Essays on

Market Microstructure -

Empirical Evidence from Some Nordic Exchanges

Jonas Niemeyer

A Dissertation for the
Doctor's Degree in Philosophy
Department of Finance
Stockholm School of Economics
1994

STOCKHOLM SCHOOL
OF ECONOMICS
THE ECONOMIC RESEARCH INSTITUTE

ISBN 91-7258-389-4

Keywords:
market microstructure
securities markets
trading systems
limit order book
bid/ask spreads
liquidity
discreteness
lead-lag relation
order flow

Stockholm 1994

Acknowledgements

When I, many years back, started my pilgrimage towards the distinguished title of Ph. D. in Finance, I was primarily motivated by my lack of understanding how the markets really function and how they interact with each other. After my Master's Degree, I still could not fully work out why the market reacted as it did and how the market prices actually came about.

Despite my notorious bad memory, I did recall that my former teacher, Staffan Viotti had suggested that I start the Ph. D. program. With a child's open-eyed curiosity, I therefore threw myself into the deep waters of fixed point theorems, incentive compatibility constraints, Itô's lemma, Cramér-Rao lower bounds and the like. However, after having tortured myself through numerous course work, I was forced to launch myself into the unknown world of academic *research*. Bewildered, I was looking for a thesis subject. Then, with his always convincing enthusiasm, Peter Högfeldt gave me an article in market microstructure to read. From that moment on, I returned to the basic questions of the price formation process in actual markets.

I quickly realized that there were two possible routes to take, either to build theoretical models with, most likely, completely unrealistic assumptions or to perform a number of empirical tests probably without being able to draw any definite conclusions. With my high risk aversion, the solution was obvious and I took off in the labyrinth of endless computer programs dealing with uncountable observations. Ever since, SAS and ORACLE have been my daily companions. However, I might not have ended up as the single most CPU intense user at the school, if the iterative process of getting the computer to do what I required, would have converged quicker.

Although I have not reached my goal of a complete understanding of how prices are generated, I hope that this thesis will give some contribution to the reader's insights into the complicated structure of real life financial markets, in the same way as it has to me.

Several persons have been instrumental in the writing of this dissertation. First of all, I would like to extend my gratitude to Staffan Viotti who gave me the idea and opportunity to consider an academic career and who has kept an eye on me, sometimes with a bird's perspective, through all the years. Secondly, I would like to thank the two other members of my thesis committee. My office neighbor, Ragnar Lindgren has always emphasized the *economic* aspects. By his prompt reactions to my numerous questions and drafts, my work has improved substantially. Furthermore, Anders Warne has explained various econometrical pitfalls, and thus kept me out of some deep waters.

Apart from the thesis committee a range of distinguished academics have had the kindness to comment on earlier versions of the essays in this dissertation. I would like to thank Bruno Biais, Rezaul Kabir, Atulya Sarin, Lal Chugh, Ked Hogan, Piet Sercu, Lars Nordén and Pradeev Yadav, who all contributed with constructive criticisms in discussions at different conferences and symposia.

It goes without saying that I have benefitted from the productive environment of my co-authors, Patrik Sandås and Kaj Hedvall. Together, we have been able to reach insights impossible to obtain alone. The fruitful cooperation with my two co-authors has been one of the personally most satisfactory aspects of the work with this dissertation.

Without a parent-like patience from a number of persons, the errors in these essays would clearly have been abundant. First of all, I would like to thank Sune Karlsson for always being available and always having a solution to every econometrical and computational problem I could conceive. Furthermore, I would like to extend my gratitude to the different market officials, especially Carl Johan Högbom at the Stockholm Stock Exchange, and Anita Redén and Björn Walman at OM, whom I have irritated with countless questions along the way.

Through the wise guidance of Rune Castenäs and Lars Bergman, I have benefitted from the uncomplicated financial support of *Bankforskningsinstitutet* and *Bröderna af Jochnicks donationsstipendium*.

Without the friendly atmosphere, personified by Kerstin Lindskog, and the open, franc and facetious ambience, personified by Peter Högfeldt and Staffan Viotti, at the department, the intellectual challenge would have been less enjoyable.

Finally, I would like to thank my family and friends for all the understanding and support they have offered me during all these years. I would especially like to apologize to Nicole and Erik, who have had to put up with a husband and father who was frequently absent, and if present, frequently absent minded.

Stockholm, November 24, 1994

Jonas Niemeyer

To the Reader

This dissertation consists of five separate and self-contained essays. They have been written as distinct papers. Although there is a fair amount of overlap and cross-reference in analysis and discussion, the intention is that potential readers should be able to read them separately.

Contents

Essay 4

An Analysis of the Lead-Lag Relationship between the OMX Index Forwards and the OMX Cash Index 91

Essay 5

Order Flow Dynamics: Evidence from the Helsinki Stock Exchange 139

Essay 1

An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange*

Abstract

This essay describes and analyzes the trading structure at the Stockholm Stock Exchange. In the empirical part, we report stylized facts based on intraday transaction and order book data, focusing on the intraday behavior of returns, trading activity, order placement and bid/ask spread, on the importance of the tick size and finally on some characteristics of the limit order book. Our main empirical conclusions are that a) the intraday U-shape in trading activity found in earlier U.S. studies on the whole also pertains to the Stockholm Stock Exchange, b) the limit order placement also follows an intraday U-shape, c) there is no distinct intraday pattern in returns, d) the volatility and bid/ask spread seems to be higher at the beginning of the trading day, e) the tick size is economically important, and f) the price impact of an order is a non-linear function of its quantity, implying price inelastic demand and supply.

1 Introduction

Standard pricing theories in finance develop the idea that securities prices are determined by variables such as, dividends, earnings per share, riskiness of cash flows

* This essay has been written together with Patrik Sandås. We wish to thank *Dextel Findata AB* and *Stockholm Fondbörs Jubileumsfond* for providing the data set. We also wish to thank participants at the CEPR workshop in Konstanz, April 1992, seminar participants at the Stockholm School of Economics and participants at the 2nd Annual Conference on European Financial Management Issues in Virginia Beach, May 1993, for helpful comments. Furthermore, we are especially indebted to Carl Johan Högbom, Peter Högfeldt, Ragnar Lindgren, Kristian Rydqvist and Tomas Valnek for their valuable comments on earlier drafts. The responsibility of all remaining errors is our own.

An earlier version of this essay has been published in *Journal of Multinational Financial Management*, Volume 3 (1993), No. 3/4, p. 63-101.

and interest rates. However, the actual price formation process has not been studied extensively. How does the market clearing price come about in reality? Furthermore, an implicit assumption in standard pricing theories is that the specific institutional market structure has no effect on the security prices. This assumption is challenged by the growing market microstructure literature, which focuses on the possible effects of the markets' institutional structure on the price formation process.

The technological development in the last decade has enabled stock exchanges to introduce centralized computer based trading systems (i.e., Paris, Toronto, Stockholm). Furthermore, the deregulation of capital markets and the liberalization of capital flows has enhanced the competition between exchanges. The actual trading system has become an increasingly important mean of competition and therefore highly relevant for both market participants and policy-makers.

Recent availability of transaction data from stock exchanges around the world has spurred research of intraday phenomena in the last decade. Several new anomalies have been reported in studies using U.S. data. One of the first studies was Wood, McInish and Ord (1985). Using NYSE[1]-data, they found distinct intraday patterns in the average market return as well as its standard deviation, contrary to all efficient market hypotheses. In another study, also using NYSE-data, Jain and Joh (1988) reported a significant U-shape[2] in trading activity over the trading day. Handa (1992) studied the bid/ask spread and also found a U-shape, using data from both the NYSE and AMEX. The Paris Bourse, with a similar trading structure to the Stockholm Stock Exchange, has been studied by Biais, Hillion and Spatt (1994). One of their findings is that the price impact of an order is a non-linear function of its quantity, and that the supply and demand are price elastic.

The purpose of this essay is twofold. In order to more accurately assess the importance of different market design features, we first describe and analyze the trading structure of the Stockholm Stock Exchange (SSE). Our second objective is to present some stylized facts. The purpose is to investigate whether certain anomalies and stylized facts found in earlier studies are specific to the studied trading structure or also present in a market-by-order trading system. By using data from the SSE, the question of generality can be addressed.

1 Explanation for abbreviations can be found at the end of the reference list.

2 I.e. high trading activity at the beginning and end of the trading day and low trading activity at midday.

The rest of the essay is organized in the following way. Section 2 gives some general information about the size of the SSE. Section 3 describes and analyses the trading system of the SSE. Our data set is presented in section 4. In section 5, we report our empirical results. We focus on 1) the intraday behavior of returns, trading activity, and order placement; 2) the bid/ask spread; and 3) the supply of immediate liquidity through the limit order book. Our empirical results are of two types. First, we report some stylized facts for the SSE. Since detailed data on prices and quotes for continuous limit order driven markets have not yet been analyzed extensively in the empirical literature, stylized facts are of interest per se. Second, we test a few empirical predictions of the existing market microstructure theories. The essay concludes with a summary of our findings in section 6.

2 The Size of the Stockholm Stock Exchange[3]

The SSE is the largest stock exchange in the Nordic countries and one of the 10 largest in Europe (see Table 1).

Table 1

The Size of a Selected Number of Stock Exchanges Around the World.

Exchange	Market Value (Dec. 1992) Billion USD	Turnover (1992) Billion USD*
NYSE + NASDAQ	4 388.5	2 636.6
Tokyo + Osaka	2 397.4	597.9
London	928.4	663.0
Toronto + Montreal	439.7[a)]	80.1[b)]
Paris	349.6	124.9
Germany (aggregated)	346.9	454.2
Madrid + Barcelona + Bilbao	287.1	42.3
Zürich + Geneva + Basel	189.1	116.5
Amsterdam	134.2	45.7
Italy (aggregated)	129.0	27.2
Stockholm	**76.2**	**27.7**
Brussels	64.1	9.8
Copenhagen	32.5	18.8
Oslo	17.8	10.1
Helsinki	12.2	2.2

Data Source: Fédération Internationale des Bourses de Valeurs Statistics (FIBV) 1992.

* Converted into USD at month-end exchange rates.

a) The market value for Toronto includes convertibles.

b) The turnover for Montreal includes transactions on warrants and rights.

[3] If not otherwise specified, the institutional description in this essay is based on the SSE's "Rules Governing Trading in Stocks and Convertible Participation Notes via the Stockholm Automated Exchange (SAX)" and the Stockholm Stock Exchange Annual Reports 1989 and 1992.

In Dec. 1992, the SSE had 111 companies listed with in total some 220 issues.[4] Furthermore, the OTC-market included 43 companies and there were 44 unofficially registered companies. Trading at the SSE is highly concentrated. In 1992, The 20 most traded companies accounted for 84 per cent of the turnover and 82 per cent of total stock market value. The ownership structure is also extremely concentrated. In Dec. 1991, the 10 largest shareholders/institutions accounted for 32 per cent and the 50 largest shareholders/institutions for 57 per cent of total stock market capitalization.[5]

3 The Trading Structure of the Stockholm Stock Exchange[6]

3.1 The Stockholm Automated Exchange

Since June 30, 1990, all stocks listed at the SSE are traded through a computer based trading system (SAX). The SAX-system is largely inspired by the trading systems in Toronto and Paris (CATS and CAC respectively).

The main features of the SAX system are (i) the continuity; (ii) the limit order book (LOB) aggregating all order placement and trading activity; and (iii) the automatic matching. In order to distinguish between, on one hand the LOB of a specialist at NYSE (including only a part of the order flow and not open to the public), and on the other hand the centralized, consolidated and open limit order book of the SSE, the latter is usually called consolidated open limit order book, or COLOB.

3.1.1 The Dealers

Only officially authorized brokerage firms[7] are eligible for membership at the SSE. Indeed, most brokerage firms are members of the exchange. Only stock exchange members have the right to enter orders directly into the SAX-system. As a consequence, all primary customers are represented by some exchange member in the market. All brokerage firms can act as dealers and brokers in the market, but there are no designated market makers.[8] The exchange fees are proportional to their commissions in the

[4] Swedish companies normally have several classes of stocks, i.e. with and without restrictions on foreign ownership and with different voting powers. These are normally called dual-class stocks. As of Jan. 1, 1993, however, all stocks are open to foreign ownership.

[5] See Sundqvist (1992).

[6] We want to stress that the trading structure at the SSE is under permanent change. For example, the stock exchange monopoly was abolished Jan. 1 1993, (the Stock Exchange Act (1992:543)). In this essay we consider the trading structure as of mid-1992.

[7] Brokerage firms can be both firms specialized in securities trading and traditional banks. Only authorized brokerage firms are permitted to trade financial assets as brokers, dealers or market makers. Authorization (according to The Securities Business Act (1991:981)) requires the compliance with certain regulations regarding equity capital and organizational structure. At the end of 1991, 27 companies were recognized as brokerage firms and could act as brokers and dealers. In addition, two firms were allowed to act only as brokers.

[8] Consequently, we will use the term "dealer" for exchange members since their role in the market is not formally restricted only to broking. On the other hand, the dealer is not a designated market maker

preceding year.[9] Brokerage firms are allowed to have significant inventory (i.e. efficiently act as broker or market maker) as long as the risk is hedged or is small compared to the equity capital of the firm.

The function of the dealers at the SSE corresponds to the one of a dual-capacity dealer. The potential conflicts of interest inherent in dual-capacity trading might therefore be of some importance here. The problem of "front-running" (dealers trading on own account before executing a customer order) is relevant in all markets where broker and dealer functions are integrated. Although hard to monitor, it is prohibited on most markets[10] (e.g. NYSE, CME).

3.1.2 Different Types of Orders

Traders have the choice of two different types of orders: market orders and limit orders. A market order is an order to buy or sell a given quantity of a stock at the prevailing market price. A limit order makes the execution conditional on a limit price. It is a firm commitment until withdrawn.

Amihud and Mendelson (1991) note three important differences between market orders and limit orders. First, market orders are executed immediately and with certainty. Second, limit orders do, but market orders do not, provide immediate liquidity to the rest of the market. Third, submitting a limit order implies the release of more information (i.e. the trader's reservation price) to the market, than submitting a market order. They summarize the difference by stating that immediacy is "*supplied* to the market by *limit* orders and *consumed* by *market* orders"[11]. There is therefore a positive externality of submitting a limit order. Since the dealers submitting limit orders get no compensation for the positive externality, the result could be lower immediate liquidity.

There are several aspects to the liquidity of a stock. In the market microstructure literature, four aspects of liquidity are often discussed.[12] Firstly, traders are generally impatient and therefore demand *immediacy*. Secondly, since the spread is a cost, traders prefer to trade stocks with a small spread (or *width*). A third aspect is *depth*, i.e. the volume possible to trade without moving prices. A fourth aspect is the market's *resiliency*, which refers to how quickly a market regains equilibrium after an imbalance created by large informationless trading. A liquid market would have instant immediacy, negligible width and infinite depth and high resiliency.

as the dealers in the SEAQ International in London or the specialists at the NYSE.

9 As of 1993, the fee is based on the number of transactions (to 1/3) and on traded volume (to 2/3).

10 See Schwartz (1991).

11 Amihud and Mendelson (1991), page 80.

12 See Harris (1990).

In a market-by-order trading system such as at the SEE, the submission of limit orders is of paramount importance since it is the only source of immediate liquidity. Within the market microstructure literature little attention has been paid to the *incentives* of placing limit orders. Handa and Schwartz (1992) develop a model where it, despite the externality problem, is rational for some traders to use limit orders. Temporary order imbalances caused by an influx of traders seeking immediacy "can induce a temporary shift in an asset's current price without there being any change in the expected future payoffs"[13]. The resulting price changes (i.e. additional short-run volatility) can be sufficient to compensate limit order traders. In another model, Glosten (1994) describes the properties of limit orders in equilibrium. He also derives some necessary conditions for the submission of limit orders.

3.1.3 The Consolidated Open Limit Order Book

The central feature of the SAX-system is the electronic COLOB. The COLOB at the SSE is a computer file showing the prices of all limit orders, the aggregate number of stocks offered or demanded at each price and the identification codes of the dealers willing to trade. An incoming market order is automatically matched against the best standing limit order in the COLOB. If an incoming limit order cannot be matched directly, it is added to the COLOB. Table 2 shows what a typical COLOB could look like.

Table 2
The COLOB for TRELLEBORG C at 10.00, December 27, 1991.

