S&P returns to the nearest positive return days, and exclude the day with the largest positive return.

strategy. In line with the logit analysis findings, market orders are decreasing in both order size and inside spread. Small limit orders are placed at market when the spread equals one, and away from the market when the spread is larger than one. As expected, more aggressive limit orders have higher execution rates.

Table 7 presents the means of the ex ante performance measure. Since the sample has a small percentage of aggressive market orders, all market orders have very small negative performance. Because they often execute, the limit orders placed at the market perform best. While limit orders placed within the inside spread have higher execution rates, they perform less well because they are more aggressive and capture a smaller gain. Since this measure penalizes severely the limit orders placed away from the market which do not execute, these limit orders have an inferior performance compared to other limit orders.

The performance of limit orders generally declines as the order size increases. Based on Table 6, larger orders have lower execution rates and should have lower ex ante performance. Based on Table 7, limit orders placed in wider spreads perform better.

With regard to the direction effect, Table 7 indicates that sell orders generally perform better than buy orders. The advantage decreases as both become more aggressive. The finding however may be attributed to the inability of our return-matching approach to eliminate completely the artificial difference in the performance of sell and buy orders.[14] Finally, the Table 6 and 7 results indicate that traders do not always place their limit orders at the position that performs best in our analysis.

Table 8 presents the means of the ex post performance measure for executed orders. As expected, more aggressive limit orders have lower performance because when the market moves through the limit orders, due to either information trading or new public information, orders placed within or at the spread are affected most.

All market orders have negative performances that are close to the magnitude of the inside spread when the order was submitted. The results suggest that market orders have no information content, which contradicts the finding that limit orders under this measure are subject to adverse selection. As Harris and Hasbrouck (1996) note, these seemingly inconsistent results may be reconciled by the fact that the spreads in pure order driven markets will always widen immediately following the execution of a market order that clears the book. Consequently, our ex post measure that uses the same side quote as the reference will underestimate the information content of market orders.[15] In general, sell orders perform better than buy orders, but the results are not statistically significant in most cases.

[14] In 22 of 28 matched subsamples, the magnitude of positive return is larger. This implies that the returns in these subsamples are still skewed towards positive returns. Actually, when we compute the performance measures using all orders in the sample, we obtain similar results to the results reported in Tables 7 and 8.

[15] Similarly, the measure that uses the other quote as a reference is likely to overestimate the information content of market orders. In the third essay, we use the quote mid point as a reference in a time series analysis that accounts for the permanent effect of trades on stock value.

5. Conclusions

In this essay we analyze empirically trading by limit versus market orders on the Saudi Stock Market. Our data set enables us to identify market and limit orders and some order characteristics. Given the literature on a trader's choice problem in order driven markets, we interpret the data using a *Random Utility Model* and approach the problem statistically using a logit model. We also examine how the orders resulting from traders' decisions perform in the market.

Consistent with order driven market models, we find a relatively strong and highly significant spread effect. The probability of placing a market order increases as the spread decreases. When the order imbalance increases in favor of the other side of the market, traders are more likely to submit market orders. More active traders and traders with small orders are more likely to place market orders. We also conclude that when traders have optimistic expectations, then the probability of placing a market buy order is higher.

Due to the structure of the market studied, the ex ante performance of market orders is small and negative. Limit orders placed at the quote, or when the spread is wide, perform best. The ex post performance indicates that limit orders are subject to a winner's curse. However, the measure cannot determine alone the magnitude of the information effect of market orders.

Appendix

Empirical Tests of the HST (1997) Model

HST (1997) obtain the following closed-form solution to the equilibrium bid-ask spread,

$$s = \psi\ (V_h - V_l) + (1-\psi)\ qH \qquad \text{where}$$

$$\psi = \frac{1+p}{1-k(1-k)(1-p)^2} - 1, \qquad q = p/(1-p),\ \ p = \delta/2 \tag{A.1}$$

They show that the equilibrium spread, s, is maximized when the proportion of limit buy orders, k, in the market equals ½. Therefore, in the region where $k < ½$, s is positively related to k, and when $k > ½$, s is negatively related to k. This implication can be empirically tested by examining the relation between the time series of spreads, s_t (or relative spreads) and a suitable proxy for the proportions of buyers in the market, k_t.

Given the time series of spreads and the corresponding proportions of buyers, $x_t = [s_t, k_t]$, the model also can be tested using the Generalized Method of Moments (GMM). The model implies that,

$$E[\varepsilon_t(x_t;\theta)\ |\Phi_{t-1}] = 0, \tag{A.2}$$

where $\varepsilon_t(x_t;\theta) = s_t - [\psi_t(V_h - V_l) + (1-\psi_t)\,qH]$ is a vector of error terms for a particular stock, Φ_{t-1} is the information set of the trader at time t-1, and $\theta = [\,p, V_h - V_l, H\,]$ is the vector of unknown parameters to be estimated.

Using a ℓ x 1 vector of instrumental variables in Φ_{t-1} , z_{t-1}, the model further implies,

$$E\left[g_t(\theta)\right]=0, \tag{A.3}$$

where $g_t(\theta)=\varepsilon_t \otimes z_{t-1}$. The GMM estimator is found by minimizing:

$$J_T(\theta)=G_T(\theta)' W_T\, G_T(\theta) \tag{A.4}$$

where $G_T(\theta)=\frac{1}{T}\sum_{t=1}^{T} g_t(\theta)$ and W_T is the inverse of a consistent estimate of the covariance matrix for the orthogonality condition in equation (A.3). To test for the goodness-fit of the model, Hansen's test (1982) can be employed,

$$T\,J_T(\theta)\sim \chi^2_{(\ell-3)} \tag{A.5}$$

To test the model's predictions. HST (1997) use data on individual stocks on the Paris Bourse. They measure k by the depth at the best bid divided by the total depth at the best quotes, and measure s using either the inside spread or the relative inside spread. The evidence on the relation and correlation between s and k is consistent with the model's predictions. They also perform a GMM estimation of the underlying model parameters and find further support for the model.

The results reported in Table A.1 show that our data also support the predicted relation between s and k. When classifying spreads (and relative spreads) by quintiles of k, the mean spread (and relative spread) attains its highest values at the middle quintile and decreases as we move to extreme quintiles. The correlation tests reported in Table

A.2 provide further support. The average correlation between s and k is positive when $k \leq \frac{1}{2}$, and significantly positive for the majority of the stocks in the sample. Similarly, it is negative when $k > \frac{1}{2}$, and significantly negative for most of the stocks in the sample.

However, the GMM tests do not provide the same support for the model. Generally, the estimated parameters are sensitive to the starting values and the types of instruments. In our GMM tests, we adopt the following strategies. To increase the possibility of finding the global minimum of the criterion function, we use 84 different sets of starting values for each stock. The starting values for parameter p are set to 0.25, 0.5, and 0.75. For the parameters H and V_h-V_l, we use 28 different sets of starting values using the range of transaction prices over the sample period as a guide. We also try three different sets of instruments: (1) constant and the lags of s, (2) constant and the lags of k, and (3) constant and the lags of both s and k. The estimates are not too sensitive for the number of lags used in each set. However, the second set always provides the best fit in terms of the value of the criterion function.[16]

In deriving the closed form solution in equation (A.1), HST (1997) assume that an informed trader buys (sells) by market order if and only if the private signal is positive (negative). This assumption has implications for the magnitude of the parameter H. Formally, the assumption constrains the value of the parameter H so that in equilibrium $q\,H < V_h - V_l$. In addition, the maximum value of p in the model is $\frac{1}{2}$.

[16] HST (1997) only use the first set of instruments.

Given these constraints, we perform three different numerical optimizations: [17]

(1) Unconstrained estimation (all the parameters in θ are unconstrained).

(2) Constrained estimation 1 (s.t. $p \in [0,1]$, $H \geq 0$ and $V_h - V_l \geq 0$).

(3) Constrained estimation 2 (s.t. $p \in [0,\frac{1}{2}]$, $q\,H < V_h - V_l$, and $H \geq 0$). [18]

In the constrained estimation 1, we restrict the parameters to be logically correct. In the constrained estimation 2, we restrict the parameters to be consistent with the model.

For each stock and each numerical optimization, we report the parameter estimates and the value of the χ^2-statistics of the model with the best fit (the model with the smallest value of the GMM criterion function among the 84 sets) in Table A.3. As the unconstrained estimation results clearly show, the model is rejected because the parameter estimates are not consistent with the model. For all but stock 2050, the estimated value of the probability of trading with an informed trader, p, and the shock to the value of the asset, H, are negative. When we constrain the value of p to be between zero and one and both H and $V_h - V_l$ to be positive, we get more consistent estimates but still reject the model for 34 of the 56 stocks (60%). The model is rejected statistically for 25 stocks, and rejected for 23 stocks because the parameter estimates are still not consistent with the model. When we further restrict all the parameters to be consistent

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[17] To minimize the criterion function, we use `fminu.m` and `constr.m` functions in the MATLAB optimization toolbox with the default options.

[18] HST (1997) fix the value of the parameter H at different values and estimate only the remaining two parameters without any additional constraints.

with the model, we get a higher statistical rejection rate. The model now is rejected for 29 stocks (51.79% of the sample).

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Table 1

Summary Statistics for Market and Limit Orders

For all 65 trading days in the period between October 31, 1996 and January 14, 1997, the number and percentage of classified market and limit orders are reported after pooling all stocks. The orders are classified by order direction (sell, buy), size (number of shares), whether the order is part of a package or not, and by the number of orders in the package that generate the order. An order package contains at least two orders.

Order Characteristics	Order Type: Market		Limit: Executed		Limit: Unexecuted		All	
Side								
Sell	34,309	(44.59%)	50,073	(54.54%)	52,369	(53.03%)	136,752	(51.12%)
Buy	42,642	(55.41%)	41,740	(45.46%)	46,384	(46.97%)	130,767	(48.88%)
Size								
≤ 100	20,993	(27.28%)	31,159	(33.94%)	11,571	(11.72%)	63,724	(23.82%)
101-500	31,873	(41.42%)	34,697	(37.79%)	34,704	(35.14%)	101,275	(37.86%)
501-1000	15,100	(19.62%)	16,268	(17.72%)	26,153	(26.48%)	57,521	(21.50%)
> 1000	8,985	(11.68%)	9,689	(10.55%)	26,325	(26.66%)	44,999	(16.82%)
Part of a package								
Yes	66,532	(86.46%)	76,785	(83.63%)	83,384	(84.44%)	226,703	(84.74%)
No	10,419	(13.54%)	15,028	(16.37%)	15,369	(15.56%)	40,816	(15.26%)
Orders per package								
2 - 5	22,255	(33.45%)	33,241	(43.29%)	40,685	(48.79%)	96,182	(35.95%)
6 - 10	11,315	(17.01%)	13,897	(18.10%)	14,999	(17.99%)	40,211	(15.03%)
11 - 15	7,086	(10.65%)	7,981	(10.39%)	8,206	(09.84%)	23,273	(08.70%)
> 15	25,876	(38.89%)	21,666	(28.22%)	19,494	(23.38%)	67,037	(25.06%)
All orders	76,951	(28.76%)	91,813	(34.32%)	98,753	(36.91%)	267,518	(100.00%)

Table 2

Summary Statistics for the explanatory variables

For all 65 trading days in the period between October 31, 1996 and January 14, 1997, the summary statistics are reported for the explanatory variables in the logit regression. The inside spread is the difference between the first best ask and the first best bid. Order imbalance is the depth at the same side divided by total depth. Direction dummy takes a value of one if order is sell and zero if it is a buy. Size is the number of shares in the order divided by 100. Number of orders per package is the number of orders in the package that generated the order. The sample used includes only orders preceded by a valid bid-ask spread.

	Mean	Min	First quartile	Median	Third quartile	Max
Inside spread	2.2266	1.0363	1.2278	1.5208	2.6546	10.66
Order imbalance	0.5126	0.4829	0.5051	0.5126	0.5204	0.5459
Direction Dummy	0.4823	0.3955	0.4717	0.4889	0.5048	0.5224
Size	8.0076	1.1936	4.7323	6.7692	10.4761	26.2281
Order per package	11.5225	3.8596	7.9012	10.1567	15.523	24.2041

Table 3

Logit Regression Results

The table reports the results for the logit regression, $E[y|x] = \Lambda(x'\beta)$, where y is a dummy variable that equals one if the order is market, and zero otherwise. The inside spread is the difference between the first best ask and the first best bid. Order imbalance is the depth at the same side divided by total depth. Direction dummy takes a value of one if the order is sell, and zero if it is a buy. Size is the number of shares in the order. Number of orders per package is the number of orders in the package that generate the order. $\Lambda(.)$ is the logistic cumulative distribution function, $e^{x\beta} / (1+e^{x\beta})$. The coefficient is the β estimate. The slope is the marginal effect of x on the probability, which is equal to $\Lambda(x'\beta)[1-\Lambda(x'\beta)]\beta$ when $\Lambda(x'\beta)$ is evaluated at the mean of the regressors. McFadden pseudo R-squared is $1-(\ln L / \ln L_0)$, where $\ln L$ and $\ln L_0$ are the log-likelihood functions evaluated at the unrestricted and restricted estimates (all coefficients, except the constant, are zero), respectively. Rejection rate is the percentage of rejecting the hypothesis that the coefficient of a given independent variable is zero for all 56 stocks.

	Mean		Min		First quartile		Median		Third quartile		Max		
No. of observations	4,003		325		906		2,488		5,920		21,220		
Dependent variable equals one	0.284		0.196		0.264		0.294		0.307		0.339		
McFadden pseudo R-squared	0.0757		0.0251		0.0518		0.0689		0.0927		0.2179		
Independent Variables	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope	Rejection rate
Constant	-0.5885		-2.3029		-0.8112		-0.5403		-0.2254		0.5148		67.86%
Inside spread	-0.39	-0.0734	-1.6198	-0.2777	-0.4803	-0.094	-0.2574	-0.0483	-0.1612	-0.0289	-0.0406	-0.0088	94.64%
Order imbalance	0.6286	0.1156	-0.8573	-0.1662	0.046	0.0091	0.5531	0.1059	1.1857	0.2026	2.9156	0.5259	69.64%
Direction dummy	0.1312	0.0179	-0.6688	-0.1303	-0.2922	-0.0604	-0.0213	-0.0041	0.4132	0.0807	1.8812	0.2363	69.64%
Size	-0.0571	-0.0108	-0.1786	-0.0383	-0.0779	-0.0136	-0.0493	-0.0098	-0.0358	-0.0068	-0.0003	-0.0001	91.07%
Orders per package	0.0125	0.0024	-0.0397	-0.0065	0.0063	0.0013	0.0131	0.0025	0.0211	0.0041	0.0645	0.0117	75.00%

The hypothesis that all the coefficients, except the constant, are zero is rejected for all stocks using both the Likelihood ratio and Wald tests.

Table 4

Queuing Model Test Results

The table reports the results for the logit regression, $E[y|x] = \Lambda(x'\beta)$, where y is a dummy variable that equals one if the order is market and zero otherwise. The set of regressors, x, include four dummy variables. d_i, $i = MS, MB, LS$ and LB, where $d_i = 1$ if the last event is i, and 0 otherwise. $\Lambda(.)$ is the logistic cumulative distribution function, $e^{x\beta} / (1+e^{x\beta})$. The predicted probabilities reported in the table are calculated using the coefficient estimates for the four dummies. Rejection rate is the percentage of rejecting the hypothesis that the coefficient of a given independent variable is zero for all 56 stocks.

Panel A: Sell Orders

	$Prob[MS\|MS]$	$Prob[MS\|MB]$	$Prob[MS\|LS]$	$Prob[MS\|LB]$
Mean	0.590	0.097	0.147	0.428
Min	0.119	0.002	0.045	0.324
First quartile	0.511	0.020	0.114	0.397
Median	0.617	0.119	0.154	0.426
Third quartile	0.709	0.148	0.176	0.458
Max	0.875	0.221	0.228	0.583
Rejection rate	58.93%	83.93%	100.00%	67.86%

Panel B: Buy Orders

	$Prob[MB\|MS]$	$Prob[MB\|MB]$	$Prob[MB\|LS]$	$Prob[MB\|LB]$
Mean	0.091	0.611	0.432	0.134
Min	0.002	0.182	0.278	0.038
First quartile	0.037	0.554	0.388	0.114
Median	0.119	0.650	0.447	0.139
Third quartile	0.132	0.744	0.490	0.160
Max	0.176	0.886	0.533	0.205
Rejection rate	91.07%	71.43%	55.36%	100.00%

Table 5

Index Returns and Ex Ante Order Performance

The table reports the ex ante performance measures classified by index return. We compute the ex ante performance measures for all orders, and the index returns for all days in the sample. We then classify the performance of buy and sell orders by the index returns.

	Mean $P^{ex\ ante}$	
Index Return	Sell orders	Buy Orders
≤ - 0.2%	0.237	0.634
-0.2% - 0%	0.548	-0.025
0% - 0.2%	0.572	-0.100
0.2% - 0.5%	0.956	-0.399
> 0.5%	0.991	-0.523

Table 6

Number of Orders and Execution Rate

For all orders in the matched subsamples, the table reports the number of orders and execution rates of sell and buy orders classified by inside spread, size, and aggressiveness. The inside spread is the difference between the first best ask and the first best bid. Order size is the number of shares in the order. *Limit away* is the limit order placed away from the same-side best quote. *Limit at* is the limit order placed at the best same-side quote. *Limit within* is the limit order placed within the prevailing inside spread. *Market* is the order with price equal to or better than the opposite best quote. The execution rate of market orders is always 100%.

Order Size	Order Aggressiveness	Inside spread at time of order entry: 1				2 or larger			
		Sell		Buy		Sell		Buy	
≤100									
	Limit away	1,931	24.08%	821	22.29%	2,098	30.12%	1,341	28.34%
	Limit at	3,457	84.50%	3,399	91.12%	1,725	81.39%	1,867	87.09%
	Limit within					1,245	88.35%	1,003	89.13%
	Market	4,846		5,549		2,945		3,009	
100-500									
	Limit away	5,495	14.39%	3,836	10.74%	5,631	20.26%	5,379	16.14%
	Limit at	5,985	84.83%	5,924	79.76%	2,777	72.96%	3,049	66.87%
	Limit within					2,191	81.74%	1,787	74.48%
	Market	7,334		8,890		4,007		4,045	
500-1000									
	Limit away	4,850	8.37%	3,859	6.30%	2,684	12.56%	2,417	7.99%
	Limit at	3,916	77.32%	4,068	66.91%	1,275	66.12%	1,313	44.25%
	Limit within					868	79.26%	634	66.88%
	Market	3,981		4,815		1,022		1,452	
>1000									
	Limit away	5,040	4.37%	4,481	2.59%	1,948	7.91%	1,441	3.19%
	Limit at	3,011	65.26%	3,503	50.41%	777	51.74%	810	31.23%
	Limit within					415	79.04%	295	65.42%
	Market	2,499		3,006		413	.	690	

Table 7

Ex Ante Order Performance

For all orders in the matched subsamples, the mean ex ante performance of sell and buy orders as measured by equation (14) are reported. The means are classified by inside spread, size, and aggressiveness. The inside spread is the difference between the first best ask and the first best bid. Order size is the number of shares in the order. *Limit away* is the limit order placed away from the same-side best quote. *Limit at* is the limit order placed at the best same-side quote. *Limit within* is the limit order placed within the prevailing inside spread. *Market* is the order with price equal to or better than the opposite best quote. *t* is the paired t-statistic for testing the equality of buy and sell means.

		Inside spread at time of order entry					
Order	Order	1			2 or larger		
Size	Aggressiveness	Sell	Buy	*t*	Sell	Buy	*t*
≤100							
	Limit away	0.97	-1.40	4.49	2.04	-0.07	2.57
	Limit at	0.76	0.78	-0.50	2.37	2.58	-1.30
	Limit within				1.45	1.92	-2.73
	Market	-0.05	-0.14	3.68	-0.23	-0.35	1.97
100-500							
	Limit away	0.61	-1.25	5.18	1.45	-0.73	2.99
	Limit at	0.76	0.58	4.65	1.90	1.12	2.79
	Limit within				1.18	0.71	1.54
	Market	-0.05	-0.15	3.33	-0.29	-0.38	1.52
500-1000							
	Limit away	0.39	-0.62	5.41	1.12	-0.69	3.35
	Limit at	0.64	0.33	5.80	1.49	0.18	4.16
	Limit within				0.94	0.06	3.50
	Market	-0.05	-0.11	2.02	-0.23	-0.30	1.15
>1000							
	Limit away	0.30	-0.62	5.15	1.05	-0.34	3.58
	Limit at	0.47	0.10	5.02	1.18	0.21	3.63
	Limit within				0.75	-0.02	1.77
	Market	-0.05	-0.08	1.52	-0.32	-0.29	-0.18

Table 8

Ex Post Order Performance

For all orders in the matched subsamples, the mean ex post performance of sell and buy orders as measured by equation (15) are reported. The means are classified by inside spread, size, and aggressiveness. The inside spread is the difference between the first best ask and the first best bid. Order size is the number of shares in the order. *Limit away* is the limit order placed away from the same-side best quote. *Limit at* is the limit order placed at the best same-side quote. *Limit within* is the limit order placed within the prevailing inside spread. *Market* is the order with price equal to or better than the opposite best quote. *t* is the paired t-statistics for testing the equality of buy and sell means.

		Inside spread at time of order entry					
Order	Order	1			2 or larger		
Size	Aggressiveness	Sell	Buy	*t*	Sell	Buy	*t*
<=100							
	Limit away	0.25	0.20	0.31	0.67	0.50	0.80
	Limit at	-0.51	-0.21	-12.48	-0.68	-0.30	-6.33
	Limit within				-1.20	-0.65	-10.23
	Market	-0.96	-0.89	-2.01	-3.26	-2.97	-1.90
100-500							
	Limit away	0.24	-0.21	3.39	0.43	0.12	1.80
	Limit at	-0.36	-0.32	-2.14	-0.65	-0.52	-2.49
	Limit within				-0.98	-0.89	-1.62
	Market	-0.90	-0.97	2.95	-3.26	-2.98	-1.67
500-1000							
	Limit away	0.22	-0.05	1.58	0.18	0.03	0.63
	Limit at	-0.35	-0.30	-1.77	-0.43	-0.47	0.59
	Limit within				-0.80	-0.75	-0.77
	Market	-0.90	-0.94	1.46	-2.71	-2.58	-1.04
>1000							
	Limit away	-0.09	-0.18	0.66	0.77	1.28	-0.33
	Limit at	-0.37	-0.32	-1.87	-0.42	-0.35	-0.92
	Limit within				-0.68	-0.66	-0.27
	Market	-0.88	-0.91	1.46	-2.61	-2.56	-0.41

Table A.1

Mean Spreads and Relative Spreads and Proportions of Buyers in the Market

For each stock, all observed inside spreads and relative spreads are classified into five quintiles using the proportions of buy orders in the market measured by $k_t = Q_{bt} / (Q_{bt} + Q_{st})$, where Q_{bt} is the quantity of shares demanded at the bid and Q_{st} is the quantity of shares offered at the ask at time t. The inside spread and relative spread are measured by $A_t - B_t$ and $200\ (A_t - B_t)/\ (A_t + B_t)$ respectively, where A_t and B_t are the best ask and bid at time t respectively. The table reports the distribution of mean spreads and relative spreads for each quintile across stocks in the sample.

Quintiles	Mean	First Quintile	Median	Third Quintile	Mean	First Quintile	Median	Third Quintile
	Inside spread				Relative inside spread			
1 (smallest)	2.225	1.173	1.424	2.369	1.694	0.730	1.515	2.207
2	2.415	1.255	1.599	2.760	1.828	0.784	1.621	2.408
3	2.431	1.350	1.669	2.984	1.913	0.795	1.659	2.603
4	2.307	1.316	1.648	2.674	1.844	0.754	1.670	2.471
5 (Largest)	1.992	1.128	1.431	2.420	1.613	0.690	1.459	2.154

Table A.2

The Correlations between the Spreads and Proportions of Buyers in the Market

For each stock, all observed inside spreads and relative spreads are classified into two groups using the value of k (when $k \geq ½$ and when $k < ½$), and the correlation between spreads and relative spreads and k is computed. k_t is measured by $Q_{bt} / (Q_{bt} + Q_{st})$, where Q_{bt} is the quantity of shares demanded at the bid and Q_{st} is the quantity of shares offered at the ask at time t. The inside spread and relative spread are measured by $A_t - B_t$ and $200\ (A_t - B_t)/\ (A_t + B_t)$, respectively, where A_t and B_t are the best ask and bid at time t, respectively. The table reports the distributions of correlation coefficients across stocks in the sample, and the percentages of stock with positive (negative) correlations when $k < ½$ ($k \geq ½$).

	Mean	First Quintile	Median	Third Quintile	%
		Inside Spread			
$k < ½$	0.102	-0.011	0.123	0.216	0.732
$k \geq ½$	-0.173	-0.248	-0.192	-0.083	0.893
		Relative Inside Spread			
$k < ½$	0.106	-0.003	0.122	0.224	0.75
$k \geq ½$	-0.17	-0.244	-0.19	-0.083	0.893

Table A.3

The GMM Test Results

The model in equation A.1 is estimated using $z_t = [constant, k_{t-1}, k_{t-3}, k_{t-5}]$ as instruments, and 84 sets of starting values for each stock. The reported results represent the case with the smallest minimized value of the GMM criterion function from the 84 sets. p is the probability of trading with an informed trader. $V_h - V_l$ is the difference of opinion between the potential buyers who attach high value to the stock and the potential sellers who attach low value to the stock. H is the shock to the value of the asset that is privately observed by informed traders. χ^2-statistic is the value of the GMM criterion function at the parameter estimates multiplied by the number of observations. The χ^2-statistic in these cases are distributed with one degree of freedom. In the unconstrained estimation we test the model without imposing any constraints on the values of the parameters. In the constrained estimation 1, we minimize subject to $p \in [0,1]$, $H \geq 0$ and $Vh - V_l \geq 0$. In constrained estimation 2, we minimize subject to $p \in [0,½]$, $q\,H < V_h - V_l$, $and\; H \geq 0$. # indicates that the model is rejected because the parameter estimates are not consistent with the model. * indicates that the model was rejected statistically at the 5% level of significance.