Dealers	*Volume*	*Bid-Price*	*Ask-Price*	*Volume*	Dealers
FB	*1000*	*110*	*112*	*1100*	SE
C,HB,C	*900*	*107*	*113*	*400*	SE
HB	*1200*	*106*	*114*	*170*	SW
SW	*700*	*105*	*115*	*500*	SW
FB,SE	*2500*	*104*	*117*	*100*	SW
SW	600	94	127	100	C

3.1.4 Trading in the SAX-system

The Opening Auction

The SAX-system opens trading with a sealed bid call auction. This opening auction can be divided into three stages. At the first stage, from 8.00 a.m. to 10.00 a.m., dealers can place sealed orders into the COLOB. The orders are sealed in the sense that the dealers can see neither the orders of other dealers nor any indicative auction prices.

[13] Handa and Schwartz (1992), page 2.

At 10.00 a.m. trading starts. The SAX-system treats the stocks sequentially. For each stock, it computes a single opening price, in order to maximize the number of stocks traded in the auction. The price is computed in the following way:

- If the highest bid quote is equal to the lowest ask quote, this will be the opening price;
- If the highest bid quote is higher than the lowest ask quote, the market opening price will be the price that maximizes trading volume in that stock;
- If the highest bid quote is lower than the lowest ask quote, or if there are no orders on one side of the market, no opening price is set.

Immediately after the completion of the auction for one stock, the continuous trading in that stock starts.

It should be noted that some details of the auction rules in the SAX-system differ from the rules of other exchanges. In Toronto (CATS), all stocks must open through an auction before the continuous trading starts. There is therefore a time gap between the opening auction and the continuous trading. Another difference is that in Toronto and Paris the dealers *can* observe indicative prices. The purpose of the auction is to incorporate as much as possible of the information, accumulated during the non-trading period, into the new equilibrium prices. For this, a certain order volume is necessary. If no indicative prices are available, the individual trader might prefer to postpone his orders since he will have significantly more information about the stock once the auction price is established. The result could be low order volumes in the auction and thereby less informative auction prices. On the other hand if indicative prices are available, order volumes in the auction might increase,[14] resulting in more informative auction prices. However, indicative prices also leave room for manipulation since the orders can be withdrawn without penalty until the auction starts, leaving the prices prior to 10:00 highly unreliable.

The final stage is the dissemination of information on opening prices. Simultaneously, orders which can be executed given the opening prices are matched and trades reported on the screen. First, priority is given to orders "deep in the money". Secondly, there is a pro rata execution on the short side. Limit orders not executed at the opening constitute the COLOB when the continuous trading starts. An example might clarify the process.

Assuming the COLOB in Table 3, the opening price will be 109 and the 500 stocks at the ask price 109 will be matched, first against the 200 stocks at bid price 110 (the stocks deepest in the money) and second against 300 of the 600 stocks offered at 109. The latter 300 stocks are selected proportionally among the limit orders offered at 109.

[14] See Harris (1990).

Table 3
An Example of a COLOB Before and After the Auction.

Before the Auction				After the Auction			
Bid		Ask		Bid		Ask	
volume	price	price	volume	volume	price	price	volume
200	110	109	500	300	109	110	700
600	109	110	700	1000	108	111	500
1000	108	111	500	.	.	.	.

Continuous Trading

After the opening auction, trading through the COLOB is continuous until the market closes at 2.30 p.m.[15] Market orders, and if possible limit orders, are *automatically* matched against the best existing limit order as soon as they arrive to the market. If there is no matching limit order, the new limit order is added to the COLOB. Limit orders at the end of the day will be deleted unless a duration condition is included in which case the order remains until the desired day.

The definitions of market and limit orders are not uniform for all stock exchanges. At the Paris Bourse, market orders are sometimes converted into limit orders. In contrast to in the SAX-system, a French market buy (sell) order is converted into a limit buy (sell) order at the best ask (bid) quotation rather than "being executed by walking up (down) the limit order book"[16]. In a sense, this creates an insurance against adverse price moves for the submitter of a market order. At the same time, the market order provides additional immediate liquidity to the market. This feature does not exist in the SAX system, i.e. if possible, market orders always clear in the LOB. However, at the SSE, the same insurance against adverse price moves can be obtained by submitting the appropriate limit order.

Small Orders in the SAX-system

Orders of less than one trading unit[17] are submitted to the small order system. In this system, transactions are always executed at the last transaction price in the normal SAX-system.[18] If it is possible to add several orders from the small order book and get a

[15] April 1, 1993, the stock exchange extended the continuous trading. Trading hours are now between 10.00 a.m. and 4.00 p.m.

[16] See Biais, Hillion and Spatt (1994), p 3.

[17] A typical trading unit is 100 or 200 stocks (occasionally 50, 500 or 1000 stocks) depending on price. A stock's trading unit is regularly revised. The principle is that a trading unit, measured in SEK, should have an approximately constant value over time and comparable across stocks.

[18] Even if there are limit orders with crossing prices in the small order book, a transaction will only take place if it can be executed at the last transaction price in the SAX-system. Furthermore, most small orders include a condition of "all or nothing". A trade will then take place only if all the stocks in that order can be executed simultaneously. Thus, despite the fact that small orders are often market orders, they are not always matched directly.

round lot, a transaction with an order in the COLOB might be executed. An order submitted to the COLOB can have an "alternative matching condition" whereby the order will be matched against orders in the small order book if matching across the two order books is possible.

3.1.5 The Information Structure

The dealers' information set in the COLOB includes the total quantity offered or demanded at each price level. Thus, dealers have no direct information on the size of each individual order, but only of the consolidated volume at each price level. Furthermore, the dealers can see the dealer identification codes, which appear in order of priority at each price level.

Information available to financial information firms (e.g. Reuters, Telerate), and thereby in principle to the public, is limited to the five best prices and consolidated volumes at each side of the market. The identification codes of the dealers in the COLOB are available only to member firms. In Table 2 above, only numbers printed in italics represent information available to financial information firms.

All information on transaction prices, volumes and dealers involved in a transaction is continuously transmitted to dealers as well as to financial information firms. Yet, a dealer's trades on his own account cannot be distinguished from his trades on behalf of his customers since all dealers are dual-capacity dealers.

Asymmetric information disclosure through firm quotes is necessary in a computerized order matching system. In contrast to the simultaneous bidding process of a call auction, the SAX-system requires one part of a potential transaction to first disclose his willingness to trade by placing a limit order with a specified and binding price, i.e. to supply immediate liquidity to the market. Furthermore, suppliers of liquidity sometimes trade with liquidity demanders who are better informed than themselves. This is a special case of the asymmetric information problem, extensively discussed in the market microstructure literature (e.g. Kyle (1985), Glosten and Milgrom (1985) and Admati and Pfleiderer (1988)). Amihud and Mendelson (1991) compare the dealer submitting a limit order to a "sitting duck", risking to be hit by a better-informed trader. Stoll (1992) also discusses this problem and describes a limit order as a free trading option.[19]

Limited Visibility of Order Volume

The SAX-system also gives the possibility to submit orders with partly hidden volume.

[19] Submitting a bid (ask) limit order can be regarded as writing an option to the rest of the market. The option is in the money if new bad (good) information arrives while the limit order is outstanding.

In this case, only a part of the order volume will appear in the COLOB. Only when the open part of the order has been executed, will the hidden part of the order become open. In this way, dealers can submit large orders without releasing information about their entire order volume to the market. On the other hand, the dealer gets lower priority, since the hidden part of the order is treated as a new order when it is transformed to an open order. This feature alleviates the asymmetric information problem discussed above. Thus, the possibility to submit hidden orders can be seen as a sacrifice of full market transparency in order to induce the submission of large orders and thereby enhance market liquidity. Without this possibility, there is a risk that large trades would be executed off-the-exchange (see below), where the asymmetric information problem is different due to the possibility of bilateral bargaining and lower transparency. The transparent structure of the SAX system is especially desirable for small and uninformed traders. Large and informed traders often prefer other, less transparent, trading structures.[20]

3.1.6 Tick Size

One important aspect of a trading structure is the minimum price difference allowed between limit orders, normally referred to as the tick size. Harris (1991, 1992, 1994) finds that the tick size used at the NYSE and the AMEX has an economically significant impact on market liquidity. Table 4 reports the tick sizes for both the SSE, the NYSE, the Paris Bourse, and the Helsinki Stock Exchange.[21]

Table 4

Tick Size at Different Stock Exchanges

Stock Price*	SSE	NYSE	Paris Bourse	Helsinki SE
0.00 - 0.10	0.01	0.03125	0.01	0.01
0.10 - 0.25	0.05	0.03125	0.01	0.01
0.25 - 1.00	0.05	0.0625	0.01	0.01
1.00 - 5.00	0.05	0.125	0.01	0.01
5.00 - 10.00	0.10	0.125	0.05	0.01
10.00 - 100.00	0.50	0.125	0.05	0.10
100.00 - 500.00	1.00	0.125	0.10	1.00
500.00 - 1000.00	1.00	0.125	1.00	1.00
1000.00 -	1.00	0.125	1.00	10.00

(Data sources: Stockholm Stock Exchange (1991), NYSE Rule 62, Biais, Hillion, and Spatt (1994), and Helsinki Stock Exchange (1991)).

* Stock prices are given in respective currency. SEK 1 is approximately equal to USD 0.14, FRF 0.72, and FIM 0.65 respectively.

[20] See Pagano and Röell (1990 and 1993).

[21] The tick size at the SSE has been reduced in two steps during 1994, (on March 4, and September 30). Presently, the tick size is 0.01 between 0.01 and 5.00, 0.05 between 5.00 and 10.00, 0.10 between 10.00 and 50.00, 0.50 between 50.00 and 500.00 and 1.00 above 500.00.

In the most relevant price range, tick sizes at the Paris Bourse are roughly a tenth of the ones at the SSE. Even the tick sizes at the less liquid Helsinki Stock Exchange are smaller than at the SSE. Tick sizes are of similar importance on the SSE and on the NYSE.[22] Clearly the tick sizes at the SSE imply minimum spreads of between 0.2 per cent and one per cent for normally priced shares and a spread as high as five per cent for shares priced just above SEK 10.00 (an unusually low price level). We will return to the importance of the tick size in section 5.5.

3.1.7 Priority Rules in the COLOB

The first basis of priority is naturally the price. At a given price level, displayed orders have priority over hidden orders. Within price and display precedence, orders are given priority according to time of entry. Furthermore, equally priced unmatched orders from the opening call auction are given random priority.

In general, the importance of secondary priority rules (such as display and time) is more considerable when the tick size is economically significant.[23] Otherwise, traders can cheaply obtain priority by slightly improving the limit price. Amihud and Mendelson also argue that since limit orders provide immediate liquidity as a positive externality, traders supplying limit orders should be compensated in order to enhance the market's immediate liquidity. Properly designed priority rules might be one way to achieve this compensation. Direct payment for order flow might be another solution. Since submitting a displayed order at an early stage implies a commitment, Harris (1990) argues that the greatest precedence should be given to "those traders who make the strongest commitment to providing liquidity"[24]. Secondary priority rules are likely to be important in the SAX-system due to the comparatively large tick size.

In the previous subsection, we reported the importance of the tick size at the SSE. Naturally, the large tick size implies comparatively large bid/ask spreads and consequently a negative effect on liquidity. Harris (1992, 1994) argues that a large tick size would make the provision of liquidity highly profitable. Strict adherence to the time priority rule in conjunction with a large tick size protects traders who expose their quotes and limit orders. Their willingness to submit limit orders is therefore enhanced and immediate liquidity increased. The consequence of a high tick size is therefore likely to be large spreads but with considerable depth at each price level. Harris (1994) tests these hypotheses and finds that the depth indeed increases with tick size.[25]

[22] Most NYSE stocks trade at prices between USD 5 and USD 50 (see Harris 1991), implying a minimum relative spread of between 0.25 and 2.5 per cent. Most Swedish stocks trade at prices between SEK 20 and SEK 500, implying a minimum relative spread of between 0.2 and 2.5 per cent.

[23] See Amihud and Mendelson (1991).

[24] Harris (1990), page 17.

[25] Niemeyer and Sandås (1994) (Essay 3 in this dissertation) reach a similar conclusion for the most

3.2 Off-Exchange Trading

In principle, there are at least three different types of off-exchange trading. The first possibility is to trade after exchange hours. All after hours trades have to be reported to the exchange no less than thirty minutes before trading resumes the following day. Apart from this rule, few restrictions are imposed on this type of off-exchange trading. More specifically, prices during after hours may deviate substantially from those during the day.

Secondly, off-the-exchange trades can also take place during normal trading hours. The rules governing these trades are stock specific. Stocks are classified in two categories according to trading volume. For the most traded stocks, all trades below 100 trading units[26] have to be executed in the SAX-system and within the bid/ask spread. Trades between 100 and 500 trading units may be settled outside the SAX-system but only within the prevailing bid/ask spread. Only large deals, of more than 500 trading units, may be struck outside the SAX-system and outside the bid/ask spread. For other stocks, the same rules apply but the limits are 50 and 250 trading units respectively. It should be noted that if a transaction is executed outside the existing bid/ask spread, the parties to the transaction have no obligation to clear the limit orders in between. In contrast, in Paris a block trade outside the existing spread has to be included in the electronic system CAC and all limit orders better than the block price must be executed. They are then executed at their respective limit prices. At the NYSE, the limit orders in the specialist's order book also have to be executed but at the same price as the block trade (i.e. better than in Paris).

Information on in-house clearing[27] and trading outside the COLOB - during trading hours has to be disclosed within 5 minutes. The restrictions concerning in-house clearing and other types of trading outside the electronic system are much stricter on some other automated exchanges, e.g. Paris.[28] The potential deterioration of price informativeness and liquidity caused by fragmented markets is usually the motive for restrictions limiting trading outside the main electronic system. In practice, the possibility to trade the same stock in other markets makes this kind of restrictions inoperative.

The third type of off-exchange trading occurs on foreign stock markets. A large part of the trading of major Swedish stocks is channelled through SEAQ-International in

---

liquid stocks at the SSE.

26 See footnote 17.

27 Dealers may match two customers' orders within the inside spread without placing any orders in the COLOB.

28 See Biais and Crouhy (1990).

London, which is a market maker based trading system. Although we lack data from London, it appears that mainly the larger trades take place in London, while smaller trades are captured in the SAX-system. In 1992, the total turnover of Swedish stocks in the SEAQ-system amounted to SEK 131 billion (41 per cent) compared to SEK 166 billion (52 per cent) for the domestic market. Trading in Swedish stocks at other international exchanges, principally NASDAQ, is limited, SEK 23 billion (7 per cent).

Compared to trading in the SAX-system, all three mechanisms for off-exchange trading have a common feature; lower transparency. One of the reasons for the success of these markets seems to be based on the asymmetric information problem mentioned above. Many large investors as well as informed ones prefer to trade on a less transparent market. As a result, we get a market segmentation.[29] Harris (1992) and Pagano and Röell (1990) discuss the importance of transparency as a determinant of market segmentation.

There is an inherent conflict between concentration and segmentation of trading. On one hand, liquidity is enhanced and the price formation process better if everyone trades in the same market place. On the other hand, different traders have different motives for trading and a specific trading structure is not necessarily optimal for all traders. It is also possible that certain trades would not take place at all if all trading was forced into the same form. It might not be feasible or even desirable to design a market structure which integrates all trading in one system. Segmentation is only a problem when it results in low price informativeness and/or low liquidity.

4 The Data Set

In the rest of this essay, we will present some stylized facts from SSE, compare these with international data and perform some tests to see if the presented stylized facts are significant.

The data used in this study come from two sources. First, the Stockholm Stock Exchange has provided transaction and order book data for the thirty stocks included in the OMX index. Second, Dextel Findata AB, the company actually calculating the OMX index, has provided minute by minute data of the index itself. The OMX index data file includes the minute by minute index values computed on transaction prices as well as on the best bid and ask prices available for each stock. The studied period is from December 3, 1991, through March 2, 1992, totalling 59 trading days.

[29] We use the term segmentation for the division of trading between different markets. Harris (1992) makes the distinction between a fragmented market and a segmented market by noting that in a segmented market at least some traders can trade in more than one segment.

The set of stock transaction data contains the time, price and the number of stocks traded, in total 85 610 observations. The data set from the electronic limit order book consists of the five best bid and ask prices, the associated quantities, and the number of orders at each bid and ask level in the COLOB, in total 157 252 observations.

The OMX index is a value weighted stock market index based on the thirty most traded stocks at the SSE. It should be noted that the stocks included in the OMX index (and thus in our sample) sometimes consist of more than one class of stocks of the same company.[30] Since the composition of the index is revised every six months (January and July) our sample before and after January 1, 1992 is not exactly the same.[31] However, we do not think this is likely to influence our results significantly.

5 Empirical Results

5.1 Descriptive Statistics

In this section, we report some general descriptive statistics from our sample. Summary statistics on trading frequency, daily trading volume and average and median transaction size are given in Table 5. The stocks are divided into three groups according to non-trading probabilities. The ten most frequently traded stocks have average non-trading probabilities of 28 per cent and 6 per cent for ten minute and thirty minute intervals respectively.

Table 5

Average Trading Frequency, Average Daily Trading Volume, Average Transaction Size and Median Transaction Size.

	Group 1	Group 2	Group 3
NT Prob. [1]	28%	54%	68%
NT Prob. [2]	6%	21%	37%
Average Daily Volume [SEK 1000]	22 014	7 326	3 731
Average Transaction Size [SEK 1000]	228	240	238
Median Transaction Size [SEK 1000]	56	55	40

The stocks are divided into three groups according to non-trading probabilities.
NT Prob [1] and NT Prob [2] denote the average non-trading probabilities, within the groups, computed on ten and thirty minute intervals respectively.
The sample period covers 1590 ten minute intervals and 531 thirty minute intervals.

Total trading volume in our sample amounted to SEK 30 648 million. Table 6 demonstrates that only a fairly limited proportion of all trades is actually matched within the SAX-system. A large proportion of trades is matched off-the-exchange (either

[30] See footnote 4.

[31] 5 old stocks were excluded and 5 new stocks included as of January 1, 1992.

during trading hours or after) and only reported to the exchange. Only 48 per cent of total trading volume in our sample (excluding four major take-overs, which would otherwise distort the statistics) was matched in the fully automatic system. In interpreting Table 6, it should also be noted that only roughly half of all trading in Swedish stocks takes place in Sweden (see section 3.2).

Table 6

Amount Traded Through Different Systems in Our Sample.

	All Transactions				Excluding 4 Major Block Trades	
	Million SEK		# of Transactions		Million SEK	
SAX	11 438	37%	75 747	88%	11 438	48%
Manual	8 074	26%	8 431	10%	8 074	34%
After hours	11 137	36%	1 432	2%	4 276	18%
Total in Sweden	30 648		85 610		23 787	

SAX refers to fully automated transactions via the COLOB.
Manual refers to manually settled transactions during normal trading hours.
After hours refers to transactions settled off-the-exchange after normal trading hours. These transactions are reported to the SAX-system before 9.30 a.m. the following trading day.

The Paris Bourse has been more successful in retaining trading in French stocks. The turnover of French stocks on the SEAQ-International in London was only 7 per cent of the Paris Bourse turnover in 1988.[32] Even if electronic trading systems, such as SAX and CAC, are designed to handle all trading, they actually capture only a fraction of it. Different groups of traders prefer to trade the same assets in different locations and/or under different trading structure. The consequence is market segmentation.[33]

Due to higher negotiation and settlement costs, we would expect larger transactions at off-exchange hours. This is largely confirmed by Table 7, showing the distribution of trade size[34] within the SAX-system, manually during exchange hours and after trading hours respectively. As expected, the SAX-system attracts the smallest transactions while most large transactions are made outside SAX and during exchange hours. The transactions after exchange hours are primarily larger than SEK 1 million. The average transaction size is SEK 151 000 within the SAX-system, SEK 958 000 off-the-exchange during normal trading hours, and SEK 7.8 million, (3.0 million excluding the four major take-overs) during after hours.

32 See Pagano and Röell (1990).

33 See Harris (1992).

34 It should be noted that the practical meaning of a transaction depends on the specific market structure. In the SAX system, one buy order which for example is matched with three sell orders will be recorded as three transactions. In a dealer based system (e.g. London) the same transaction would be recorded as four different transactions because the dealer will normally be the counter part in all transactions. Naturally, these technical differences have an impact on market statistics such as number of transactions and average transaction size.

5.2 Intraday Patterns in Trading Activity

In this section we document some intraday patterns in trading activity at the SSE. A significant intraday pattern in trading activity could imply that the information contents in prices differ in different periods of the trading day. Since information is incorporated into prices, at least partly through trading, a period of high trading activity would produce more informative prices than a period of low trading activity.

Table 7
Distribution of Stock Trades

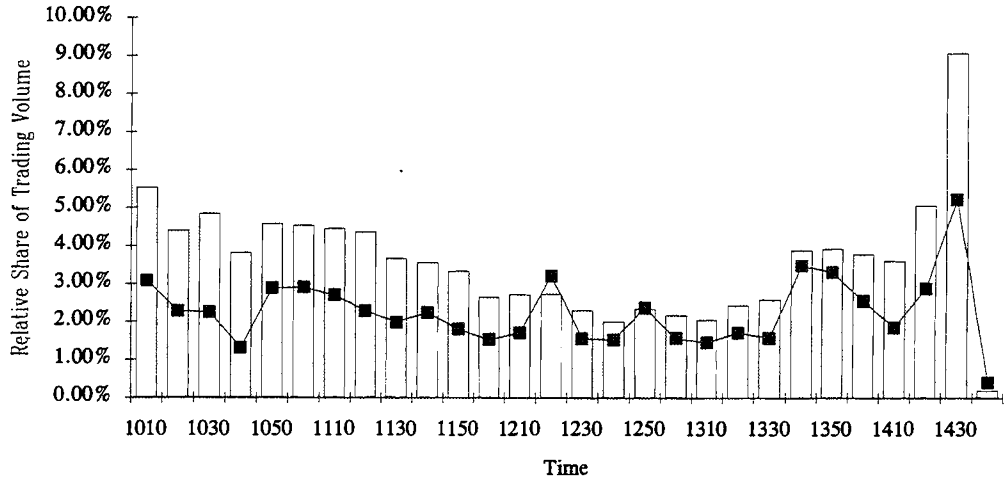
Trade Size	Within SAX		Manually		After Hours	
	# of Trades	C-Freq	# of Trades	C-Freq	# of Trades	C-Freq
0 - 0.1	49 628	0.655	3 323	0.394	105	0.073
0.1 - 0.2	10 676	0.796	1 218	0.539	113	0.152
0.2 - 0.3	5 092	0.863	621	0.612	69	0.200
0.3 - 0.4	2 773	0.900	347	0.653	59	0.242
0.4 - 0.5	1 907	0.925	236	0.681	59	0.283
0.5 - 0.6	2 055	0.952	370	0.725	63	0.327
0.6 - 0.7	641	0.961	163	0.745	35	0.351
0.7 - 0.8	538	0.968	116	0.758	29	0.372
0.8 - 0.9	346	0.972	80	0.768	30	0.392
0.9 - 1.0	370	0.977	116	0.782	45	0.424
0 - 1	74 026	0.977	6 590	0.782	607	0.424
1 - 2	1 403	0.996	776	0.874	273	0.615
2 - 3	262	0.999	434	0.925	164	0.729
3 - 4	29	1.000	171	0.945	79	0.784
4 - 5	12	1.000	96	0.957	64	0.829
5 - 6	12	1.000	140	0.973	77	0.883
6 - 7	2	1.000	39	0.978	31	0.904
7 - 8	0	1.000	23	0.981	20	0.918
8 - 9	1	1.000	19	0.983	14	0.928
9 - 10	0	1.000	19	0.985	9	0.934
10 -	0	1.000	124	1.000	94	1.000
Total	75 747		8 431		1 432	

Trading is divided into trading during normal hours (within the SAX-system and manually) and after hours. C-Freq is the cumulative frequency.

Jain and Joh (1988) report a statistically significant U-shaped pattern in stock trading volume at the NYSE. The highest volume occurs at the opening. During the trading day, the volume then subsides and near the close it increases again, albeit not to the same level as at the opening. Foster and Viswanathan (1993) test and reject the hypothesis of equal volumes across different hours of the trading day (using data from the NYSE and the AMEX). In Figure 1, we report the average intraday pattern of the trading volume (bars), as per cent of the total daily trading volume, and standard deviation (dotted line) by each ten minute interval[35] excluding after hours trading for the SSE.

Figure 1

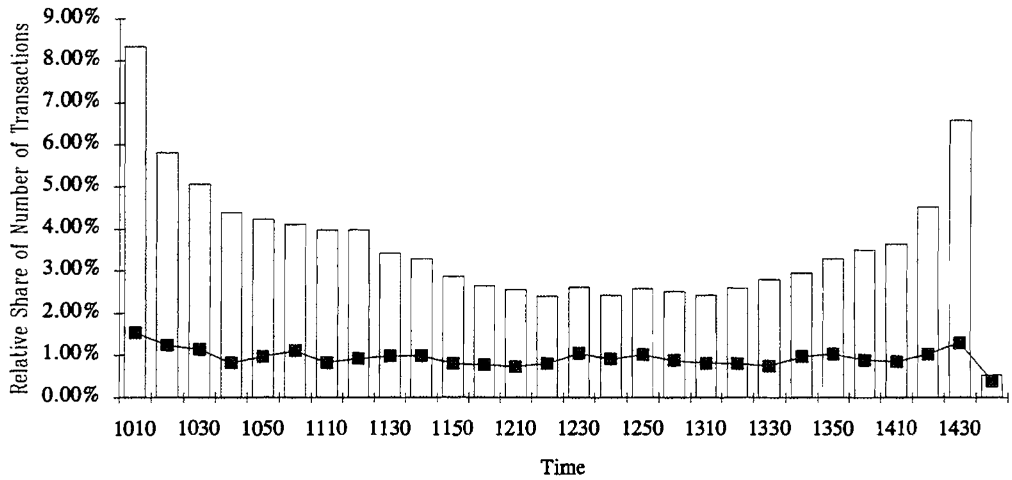
Average Intraday Proportion of Daily Trading Volume (in SEK)



Average proportion is indicated by bars and the standard deviation across days by the dotted line. After hours trading is excluded.

Figure 2

Average Intraday Proportion of Number of Transactions



Average proportion is indicated by bars and the standard deviation across days by the dotted line. After hours trading is excluded.

Figure 2 gives the SSE intraday pattern of the number of transactions[36] (bars) as proportions of the total daily number of transactions and standard deviation (dotted line) by each ten minute interval. The pattern in the numbers of transactions is clearly U-

---

[35] Due to technicalities in the reporting system, there might arise a lag of a few seconds between the trading and the reporting system during intensive trading. This explains why we observe some trades after 2.30 p.m. (14.30), the official closing hour of the exchange.

[36] See footnote 35.

shaped. The intraday pattern of volume exhibits a somewhat U-shaped pattern but not as clearly as for number of transactions. If we aggregate trading volume during thirty minute intervals (not shown) the U-shaped pattern will be more pronounced.

In order to test if the U-shapes suggested by Figure 1 and 2 are significant, we need the observations to be statistically independent. This is not the case in Figure 1 and 2 since the proportions always add up to unity every day. Therefore, we compute related statistics which are independent. For each stock, we take the number of stocks traded per thirty minute interval at different days, divided by the number of outstanding stocks. Taking the unweighted average across stocks for every time interval and day yields a series of 59 observations of the trading activity across days for each interval. Similarly, we take the number of transactions per stock, divide with the number of outstanding stocks, take the unweighted average across stocks to get a series of 59 observations across days for each interval. Table 8 lists the two means for each time interval. The null hypotheses of equal means are rejected at a one per cent significance level in both cases (F-value = 12.60 for the number of stocks and F-value = 66.72 for the number of transactions; critical $F(8,522) = 2.51$). Table 8 also lists the successive t-values when testing two adjacent means against each other.[37]

Table 8

Significance of U-Shape in Trading Activity (Thirty Minute Intervals).

Time	10.00-10.30	10.30-11.00	11.00-11.30	11.30-12.00	12.00-12.30	12.30-13.00	13.00-13.30	13.30-14.00	14.00-14.30
Average Number of Traded Stocks (x 100) as % of Outstanding	1.956	1.894	1.969	1.664	1.355	1.093	1.252	1.943	2.677
t-value of Diff.		-0.32	0.40	-1.78	-1.89	-1.80	1.25	3.16**	2.84**
Average Number of Transactions (x 100,000) as % of Outstanding	2.465	1.742	1.591	1.311	1.196	1.117	1.239	1.352	1.883
t-value of Diff.		-7.46**	-1.93	-3.87**	-1.71	-1.42	2.15*	1.76	7.23**

We report average intraday proportions and t-statistics for the difference between intraday successive averages.
Significance is reported at the 1 per cent level with ** and at the 5 per cent level with *.

On the whole, our tests support the hypothesis of a U-shape in trading activity and are thus in conformity with the findings of both Jain and Joh (1988) and Foster and

[37] Strictly statistically speaking, we cannot draw any overall conclusion from the t-tests. We cannot control for the aggregated significance level since we do not perform a joint test but several individual tests. Still, in this case the t-tests may add something to the inference.

Viswanathan (1993). One difference from the American studies is that the increased volume during the last ten minutes is more pronounced at the SSE. The relative share of the last interval during the day (i.e. trading between 14.20 and 14.30) is considerably higher than in any other interval. Increased trading activity prior to the close of the market may reflect investors closing open positions, they do not desire to hold overnight. However, it is still an unresolved question why this effect would be more pronounced at the SSE than in the U.S. Furthermore, an analysis of the average transaction size (not shown) indicates on average smaller transactions during the first ten minutes of the trading day and larger transactions during the last ten minutes.

There are only a few theoretical models trying to explain the concentration of trading volume. In the Admati and Pfleiderer (1988) model, concentrated trading patterns arise endogenously as a result of strategic behavior of liquidity traders and informed traders. However, their model does not explain when, during the trading day, the concentration of trading will occur. The Brock and Kleidon (1992) model extends the Admati and Pfleiderer model and tries to relate the trading patterns to the opening hours of the exchange. Their model argues that optimal portfolios are different when the exchange is open and closed. Trading to rebalance portfolios would induce U-shaped volume over the trading day, consistent with our data.

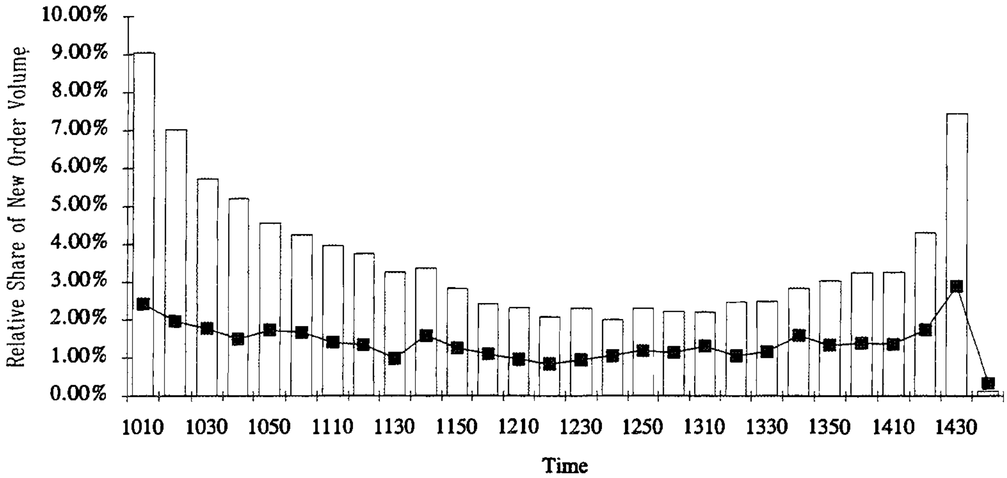
5.3 Intraday Patterns in the Placement of New Limit Orders

Another way to measure trading activity in an order book driven system such as at the SSE is to focus on the submission of new limit orders. Regardless of whether a new limit order immediately results in a transaction or not, it will bring new information to the market. The information content of the bid and ask prices is therefore, ceteris paribus, likely to be larger when the submission rate of new limit orders is high. Until recently there are few studies focusing on the submission rate of new limit orders.

The intraday pattern in the average proportions of the placement of new limit orders (bars) and the standard deviation over days (dotted line) (excluding orders submitted before and executed in the auction) are shown in Figure 3 and Figure 4. The pattern is U-shaped both in terms of volume (Figure 3) and in terms of number of orders (Figure 4).