	Unconstrained Estimation				Constrained Estimation 1				Constrained Estimation 2			
	Parameter Estimates				Parameter Estimates				Parameter Estimates			
Stock ID	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2
1010	-5.39	1.18	-1.41	0.0168 #	0.25	3.26	0.15	1.3867	0.25	3.26	0.13	1.3844
1020	-4.54	1.57	-1.96	0.1991 #	0.11	0.84	14.69	2.6685 #	0.06	1.58	25.25	1.2976
1030	-7.47	1.87	-2.12	0.0029 #	0	9.15	0.37	64.6276 *	0	9.15	0.18	64.6303 *
1040	-5.13	10.66	-12.15	0.0067 #	0.03	0	401.27	1.3032 #	0.35	10.2	18.74	150.2267 *
1050	-18.65	1.35	-1.47	0.0050 #	0.11	0	16.2	2.9035 #	0.47	1.43	1.6	8.6112 *
1060	-22.4	4.04	-4.33	0.0002 #	0.15	13.45	0.01	0.1692	0.15	13.45	0.01	0.1691
1070	-19.69	4.43	-4.41	0.0012 #	0	19.82	0.26	1.6680	0	19.82	7.02	1.6680
1080	-21.36	3.79	-3.66	0.0033 #	0	15.67	0.26	8.6456 *	0	15.41	0.71	8.6265 *
1090	-16.4	4.36	-4.8	0.0011 #	0	21.09	74.4	136.81 *	0	21.09	0.32	136.8122 *
1100	-27.59	2.14	-2.32	0.0009 #	0.29	5.64	0.14	1.3907	0.29	5.64	0.11	1.3905
1120	-5.71	3.11	-3.64	0.0708 #	0.42	6.19	0.09	2.4648	0.43	6.19	0.08	2.4646
2010	-16.78	1.44	-1.47	0.0894 #	0.22	0	7.27	11.5493 *#	0.5	2.18	0.42	14.3049 *

Table A.3 *continued*

	Unconstrained Estimation				Constrained Estimation 1				Constrained Estimation 2			
	Parameter Estimates				Parameter Estimates				Parameter Estimates			
Stock ID	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2
2020	-19.55	2.3	-4.64	0.0079 #	0.11	15.22	1.48	5.4802 *	0.08	16.17	1.93	5.7344 *
2050	0.17	8.56	0.02	0.2862	0.17	8.56	0.02	0.2865	0.17	8.56	0.02	0.2862
2060	-6.48	1.35	-1.52	0.0009 #	0	6.44	0.43	5.3576 *	0	6.44	0.11	5.3575 *
2070	-116.5	1.35	-1.39	0.0104 #	0.6	0	2.48	1.8665 #	0.05	1.36	23.7	1.9648
2080	-4.3	1.64	-1.95	0.0108 #	0.16	4.85	0.04	0.0118	0.16	4.85	0.04	0.0117
2100	-0.16	1.66	-16.24	0.1467 #	0.79	0	2.88	0.1417 #	0.02	2.16	99.03	0.6343
2110	-1.31	1.59	-2.8	0.0011 #	0.35	0	5.26	15.4507 *#	0.5	2.42	0.4	16.8379 *
2130	-1.93	1.06	-1.71	0.0000 #	0.27	3.02	0.21	2.1312	0.27	3.02	0.21	2.1300
2140	-1.38	2.66	-4.33	0.0013 #	0.35	5.08	0.19	3.6978	0.35	5.08	0.19	3.6967
3010	-14.42	1.38	-1.44	0.0141 #	0.3	3.31	0.21	2.1139	0.3	3.31	0.21	2.1137
3020	-11.99	1.96	-2.1	0.0023 #	0	10.18	439.4	13.1536 *	0	10.19	50.97	13.1485 *
3030	-59.62	1.16	-1.1	0.0126 #	0.6	0.86	1.05	7.3162 *#	0.5	1.13	1.13	7.4379 *
3040	-3.37	1.86	-2.33	0.0015 #	0.03	8.54	0.06	0.0995	0.03	8.54	0.03	0.0995
3050	-9.16	6.02	-7.79	0.0012 #	0.01	0	671.93	991.71 *#	0.41	7.01	10.04	1509.96 *
3060	-3.31	1.94	-2.4	0.0000 #	0.12	0	17.82	70.1753 *#	0.5	1.73	1.75	76.5112 *
3080	-23.74	2.49	-2.72	0.0009 #	0.2	7.77	0.03	0.8887	0.2	7.77	0.03	0.8885
3090	-8.74	1.13	-1.21	0.0115 #	0.29	0	4.37	6.5491 *#	0.5	1.08	1.1	9.5302 *
4010	-2.14	3.16	-4.52	0.0005 #	0.01	0	626.55	100.53 *#	0.45	3.45	4.18	365.2850 *
4020	-7.53	2.95	-3.68	0.0066 #	0.04	1.93	97.93	6.4867 *#	0.26	3.37	9.41	24.2698 *
4030	-12.65	1.07	-1.15	0.0032 #	0.01	0.43	80.18	0.5452 #	0.5	1.05	1.05	8.7124 *
4040	-24.07	1.09	-1.13	0.3818 #	0.21	3.4	0.14	2.0372	0.21	3.42	0	2.0259
4050	-36.42	1.12	-1.23	0.0003 #	0.05	4.89	0.01	1.2555	0.05	4.89	0.01	1.2501

Table A.3 *continued*

	Unconstrained Estimation				Constrained Estimation 1				Constrained Estimation 2			
	Parameter Estimates				Parameter Estimates				Parameter Estimates			
Stock ID	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2	p	$V_h - V_l$	H	χ^2
4060	-7.49	1.08	-1.27	0.0001 #	0.18	3.48	0.04	4.8488 *	0.18	3.48	0.04	4.8478 *
4070	-4.07	2.2	-3.04	0.0072 #	0.03	0	112.74	122.59 *#	0.48	2.29	2.44	198.1495 *
4080	-1.7	1.49	-2.34	0.0001 #	0.58	1.65	0.81	0.2458	0.5	1.62	1.27	0.2313
4090	-4.25	1.01	-1.26	0.0103 #	0.3	0	4.2	15.7849 *#	0.5	1.25	0.75	17.3500 *
4100	-17.96	1.33	-1.29	0.0013 #	0.05	7.25	0.13	41.8683 *	0.05	7.25	0.11	41.8681 *
4110	-1.34	1.1	-1.85	0.0065 #	0.12	4.17	0.81	0.2358	0.09	4.13	1.98	0.2434
4120	-2.76	2.65	-3.24	0.0208 #	0.32	0.05	9.62	8.1829 *#	0.47	2.53	2.81	12.0568 *
4130	-3.44	1.54	-1.85	0.0089 #	0.03	0.62	60.72	0.1921 #	0.22	1.51	5.24	157.9475 *
4150	-35.37	1.1	-1.14	0.0147 #	0.52	1.33	0.73	0.0520	0.48	1.31	0.94	0.0544
4061	-17.98	4.36	-4.92	0.0180 #	0.02	19.5	0	5.2322 *	0.02	19.48	0	5.2320 *
5010	-3.8	1.47	-1.81	0.0000 #	0	6.76	0.1	2.6538	0	6.76	0.11	2.6538
5020	-1.66	1.59	-2.52	0.0058 #	0.04	0	45.06	22.1225 *#	0.5	1.52	1.52	57.2605 *
5030	-21.17	3.43	-3.66	0.0021 #	0.06	13.47	0	0.8643	0.06	13.47	0	0.8656
6010	-6869	-0.38	-0.51	0.0485 #	0.7	0	2.14	0.2344 #	0.13	1.4	9.44	0.7099
6020	-2.36	1.05	-1.61	0.0045 #	0.42	1.49	1	10.0169 *	0.21	1.4	3.6	10.7714 *
6030	-16.94	1.27	-1.32	0.0000 #	0.01	9.85	0	0.2992	0.01	9.85	0	0.2984
6040	-20.03	1.59	-1.89	0.0422 #	0.32	4.07	0.28	0.4899	0.32	4.07	0.29	0.4877
6050	-29.08	16.81	-8.95	0.1933 #	0.02	0	466.22	666.11 *#	0.44	5.73	7.27	1044.29 *
6060	-8.67	1.33	-1.37	0.0004 #	0.55	0	2.58	22.1780 *#	0.47	1.31	1.48	36.9430 *
6070	-3.24	1.21	-1.53	0.0025 #	0.29	2.64	0.34	0.5582	0.29	2.64	0.34	0.5582
6080	-2.43	1.48	-2.07	0.0000 #	0.82	0	1.87	3.0101 #	0.49	1.47	1.55	3.4229
6090	-3.53	1.18	-1.68	0.0001 #	0.41	2.18	0.5	4.9113 *	0.41	2.18	0.51	4.7207 *

Figure 1

The Size and Position of the Spread and the Proportion of Buyers

Figures 1A and 1B plot the position of the spread (Ask-Bid) and the spread with changes in the proportion of buyers in the market (k). The figures are based on the assumptions that V_h (the buyer's valuation for the stock) = 105, V_l (the seller valuation for the stock) = 95, H (the private signal) = 2, and p (probability of trading with an informed trader) = 0.2. As k increases, μ (the relative non-execution risk for the buyer) approaches one, the equilibrium ask approaches V_h, and the uninformed buyer's gain from trade goes to zero. Conversely, as k decreases, λ (the relative non-execution risk for the seller) approaches one, the equilibrium bid approaches V_l, and the uninformed seller's gain from trade goes to zero.

Figure 1A: The Spread Size

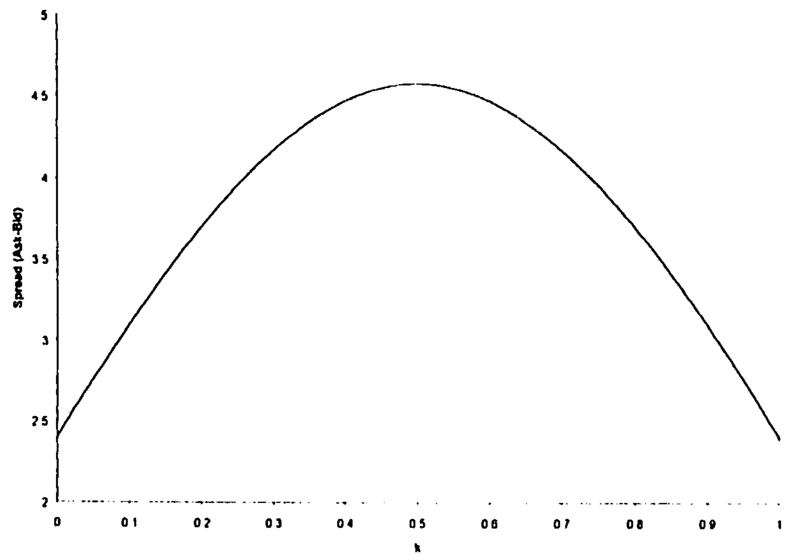
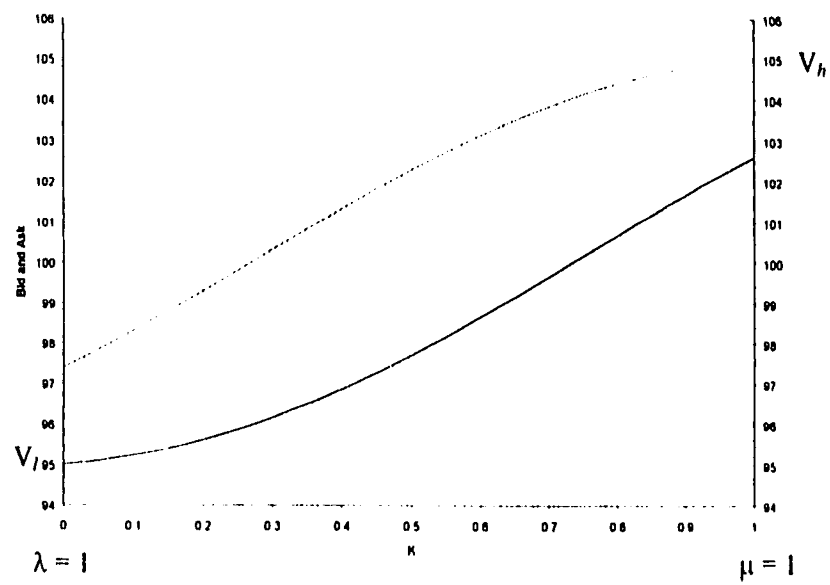


Figure 1B: The Spread Position



Essay 3

The Information Content of Orders: A Vector Autoregressive Analysis

1. Introduction

In a market with asymmetrically informed traders, order flow conveys information which affects the size and position of the bid-ask spread, and ultimately the behavior of transacted prices. When asymmetric information exists, liquidity suppliers (either market makers, limit order traders or both) lose on average to informed traders. To compensate themselves for this adverse selection cost, liquidity suppliers tend to widen the spread. Asymmetric information also causes the liquidity suppliers to view the order flow as originating with some positive probability from an informed trader. As such, order flow conveys information and motivates quote changes. For example, a market order to sell could signal that the trader has received bad news. The uninformed liquidity supplier, knowing that the order might be information motivated, may revise his expectations of future stock value downward. In turn, this lowers the bid and ask quotes. One of these quotes subsequently is observed when the next market order arrives into the market.