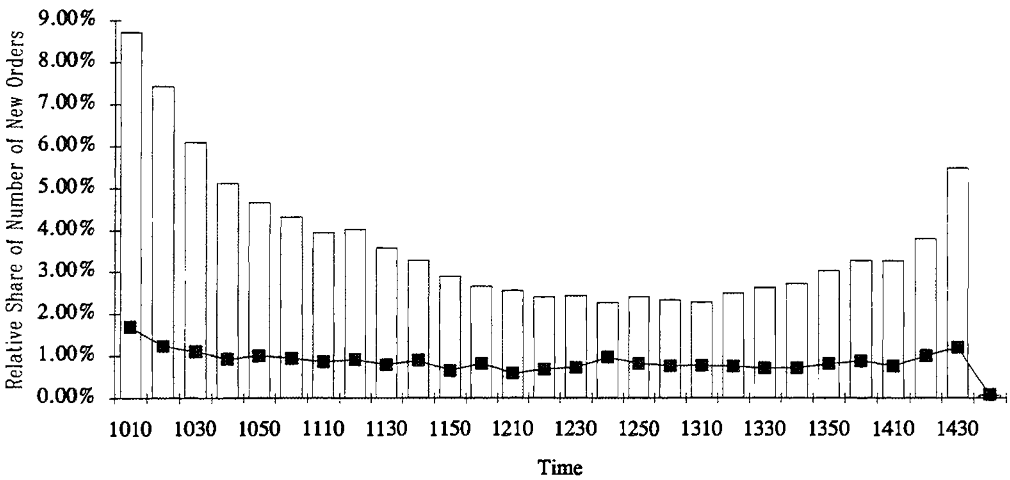
The high level of new limit orders at the very end of the trading day is a bit surprising. Our findings are likely to at least partly be a result of the reporting system. If the price of an outstanding limit order is changed, it will be recorded as a new limit order. As a consequence, investors, with an outstanding unmatched limit order who are forced to trade a specific day, will have to worsen their price in order to trade. Since the tendency is to wait with the necessary change as long as possible, the system produces a large reported influx of new orders during the last minutes. However, it is still somewhat of a puzzle that so many investors choose to submit a new *limit* order when forced to trade. Investors wanting to close open positions would presumably use market orders rather than limit orders during the last minutes. Is there possibly another explanation? The puzzle is left for future research.

Figure 3
Average Intraday Proportion of Daily Volume of New Limit Orders



Average proportion is indicated by bars and the standard deviation across days by the dotted line.

Figure 4
Average Intraday Proportion of Daily Number of New Limit Orders



Average proportion is indicated by bars and the standard deviation across days by the dotted line.

In Table 9 we test, on half hour basis, whether the apparent U-shapes in Figure 3 and 4 are significant. In order to obtain independence, we calculate new measures (parallel to the ones in Table 8). For each stock, we take the sum of the number of stocks of all limit orders submitted during a specific interval and day, and divide by the total number of outstanding stocks. Repeating for every thirty minute interval and day, and then taking the unweighted average across stocks for every time interval and day yields a series of 59 observations of the submission rate across days for each interval. Similarly, we take the number of new limit order per stock, divide with the number of outstanding stocks, take the unweighted average across stocks to get a series of 59 observations across days for each interval. Table 9 lists the two means for each time interval.

Table 9

Significance of U-Shape in Submission of New Limit Orders (Thirty Minute Intervals).

Time	10.00-10.30	10.30-11.00	11.00-11.30	11.30-12.00	12.00-12.30	12.30-13.00	13.00-13.30	13.30-14.00	14.00-14.30
Average Order Volume; Number of Stocks (x 100) as % of Outstanding Stocks	4.958	3.465	2.921	2.442	2.102	1.910	2.265	2.562	4.391
t-value of Diff.		-5.70**	-2.86**	-2.80**	-2.28*	-1.43	1.79	1.29	7.15**
Average Number of Orders (x 100,000) as % of Outstanding Stocks	4.098	3.138	2.722	2.244	2.039	1.842	2.035	3.460	4.147
t-value of Diff.		-5.65**	-2.94**	-3.74**	-1.76	-1.95	2.05*	2.77**	8.13**

We report average intraday proportions and t-statistics for the difference between intraday successive averages. Significance is reported at the 1 per cent level with ** and at the 5 per cent level with *.

The null hypotheses of equal means in Table 9 are rejected at a one per cent significance level in both cases (F-value = 47.91 for the number of stocks and F-value = 66.10 for the number of new limit orders; critical $F(8,522) = 2.51$). Table 9 also lists the successive t-values when testing two adjacent means against each other.[38] The statistics all strongly indicate clear U-shapes.

5.4 Intraday Patterns of Returns and Volatility

In this section we document some intraday patterns in returns and return volatility at the SSE. The economic significance of an intraday pattern in returns is obvious. Patterns in

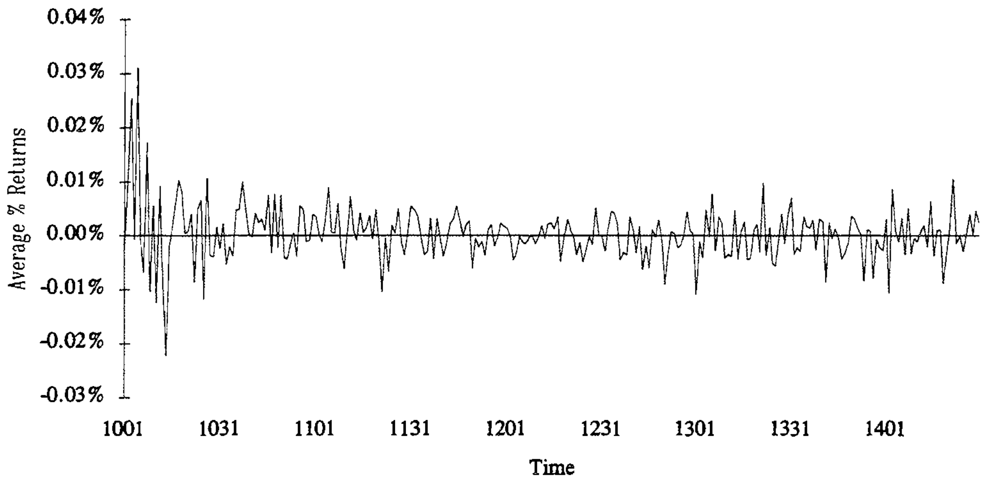
[38] See footnote 37.

returns and/or volatilities would indicate profit opportunities, at least for traders with small transaction costs (i.e., dealers). Furthermore, intraday patterns in volatilities would have obvious consequences for option pricing and could also affect the profitability of submitting limit orders (a short term volatility could imply a certain compensation for submitting limit orders (see section 3.1.2)).

The results of several earlier studies (Wood, McInish, and Ord (1985), Harris (1986), Jain and Joh (1988) and Foster and Viswanathan (1993)) suggest that mean returns and volatilities exhibit distinct intraday patterns, with overall high returns at the beginning and end of the trading day. Our data enable us to compare these results with the ones for the SSE.

Figure 5 shows the average minute by minute return on the OMX-index, based on transaction prices. Figures based on ask or bid prices (not shown) are very similar.

Figure 5
The Average Minute by Minute Returns on the OMX Index.



Returns are calculated as $ln(I_t) - ln(I_{t-1})$, where I_t denotes the index value at time t. Overnight returns are excluded.

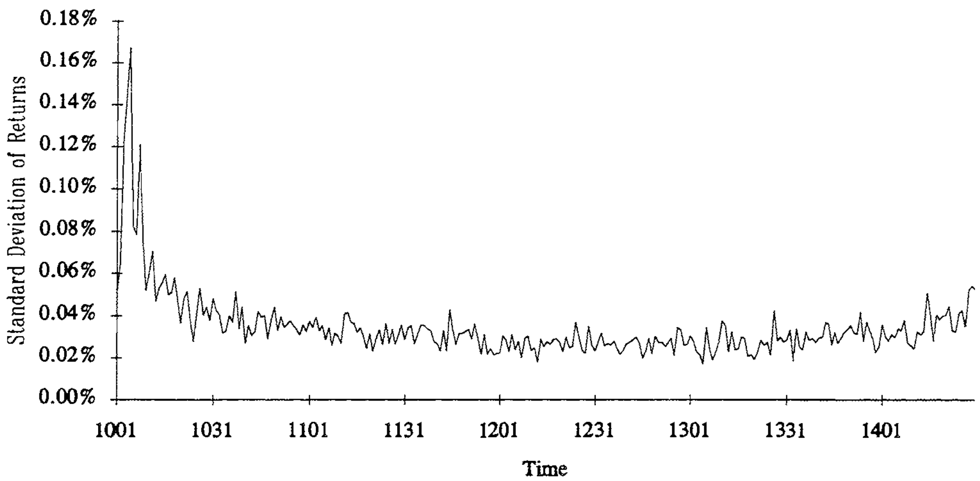
In contrast to the results of the American studies, there is no clear pattern. Wood, McInish and Ord report weak evidence of positive returns during the first trading minutes. Harris, using data from 287 trading days and a portfolio of 1616 equally weighted NYSE stocks, reports significant positive returns both during the first 45 minutes (except Mondays) and during the last 15 minutes of the trading day. Jain and Joh, using 1263 trading days of data, find a higher return on the S&P500 index during the first trading hour (except Mondays) than during the rest of the day.

Wood, McInish and Ord (1985) as well as Foster and Viswanathan (1993) report a U-shape in volatility for the NYSE stocks during the trading day. The volatility is typically high at the opening, falls during the first hour, only to rise slowly during the last hour of trading.

For the SSE-data, Figure 6 clearly demonstrates the higher volatility in the first 15 minutes of trading than during the rest of the day. Compared to the U.S. studies, the fall in volatility seems to be quicker at the SSE. Furthermore, is there no evidence of an increased volatility at the end of the day as in the U.S. studies.

Figure 6

The Standard Deviation of the Minute by Minute Returns on the OMX Index.



Returns are calculated as $ln(I_t) - ln(I_{t-1})$, where I_t denotes the index value at time t. Overnight returns are excluded.

The higher volatility at the beginning of the trading day could be due to be the greater uncertainty following the non-trading period. However, a specific trading feature might also be important. The opening call auction at the SSE is a sequential procedure and this affects the behavior of the returns during the first few minutes. During that period, the index is calculated with some stock prices from the current trading day and some prices from the end of the previous trading day. The "true" volatility of the opening prices is thus spread out over several minutes after the opening.

A higher price variability in periods of concentrated trading is consistent with the Admati and Pfleiderer (1988) model. Our data with high volume and high volatility at the beginning of the trading day is therefore consistent with their model. However, it can also be noted that the volatility does not increase significantly during the last ten minutes of trading despite a sharp increase in trading volume.

5.5 The Importance of the Tick Size

The price discreteness imposed by the tick size forms a lower bound for the difference between levels in the COLOB. No difference between two adjacent levels in the order book can be less than one tick, since traders can submit orders only at prespecified prices separated by one tick. The cross-sectional statistics of the average bid/ask spread measured in number of ticks across stocks in our sample are reported below:

	average	min	25%	median	75%	max
Inside Spread[39] [# of ticks]	2.58	1.11	1.73	2.27	3.48	5.40

The average inside spread is considerable larger than one tick, suggesting that the tick size is not an important factor in determining the inside spread. However, Table 10 demonstrates that for some stocks at least, the tick size is important. For one of the most liquid stocks LM Ericsson BF, the tick size is binding in 90 per cent of the observations in the COLOB. For ten stocks, the tick size is binding in at least half of the observations of the inside spread.

Table 10

The Importance of the Tick Size

Stock	One Tick Spreads as %	Average Midquote	Average Daily Volume
Ericsson, Tel.-ab. LM, ser. B fr	90	110	51.3
Skandi. Enskilda Banken, ser. A	83	48	10.7
Trelleborg AB, ser. B	76	108	12.4
Sydkraft AB, st ser. C	70	141	4.3
Skanska AB, ser. B	64	124	5.3
SKF, AB, ser. B fr	63	99	9.8
Electrolux, AB, ser. B fr	61	242	22.2
Sv. Cellulosa AB SCA, ser. B	60	105	4.1
Investor, AB, ser. B fr	56	123	4.5
Sv. Cellulosa AB SCA, ser. B fr	51	104	3.4
Astra, AB, ser. A	49	522	50.6
Procordia AB, ser. B	49	198	5.2
Proventus AB, ser. B	49	53	1.6
ASEA AB, ser. B fr	48	306	12.4
Argonaut AB, ser. B	47	45	1

The Proportion of Observations in the COLOB for which the Inside Spread Equals One Tick, Average Midpoint Quote and Average Daily Trading Volume [In Million SEK] (Excel. After Hours Trading), for Selected Stocks.

Using U.S. data, Harris (1994) finds that a significant reduction in bid/ask spreads would be obtained if smaller tick sizes were introduced at the NYSE. The positive effect

[39] In principle, the differences between different levels in the limit order book (e.g. between the fourth and third best ask prices) can all be termed spreads. When we want to discuss the specific spread between the best ask and best bid price, we will use the term inside spread.

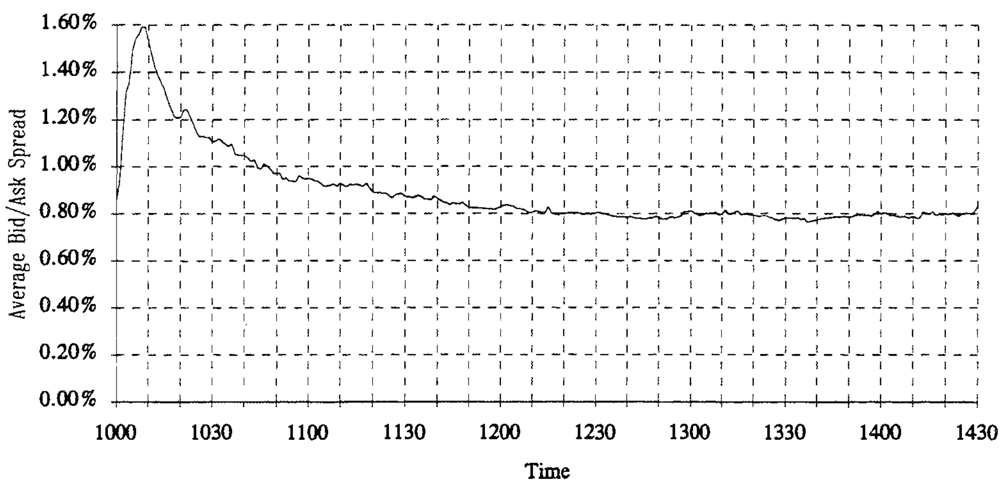
on liquidity of reduced bid/ask spreads would on the other hand be countered by a reduction in displayed quotation sizes or market depth. The net effect on overall liquidity is therefore ambiguous. Since the tick size in the SAX-system is comparatively large, it may have an economically significant impact on both market width and market depth. Using data from the SSE, Niemeyer and Sandås (1994) (Essay 3 in this dissertation) indeed report a significant impact on market width. They find evidence that a lower tick size would imply a lower depth at the SSE, at least for the most liquid stocks.

5.6 Intraday Behavior of the Bid/Ask Spread

Handa (1992) reports largely U-shaped intraday pattern for bid/ask spreads at the NYSE and the AMEX. Market makers post a large spread in the morning and in the afternoon, but lower spreads during midday. Handa finds a significant increase shortly before the close to be followed by a sharp drop at the close.

Figure 7

The Intraday Behavior of the Market Inside Spread



Fictitious bid/ask prices on the OMX-index were calculated by weighting together the best bid and ask prices of the individual stocks with the same weights as the OMX-index. The fictitious index bid/ask prices were then used to calculate the spread as 200*(ask-bid)/(ask+bid). The reported spread is calculated by taking minute-to-minute point estimates and averaging over days.

Our aim is to see whether this overall pattern is present at the SSE. Figure 7 shows the intraday average bid-ask spread, as per cent of the quote midpoint, for the OMX index. Since the OMX index includes the thirty most traded stocks, the spread reported can be seen as the value weighted average spread for the stocks in our sample. The average spread reaches a peak of 1.6% shortly after the opening and falls, remarkably slowly, during the two first hours of trading to a level of 0.8 per cent.

On a thirty minute interval basis, the successive fall until noon of the average inside spread is statistically significant[40] at the one per cent level, as is shown in Table 11. However, the spread does not change significantly prior to the close as in Handa (1992).