The models focusing on the adverse selection problem confronting market makers (asymmetric information models) were first suggested by Bagehot (1971), and were formally analyzed by Copeland and Galai (1983), Glosten and Milgrom (1985) and Kyle (1985).[1] Although these models generally consider a specialist market in which a designated market maker exposes bid and ask quotes to the trading public, the predictions of these models are readily extended to a market where the sole liquidity suppliers are limit order traders. As Handa and Schwartz (1997) demonstrate, limit order traders resemble market makers in that they provide liquidity to the market. Furthermore, they face an adverse selection problem similar to market makers. Handa, Schwartz and Tiwari (1997) formally model a pure order driven market with asymmetric information. Consistent with previous asymmetric information models, this model implies that the spread and stock value are a function of adverse selection.[2]

In this essay, we examine the dynamic behavior of order and stock prices in order to assess the information content of newly submitted orders on the Saudi Stock Market (SSM). The SSM provides a favorable environment for studying the impact of asymmetric information. First, there is a high potential for insider trading on the SSM because no laws exist to prevent insiders from trading company shares based on inside information. Second, the market is relatively small compared to other stock markets, which may aggravate the asymmetric information effect on other traders. Third, the

[1] For more on the development of asymmetric information models, see O'Hara (1995).

[2] In this model, which was presented in more detail in the second essay, a proportion of the traders receive a private signal about a change in the value of the stock. The private signal takes a given value of $+H$ or $-H$ with equal probability. The private information lasts for one trade, after which it is publicly revealed and traders on both sides of the market revise their expectations about the value of the stock upward or downward by an amount H.

market is completely computerized and relatively transparent, which should enhance the informational trading effect. Traders can observe the best two quotes and their associated depths. They also can infer the characteristics of new orders (size, direction, market or limit) by monitoring changes in the visible portion of the order book. Finally, the reporting of trading events is instantaneous. Since the studied microstructure phenomena are confined to short horizons, quick reporting of trading events allows their information content to be measured correctly.

The primary statistical technique employed herein is the Vector Autoregressive (VAR) model advocated by Hasbrouck (1991a, 1991b). Previous studies primarily used VAR specifications which include only trade (market order) variables. Our data set allows us to expand the specification to include limit orders, which are already embodied in the information set of market participants. Beyond the order size effect, the new specification allows us to investigate the information content of orders with different levels of aggressiveness. We also examine the cross-stock and cross-time differences in the order informativeness measures.

Our analysis is related to several empirical studies which seek a measurable proxy for information asymmetry in stock markets. These include studies that use different approaches to measuring the extent to which the trading process conveys information [e.g. Easley et al. (1996), Easley, Kiefer, and O'Hara (1997)], studies of the price impact of trades [e.g. Glosten and Harris (1988), Stoll (1989), Hausman, Lo and MacKinlay(1992)], and studies that use either bid-ask spreads or the adverse selection component of spreads to measure the extent of asymmetric information [e.g. Foster and Viswanathan (1993), Laux (1993), and Lin, Sanger and Booth (1995)].

The rest of the essay is organized as follows. In the next section, the econometric model of price and order attributes is described. Various descriptive statistics compiled from the data used are presented in section 3. The empirical results are presented and analyzed in section 4. The conclusions are summarized in section 5.

2. Econometric Model

Hasbrouck (1991a) models the interaction of stock trades and quote revisions as a VAR system. Unlike simple microstructure models, this model considers orders and quote revisions as a system characterized by auto- and cross-correlations of a very general nature. Using this model, it is possible to characterize the persistent impact of the unexpected component of order flow on the quote midpoint. This can be used to summarize the informativeness of orders.[3]

The VAR model is relatively easy to interpret using impulse response functions and variance decomposition. Hasbrouck (1991a) uses impulse response functions to illustrate the dynamic behavior of the system subsequent to a trade with specific attribute (e.g. trade size). Variance decomposition is used to measure the relative importance of the order variables in deriving quote revisions. Hasbrouck (1991b) combines the VAR model with results from the random walk decomposition literature to devise a new relative measure of trade informativeness. Compared with other measures of the market's assessment of information asymmetry (such as the inside spread and impulse the response

[3] As Hasbrouck (1991a) notes, the persistent impact of orders on the quote midpoint is preferred to the immediate impact because the latter may be contaminated by transient liquidity effects. Using the order innovation rather than orders excludes the predictable portion of the order flow, which by definition conveys no new information.

function), this measure has the advantage of being relative to the total information effect on the stock's value and unconditional on particular trade attributes. Applications of the model include Hasbrouck (1991a, 1991b, and 1996) and Hamao and Hasbrouck (1995). We now review the model and discuss its main assumptions.

2.1 The Model

From an economic perspective, the actual quote midpoint in many market microstructure models is interpreted as a true-efficient price, which is disturbed by various microstructure imperfections such as price discreteness and lagged adjustment to information. Specifically:

$$q_t = m_t + s_t \tag{1}$$

where q_t is the quote midpoint, m_t is the efficient price (the expected value of the stock conditional on time t public information, I_t), and s_t is the pricing error that embodies all the transient microstructure imperfections. It is assumed that:

$$m_t = m_{t-1} + w_t \tag{2}$$

$$Ew_t=0, Ew_t^2=\sigma_w^2, Ew_t w_k=0 \; \forall t \neq k, Es_t=0, Es_t^2=\sigma_s^2 \tag{3}$$

where w_t is an innovation that reflects updating to the public information set.

It is further assumed that s_t is joint covariance stationary with w_t. The assumption implies that $E[s_{t+k} \mid I_t] = 0$ as $k \to \infty$. This reflects the transience of microstructure effects. Given the above assumptions, it is possible to decompose the changes in q_t into their permanent (informational) and transitory (market friction-related) components.

To measure order informativeness, we further need to decompose the *source* of the changes in q_t into two components: order flow induced, and other. Given these two decompositions, the market assessment of the information content of the order is measured by the permanent order-induced change in q_t. For this purpose, define $\mathbf{x}_t - E[\mathbf{x}_t \mid I_{t-1}]$ as the current order innovation, where $\mathbf{x}_t$ is the vector of attributes for the order. Consequently, if there is any private information to be inferred for an order, it must be in this innovation. The order innovation can affect both the permanent and transitory components of q_t. We are interested in the portion of the permanent movements in q_t that can be attributed to these innovations, which can be measured by the impact of the order innovation on the efficient price innovation, $E[w_t \mid \mathbf{x}_t - E[\mathbf{x}_t \mid I_{t-1}]]$. Therefore, two useful measures of order informativeness are:

$$Var(E[w_t \mid \mathbf{x}_t - E[\mathbf{x}_t \mid I_{t-1}]]) \qquad \text{(Absolute measure)} \qquad (4)$$

$$\frac{Var(E[w_t \mid \mathbf{x}_t - E[\mathbf{x}_t \mid I_{t-1}]])}{Var(w_t)} \qquad \text{(Relative measure)} \qquad (5)$$

The random walk decomposition (1) on which this measure is based is unobservable. The connection to observable data follows from the VAR model:

$$\mathbf{y}_t = \sum_{j=0}^{p} \Phi_j \mathbf{y}_{t-j} + \mathbf{v}_t \qquad (6)$$

where

$$\mathbf{y}_t=\begin{bmatrix}\mathbf{x}_t\\ \Delta q_t\end{bmatrix},\ \Phi_0=\begin{bmatrix}\mathbf{0} & 0\\ \phi & 0\end{bmatrix},\ \mathbf{v}_t=\begin{bmatrix}\mathbf{v}_{x,t}\\ v_{\Delta q,t}\end{bmatrix}$$

where $\Delta q_t = q_t - q_{t-1}$ is the quote revision. If $\mathbf{x}_t$ is a k-vector, then $\mathbf{0}$ is a $k \times k$ matrix and ϕ is a $1 \times k$ vector.

The inclusion of the contemporaneous order attributes, $\mathbf{x}_t$, in the Δq_t equation imposes a recursive structure that reflects the ordering at time t of the order and quote revision.[4] This implies that E $[v_{\Delta q,t}\, \mathbf{v}_{x,t}] = 0$, and hence:

$$Var(v_t)=\begin{bmatrix}\Omega & 0\\ 0 & \sigma^2_{\Delta q}\end{bmatrix} \tag{7}$$

where $\Omega = var(\mathbf{v}_{x,t})$ is a $k \times k$ matrix. If Δq_t and $\mathbf{x}_t$ are covariance stationary, then the Vector Moving Average (VMA) representation of (6) is,

$$\mathbf{y}_t=\sum_{j=0}^{\infty}\Psi_j\mathbf{v}_{t-j} \tag{8}$$

Under the assumption that the public information set is the quote and order history, $I_t=\{\mathbf{x}_t,\Delta q_t,\mathbf{x}_{t-1},\Delta q_{t-1},\ldots\}$, then by linear projection:

$$E\left[w_t \mid \mathbf{x}_t - E[\mathbf{x}_t \mid I_{t-1}]\right] = \hat{E}[w_t|\mathbf{v}_{x,t}] \tag{9}$$

where $\hat{E}$ denotes the linear projection. The order informativeness measure in (5) becomes:

[4] In both the asymmetric information models and actual market operations the quotes are usually adjusted subsequently to the order placement [Hasbrouck (1991b)].

$$R = \frac{Var\left(\hat{E}[w_t | \mathbf{v}_{x,t}]\right)}{Var\left(w_t\right)} \equiv \frac{\sigma^2_{w,x}}{\sigma^2_w} \tag{10}$$

where $\sigma_{w,x}$ is the absolute measure of informativeness. This measure can be computed from the VMA representation in (8). The VMA in (8) is written more compactly as:

$$\begin{bmatrix} \mathbf{x}_t \\ \Delta q_t \end{bmatrix} = \begin{bmatrix} \mathbf{A}(L) & \mathbf{b}(L) \\ \mathbf{c}(L) & d(L) \end{bmatrix} \begin{bmatrix} \mathbf{v}_{x,t} \\ v_{\Delta q,t} \end{bmatrix} \tag{11}$$

where $\mathbf{A}(L)$, $\mathbf{b}(L)$, $\mathbf{c}(L)$, and $\mathrm{d}(L)$ are the lag polynomial operators. Using (11), the Δq_t equation (11) can be written as:

$$\Delta q_t = \mathbf{c}(L)\,\mathbf{v}_{x,t} + d(L)\,v_{\Delta q,t} \tag{12}$$

Differencing (1) gives:

$$\Delta q_t = w_t + (1-L)s_t \tag{13}$$

Equations (12) and (13) lead to two alternative representations of the autocovariance generating function for Δq_t.[5] From (12), we obtain the following autocovariance generating function:

$$G_{\Delta q}(z) = \mathbf{c}(z)\Omega\,\mathbf{c}(z^{-1})' + d(z)d(z^{-1})\sigma^2_{\Delta q} \tag{14}$$

From (13), we obtain:

[5] The autocovariance generating function for a time series vector $\mathbf{y}_t$ with absolutely summable autocovariances is defined as $G_y = \sum_{j=-\infty}^{\infty} \Gamma_j z^j$, where $\Gamma_j = E[\mathbf{y}_t \mathbf{y}_{t-j}]$ is the autocovariance matrix and z is a complex scalar. If $\mathbf{y}_t$ has a VMA representation such as (8), then G_y can be written as $G_y = \Psi(z)\Omega\Psi(z^{-1})$ [Hamilton (1994, p. 266)].

$$G_{\Delta q}(z) = G_w(z) + (1-z^{-1})G_{ws}(z) + (1-z)G_{sw}(z) + (1-z)(1-z^{-1})G_s(z) \tag{15}$$

Letting $z = 1$ implies:

$$G_{\Delta q}(1) = G_w(1) = \sigma_w^2 = \mathbf{c}(1)\,\Omega\,\mathbf{c}(1)' + [d(1)]^2\sigma_{\Delta q}^2 \tag{16}$$

Since the lag polynomials evaluated at unity are equal to their respective coefficient sums, the random walk variance is:

$$\sigma_w^2 = \left(\sum_{i=0}^{\infty}\mathbf{c}_i\right)\Omega\left(\sum_{i=0}^{\infty}\mathbf{c}_i'\right) + \left(1+\sum_{i=1}^{\infty}d_i\right)^2\sigma_{\Delta q}^2 \tag{17}$$

and the contribution of orders to this variance is:

$$\sigma_{w.x}^2 = \left(\sum_{i=0}^{\infty}\mathbf{c}_i\right)\Omega\left(\sum_{i=0}^{\infty}\mathbf{c}_i'\right) \tag{18}$$

Equations (17) and (18) are used to obtain estimates for the order informativeness measures. We first estimate the VAR specification in (6) for a given order, p. Following the procedures described by Hamilton (1994, p.319), the estimated coefficient matrices, $[\hat{\Phi}_1, \hat{\Phi}_2, \ldots, \hat{\Phi}_p]$, is used to compute the impulse coefficient matrices in VMA representation in (8), $[\hat{\Psi}_1, \hat{\Psi}_2, \hat{\Psi}_3, \ldots, \hat{\Psi}_n]$, for sufficiently large n. The estimated VMA is then used to compute the accumulated responses for a specific order shock. The estimates of covariance matrix, $\hat{\Omega}$, variance of Δq, $\hat{\sigma}_{\Delta q}^2$, $\hat{\mathbf{c}}$, and $\hat{d}_i$ (after partitioning $\hat{\Psi}_i$ using (11)) are finally used to compute estimates for $\sigma_{w.x.}$ $\sigma_{w.}$ and R given by (18), (17) and (10), respectively.