Table 11

Average Intraday Percentage Spread for the OMX Index

Time	10.00-10.30	10.30-11.00	11.00-11.30	11.30-12.00	12.00-12.30	12.30-13.00	13.00-13.30	13.30-14.00	14.00-14.30
Avg. Spread	1.27%	1.01%	0.91%	0.84%	0.81%	0.79%	0.79%	0.78%	0.80%
t-value of Diff.		-4.35**	-2.73**	-2.11*	-1.21	-0.83	0.26	-0.37	0.35

We compute the average spread for the OMX-index during different thirty minute periods during the day, using 58 days of data. We also report t-statistics for the difference between intraday successive means. Significance is reported at the 1 per cent level with ** and at the 5 per cent level with *.

The daily fall in the spread can probably be explained by the market information flow by which the market gets tighter as the dealers learn about the overall market movements from the first trades. The large tick sizes at the SSE, discussed above, are also likely to affect the spreads. The prediction of the Brock and Kleidon (1992) model is that the spread would be U-shaped. However, we do not observe higher spreads at the close.

The level of the bid/ask spread seems to be rather large compared to other stock markets. Pagano and Röell (1990) find an average inside spread for the most traded stocks of 0.80-0.85 per cent of quote midpoint in London and 0.52-0.67 per cent in Paris respectively. Handa (1992) reports average spreads between 0.50 and 0.60 per cent of quote midpoint for the ten per cent largest stocks at the NYSE and AMEX.

5.7 Cross-Sectional Characteristics of the Limit Order Book

With data from an entire order book, it is possible to calculate the immediate price impact of a specific transaction size. This forms an approximation of the slope of the limit order book.[41] Glosten (1994) denotes this marginal price function of the limit order book by $R'(q)$. Most other theoretical models use a stylized specialist model (market-by-quote-system) rather than a limit order model (market-by-order-system). In the latter models, the comparable measure is normally referred to as λ (e.g. Kyle (1985)). Most models assume a constant λ, i.e. a linear slope. One model, Easley and O'Hara (1987), allows for a non-constant λ. Empirically, the slope of the LOB can be decomposed into

[40] See footnote 37.

[41] We use the term slope of the limit order book to refer to the plot of price changes as a result of trades of different sizes. In other words, the slope of the limit order book is a measure of the price elasticities of demand and supply.

two different components: the volume at each level in the LOB and the difference between adjacent prices in the LOB. However, existing theories do not provide any predictions about the different components of the slope.

Using data from the Paris Bourse, Biais, Hillion, and Spatt (1994) find that the LOB is non-linear with the steepest slope close to the spread. The inside spread is more than twice as large as the differences between other levels in the LOB. The volumes offered or demanded at the best levels are smaller than the volumes further away from the best levels.

With our SSE data, average relative differences between the levels in the COLOB were computed for each stock in order to measure the slope of the LOB. We report the cross sectional variation in these differences in the upper part of Table 12. For instance, the column B3-B4 refers to the relative difference between the third best bid price (bid price 3) and the fourth best bid price (bid price 4). This difference is then calculated as 200*(bid price 3 - bid price 4)/(bid price 3 + bid price 4). The A1-B1 column gives the inside spread. The median value of 1.12% indicates that on average, only half of Sweden's thirty "blue chip" stocks have individual spreads below 1.12 per cent. In our opinion this is high.

Table 12

Relative Differences Between Successive Levels in the Limit Order Book.

	B4-B5	B3-B4	B2-B3	B1-B2	A1-B1	A2-A1	A3-A2	A4-A3	A5-A4
Max.	13.79	13.56	15.92	4.99	4.36	5.95	7.92	11.12	18.37
75%	3.26	2.93	2.24	1.41	1.51	1.58	2.13	2.45	2.59
Median	2.53	2.20	1.78	1.17	1.12	1.10	1.41	1.83	1.98
25%	1.56	1.54	1.16	0.85	0.91	0.84	1.05	1.20	1.25
Min.	0.73	0.86	0.56	0.36	0.38	0.31	0.38	0.46	0.54
Avg.	2.74	2.47	2.11	1.31	1.36	1.51	2.07	2.52	2.91

Diff	B45-B34	B34-B23	B23-B12	B12-A1B1	A1B1-A21	A21-A32	A32-A43	A43-A54
t-value	0.53	0.65	1.81	-0.26	-0.59	-1.51	-0.91	-0.55

Diff	B45-B23	B34-B12	B23-A1B1	A1B1-A32	A21-A43	A32-A54
t-value	1.13	3.05**	1.71	-2.17*	-2.24*	-1.26

Summary statistics across the stocks (35) in the sample. Differences are calculated as follows:
B4-B5 = 200*(bid price 4 - bid price 5) / (bid price 4 + bid price 5).
Differences between the mean of the first differences are tested with t-tests
where B34-B23 refers to the difference between B3-B4 and B2-B3.
Significant t-values are denoted by ** and * for the 1% and 5% level respectively.

It is also clear from Table 12 that the spreads between the levels of the COLOB generally are wider further away from the inside spread. This is likely to be a natural consequence of the focus of interest on the inside spread and nearby spreads. A null hypothesis of equal means of the nine differences is rejected at the one per cent level, (F-value = 2.92; critical value F(8,306) = 2.51). It is also noteworthy that the successive spreads generally are larger on the bid than on the ask side. The reasons for these differences are not fully transparent. One possible explanation is that the same SEK spread automatically will produce a higher spread for lower prices (bids) than for higher prices (asks). With a significant tick size, this *could* possibly be important. Contrary to our findings Biais, Hillion and Spatt (1994) report larger spreads on the ask than on the bid side.

In the lower part of Table 12, we also test whether there is a statistically significant change in the differences between the levels of the LOB as we move from the fifth best bid to the fifth best ask level. We take the adjacent average spreads (e.g. between B4-B5 and B3-B4; labelled B45-B34) and test if these are significantly different. We also test if the next-to-adjacent average spreads (e.g. between B4-B5 and B2-B3; labelled B45-B23) are significantly different. In Table 12 we report the simple t-statistics.[42] This test procedure approximates a test of the second derivative of the slope of the LOB. The t-values give weak support for a steeper slope further out from the inside spread, i.e. for non linearity. Our results are different from the ones in Biais, Hillion, and Spatt (1994). Both their study and ours indicate non linearity, but of different sort. In contrast to our results they find that the inside spread is more than twice the average relative spreads further out in the LOB.

Table 13

Average Volume [Thousand SEK] at Different Levels in the COLOB

	BV5	BV4	BV3	BV2	BV1	AV1	AV2	AV3	AV4	AV5
Max.	820	1 097	1 787	2 673	2 102	2 404	2 968	1 895	1 303	924
75%	267	454	541	822	897	660	788	589	370	265
Median	147	233	356	550	566	495	495	315	187	129
25%	68	126	228	330	374	365	320	212	138	71
Min.	0	4	25	135	165	177	131	98	24	4
Avg.	212	325	478	685	679	589	597	422	289	208
Diff.	B5-B4	B4-B3	B3-B2	B2-B1	B1-A1	A1-A2	A2-A3	A3-A4	A4-A5	
t-value	-1.90	-1.90	-1.93	0.05	0.95	-0.08	1.74	1.78	1.38	
Diff.		B5-B3	B4-B2	B3-B1			A1-A3	A2-A4	A3-A5	
t-value		-3.60**	-3.67**	-2.15*			1.89	3.26**	3.10**	

BV4 refers to the volume at the fourth best bid price. Sample size: 35 stocks.
Differences between means are tested with t-tests,
where B4-B3 refers to the difference between BV4 and BV3.
Significant t-values are denoted by ** and * for the 1% and 5% level respectively.

[42] See footnote 37.

In the upper part of Table 13, the cross-sectional variation in the average volume offered or demanded at each level in the COLOB is reported. In this table the column BV4 refers to the total volume offered on the fourth best bid price level. We also test whether the ten averages of Table 13 are significantly different. The null hypothesis of equal means is rejected at the one per cent level of significance, (F-value = 9.01; critical F(9,340) = 2.41). In the lower part of Table 13, we use t-tests to test the mean values of volume offered at different levels of the LOB. T-values for differences between adjacent levels as well as differences between the fifth and the third best bid levels, etc. are reported.

In contrast to the results of Biais, Hillion and Spatt (1994), we find a higher average volume close to the inside spread and lower volumes further out on the bid and the ask side. Our tests[43] indicate that the volumes offered or demanded in the LOB exhibit an inverted U-shape. Thus, our study shows that the liquidity is primarily supplied close to the midquote while it in their study is supplied further out in the COLOB. The interpretation of Biais et al is that the adverse selection problem is more pronounced the closer to the inside spread we get. The difference between the results could be explained by the coarser price grid at the SSE.[44] A large tick size might indirectly make it more profitable to supply liquidity and this could produce our results (see also section 3.1.6 and 3.1.7). Our data does not allow us to discern how volumes would be distributed under a finer price grid regime.[45] Therefore, our results are not necessarily incompatible with the ones of Biais et al. One possible hypothesis is that the asymmetric information effect dominates when the tick size is small, whereas the profits from liquidity supply more than compensate for the risk of being "picked off" when the tick size is large.

From Table 13, it can further be noted that the bid side normally has a somewhat larger depth than the ask side. The overall level of liquidity seems to be considerable. All stocks in our sample have an average depth both at the best bid and ask levels exceeding an average sized transaction, (SEK 151 000 see section 5.1), and 75% of the stocks have an average depth of more than twice that amount. As a consequence, the bid- and ask prices change remarkably seldom.

The overall conclusion of this section is that the slope of the COLOB is non-linear and that the demand and supply are price inelastic. The non linearity can be divided into two parts. Both the average differences between different price levels of the LOB and the

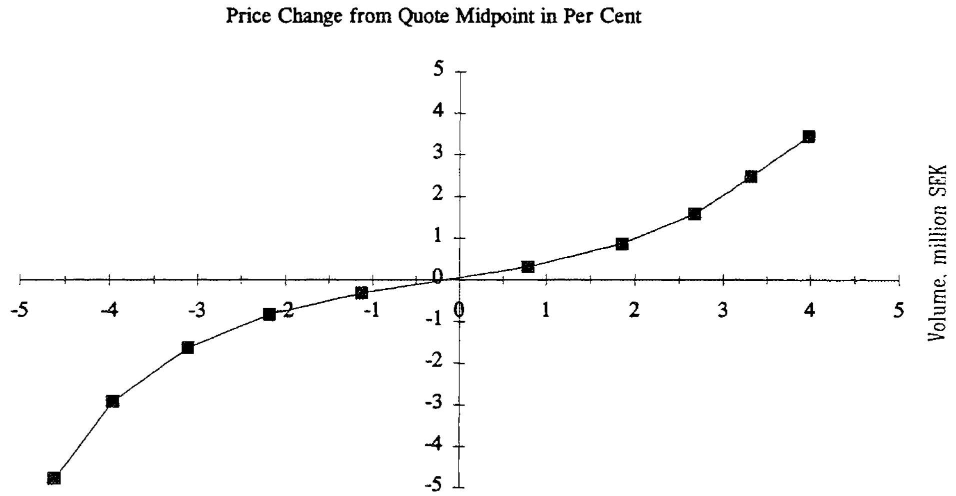
[43] See footnote 37.

[44] Due to the coarser price grid (i.e. larger tick size), the five best bid and ask price levels in the LOB at the SSE normally covers a wider relative price range around the quote midpoint than the corresponding levels at the Paris Bourse.

[45] A replication of this study might be warranted using data from the period after September 1994 and the reduction of the tick size at the SSE.

average volume at each level contribute to the non linearity. The non-linear relation between price changes in the COLOB and the volumes offered is illustrated in Figure 8, which plots the relation between average price changes and average accumulated volume offered or demanded for the COLOB for a typical stock (Volvo B) in our sample.

Figure 8
The Average LOB of a Typical Stock



The stock in the example is Volvo B. Volumes on the x-axis are in million SEK. Negative volumes represent sell transactions. Price changes on the y-axis are the price change calculated from the midpoint of bid/ask prices.

The plotted function in Figure 8 is equivalent to the $R'(q)$ function in Glosten (1994). His prediction of the slope of the function is in accordance with our empirical findings. In interpreting the non linearity of Figure 8, it should be noted that as the price of a stock changes, there is a subsequent shift in price focus. The COLOB will probably not include all possible limit orders. When a stock's bid;ask rises from for instance 150;151 to 151;152, the interest will quickly focus on the new inside spread. The likely consequence is an influx of new orders *both* at bid 151 and at ask 152, producing more volume at both levels and possibly a more linear slope of the limit order book. The interpretation regarding the elasticities and slope of the order book should therefore be made with caution. A more extensive analysis of the inter-temporal aspects of liquidity is beyond the scope of this essay.[46]

[46] For a study of the intertemporal aspects on similar stock exchanges see Biais, Hillion and Spatt (1994) and Hedvall and Niemeyer (1994) (Essay 5 in this dissertation).

6 Conclusions

In this essay we analytically describe the market trading structure at the Stockholm Stock Exchange. We point to the conflict between different aspects of the immediate liquidity in terms of immediacy, depth, width and resiliency. We also discuss the asymmetric information problem as it affects the trading structure at the SSE in terms of free trading options, etc. Furthermore, we note the impact of an important tick size and how it is possible to modify the negative effects of the significant tick size by priority rules and other measures. All these issues are important not only for the SSE as means of competition in a deregulated competitive international surrounding, but also for all traders considering the possibility to trade at the SSE.

In our empirical part, we report a number of results related to the market microstructure of the SSE. Our key empirical findings are:

- The intraday pattern in trading activity corresponds on the whole to the American findings (Jain and Joh (1988) and Foster and Viswanathan (1993)) with the exception that the trading volume shortly before trading halts is extraordinary large at the SSE.
- The intraday pattern in the placement of limit orders follows the pattern of the overall trading activity. A surprisingly high frequency of limit orders placed during the last minutes of the trading day is probably due to the reporting system.
- We find no evidence of intraday pattern in returns, like in the USA.
- There is a higher standard deviation of returns shortly after the opening, but no increase shortly before the close as in U.S. studies (Wood, McInish and Ord (1985) and Jain and Joh (1988)).
- The average inside spread is comparatively large at the SSE. The inside spread of the market index typically falls significantly under the first two hours of trading, but does not increase again shortly before the close such as in the U.S.
- The tick sizes seem to be an important determinant of the spread at least for some stocks.
- The slope of the limit order book is non-linear, both with respect to volumes in the LOB and differences in price. The demand and supply are both price inelastic contrary to the findings in Biais, Hillion and Spatt (1994).

References

Admati, A. R. and P. Pfleiderer, (1988), "A Theory of Intraday Patterns: Volume and Price Variability", *Review of Financial Studies*, 1, 3-40.

Amihud, Y. and H. Mendelson, (1991), "How (Not) to Integrate the European Capital Markets", December, (Paper prepared for the CEPR-IMI Conference on European Financial Integration, January 1990) in A. Giovannini and L.. Mayer (eds.) *European Financial Integration.* Cambridge University Press 1991, p. 73-111.

Biais, B. and M. Crouhy, (1990), "'The French Revolution', Market Microstructure In Paris: Modernization and Issues", Paper presented at the International Colloquium on Options and Futures" organized by MATIF in March 1990.

Biais, B., P. Hillion and C. Spatt, (1994), "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse", Working Paper, March 1994.

Brock, W. A. and A. W. Kleidon, (1992), "Periodic Market Closure and Trading Volume: A Model of Intraday Bids and Asks", *Journal of Economic Dynamics and Control*, 16, 451-489.

Easley, D. and M. O'Hara, (1987), "Price, Trade Size, and the Information in Securities Markets", *Journal of Financial Economics*, 19, 69-90.

FIBV Statistics, (1992), Statistical Supplement to the Fédération Internationale des Bourses de Valeurs Annual Report 1992, Paris.

Foster, F. D. and S. Viswanathan, (1993), "Variations in Trading Volume, Return Volatility, and Trading Costs: Evidence on Recent Price Formation Models", *Journal of Finance*, 48, 187-211.

Glosten, L. R., (1994), "Is the Electronic Open Limit Order Book Inevitable?", *Journal of Finance*, 49, 1127-1161.

Glosten, L. R. and P. R. Milgrom, (1985), "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics*, 14, 71-100.