2.2 Discussion of the Model's Assumptions

The applicability of the VAR model rests on several assumptions. The first is the stationarity of $\mathbf{y}_t$. If $\{\mathbf{x}_t, \Delta q_t\}$ are jointly covariance stationary, then the Wold theorem ensures that the model has a VMA representation. If this VMA representation is invertible, then the series have an infinite convergent VAR representation. In microstructure applications, the invertibility assumption is violated by overdifferencing and cointegration. Our data and the structure of our market make such violations unlikely. In a specialist market, overdifferencing is possible because the trade variable is the negative first difference of the (presumably stationary) inventory series. However, in our market, inventory control is not an issue since liquidity is supplied largely by a diverse and changing population of agents. Likewise, cointegration is unlikely since the VAR specification includes only the quote midpoint, and not two or more prices for the same stock.

The assumed joint stationarity of $\{s_t, w_t\}$ also implies homoskedasticity. Taking into consideration the U-shaped intraday patterns in the squared returns of quote midpoints (see Figure 2B in essay 1), and rejecting the null hypothesis of no autoregressive conditional heteroskedasticity (ARCH) effects in the VAR residuals, this assumption calls for new explanations or a modification in the estimation procedure. Hasbrouck (1991b) suggests three alternatives. The first is to view stationarity as being applicable to data sequenced by an index t that preserves the ordering of events, but from which the natural time and date stamps have been suppressed. Based on this view, the model is interpreted as an unconditional one that reflects the average behavior of the data over all times and days. This view is formally correct but it may be unattractive because it ignores information available to both market participants and econometricians.

A second approach involves defining the subscript t. Since trading activity also has a U-shape (see Figure 4 in essay 1), the variances per event (order placements and quote revisions) are likely to be more constant than variances per unit of time. Therefore, the nonstationarity can be mitigated by defining t as an event counter, rather than as an index of real time. This approach is also preferable to real time modeling when investigating causal relations (as in our analysis) that are obscured by aggregation. Time aggregation, as we show later, also leads to co-determined model disturbances and the consequent necessity of identification restrictions.

The best approach is to model conditional nonstationarity explicitly. Harvey, Ruiz and Sentana (1992) consider an unobserved component time series model with ARCH disturbances and derive a filter that provides the basis for the estimation. The problem with such approach is that, unlike standard ARCH models, the past values of the disturbances (as w_t and s_t in our models) are not observable. Since the past observations do not, in general, imply knowledge of past disturbances, any alternative estimation is not optimal. An alternative technique, as in Hasbrouck (1991b), is to estimate the specification over various intraday intervals. From the above alternatives, we adopt the view that t is an event counter, and estimate the VAR model over eight intraday intervals.

The random walk model is often generalized to include a drift term representing the unconditional expected price change. Although we can generalize the model to include a constant drift, practical econometric considerations favor suppression. As noted by Merton (1980), if the data set that has a large number of observations over a relatively short period of time (like most market microstructure data sets), then the precision of the variance estimate increases by more frequent sampling, while the mean estimate does not. Consequently, they suggest that the variance estimate will have smaller estimation error if centered around zero, rather than the sample mean. Using our data, the results from estimating the VAR model with a constant does not alter our conclusions.

The informativeness measure derived in the VAR model identifies all public information with the quote revision innovation, $v_{\Delta q,t}$, and all private information with the trade innovation, $\mathbf{v}_{\mathbf{x},t}$. The dichotomy is not as clean in practice. If the limit order traders also have superior information, then $v_{\Delta q,t}$ reflects both this private information and the public information. However, the informed trader, as in Handa, Schwartz and Tiwari (1997), is more likely to use market orders to take advantage of the dissipating value of their information. However, if market quotes do not adjust quickly to public information, then $\mathbf{v}_{\mathbf{x},t}$ may also contain public information. This happens if market features, such as price smoothing and stale quotes, impair the quote revision process, and thereby constrain the quote revision from fully reflecting public information. Fortunately, there is no price-smoothing requirement on the SSM. However, the cost of continuously monitoring the market can create stale quotes that do not adjust completely to reflect public information.

3. Data and Variable Descriptions

The data set provided by SAMA includes the orders for 56 stocks submitted to the market during the period from 31 October 1996 to 14 January 1997. We identify executed orders and differentiate between the market and (executed) limit orders using the procedures described in the second essay. Table 1 describes the variables used. Since it is important for all included variables to be public knowledge and market participants can only observe the best two quotes, we only include orders placed at or within the second best quotes. Furthermore, the construction of the quote revision variable, Δq_t, requires orders to be preceded and succeeded by a valid bid-ask spread. A valid bid-ask spread is defined as one in which both the bid and ask quotes are established and visible to the market participants.

Table 2 presents summary statistics for the order and quote revision variables. The statistics on quote revisions, Δq_t, in Table 2 represent the immediate impact on the quote midpoint of different types of orders. As expected, the table reveals that buy (sell) orders are associated with positive (negative) quote revisions. On average, buy orders lead to a 0.19% increase in quote midpoints, while sell orders lead to a 0.12% decrease in quote midpoints. When classified by their aggressiveness, more aggressive orders tend to have a smaller order size but generate a larger instant impact. Compared to market orders and limit orders within the spread, limit orders at or away from the market have contrary and very small average quote revisions.

Since it is necessary to work with stationary data, we run unit root tests on all the time series included in the VAR specifications. The absence of significant unit roots suggests stationarity of the time series.

4. Empirical Findings

After discussing some specification issues, we use impulse response functions to investigate the effect of order size and aggressiveness on quote revisions. Using summary statistics for market value and order frequency subsamples we examine the cross-sectional effect on order informativeness. We conclude this section by dividing the trading day into eight intervals, and analyzing the intraday patterns in the VAR statistics.

4.1 Specification issues

The VAR model considered above allows a bivariate VAR as a special case. This model was first estimated using trade sign and quote revision [Hasbrouck (1991a)]. To incorporate the trade size effect and to approximate the nonlinearity in the trade-price impact, this VAR specification was generalized to include signed trade size and a nonlinear (square root or quadratic) transformation of trade size [Hasbrouck (1991a,1991b,1996a), and Hamao and Hasbrouck (1995)]. The information set of a trader, at least in our market, includes not only the trades (market orders) but also a subset of the limit orders. As such, we replace trades with orders in our specifications of the $\mathbf{x}_t$ vector. To capture the degree of aggressiveness of orders, we construct an additional signed variable that indicates the degree of order aggressiveness. Since the asymmetric information models usually assume that traders with private information submit market orders, we also examine a specification that includes only market orders. In defining the quote revision variable, Δq_t, we use the logarithm of the quote midpoint to facilitate the comparison of statistics across stocks with different share prices.

Model order is another specification issue. The VAR and VMA representation presented above are infinite in length. When applying the models to real data, it is necessary to use truncated specifications. Some of the usual statistical tests for VAR order tend to select long lags while others select a small number of lags. Since the selection criteria are usually interpreted as methods for determining a filter that transforms the given data into a white noise series, we run the modified Li and McLeod (1981) portmanteau test to check the overall significance of the residual autocorrelations. For most stocks in the sample, lags between 5 and 10 seem to be adequate. Specifications 3 and 4 and specifications 7 and 8 in Table 3 shows that the estimation of order informativeness is not very sensitive to model order. Based on this result, we perform our subsequent empirical analyses using specifications truncated at five lags. The VMA representation is truncated at 30 lags. For all stocks in the sample, the order is large enough for adjustments to converge.

Table 3 shows how different VAR specifications affect the estimated relative measure of order informativeness as defined by equation (10). More comprehensive specifications attribute slightly more of the efficient price variance to orders. The mean, median and weighted average of order and trade informativeness increase as more order attributes are added to vector $\mathbf{x}_t$. Excluding information in order flow seems to overstate order informativeness. Specifications 5-8, which include only trades (market orders), lead to higher estimates of informativeness than specifications 1-4, which include all market and limit orders. In specifications 1-4, the weighted averages of the estimate range from 0.163 to 0.204, compared to 0.435 to 0.544 for specifications 5-8. This result is reasonable given the correlation between market and limit orders.[6] Unless otherwise noted, subsequent report results are from VAR specification 3, which includes market and limit orders.

Hamao and Hasbrouck (1995) and Hasbrouck (1996a) estimate the VAR model with a one-minute sampling interval. They compute the quote revision using the end-of-minute quotes, whereas signed orders and trades are cumulated over the minute. Changing the time subscript, t, to refer to minutes and not to transactions is suitable for certain applications, but may not be the best for ours. Hamao and Hasbrouck (1995) use it because the standard clock time plays a central role on the Tokyo Stock Exchange (TSE) due to its price limit mechanism. Hasbrouck (1996a) uses it to study the impact of different order variables (program, non-program, index, and non-index-arbitrage orders). We do not use the time aggregation approach here for several reasons. Clock time does not play a central role on the SSM as on the TSE. In our analysis we investigate the impact of one order that can have different attributes (e.g. size and aggressiveness). Such orders are analyzed more easily using an event time approach. As noted above, time aggregation leads to co-determined model disturbances and the necessity of imposing identification restrictions, whereas event time approach leads to a recursive structure that allows us to determine the impact of an order on quote revision more precisely. Finally, as explained in section 2.2, using event time rather than real time may mitigate heteroskedasticity.

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[6] As Hasbrouck (1991b) asserts, the informativeness measure quantifies the explanatory power of trades in a regression in which the dependent variable is the innovation in the random walk price implicit in the quote midpoint. If trades are correlated with an omitted public information variable, such as limit orders on the SSM, the measure overstates the informativeness of trades.

To show how time aggregation may affect our results, the VAR model is estimated with a five-minute sampling interval and three variables: Quote revisions (computed using end of interval quotes), signed market order, and signed limit order cumulated over the five minutes. Given this specification, it is still reasonable to assume that the quote revision is determined last (i.e. a quote revision over a given interval does not affect order placements within that interval). However, simultaneity among limit and market orders is possible. As a consequence, the VAR disturbance is not identified. Identification requires imposing a particular contemporaneous recursive structure. As the last two rows in table 3 show, the relative measure of market order informativeness alters as we change the ordering of model structural innovation from limit orders, market orders, quote revisions to market order, limit order, quote revision. Finer classification of orders leads to a more difficult identification problem.

4.2 The Effect of Order Size and Aggressiveness

In this subsection we use impulse response functions to examine the accumulated response of quote revisions to orders of different size and aggressiveness. We illustrate using a buy order. In constructing the initial shocks, we use four different sizes (100, 500, 1,000, and 5,000 shares) and the five aggressiveness levels assigned to variable x_{3t}. Since the present VAR specification involves four order variables, we specify the initial values of these four variables for each order shock. For example, the arrival of a 100 share market buy order at time t is represented by letting $\mathbf{v}_t = [1,100,10,5,0]'$.

Figure 1 plots 9 representative cases from the 20 shock combinations. In Figure 1A, we plot the accumulated response of the quote revision variable, Δq_t, to four market orders that differ in their size through 30 order events. Figure 1B plots the same for five orders that differ in their aggressiveness level but have the same order size of 5000 shares. The other combinations of initial shocks have similar effects to the cases plotted in Figure 1.

If informed traders prefer to trade larger quantities, as in the microstructure model of Easley and O'Hara (1987), then the information content and hence the price impact of large orders differs from that for small orders. Figure 1A clearly shows that the price impact of market orders increases with order size. This finding is consistent with the model of Easley and O'Hara, and the empirical findings of Easley, Kiefer and O'Hara (1997). The result also is consistent with other empirical studies that find a positive relation between order size and the adverse selection component of the spread [e.g., Lin, Sanger and Booth (1995)].