Handa, P., (1992), "On the Supply of Liquidity at the New York and American Stock Exchanges", Working Paper, New York University, February 1992.

Handa, P. and R. A. Schwartz, (1992), "Limit Order Trading", Working Paper, New York University, January 1992.

Harris, L., (1986), "A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns", *Journal of Financial Economics*, 16, 99-117.

Harris, L., (1990), "Liquidity, Trading Rules, and Electronic Trading Systems", *New York University Salomon Center, Monograph Series in Finance and Economics 1990-4.*

Harris, L., (1991), "Stock Price Clustering and Discreteness", *Review of Financial Studies*, 4, 389-415.

Harris, L., (1992), "Consolidation, Fragmentation, Segmentation, and Regulation", Working Paper, University of Southern California, March 1992.

Harris, L., (1994), "Minimum Price Variations, Discrete Bid/Ask Spreads, and Quotation Sizes", *Review of Financial Studies*, 7, 149-178.

Hedvall, K. and J. Niemeyer, (1994), "Order Flow Dynamics: Evidence from the Helsinki Stock Exchange", Working Paper, November 1994.

Helsinki Stock Exchange, (1991), "Rules and Regulations of the Helsinki Stock Exchange, Vol. 2", The Helsinki Stock Exchange.

Jain, P. C. and G.-H. Joh, (1988), "The Dependence between Hourly Prices and Trading Volume", *Journal of Financial and Quantitative Analysis*, 23, 269-283.

Kyle, A. S., (1985), "Continuous Auctions and Insider Trading", *Econometrica*, 53, 1315-1335.

Niemeyer, J. and P. Sandås, (1994), "Tick Size, Market Liquidity and Trading Volume: Evidence from the Stockholm Stock Exchange", Working Paper, Stockholm School of Economics, November 1994.

NYSE Rule 62, New York Stock Exchange Guide, Rules of Board, Rule 62.

Pagano, M. and A. Röell, (1990), "Stock Markets", *Economic Policy*, April 1990 64-115.

Pagano, M. and A. Röell, (1993), "Shifting Gears: An Economic Evaluation of the Reform of the Paris Bourse", in Conti, V. and R. Hamaui (eds.) *Financial Markets' Liberalisation and the Role of Banks*, Cambridge University Press 1993, p. 152-177.

Schwartz, R. A., (1991), "*Reshaping the Equity Markets: A Guide for the 1990s*", Harper Business, N.Y.

Stockholm Stock Exchange Annual Reports 1989 and 1992, The Stockholm Stock Exchange.

Stoll, H. R., (1992), "Principles of Trading Market Structure", *Journal of Financial Services Research*, 6, 75-107.

Sundqvist, S.-I., (1992), "*Owners and Power in Sweden's Listed Companies*", Dagens Nyheters Förlag, Stockholm.

Wood, R. A., T. H. McInish and J. K. Ord, (1985), "An Investigation of Transactions Data for NYSE Stocks", *Journal of Finance*, 40, 723-741.

References in Swedish Only

Rules Governing Trading in Stocks and Convertible Participating Notes via the Stockholm Automated Exchange (SAX). (in Swedish: **"Regler för handel i aktier och konvertibla vinstandelsbevis via Stockholm Automated Exchange (SAX)".**), Stockholm Stock Exchange, Last revised May 7, 1991, Version 1.2.

The Securities Business Act (in Swedish: "lag om värdepappersrörelse" (1991:981)).

The Stock Exchange Act (in Swedish: "lag om börs- och clearingverksamhet" (1992:543)).

Abbreviations

AMEX	American Stock Exchange
CAC	Cotation Assistée en Continu
CATS	Computer Assisted Trading System
CME	Chicago Mercantile Exchange
COLOB	Consolidated Open Limit Order Book
ISE	International Stock Exchange
NASDAQ	National Association of Security Dealers' Automated Quote System
NYSE	New York Stock Exchange
LOB	Limit Order Book
SAX	Stockholm Automated Exchange
SEAQ	Stock Exchange Automated Quote system
SSE	Stockholm Stock Exchange

Essay 2

An Empirical Analysis of the Trading Structure at the Stockholm Options and Forwards Exchange, OM*

Abstract

We first describe and analyze the trading structure at the Stockholm Options and Forwards Exchange, OM Stockholm. It is characterized by some interesting market microstructure features, such as a high degree of transparency in a fully computerized trading system and a possibility to submit combination orders. We also present empirically results from tests on the intra- and interday trading volume of the OMX index derivatives, both in terms of number of contracts traded and in terms of number of transactions. There is evidence of a high degree of *intra*day variation in trading volume and some *inter*day variation. The extension of trading hours of the underlying stocks, during the studied period should, according to modern trade concentration models, affect the distribution of trading across the day. Although no formal test of the models is possible with this data set, we are able to shed some supportive additional light on all of these models.

1 Introduction

Recently, there has been increased interest in the variations in trading volume of financial markets. Following the stock market crash in October 1987, where extreme price variability and high trading volume coincided, there has been a spur of academic papers trying to take the impact of trading volume on prices and volatility into account.

* I wish to thank *OM Stockholm* for providing the data set. A number of OM officials have assisted with detailed answers to endless questions. I would especially wish to thank Anita Redén and Björn Walman. Furthermore, I am grateful to Ragnar Lindgren for helpful comments. All remaining errors and omissions are my sole responsibility.

Most of these studies have used U.S. data. Another concern after the crash was the relationship between derivatives markets and the stock market.

The academic interest in trading volume started off by a number of empirical papers documenting distinct intraday regularities in traded volume. Several studies have reported significant intraday U-shaped patterns in trading volume in different stock markets.[1] The empirical findings spurred more theoretical academics and a number of models emerged, trying to explain the observed phenomena in different stylized models.[2] The idea was to combine a typical investor's optimal trading strategy with concentrated trading. However so far, only a few empirical studies have used data from derivatives markets.[3] One purpose of this essay is to document any *intra*- and *inter*daily patterns in derivatives trading volume from a small derivatives market.

The Swedish options and forward market, OM Stockholm, is both fairly unknown in academic circles and has some very unusual and interesting features. It is a fully electronic trading system with a high degree of ex ante transparency. Furthermore, it is possible to submit combination orders into this full computerized trading system. In this way, investors can trade for instance a synthetic forward without any risk of only getting one leg of the combination matched. In section 2, we therefore describe and analyze some characteristics of the trading structure at the Swedish Options and Forwards Market, OM Stockholm, from a market microstructure perspective.

After having presented our data in section 3, we will discuss some of these theories in section 4 and without formally testing them, and in section 5 see if the data supports any of the theories. Empirically we will concentrate on the trading volume figures, using 22 months of intraday transaction data. We limit ourselves to the trading in OMX derivatives. The trading day of the underlying stocks, was extended during the studied period. Since the models imply different trading patterns before and after the extension of trading hours, our sample is divided in two subsamples and we examine the volume patterns in both periods. Finally, we conclude with a summary in section 6.

1 Using U.S. stock data, both Jain and Joh (1988) and Foster and Viswanathan (1990) find a significant intraday U-shaped pattern in traded volume. Hamon and Jacquillat (1992) and Biais, Hillion and Spatt (1994) reveal intraday U-shaped traded volume patterns on the French Bourse. Furthermore, Niemeyer and Sandås (1993) (Essay 1 in this dissertation) report an intraday U-shaped traded volume pattern, using Swedish stock exchange data.

2 References include, Admati and Pfleiderer (1988), Foster and Viswanathan (1990) and Brock and Kleidon (1992).

3 References include Stephan and Whaley (1990) for call options and Easley, O'Hara and Srinivas (1993) for call and put options.

2 The Trading System at the Stockholm Options and Forwards Exchange, OM[4]

During the latter part of 1991, the Swedish Options and Forwards Exchange, OM introduced a computerized trading system, called the "Click Trading"[5] system (the CT-system). By December 17, 1991, the new system had been introduced for all trading in stock options and futures as well as index options and futures. The CT-system uses an open limit order book which resembles the OLOB at the Stockholm Stock Exchange (SSE).[6] In the derivatives market, there is however no opening call auction. The order matching procedure is similar to the one used at the SSE. Some orders are executed manually (e.g. interest and combination orders, see below, as well as some block trades) but approximately 80 per cent of the volume and 90 per cent of the transactions are executed entirely electronically.

2.1 Market Participants

There are three types of market participants: end-customers, brokers (who may be trading on own account) and market makers. The latter two have to be members and end-customers can only trade through members. We will refer to the two types of members as dealers. All market participants, including the end-customers, have to trade on individual (but anonymous) accounts, thus enabling OM to calculate the required individual collateral directly. As investor you can have one collateral account even if you trade through different dealers. In this way it is possible for OM to calculate the net collateral for each end-customer separately.

There are designated market makers in all option and futures series at OM. The market makers are required to quote binding prices on each side of the market. Table 1 lists the maximum spreads presently allowed for market makers.

Table 1
Maximum Spreads for Market Makers [in SEK]

Option Premium/Forward Price	Maximum Spread
0 - 1	1
1 - 10	2
10 - 20	3
20 - 30	4
30 -	6

4 OM also has a wholly owned subsidiary in London. It is linked in real time to OM Stockholm and can thus be seen as a satellite market. The structure of OM London is equivalent to the one of OM Stockholm.

5 The name "Click Trading" refers to the fact that you only need the mouse at your trading station to enter, change or remove an order.

6 See Niemeyer and Sandås (1993) (Essay 1 in this dissertation) for a description of the trading structure at the Stockholm Stock Exchange.

There is also a minimum volume of ten contracts that each market maker has to quote.[7] The market makers' compensation for providing the liquidity is a discount on the transaction fees paid to OM. However, this discount is only given on transactions where the market maker trade on his own account. For almost all contracts, there are more than one market maker. In total, there are presently 15 market makers at OM, of which 5 are based in London. In addition, there are 90 brokers,[8] of which 57 are based in London.

2.2 The Electronic Limit Order Book

The central feature of the trading system at OM is its electronic open limit order book (OLOB). It is a computer file registering the price and volume of all limit orders. The identity of the dealers is not reported on the screen. Only dealers can directly submit new market and limit orders. If possible, a new buy (sell) order is automatically matched against an existing best limit sell (buy) order. If there is no matching limit sell (buy) order, and if the new order is a limit order, it is added to the OLOB. Table 2 describes a typical OLOB. Since all information is readily available in spread sheet format, any calculation of the effect of potential positions can easily be performed.

Table 2
The OLOB in Principle

Bid		Ask	
Price	Quantity	Price	Quantity
44.50	100	44.75	20
44.50	50	45.00	70
44.25	20	45.00	50
44.00	90	45.00	10
44.00	10	45.25	30
.	.	.	.

2.3 Trading in the CT-system

A dealer has three main trading alternatives. First, he can hit an existing buy (sell) limit order in the OLOB by placing a sell (buy) market order. Second, he can place a limit order in the OLOB and wait for someone else to hit it. Third, he may decide to trade manually, in which case he will communicate his order over the telephone to OM. There are two types of manually traded orders, interest orders and complex combination orders.

An order can also have standardized restrictions on volume such as "Fill or Kill" or "Fill

7 Most of the time the actual spreads are significantly lower than the ones in Table 1. However, at extreme market conditions, there is a possibility to enlarge the spreads. There is a difference between a "small" and a "large" market maker. The "large" market maker has to quote a minimum volume of 20 contracts for OMX derivatives.

8 I.e. firms connected to the CT-system but without market maker obligations.

and Kill". The first term refers to orders which must be filled completely or cancelled. The second term is used for orders which may be partly filled but which should be cancelled immediately after the first (and only) execution. All trading is reported immediately on the screens.

A general feature of OLOB trading is the distinction between transactions and trades. When prices match in the OLOB, the order submitted by the active part will be matched against one or frequently several limit orders at the best level on the opposite side. Thus in many cases, there will be more than one transaction per trade.

2.4 The Information Structure

The dealers have access, through the CT-system, to most information on prices and volumes, both of orders and of transactions. There is a very high degree o both ex ante and ex post transparency.[9] As is evident from Table 2, the dealers can obtain information on each individual order. It is also possible to see a consolidated version of the OLOB. However, information on the identity of the dealers is not available. Comparing the information structure between the SSE and OM, there are two distinct differences. At the SSE, the dealers can see the identity of different dealers (and their priority order) but cannot observe the individual orders themselves. At OM, dealers cannot see the identity of the different dealers, but they can see prices and volumes of individual orders.

The information available to the public through financial information firms is restricted to 1) best bid and ask quotes; 2) open, high, low and last prices; and 3) total volume.

2.5 OM Specific Orders

Interest Orders

Apart from simple market and limit orders, a dealer can also submit an "interest" to trade a specified volume at a specified price without revealing it on the screen. Most of the time the "interest price" is within the spread. OM will try to find a counterpart without officially registering the order. If this succeeds, trading takes place and the trade will be registered in the normal way. If OM is unable to find a counterpart, the dealer must choose whether to transform the order into a normal order or to withdraw it. In the latter case, the order will never be registered. The possibility to submit interest orders is an appreciated feature by the members. Interest orders, in the same way as off-exchange trading in stocks, can be seen as a solution to the asymmetric information problem inherent in most markets.[10] In this case the solution is to limit the market's transparency.

---

9 Ex ante transparency normally refers to the possibility to observe order (i.e., limit orders) before they are matched, while ex post transparency relates to transactions already performed.

10 See Glosten and Milgrom (1985) for a discussion of the asymmetric information problem in securities

It is, however, not fully clear to what extent this type of trading reduces the asymmetric information problem. Dealers are still anonymous and there is no direct communication between the potential counterparts of the deal before it is settled. Placing an interest order is still equivalent to writing a free trading option[11] to the market, although the possibility to exercise the option is limited to one dealer at a time, as OM searches for counterparts.

Combination Orders

One very interesting feature of the trading structure at OM is the possibility to submit combination orders. In this way a trader can simultaneously offer to buy (sell) two or more different types of contracts on the same underlying claim. It is therefore possible to significantly expand the number of derivatives contracts while retaining full control that all parts of the complex security are traded. The risk of getting stuck with only one leg in a combined strategy is thereby nil.

A combination order is quoted as the net price of the two options and can be seen as a combination of on the one hand a limit order and on the other hand a market order conditional on the limit order. Thereby, trading is simultaneous in all options constituting the combination order. Certain standardized combination orders can be traded within the CT-system. Presently, there are three types of standardized combination orders, "price spreads", "time spreads" and "synthetic forwards". Since the index options are standardized European style options, it is easy to construct a synthetic forward. A combination order of two call options (alternatively two put options) is treated as an implicit order on the option with the highest premium, conditional on the one with a lower premium. In the case of a combination order of a call and a put option, the implicit order is recorded on the call option, conditional on the put option. Other more complex combination orders are traded manually.

2.6 Priority Rules in the OLOB

If there are multiple limit orders at a price, priority is given according to time. Market makers have no (dis-)advantage to other dealers. This is in contrast to the rules at the NYSE by which public orders always have priority over specialist orders at all quoted price levels. Implicit orders derived from combination orders have both a price and time priority. If there is a price change in one contract of the combination order, resulting in a new price level for the combination order, the priority of the combination order at the new price will depend on a strict time priority among the orders at the new price level. The combination order is always given priority according to when it first was submitted.

markets. The problem is also discussed with reference to the Stockholm Stock Exchange in Niemeyer and Sandås (1993) (Essay 1 in this dissertation).

[11] See Stoll (1992).

Minimum Tick Size

The minimum tick sizes for OM's stock and stock index options are given in Table 3.

Table 3

The Tick Sizes for OM's Options and Forwards

[Option Premium, SEK]	[Tick Size, SEK]
0.00 - 0.10	0.01
0.10 - 10.00	0.05
10.00 -	0.25

It is not impossible that these tick sizes could impose binding restrictions on observed quoted spreads, at least for at-the-money options. On the other hand, evidence from the NYSE indicates clustering to specific price levels, often with higher spreads than the minimum ones.[12]

2.7 Off Exchange Trading in Options

In-house clearing of option transactions is also allowed and information of these trades must be disclosed before 9:45 a.m. the following day. Moreover, the trade has to be within ± 30% of the inside spread at the time of trade. We do not have any data on off exchange activity in options, but our overall impression is that this type of trading is limited.

2.8 The Viability of an OLOB

A trading system based on an OLOB is by definition based on the asymmetric disclosure of information. The dealer submitting a limit order effectively writes a free trading option to the market.[13] This immediate liquidity is of paramount importance in a limit order based trading system. If the market conditions change, either the order will be hopelessly out of date, or it will immediately be traded. In a sense, limit orders are per definition stale. Yet, the entire trading system is based on them. Only if market conditions remain unchanged, and there is an influx of liquidity motivated orders, will the supplier of liquidity through the limit orders receive any remuneration for his risk. A trading system, such as OM's, with its high degree of transparency only reinforces this problem. If ex ante (and possibly ex post) transparency is high, informed traders will be reluctant to trade large amounts, since the immediate impact on prices is likely to be large. Therefore, such traders are likely to try and trade through different channels, and the possible informational advantage of immediately releasing all information to everybody vanishes.

[12] See Harris (1991).

[13] See Stoll (1992).

The opportunity to use interest orders, as well as manual and off-book trading can be seen as a response to the need of some investors to temporarily hide their information. If no trader can transform his informational advantage into profits, there will be no information gathering and the markets will not incorporate any new information.[14] Furthermore, at OM liquidity is also provided by a number of independent market makers. Their obligation to submit both bid and ask limit orders is remunerated by the reduction in commissions to OM. From OM's perspective, there is a trade-off between the reduction in commissions and the increased liquidity supplied by the market makers. The latter is of course dependent on the bid/ask spreads and volumes they quote, see Table 1. The trading system at OM, is thus an interesting combination of an OLOB market and a system with competing market makers. OM tries to capture the advantages of both systems.

This concludes the descriptive part of the essay. In the second half, we will present our data set and test a certain number of inter- and intraday volume regularities on the derivatives market in Sweden.

3 The Data Set

Our data set includes all transactions on all traded options and futures on the OMX-index during the period December 1, 1991 through September 30, 1993. Only OMX-index derivatives are included. The data have been obtained directly from OM Stockholm and include date, time, type of derivative, exercise price (if option), price and quantity. The data set is based on trades rather than transactions. Therefore, if one sell order is matched against several (say three) buy limit orders, there will only be one observation. If one buy order is matched against several sell limit orders, there will still only be one observation.

The data has been divided into two sub-periods. During the first sub-period, from December 1, 1991 to March 31, 1993 (327 trading days), the *stock* exchange closed at 1430 (2.30 p.m.) while the *derivatives* trading went on until 1600 (4.00 p.m.). As of April 1, 1993, the trading hours at the stock exchange were extended until 1600. The second sub-period includes data from April 1, 1993 to September 30, 1993 (124 trading days).

[14] See Grossman and Stiglitz (1980).

4 Theoretical Framework and Earlier Literature

As a response to empirically reported intraday and interday patterns in trading volume and trading costs, several theoretical models have emerged trying to explain the observed regularities. The firsts to come up with a theory of intraday patterns were Admati and Pfleiderer (1988), henceforth AP. The basic idea is that liquidity generates more liquidity. If there are liquidity traders who can choose the exact time of trading (the so called discretionary liquidity traders), they will try to trade when the liquidity of the market is the highest and when the trading costs are the lowest. Since informed traders will want to hide behind liquidity traders, they will also want to trade when the market is as liquid as possible. The result is likely to be a concentration of trading to certain time periods. However, when the informed trading is high, the terms-of-trade will reflect the higher degree information trading. As a consequence, trading costs might rise by an increase in the asymmetric information component of the bid/ask spread.[15] If this is the case, discretionary liquidity traders could prefer to trade at another time period. However, AP shows that a concentrated trading pattern is likely to emerge even if the informed traders are heterogeneously informed. In equilibrium, AP's model implies that high volume and low trading costs will be correlated.

One disadvantage of the AP model is that it does not formally specify *when* the high (low) volume periods will occur. It only says that *if* everybody knows that there will be high trading volume in one period, other dealers will also want to trade in that period. Almost all empirical findings show high trading volume at the beginning of the trading day and before the close. In their conclusion AP argues that the disruption of trading "may cause an increase in (nondiscretionary) liquidity trading ... As a result, discretionary liquidity trading (as well as informed trading) will also be concentrated in these periods"[16].

Another model, focusing more on the *inter*day than on the *intra*day trading patterns is Foster and Viswanathan (1990), henceforth FV. They analyze a model without discretionary liquidity traders and where the information is long-lived, arrives at a constant rate across days and is only slowly disseminated through public signals. They argue that since the price in itself is information for the uninformed traders, the informed traders have "the greatest advantage when the market first opens; and, the longer the market is closed, the more significant the advantage"[17]. Since the informed traders' information advantage is larger in the beginning of the week, we should observe low volume on Mondays and higher at the end of the week. If the argument would be applied in an intraday setting, which FV carefully avoids, we should observe the *lowest*

15 See Glosten and Milgrom (1985).

16 Admati and Pfleiderer (1988), p. 34.

17 Foster, and Viswanathan (1990), p. 594.

trading volume at the beginning of the trading day.

A third interesting model is Brock and Kleidon (1992), henceforth BK. Their approach is quite different. They adopt a portfolio perspective rather than an asymmetric information argument. Their paper extends Merton (1971) by studying portfolio holdings in continuous markets *with* periodic market closures. The main findings are that the periodic closures induce increased and less elastic demand to trade at the open and at the close, for two reasons.

> "First, the accumulation of overnight information in the absence of an opportunity to trade means that portfolios at the open have in general deviated from optimal holdings, resulting in opening trade to reestablish optimal portfolios. Second, in preparation for an overnight non-trading period, the optimal portfolios at the close will differ from those that are optimal during the continuous trading interval."[18]

The implication of this model is therefore, specifically a U-shaped trading volume pattern.

Foster and Viswanathan (1993) tries to shed empirical evidence on the implications of the AP and FV models respectively. They find that high asymmetric information costs occur at the same time of the trading day as high volume, inconsistent with the AP model. On the other hand, trading volume is lower on Mondays than on other days. Following the FV model, this is exactly when the asymmetric information costs are higher and thus consistent with their model.

Hedvall (1994) uses data from another small market to test the AP model against the BK model. In his data set, from the Helsinki Stock Exchange, there is mixed evidence. On the one hand, the simultaneous correlation of high trading costs and high trading volume in the beginning of the trading day does not support the AP model. On the other hand, there is also high trading volume at the end of the trading day, where the trading costs are the lowest. This, of course, is in full accordance with the AP model. In Helsinki, a large portion of trading is off-book trading. If we assume that some traders (i.e., small traders) are limited to trading on-the-book while other traders (i.e., larger traders) can choose to trade on-the-book or off-the-book, BK would predict different trading volume patterns. Since on-the-book trading peaks prior to the close when the off-book trading is flat (it peaks *after* the close), Hedvall interprets this as evidence in favor of the BK model.

[18] Brock and Kleidon (1992), p. 452.

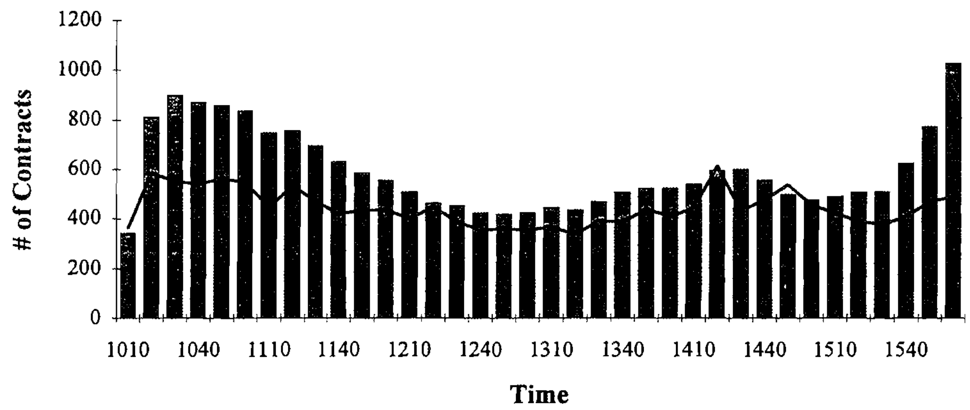
Even if there is likely to be a very close relationship between intraday (as well as interday) variations trading costs and trading volume, the purpose of this essay is *not* to test the different models but rather to shed some light as to the trading volume patterns in the Swedish derivatives markets. A possible extension would be to use a fuller data set, including the trading costs, to try to test the models given in a similar fashion as Hedvall (1994).

5 Empirical Findings

5.1 Intraday Volume Patterns

Without making any distinction between a call, a put or a forward trade, Figure 1 describes the intraday pattern in trading measured as the number of contracts traded. In Figure 2, the number of transactions is used as the measured variable. In these and all the following figures, the inserted line represents the standard deviation across days for each individual interval.

Figure 1
Average Intraday Derivatives Trading
Bars: Number of Contracts, Line: Standard Deviation Across Days
Dec. '91 - Mar. '93 (327 days)



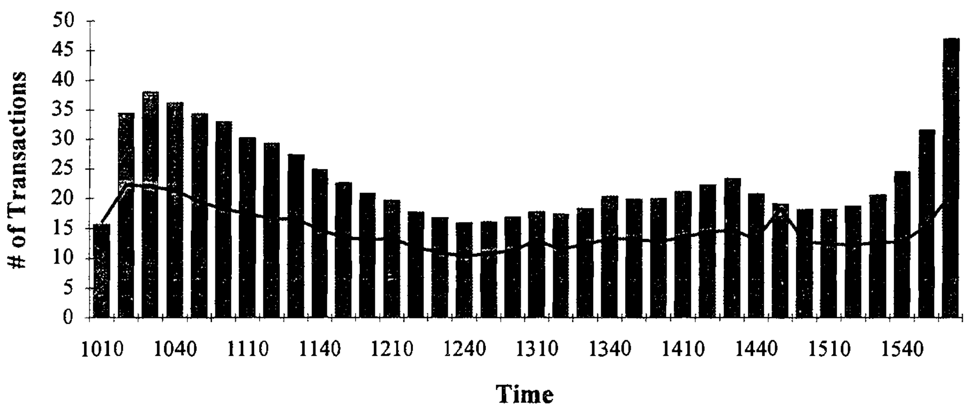
The familiar U-shaped form found in stock markets is clear from these figures. The peak during the last ten minute interval is highly pronounced, more so than in studies using stock market data. Furthermore, in contrast to the stock market, it normally takes about 20-30 minutes before the derivatives trading takes off in the morning. This could be caused by the sequential call auction used at the opening of the trading in the underlying stocks. It often takes about fifteen minutes before all stocks have opened.[19] However, this period is substantially shorter than reported from U.S. derivatives markets where no

[19] See Niemeyer and Sandås (1993) (Essay 1 in this dissertation).

sequential call opening procedure is used.[20] One possible reason for this difference is that the trading systems of the underlying stocks and the index derivatives at OM, both based on a fully transparent OLOB, enhances the information flow between markets, compared to the trading system at the U.S. markets.

Figures 1 and 2 use data for period 1. Interestingly, there is some evidence of higher derivatives trading just prior to the close of the stock exchange.

Figure 2
Average Intraday Derivatives Trading
Bars: Number of Transactions, Line: Standard Deviation Across Days
Dec. '91 - Mar. '93 (327 days)



Turning to Figures 3 and 4, they are exactly parallel to Figures 1 and 2, but for period 2. Although the pattern is less pronounced due to a shorter time period (only including the summer months), there is still clear evidence of a U-shaped trading pattern, with possibly an even more pronounced peak at the end of the trading day.

An F-test of equality across the 36 ten minute intervals is rejected in both periods. In period 1, we get $F_{(35,\,11736)} = 44.25$ ($p<0.001$) and $F_{(35,\,11736)} = 82.19$ ($p<0.001$) when the volume is calculated from the number of contracts and the number of transactions respectively. In period 2, the corresponding F-tests are $F_{(35,\,4428)} = 19.72$ ($p<0.001$) and $F_{(35,\,4428)} = 34.09$ ($p<0.001$) Even if the first and last ten minute intervals were removed, equality can be rejected at any reasonable significance levels in both periods ($p<0.001$ in all cases).

[20] Stephan and Whaley (1990) report a trading volume peak after about 40-55 minutes for U.S. stock call options, while Easley, O'Hara and Srinivas (1993) report a trading peak after 45 minutes for U.S. stock options (both call and put options).

Figure 3
Average Intraday Derivatives Trading
Bars: Number of Contracts, Line: Standard Deviation Across Days
Apr. '93 - Sep. '93 (124 days)

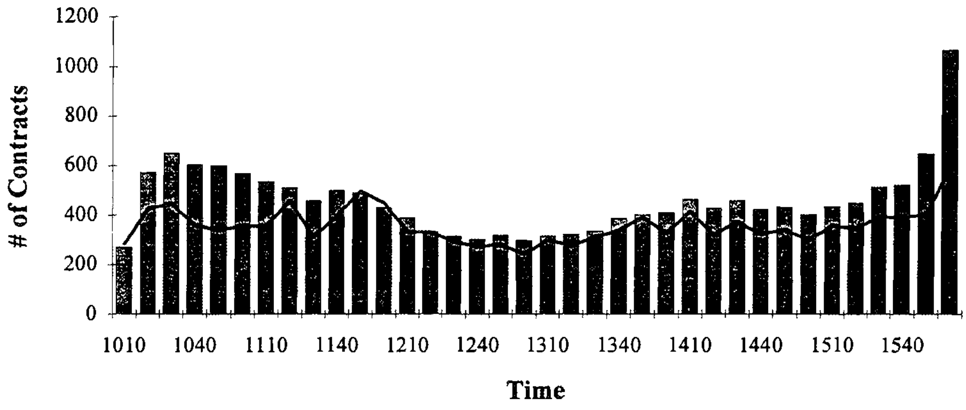
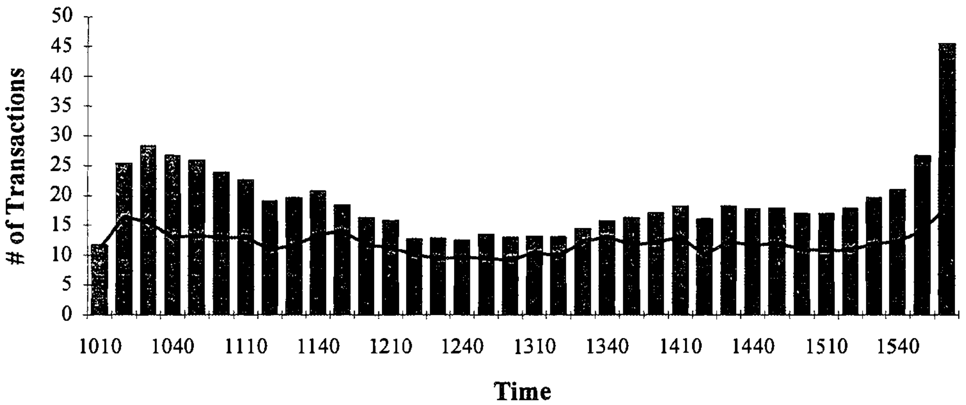


Figure 4
Average Intraday Derivatives Trading
Bars: Number of Transactions, Line: Standard Deviation Across Days
Apr. '93 - Sep. '93 (124 days)



We have also run the same tests for call options, put options and forwards separately (not reported). Although the figures per ten minute interval are less "smooth", they all show a clear U-shaped form, with comparatively lower volume the first 10-20 minutes, both in terms of number of contracts traded and in terms of number of transactions, as well as for both periods. Furthermore, in all cases we can reject the hypothesis of an equal distribution across all ten minute intervals.

One could possibly argue that a more interesting measure would be how the *proportion* of the total daily trading volume (rather than the *absolute* number of contracts (transactions)) is divided across different intervals of the day. In a strict statistical sense, the different observations across the day are then *not* independent and the F-statistic not valid. However, with 36 different intervals, this dependence is not considerable. In any case, the results from tests using daily proportions (not reported) are totally in line with the tests using absolute numbers and equality between periods can be rejected both for number of transactions and number of contracts, for both periods and for all individual types of contracts.

In order to control for possible expiration day effects, we ran the same tests for the day before expiration as well as the expiration day of each contract. If all types of contracts are aggregated there is still clear evidence of a U-shape for both periods and equality across the 36 ten minute intervals can be rejected, in all cases.[21]

If we aggregate data into thirty minute intervals, the same U-shaped pattern still exists (not shown). Furthermore, we can still reject equality between intervals in *all* cases.