Figure 1B reveals that more aggressive orders have higher price impacts. This agrees with the asymmetric information models that usually assume that informed traders seek immediate execution by using more aggressive order placement strategies. The puzzling result in this figure is the quote revision process subsequent to the submission of limit buy orders away from the market. Unlike other limit orders, the limit orders away and further away from the first best quote have negative impacts on quote revisions.

Since prior empirical work uses only market orders, the limit order informativeness is not compared with other types of orders in the literature. The above results might suggest that limit buy (sell) orders away from the market signal bad (good) private news as in the case for market sell (buy) orders. However, a closer examination of the data reveals that the frequency of other side market orders is high after the submission of limit orders away on the same side of the market. In Table 4, we summarize the computed empirical percent frequencies of the ten events assigned to variable x_{3t} (1 to 5 for buy orders and -1 to –5 for sell orders) conditional on the previous event being a limit order away (2 and –2) or further away (1 and –1). Limit orders away are usually followed either by the same event or by market orders from the other side of the market. The correlation is prevalent well beyond one lag.

The observed high correlation between limit orders away and market orders may explain the above puzzling result. We offer two possible explanations why this phenomenon happens in the market. First, in anticipation of adverse news, the uninformed limit orders move their quotes away from the market, as is assumed in the asymmetric information models. Second, informed traders who prefer to transact larger quantities wait until the depth on the opposite side increases before submitting their market orders.

4.3 Cross-sectional Analysis

The stocks with high market value and order frequency tend to have a greater amount of information events (and therefore higher arrival rates of informed traders) and are more widely held by liquidity traders. Therefore, the arrival rates of informed traders are more likely to be offset by the higher arrival rates of liquidity traders. In contrast, smaller and less active stocks face a greater risk of informed trading. When shares are not widely held and are infrequently traded, any trade is viewed as originating with higher probability from informed traders. The observed spreads in many markets including the

SSM are consistent with this information-based explanation.[7] As Tables 5 and 6 show, the relative inside spreads decrease monotonically with both market value and trading frequency. This result is confirmed in Table 7, where the rank-order correlation between spread and market capitalization and order frequency are –0.714 and –0.741, respectively.

The statistics from the VAR model provide additional insights. The impulse response functions (IRF) used in the subsequent analyses are based on a 1000 share market buy order. Based on the results reported in Tables 5 and 6, the IRFs have the same pattern as the inside spread. (From Table 7, the rank-order correlations between IRF and each of market capitalization, order frequency, and spread are –0.571, -0.551, and 0.766, respectively.) Similarity in the results for the market capitalization and order frequency subsamples also occur in the behavior of σ_w (a measure of public information intensity) and $\sigma_{w.x}$ (a measure of absolute contribution of all orders to efficient price movement). Based on Table 7, the correlation between these standard deviations and both order frequency and market capitalization are similar in sign and magnitude. The results are expected given the significant positive correlation between order frequency and market capitalization.

As was noted earlier, IRF, the spread and $\sigma_{w.x}$ are all absolute measures of informativeness. The more relevant measure is the relative measure, *R*, whose relationship with market capitalization is generally negative and not significant. In

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[7] For example, Easley *et al* (1996) provide statistics showing that infrequently-traded stocks have larger bid-ask spreads on the London Stock Exchange and NYSE. Lehmann and Modest (1994) identify a similar pattern on the Tokyo Stock Exchange.

contrast, the negative relation between this relative measure and order frequency is highly significant. The results imply that orders are more informative for less active stocks, a finding which is consistent with Easley *et al.* (1996).

Using a sample of NYSE listed companies, Hasbrouck (1991b) finds that, on average, the relative measure of informativeness equals 0.34 (i.e. roughly 34% of the variance in the random walk component of the stock price is attributable to trades). Since he uses only trades, the comparable measure in our analysis is $R_{market\ order}$. The average value for $R_{market\ order}$ in our sample is 0.53, which may imply the presence of a very large quantity of asymmetric information on the SSM.

Based on the last column of Table 7, the correlations between the spread and the statistics of the VAR model are positive. The relation is very strong and highly significant for IRF, σ_w and $\sigma_{w.x}$. The absolute measures (IRF, spread and $\sigma_{w.x}$) agree more often on ranking the stocks on the basis of the market's assessment of information asymmetry. The correlation between the relative measure, *R*, and spread is less significant than the other correlations. This supports the Hasbrouck (1991b) empirical observation that the spread and *R* "appear to be measuring different things and cannot be used interchangeably".

4.4 Intraday Analysis

We end our empirical analysis by inspecting the intraday patterns in the statistics of the VAR model. In our analysis of the order book and order flow in the first essay, we find that spreads, order flow and transactions exhibit certain patterns. Some of the models that can explain these patterns were discussed in sections 4.4 and 5.3 of essay 1. We revisit this issue now.

The typical trading day has two trading sessions of two hours each. We divide the data into eight subsamples, where each subsample includes one half-hour of trading data. We restrict the analysis to the 38 stocks that have at least 100 observations in each subsample.

Although the spread has a generally decreasing pattern, other absolute measures of order informativeness (IRF and $\sigma_{w;x}$), σ_x (a measure of trading activity), and σ_w do not exhibit systematic patterns. The relative measure of order informativeness, R, is generally increasing. This further supports Hasbrouck's empirical observation cited above. The intraday behavior of R implies that, in a relative sense, orders are more informative at the end of the trading day than at other times. Given that trading activities have a U-shaped pattern in each trading session (see Figure 4 in essay 1), the result is still inconsistent with the hypotheses advanced to explain concentration in trading activities.[8]

5. Conclusions

Using order data for the Saudi Stock Market (SSM), we employ a new specification of the VAR model advocated by Hasbrouck (1991a, 1991b) to assess the information content of a newly submitted order on the SSM. In addition to trade (market orders), the new specification includes those limit orders which are in the information set of market participants.

[8] See the discussion of the models of Admati and Pfleiderer (1988) and Brock and Kleidon (1992) in section 4.4 of the first essay.

As predicted by the asymmetric information models, we find that larger and more aggressive orders are more informative. Compared to previous findings, our results imply the presence of a very large quantity of asymmetric information on the SSM. Like many previous empirical studies, the relative measure of order informativeness implies that private information is more important for infrequently traded stocks.

Although the absolute measures of order informativeness derived from the VAR model and spread often agree on their stock ranking based on the market's assessment of information asymmetry, the weak correlation between the relative measure of informativeness (also derived from the VAR model) and the spread provide further support to previous observations that the two variables measure different things, and should not be used interchangeably.

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Table 1

Definitions of the Variables

The table describes the construction of the time series vector, $\mathbf{y}_t$, which is used in the empirical analysis in this essay. $\mathbf{y}_t = [\mathbf{x}_t, \Delta q_t]'$, where $\mathbf{x}_t = [x_{0t}, x_{1t}, x_{2t}, x_{3t}]'$.

A_{t-1}	Prevailing ask one second before submitting the order
B_{t-1}	Prevailing bid one second before submitting the order
A_t	Prevailing ask one minute after submitting the order
B_t	Prevailing bid one minute after submitting the order
P_t	Order price
G_t	Order aggressiveness indicator, $1-2(A_{t-1} - P_t)/(A_{t-1} - B_{t-1})$ for buy orders and the negative of this quantity for sell orders.
q_s	The logarithm of quote midpoint, $q_s = \log((A_s + B_s) / 2)$, $s = t-1, t$
Δq_t	Quote revision: continuously compounded rate of change in quote midpoint, $\Delta q_t = \ln(q_t) - \ln(q_{t-1})$
x_{0t}	Side indicator variable, 1 for buy orders and -1 for sell orders.
x_{1t}	Signed order quantity, signed positively for buy orders, and negatively for sell orders.
x_{2t}	Signed square root order variable, $sign(x_{1t})\,\lvert x_{1t}\rvert^{1/2}$
x_{3t}	Signed aggressiveness indicator that equals 5 if $G_t \geq 1$ (market order), 4 if $1 > G_t > -1$ (limit order within the inside spread), 3 if $G_t = -1$ (limit order at the best quote), 2 if $-1 > G_t \geq -2$ (limit order away), 1 if $G_t < -2$ (further away limit order). Sell order is classified analogously but has a negative sign.

Table 2

Summary Statistics for Orders and Quote Revisions

The table reports the number and percentage of orders, order size (number of shares) and quote revisions classified by order direction (sell, buy) and aggressiveness.

Order Characteristics	Number and percentage of orders		x_{2t}: Order Size		Δq_t: Quote revision (x100)	
			Mean	Std. Deviation	Mean	Std. Deviation
x_{0t}: Order side						
1: Buy orders	91295	52.87%	775.11	503.79	0.1919	0.129
-1: Sell orders	81399	47.13%	674.81	369.54	-0.1268	0.1393
x_{3t}: Order Aggressiveness						
Buy orders						
5: Market	40865	44.76%	567.1	286.82	0.5819	0.436
4: Limit Within	5522	6.05%	664.08	381.9	0.4751	0.3388
3: Limit at	32868	36.00%	745.77	531.03	-0.0557	0.0682
2: Limit away	4347	4.76%	1452.11	1332.46	-0.048	0.1286
1: Further away	7693	8.43%	1466.31	1316.85	-0.0488	0.139
Sell Orders						
-5: Market	33205	40.79%	516.36	268.9	-0.3837	0.3217
-4: Limit Within	6362	7.82%	608.17	383.19	-0.4194	0.3085
-3: Limit at	30237	37.15%	691.86	372.99	0.1759	0.1292
-2: Limit away	4242	5.21%	1086.35	866.17	0.0454	0.1141
-1: Further away	7353	9.03%	1075.94	679.03	0.0774	0.1145

Table 3

Informativeness Measures for Different VAR Specifications

For the total sample of 56 stocks, the table reports the cross-sectional summary statistics of the relative measure of order informativeness defined by equation (10) using different VAR specifications. Specifications 1-4 use market and limit orders, whereas specifications 5-8 use only market orders (orders that have an aggressiveness indicator equal to 5 or -5). The weighted average is the average of order informativeness across all stocks weighted by market capitalization as of the end of the second quarter of 1996. The variables used in these eight specifications are defined in Table 1. Specifications 9-10 use time aggregated data with a five-minute sampling interval and three variables: Quote revisions (computed using end of the interval quotes), signed market order (x_m), and signed limit order (x_l) cumulated over the five minutes. In specification 9, the ordering of model structural innovation is assumed to be: market orders, limit orders, quote revisions. In specification 10, it is assumed to be: limit order, market order, quote revision. The reported measure for these two specifications is the relative measure of market order informativeness.

Specifications of $\mathbf{x}_t$ and model order (p): $\mathbf{x}_t$	p	Mean	Std. deviation	Min	First Quintile	Median	Third Quintile	Max	Weighted average
1: $[x_{0t}, x_{3t}]$	5	0.171	0.063	0.053	0.134	0.167	0.217	0.375	0.163
2: $[x_{0t}, x_{1t}, x_{3t}]$	5	0.195	0.066	0.061	0.154	0.193	0.228	0.418	0.177
3: $[x_{0t}, x_{1t}, x_{2t}, x_{3t}]$	5	0.204	0.071	0.060	0.161	0.203	0.238	0.453	0.182
4: $[x_{0t}, x_{1t}, x_{2t}, x_{3t}]$	10	0.245	0.095	0.068	0.197	0.230	0.275	0.512	0.204
5: $[x_{0t}]$	5	0.494	0.168	0.195	0.381	0.465	0.633	0.928	0.435
6: $[x_{0t}, x_{1t}]$	5	0.517	0.171	0.186	0.403	0.485	0.662	0.930	0.446
7: $[x_{0t}, x_{1t}, x_{2t}]$	5	0.530	0.179	0.193	0.399	0.500	0.687	0.929	0.454
8: $[x_{0t}, x_{1t}, x_{2t}]$	10	0.518	0.214	0.085	0.373	0.479	0.677	0.998	0.447
9: $[x_m, x_l]$	5	0.217	0.122	0.007	0.097	0.228	0.310	0.489	0.278
10: $[x_l, x_m]$	5	0.254	0.141	0.012	0.136	0.270	0.374	0.528	0.344

Based on Wilcoxon matched-pair nonparametric tests, we reject the null hypothesis of no difference between any two combinations of relative measures estimated by the above specifications.

Table 4

Order Flow Conditional Frequencies

For all the data used in the VAR estimations, the table reports the empirical percent frequencies for ten events assigned for variable x_{3t} in Table 1 conditional on the previous event being a limit order away from first best quotes. MB: market buy, LB: limit buy, MS: market sell, and LS: Limit sell

		x_{3t}									
		MB	LB within	LB at	LB Away	LB further away	LS further away	LS away	LS at	LS within	MS
		5	4	3	2	1	-1	-2	-3	-4	-5
x_{3t-1}	2	0.0352	0.1165	0.1952	**0.1941**	0.0023	0.0129	0.0532	0.1169	0.1227	**0.151**
	1	0.0606	0.0052	0.2209	0.009	**0.204**	0.0874	0.0062	0.22	0.0082	**0.1784**
	-1	**0.1734**	0.0065	0.1593	0.006	0.0777	**0.2289**	0.0076	0.2179	0.0087	0.114
	-2	**0.1956**	0.079	0.0892	0.0564	0.0068	0.0017	**0.2692**	0.1458	0.1045	0.0517
x_{3t-2}	2	0.0997	0.0836	0.1788	0.1488	0.018	0.018	0.0509	0.1175	0.0751	**0.2096**
	1	0.141	0.0096	0.2379	0.0129	0.1385	0.0635	0.0075	0.1845	0.0114	**0.1931**
	-1	**0.2417**	0.0122	0.1826	0.0075	0.0614	0.161	0.0098	0.1817	0.0131	0.1291
	-2	**0.2743**	0.0539	0.1082	0.0447	0.0142	0.0154	0.1947	0.1366	0.0754	0.0827
x_{3t-3}	2	0.1219	0.0779	0.1835	0.1136	0.0212	0.0175	0.0442	0.1187	0.0668	**0.2346**
	1	0.155	0.0121	0.2312	0.0118	0.1146	0.0554	0.0091	0.1878	0.0142	**0.2087**
	-1	**0.2535**	0.0136	0.1788	0.0091	0.0553	0.1353	0.0097	0.1789	0.0161	0.1498
	-2	**0.3069**	0.0522	0.1054	0.0411	0.0149	0.0194	0.1532	0.1378	0.0671	0.1019
x_{3t-4}	2	0.1448	0.0701	0.1784	0.1017	0.0258	0.0212	0.0433	0.1107	0.0675	**0.2365**
	1	0.169	0.0163	0.2253	0.0148	0.103	0.054	0.0103	0.1813	0.0169	**0.2091**
	-1	**0.2533**	0.0153	0.1852	0.0124	0.0526	0.1143	0.0133	0.1832	0.0195	0.151
	-2	**0.3152**	0.0508	0.1118	0.0369	0.0175	0.0241	0.1355	0.1424	0.0549	0.1109
x_{3t-5}	2	0.1558	0.0602	0.1823	0.0901	0.0293	0.0279	0.0364	0.1272	0.0613	**0.2294**
	1	0.1688	0.0193	0.2216	0.0152	0.0891	0.0517	0.0129	0.1871	0.0217	**0.2125**
	-1	**0.2667**	0.0159	0.1843	0.0132	0.0488	0.1066	0.0133	0.176	0.0192	0.156
	-2	**0.3166**	0.052	0.1239	0.0369	0.0194	0.0232	0.1225	0.136	0.0499	0.1197

Based on χ^2 test, we reject the null hypothesis of independence between current and previous order events at the 1 percent level.

Table 5

Cross-Sectional Statistics for Total Sample and the Market Capitalization Subsamples

The table reports the cross-sectional summary statistics for total sample and the market capitalization subsamples. Standard deviations are in the parenthesis. Values are averages for total sample of 56 stocks and subsamples based on market capitalization quartiles. Market capitalization is at the end of the second quarter of 1996. *IRF* is the accumulated response of quote revisions to a 1000 share market buy order. σ_x is the per hour standard deviation of the innovation in the signed trade equation, x_{1t} (in 100 shares). σ_w is the per hour standard deviation of the innovation in the quote revision equation, Δq_t. $\sigma_{w.x}$ is the per hour square root of the absolute measure of order informativeness estimated using equation (18). σ per hour is calculated by $\sigma n / h$, where n is the number of observations and h is the number of trading hours in the sample. $R_{\,all\ orders}$ is the relative measure of order informativeness estimated by equation (10) using VAR specification that includes market and limit orders (specification 3 in Table 3). $R_{\,market\ orders}$ is the same as $R_{\,all\ orders}$ estimated using only market orders (specification 7 in Table 3). Spread is the relative inside spread.

	All stocks	Market Capitalization sub-samples 1 (lowest)	2	3	4 (highest)
No. of stocks	56	14	14	14	14
Market Capitalization	2908	146	614	1762	9109
	(5968)	(55)	(249)	(637)	(9670)
No. of observations	3079	1512	2308	2912	5584
	(3106)	(1387)	(2301)	(2181)	(4333)
IRF (x100)	0.752	0.987	0.982	0.527	0.510
	(0.466)	(0.447)	(0.526)	(0.299)	(0.345)
σ_x	461.07	517.45	426.96	343.66	556.23
	(423.13)	(477.93)	(399.76)	(308.18)	(494.97)
σ_w *(x100)*	1.533	1.928	1.646	1.300	1.257
	(0.806)	(1.052)	(0.951)	(0.548)	(0.337)
$\sigma_{w.x}$ *(x100)*	3.524	4.226	3.672	3.198	3.001
	(1.732)	(1.763)	(2.344)	(1.472)	(0.980)
$R_{\,all\ orders}$	0.204	0.206	0.228	0.196	0.184
	(0.071)	(0.066)	(0.068)	(0.097)	(0.040)
$R_{\,market\ orders}$	0.530	0.637	0.566	0.460	0.459
	(0.179)	(0.205)	(0.174)	(0.166)	(0.106)
Spread (x100)	1.778	2.860	2.083	1.137	1.032
	(1.197)	(1.130)	(1.090)	(0.636)	(0.887)

Table 6

Cross-Sectional Statistics for Total Sample and the Order Frequency Subsamples

The table reports the cross-sectional summary statistics for total sample and the order frequency subsamples. Standard deviations are in the parenthesis. Values are averages for total sample of 56 stocks and subsamples based on order frequency quartiles. Order frequency is calculated based on the number of orders submitted during the sample period. *IRF* is the accumulated response of quote revisions to a 1000 share market buy order. σ_x is the per hour standard deviation of the innovation in the signed trade equation, x_{lt} (in 100 shares). σ_w is the per hour standard deviation of the innovation in the quote revision equation, Δq_t. $\sigma_{w,x}$ is the per hour square root of the absolute measure of order informativeness estimated using equation (18). σ per hour is calculated by $\sigma n / h$, where n is the number of observations and h is the number of trading hours in the sample. $R_{all\ orders}$ is the relative measure of order informativeness estimated by equation (10) using VAR specification that includes market and limit orders (specification 3 in Table 3). $R_{market\ orders}$ is the same as $R_{all\ orders}$ estimated using only market orders (specification 7 in Table 3). Spread is the relative inside spread.

		Order Frequency sub-samples			
	All Stocks	1 (lowest)	2	3	4 (highest)
No. of stocks	56	14	14	14	14
Order frequency	4777	634	2165	4607	11702
	(5085)	(190)	(556)	(1117)	(5504)
No. of observations	3079	425	1538	3044	7309
	(3106)	(164)	(380)	(835)	(3248)
IRF (x100)	0.752	1.069	0.809	0.682	0.446
	(0.466)	(0.643)	(0.375)	(0.332)	(0.196)
σ_x	461.07	140.26	466.22	501.29	736.52
	(423.13)	(90.36)	(449.55)	(341.7)	(485.93)
σ_w *(x100)*	1.533	1.084	1.623	1.674	1.751
	(0.806)	(0.535)	(0.973)	(0.716)	(0.839)
$\sigma_{w,x}$ *(x100)*	3.524	2.343	3.604	3.909	4.242
	(1.732)	(1.236)	(1.755)	(1.596)	(1.821)
$R_{all\ orders}$	0.204	0.245	0.201	0.195	0.174
	(0.071)	(0.095)	(0.055)	(0.061)	(0.049)
$R_{market\ orders}$	0.530	0.551	0.568	0.513	0.490
	(0.179)	(0.207)	(0.213)	(0.162)	(0.130)
Spread (x100)	1.778	2.828	2.063	1.394	0.827
	(1.197)	(1.068)	(1.295)	(0.814)	(0.415)

Table 7

Correlation Tests

The table reports the rank-order correlation coefficients between stock characteristics and some quantities estimated from the VAR model. Market capitalization is at the end of the second quarter of 1996. Order frequency is calculated based on the number of orders submitted during the sample period. *IRF* is the accumulated response of quote revision to a 1000 share market buy order. σ_x is the per hour standard deviation of the innovation in the signed trade equation, x_{1t} (in 100 shares). σ_w is the per hour standard deviation of the innovation in the quote revision equation, Δq_t. $\sigma_{w,x}$ is the per hour square root of the absolute measure of order informativeness estimated using equation (18). σ per hour is calculated by $\sigma n / h$, where n is the number of observations and h is the number of trading hours in the sample. R is the relative measure of order informativeness estimated by equation (10) using VAR specification that includes market and limit orders (specification 3 in Table 3). Spread is the relative inside spread.

	Order Frequency	*IRF (x100)*	σ_x	σ_w (x100)	$\sigma_{w,x}$ (x100)	R	Spread
Market Cap.	0.502*	-0.571*	-0.352*	-0.688*	-0.689*	-0.234	-0.714*
Order Frequency		-0.551*	0.131	-0.560*	-0.629*	-0.382*	-0.741*
IRF (x100)			0.296**	0.766*	0.873*	0.452*	0.766*
σ_x				0.441*	0.325**	-0.192	0.321**
σ_w *(x100)*					0.917*	0.074	0.865*
$\sigma_{w,x}$ *(x100)*						0.415*	0.893*
R							0.324**

* Statistically significant at the 1% level.
** Statistically significant at the 5% level.

Table 8

Summary Statistics for the Intraday Subsamples

The table reports the summary statistics from the VAR estimation over eight session intervals. Values are averages for total sample of 38 stocks and subsamples based on one half-hour trading data. Standard deviations are in the parenthesis. *IRF* is the accumulated response of quote revisions to a 1000 shares market buy order. σ_x is the per hour standard deviation of the innovation in the signed trade equation, x_{1t} (in 100 shares). σ_w is the per hour standard deviation of the innovation in the quote revision equation, Δq_t. $\sigma_{w,x}$ is the per hour square root of the absolute measure of order informativeness estimated using equation (18). σ per hour is calculated by $\sigma n / h$, where n is the number of observation and h is the number of trading hours in the sample. R is the relative measure of order informativeness estimated by equation (10) using VAR specification that includes market and limit orders (specification 3 in Table 3). Spread is the relative inside spread. $\chi^2_{(7)}$ is the Friedman test statistic, which is a nonparametric test for the null hypothesis that the distributions of a given measure, such as σ_x, are identical across the eight intervals. The test statistic has a chi-square distribution with 7 degrees of freedom.

	First trading session				Second trading session				
Half-hour trading intervals	1	2	3	4	1	2	3	4	$\chi^2_{(7)}$
No. of observations	488	565	568	625	419	462	463	612	
	(434)	(448)	(411)	(437)	(385)	(333)	(314)	(431)	
IRF (x100)	0.327	0.445	0.547	0.491	0.524	0.645	0.573	0.604	25.92*
	(0.728)	(0.449)	(0.439)	(0.572)	(0.463)	(0.834)	(0.423)	(0.462)	
σ_x	168.77	210.29	200.33	203.59	172.36	185.64	177.77	209.42	1.92
	(130.41)	(212.72)	(159.14)	(165.89)	(151.79)	(151.67)	(138.32)	(180.93)	
σ_w *(x100)*	0.589	0.614	0.647	0.743	0.516	0.636	0.521	0.644	5.1
	(0.345)	(0.452)	(0.506)	(0.761)	(0.419)	(0.468)	(0.318)	(0.355)	
$\sigma_{w,x}$ *(x100)*	1.493	1.513	1.416	1.702	1.118	1.379	1.174	1.279	23.79*
	(0.660)	(1.168)	(0.921)	(1.326)	(0.752)	(1.158)	(0.803)	(0.772)	
R	0.178	0.201	0.221	0.190	0.257	0.263	0.243	0.292	29.93*
	(0.132)	(0.111)	(0.105)	(0.089)	(0.188)	(0.133)	(0.133)	(0.135)	
Spread	1.849	1.821	1.796	1.769	1.740	1.747	1.745	1.750	113.63*
	(1.238)	(1.221)	(1.208)	(1.187)	(1.185)	(1.194)	(1.172)	(1.181)	

* Statistically significant at the 1% level.

Figure 1

Estimated Responses of Quote Revisions to Different Buy Orders

The figure plots the average accumulated quote revision implied by VAR model specification 3 in table 2 subsequent to four initial shocks corresponding to four different sizes of a market buy order (Figure 1A), and subsequent to five initial shocks corresponding to five 5,000 shares buy orders with different levels of aggressiveness (Figure 1B). All averages are weighted using market capitalization as of the end of the second quarter of 1996.

Figure 1A: Quote Revision and Order Size

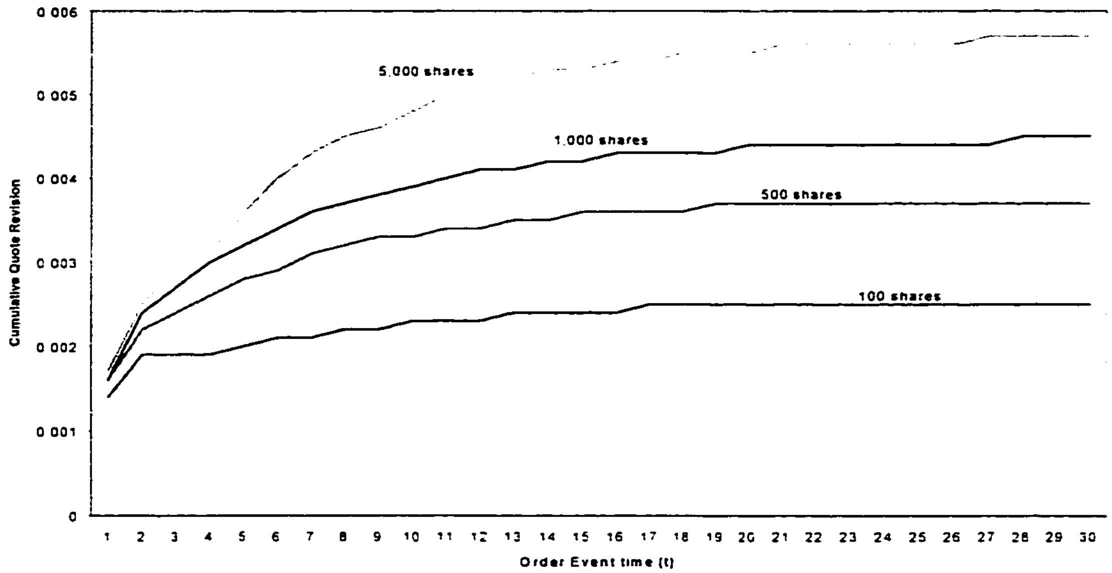
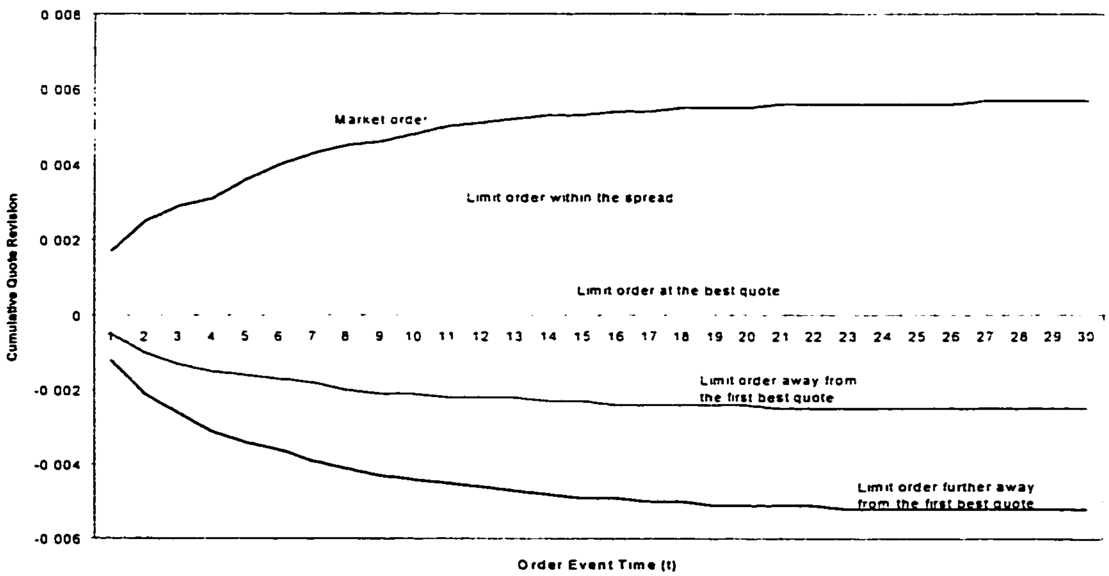


Figure 1B: Quote Revision and Order Aggressiveness



Major Findings, Policy Implications, and Directions for Future Research

Using data sets on orders, order packages, quotes, trades and market-limit orders, we investigate several aspect of the microstructure of the SSM under the computerized trading system, ESIS. We study the order book and order flow, limit order execution, trading by limit versus market orders, order performance, and the information content of newly submitted orders. Our findings provide new evidence on several issues and have important implications for the design of the trading mechanism on the SSM.

Although the SSM has a distinct structure, its intraday patterns are surprisingly similar to those found in other markets with different structures. These include U-shaped patterns in traded volume, number of transactions and volatility. Like other order-driven markets, the SSM exhibits a U-shaped pattern in the placement of new orders.

On the SSM, the relative inside spread is higher only at the open and declines gradually afterwards. This pattern is similar to the one observed for a number of markets without designated market makers. The average relative inside spread is large compared to other markets, mainly due to a relatively high tick size. Tick size is an important determinant of the inside spreads for low priced stocks, and for all other relative spreads.

As in other studies, we detect a "diagonal effect" in order flow. Strategic order splitting rather than imitation appears to be the dominant factor causing this effect.

Liquidity, as commonly measured by width and depth, is relatively low on the SSM. However, it is exceptionally high when measured by immediacy. Limit orders that are priced reasonably, on average, have a short duration before being executed, and have a high probability of subsequent execution.

The analysis of market versus limit order trading on the SSM significantly supports the spread effect predicted by order driven market models. The probability of placing a market order increases as the spread decreases. When the order imbalance increases in favor of the other side of the market, traders are more likely to submit market orders. More active traders and traders with small orders are more likely to place market orders. We also conclude that when traders have optimistic expectations, then the probability of placing a market buy order is higher.

The performance of orders resulting from a trader's decision predicts limit orders placed at the quote, or when the spread is wide, perform best. Due to the structure of the market studied, the ex ante performance of market orders is small and negative. The ex post performance indicates that limit orders are subject to a winner's curse.

The assessment of the information content of orders implies the presence of a very large quantity of asymmetric information on the SSM. As predicted by the asymmetric information models, we find that larger and more aggressive orders are more informative. Like many previous empirical studies, the relative measure of order informativeness implies that private information is more important for infrequently traded stocks.

The absolute measures of order informativeness derived from the VAR model and spread often agree on their stock ranking based on the market's assessment of information asymmetry. In contrast, the correlation between the relative measure of informativeness (also derived from the VAR model) and the spread is weak. This further supports previous observations that the two variables measure different things, and should not be used interchangeably.

Our findings generally indicate that the SSM is not liquid in some respects and has a high level of information trading. This implies that informed traders gain at the expense of uninformed traders. The gains provide the motivation to the incorporate information into stock prices, which improves the informational efficiency of the market. However, a market with too much informational trading may not succeed. If some traders have superior information and can not be identified, other traders will be reluctant to trade. This tradeoff between the operational efficiency of the market mechanism and its informational efficiency complicate the task of market design. The operational efficiency of the order driven SSM depends critically on traders who voluntarily provide liquidity to the market by posting limit orders. Thus, the design of the trading mechanism on the SSM should provide more incentives for participation by limit order traders. We now propose several measures that are expected to increase the level of participation by limit order traders.

Insider Trading: As noted above, trading on information improves the informational efficiency of the market. Trading on information, as in Shin (1996), can originate from illegal insider trading and market professional trading, which is not subject to regulation. An insider usually has costless access to precise private information about a given stock. In contrast, market professionals improve the precision of their information by conducting costly research. The analysis of the information content of orders on the SSM implies the presence of a very large quantity of asymmetric information. A large portion of information based trading on the SSM probably originates from inside information. Although trading based on such information is prohibited by current regulation, there is no effective mechanism to prohibit such practices. With a stricter regulation policy, insiders will adopt less aggressive trading strategies and market professionals will increase the precision of their information due to expected increases in their marginal profits. Likewise, improving the collection and dissemination of information is expected to increase the precision of market professionals and reduce their costs. Such regulation will provide more protection for liquidity traders from insiders, and provide more incentives for market professionals to conduct research. Malaikah (1990) and Almweisheer (1996) provide several practical suggestions for improving information disclosure and enhancing the monitoring of insider trading.

Market Transparency: Market transparency as defined by O'Hara (1995) is "the ability of market participants to observe the information in the trading process". A market is said to be more transparent if more information about orders and last transactions is observable. For example, useful information on a given order includes price, size, direction, timing, type (limit or market), and who submitted the order. Market transparency is important because the amount of information available can affect the strategies of traders. It is generally believed that a greater transparency leads to greater exposure of informed traders, and reduces their ability to profit from their information. In turn, this reduces the losses of uninformed traders [e.g. Pagano and Röell (1996)]. Nonetheless, more transparency increases the option value of limit orders (especially large orders) and may reduce the welfare of uninformed traders. If the objective is to give limit order traders more incentives to supply liquidity, then we suggest a modification to the priority rules. Allowing traders to specify how much information to display about their orders, and giving the display a second priority (after price and before time) may enhance market liquidity. Adapting such a rule is desired particularly to encourage large traders to make markets in stocks. Hiding a part of the order size, over a minimum quantity, reduces the option value of the limit orders and can increase market depth. Because informed traders do not want to be identified, permitting traders to display their identity can help some large traders develop a good reputation as market makers.

Commission Structure: Since the provision of liquidity is voluntary on the SSM, a special incentive program to encourage market making in stocks can be implemented [Angel (1996)]. An example of such a program is a plan to reduce commissions charged on traders who place two-sided limit orders especially in less liquid stocks. To ensure that the traders supply good quotes, the incentive program should be conditioned on the size of the inside spread and the quantities offered.

Call versus Continuous Market: Traders during continuous trading know more information than they do in call markets. In a call market, as discussed in Madhavan (1992), traders' information essentially becomes averaged over all trades. This allows market-clearing prices to work on average rather than for each individual trade. This aggregation reduces transparency, but can overcome the problem of information asymmetry. As Harris (1991) explains, when uninformed traders pool their trades at a single point of time, informed traders must trade at that time. This tends to reveal their information so that uninformed traders can take such information into account when trading. Since a call market executes orders at a single price that reflects aggregate supply and demand for the stock, poorly informed traders need not worry much about whether their limit prices reflect current information. Instead, they can rely in part on the efforts of other traders to set a fair price. Finally, the option value of limit orders is smaller in call markets because they are good at the time of the call and can be executed at a better price.

Our results show that less active stocks have a higher level of information-based trading. This suggests that switching the trading in these inactive stocks to periodically call auctions may make trading in these stocks for uninformed traders less risky than under continuous trading. Since these stocks are illiquid, the call market will focus orders at a single point in time, which should increase the liquidity supplied at that point in time.

Tick Size Rule: The minimum price variation rule is important. A large relative tick size provides an incentive for traders to make markets in stocks. As noted by Harris (1991), a nontrivial tick simplifies the trader's information set and reduces the potential for costly errors. It is also important for enforcing time and price priority in a limit order book, which give incentives for limit order traders to provide liquidity with limit orders. The nontrivial tick size also creates a minimum inside spread, which provides a further incentive for limit order traders to make markets by posting limit orders. In turn, this increases liquidity on both sides of the market. In contrast, a larger tick increases transaction costs for market order traders, which may reduce overall liquidity for stocks. The optimal tick, as Angel (1997) concludes, is not zero. Its optimal size represents a tradeoff between the benefits of a nonzero tick and the cost that a tick imposes.

Our analysis of the constant tick size on the SSM reveals that the median relative tick size (and as a consequence, the median inside spread) is relatively large compared to other major stock markets. Our analysis shows that tick size is an important determinant of the inside spreads for low priced stocks, and for all other relative spreads. If the relative tick size in the major markets is optimal, then our findings suggest a reduction in the tick size on the SSM is warranted. When considering a modification of the tick size, market regulators can not completely control the tick size for a given stock. Stock companies, as Angel (1997) demonstrates, can also affect the relative tick size when deciding how many shares to issue when they go public or by splitting their stock, even if the tick size is fixed by the market regulators. Hence, the main decision market regulators face is whether to adhere to a constant absolute tick size, and let companies decide on their relative tick size, or have a step function in tick sizes based on share prices. Given the large differences between share prices and because splits are uncommon on the SSM, a constant absolute tick size seems sub-optimal for the market. We suggest that the market adopt a small number of absolute tick sizes (as on, for example, Canadian markets). How to determine the optimal price levels for these tick size categories remains as a task for future research.

Market Manipulation: Market manipulation refers to the interference with normal market forces. This usually occurs in two typical forms. One or more manipulators use buy or sell orders deliberately to affect prices and/or volumes, in order to create an opportunity for profit. In the other form, false or misleading information is spread in order to influence others to trade in a certain way for the same purpose. The problem is elevated by market thinness. Surveillance analysts usually look for abnormal patterns in trading activities, which may indicate that an attempt is being made to interfere with normal market forces. Although it is more difficult for one trader to manipulate the market, two or more can easily do. Market abuse is one of the great challenges for market surveillance on the SSM. How to design the system to eliminate this problem remains a very interesting topic for future research.

Our empirical microstructure research in this thesis has provided further insight on the behavior of prices and market participants, and has direct policy implications that are expected to enhance the ESIS (the current trading mechanism employed on the SSM). A good trading mechanism is not sufficient since the rest of the market infrastructure must be revised so the traders can have more confidence in the market. In addition to greater information disclosure and transparency, a separate and independent regulatory body should be established, and the initial public offering process should be reformed, and brokerage firms should be regulated.

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