We also divided the options into in-the-money and out-of-the-money options. In the first period, there is weak evidence (not shown) that in-the-money options are traded less intensely compared with the out-of-the-money options, during the first 20 minutes and last ten minutes of the day. However, this difference is not persistent into the second period. Our conclusion is therefore that there is no systematic difference in intraday trading patterns between in-the-money and out-of-the-money options.

5.2 Differences Between Periods

One interesting question is if the extension of the trading hours at the stock exchange from 1430 to 1600 affected the intraday volume pattern of derivatives trading in any significant way. Since the overall trading volume is somewhat lower in the second period than in the first period (possibly due to seasonality effects - trading volume often being lower in the summer months), a more interesting measure would be the proportion of trading in each ten minute interval. The concentration of trading to the last ten minutes could be in line with both the AP model and the BK model. However the observed relatively high derivatives trading volume around the close of the stock exchange in the first period would lend support to the BK model. In period one, investors could not rebalance their portfolios in the stock market anymore, but would have to do that in the derivatives market. However, if this is true the concentration of volume around 1430 would disappear in the second period, where the investors had the stock market at their disposal also after 1430.

[21] When looking at the individual contracts, the number of observations is low and since the size of the forward trading is volatile, we are not able to reject equality across intervals for forwards.

Table 4
Testing Differences Between Periods

	Volume Period 1	Volume Period 2	t-test	Transact. Period 1	Transact. Period 2	t-test
1010	1.48%	1.49%	0.07	1.69%	1.62%	-0.51
1020	3.70%	3.38%	-1.66	3.96%	3.71%	-1.33
1030	4.21%	3.89%	-1.60	4.45%	4.20%	-1.32
1400	2.46%	2.42%	-0.22	2.35%	2.44%	0.64
1410	2.47%	2.79%	1.41	2.48%	2.60%	0.85
1420	2.75%	2.74%	-0.06	2.61%	2.41%	-1.63
1430	2.76%	2.83%	0.36	2.73%	2.69%	-0.23
1440	2.66%	2.57%	-0.41	2.46%	2.65%	1.21
1450	2.23%	2.77%	2.07	2.20%	2.65%	2.89
1500	2.16%	2.39%	1.55	2.14%	2.46%	2.56
1510	2.33%	2.61%	1.43	2.16%	2.48%	2.57
1520	2.36%	2.73%	1.82	2.20%	2.61%	3.46
1530	2.39%	3.03%	3.51	2.44%	2.91%	3.31
1540	3.00%	3.24%	1.10	2.97%	3.20%	1.36
1550	3.69%	3.96%	1.23	3.83%	3.99%	0.98
1600	4.97%	6.77%	5.72	5.69%	7.02%	5.74

Apart from studying the proportions traded around 1430, it could also be interesting to study the differences in proportions traded during the first half hour and during the period where the stock exchange is not open. Table 4 reports t-test of the different intervals. At the beginning of the trading day, there is no significant difference between the periods, either in volume or in number of transactions. Surprisingly, the proportions of trading volume, both in terms of contracts and transactions are not significantly lower around 1430. In that sense, there is no direct evidence supporting the BK model.

However, a more specific test of concentration prior to 1430 in period 1 and 2, can be performed by testing the mean trading volume between 1400 and 1430 against the surrounding thirty minute intervals in both periods. Table 5 clearly shows that in period 1, trading volume (both in terms of contracts and transactions) increased significantly from 1330-1400 to 1400-1430 (t-values of 2.20 and 3.81 respectively) and fell significantly from 1400-1430 to 1430-1500 (t-values of -2.29 and -4.66 respectively). In period 2, none of the t-statistics are significant. There is therefore after all some evidence that the closing of the stock exchange induced more trading volume, which would be in line with the BK-model.

One interesting feature of Table 4 is that it emphasizes the shift in the intradaily distribution of trading volumes between periods. The fact that the *stock* exchange was open also after 1430 in the second period seems to have resulted in a larger proportion of derivatives trading after 1450, at least in terms of the number of transactions. Does the possibility to trade also in the stock market stimulate trading in the derivatives market, i.e. are the two trading modes complementary? Since the proportion of the number of transactions, but only to a lesser degree of trading volume, increases after 1430 in the second period, the average trading size has probably fallen in the late afternoon. This could be a result of increased trading by smaller investors, who did not have efficient access to off-exchage trading in stocks, but with the extension of the trading hours at the SSE, now extend their total trading hours at OM. A lower total trading volume in the second period could on the other hand indicate that the two trading modes are substitutes. To make any final inference, a longer sample from the second period would be needed, as well as simultaneous volume data from the stock exchange.

Table 5

Testing Specific Differences Between Intervals

	Period 1		Period 2	
	Contracts	Transact.	Contracts	Transact.
t-test $\text{mean}_{(1400\text{-}1430)}$- $\text{mean}_{(1330\text{-}1400)}$	2.20	3.81	1.46	0.91
t-test $\text{mean}_{(1430\text{-}1500)}$- $\text{mean}_{(1400\text{-}1430)}$	-2.29	-4.66	-0.92	0.04

The largest difference in proportions occurs in the last ten minutes, indicating that the concentration has become more significant after the extension of trading hours at the stock exchange. Still, without data on trading costs no direct test of the AP versus the KB models can be performed.

5.3 Interday and Intraday Trading Patterns

Using NYSE data, Jain and Joh (1988) report an inverted U-shape across the weekdays for each individual trading hour of the day. To put it differently, looking at the trading volume during the first hour of trading each day, it is on average lowest on Mondays, increases over Tuesday to reach a peak on Wednesdays in order to slowly fall on Thursdays and Fridays. For all other trading hours the same pattern is found, with Wednesdays as the day with the highest trading volume. An F-test of equality across days is rejected for all trading hours. A similar result is reported in Foster and Viswanathan (1993), but the two only significant differences in their sample are between Mondays and Tuesdays, and between Mondays and Wednesdays.

When investigating the interday variations in trading volume for each hour in our sample, we only include trading days from full trading weeks, i.e. we reduce our samples with all trading days from weeks with less than five trading days. Figures 5 and 6 show the volume patterns across the weekdays for each trading hour of the day for the first period for number of contracts and number of transactions respectively. Figures 7 and 8 report the evidence from the second period. There seems to be weak evidence of an inverted U-shape across days in the same manner as in Jain and Joh (1988). If possible, the difference in trading between days seems to be more pronounced in the second period.

Figure 5
Average Intraday and Interday Derivatives Trading
Dec. '91 - Mar. '93 (272 days)

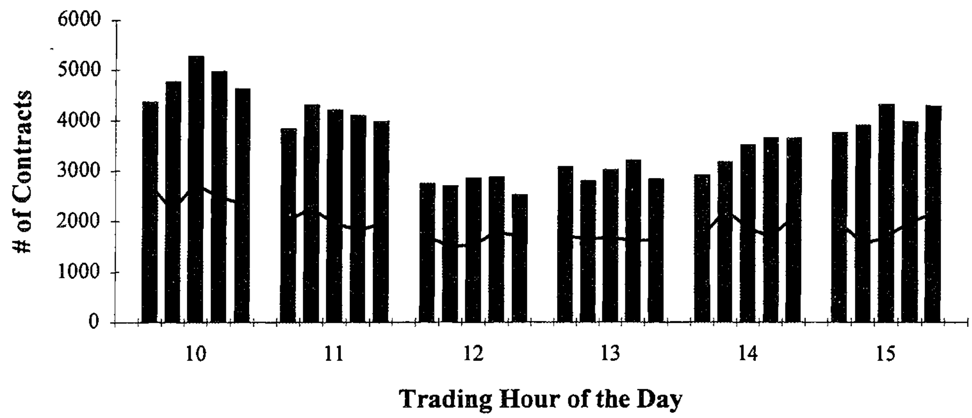


Figure 6
Average Intraday and Interday Derivatives Trading
Dec. '91 - Mar. '93 (272 days)

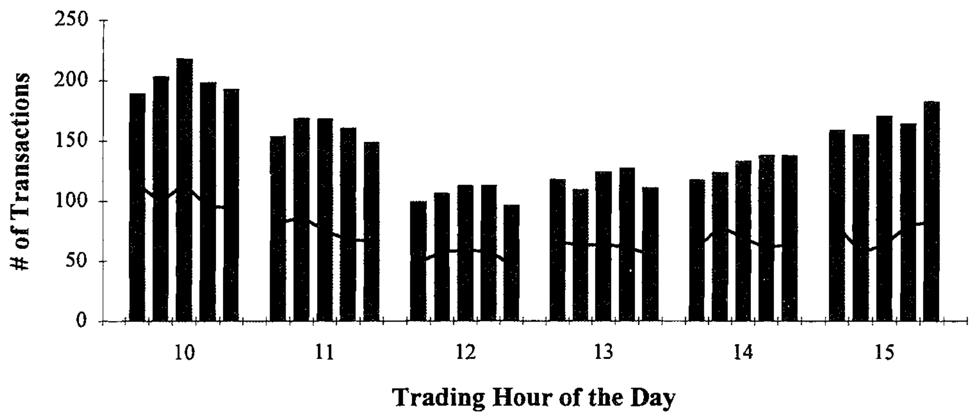


Figure 7
Average Intraday Derivatives Trading
Apr. '93 - Sep. '93 (105 days)

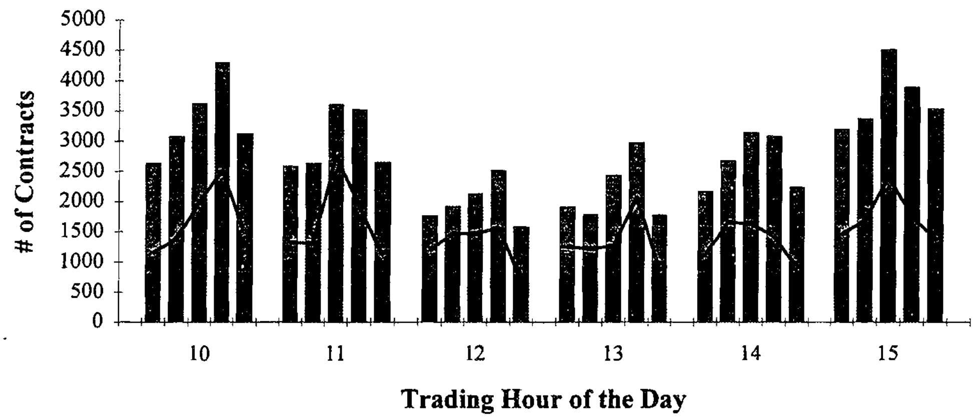
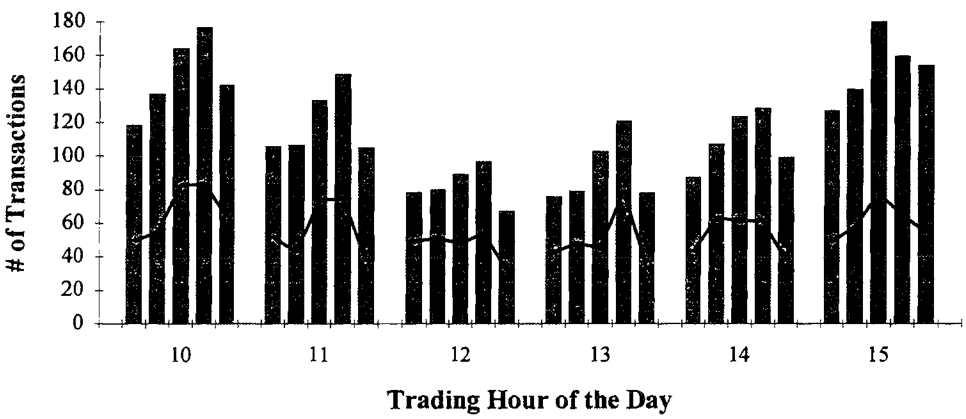


Figure 8
Average Intraday Derivatives Trading
Apr. '93 - Sep. '93 (105 days)



To test whether the inverted U-shape is statistically significant, we perform a series of F-tests, which are reported in Tables 6 and 7 for number of contracts and number of transactions respectively, for the first period. The second period results are summarized in Tables 8 and 9.

Table 6

Trading Volume for Each Hour of the Week
Number of Contracts, Period 1

	Mond.	Tuesd.	Wednesd.	Thursd.	Frid.	Mean	F-Day[a]	p-value
10	4479[b]	4816	5433	4988	4691	4883	1.27	0.281
10	(2735)	(2226)	(2738)	(2531)	(2415)	(2539)		df (4, 267)
11	3931	4334	4336	4125	4008	4148	0.68	0.607
11	(2025)	(2315)	(1947)	(1844)	(1913)	(2009)		df (4, 267)
12	2810	2740	2929	2943	2549	2796	0.70	0.592
12	(1727)	(1528)	(1546)	(1828)	(1721)	(1667)		df (4, 267)
13	3105	2802	3100	3148	2849	3001	0.65	0.630
13	(1745)	(1691)	(1695)	(1540)	(1643)	(1659)		df (4, 267)
14	2935	3214	3593	3677	3574	3396	1.20	0.309
14	(1738)	(2275)	(1874)	(1697)	(2034)	(1942)		df (4, 267)
15	3780	3981	4373	4013	4309	4090	0.77	0.545
15	(2047)	(1550)	(1716)	(2030)	(2206)	(1920)		df (4, 267)
Mean	3507	3648	3961	3816	3664	3719	2.59	0.035
Mean	(2106)	(2098)	(2125)	(2038)	(2133)			df (4, 1627)
F-Hour[a]	5.78	10.51	12.68	7.87	9.22	43.76		
p-value	0.000	0.000	0.000	0.000	0.000	0.000		
df	(5, 324)	(5, 324)	(5, 324)	(5, 318)	(5, 312)	(5, 1626)		

[a] F-Day tests whether the means across days are equal. F-Hour tests if all six hour means are equal.
[b] Standard deviations across days for each weekday and hour are given in parenthesis.

Tables 6-9 clearly demonstrates that there is a high degree of intraday variation in trading volume in our samples. We can reject the hypothesis of equality between different trading hours for all weekdays in both periods and both if we measure the volume as number of contracts or as number of transactions, since the F-Hour statistic is significant in *all* cases.[22] Our conclusion from Figure 1-4 of distinct intraday variations in trading volume remain and seem to be valid for each individual weekday, regardless of period under investigation.

However in the case of *inter*day variations, Tables 6-9 reveal different patterns in the two sub-periods. In the first period, there is no difference between weekdays in any one single trading hour. Focusing on the mean trading volume each day, we can reject the hypothesis of equality at the five per cent significance level. In the second period, there is clearer indication of an intraweekly trading pattern. We can reject the null of an equal distribution across days of the week at least for the morning and mid-day hours. Furthermore, the mean over all hours is clearly different across days. The lowest trading volume occurs on Mondays. The trading intensity tends to increase through Tuesday to

[22] Except for number of contracts on Thursdays in the second period on the one per cent significance level.

Wednesday and Thursday, only to decline towards Friday. The evidence of an inverted U-shape over the days of the week, reported in Jain and Joh (1988) and Foster and Viswanathan (1993), is thus supported by our data.

Table 7

Trading Volume for Each Hour of the Week
Number of Transactions, Period 1

	Mond.	Tuesd.	Wednesd.	Thursd.	Frid.	Mean	F-Day[a]	p-value
10	194[b]	206	225	200	195	204	1.08	0.366
10	(116)	(100)	(113)	(96)	(97)	(105)		(4, 267)
11	158	170	173	161	151	163	1.19	0.315
11	(81)	(89)	(74)	(69)	(67)	(76)		(4, 267)
12	101	108	116	115	97	107	1.47	0.211
12	(49)	(58)	(59)	(59)	(48)	(55)		(4, 267)
13	118	110	128	126	111	119	1.06	0.374
13	(68)	(64)	(64)	(59)	(55)	(62)		(4, 267)
14	119	125	136	138	137	131	0.66	0.617
14	(62)	(80)	(69)	(62)	(64)	(68)		(4, 267)
15	160	158	174	165	182	168	0.72	0.577
15	(82)	(57)	(63)	(81)	(84)	(74)		(4, 267)
Mean	142	146	159	151	146	149	2.66	0.031
Mean	(85)	(84)	(84)	(77)	(79)			(4, 1627)
F-Hour[a]	10.55	13.94	15.80	10.09	15.58	63.46		
p-value	0.000	0.000	0.000	0.000	0.000	0.000		
df	(5, 324)	(5, 324)	(5, 324)	(5, 318)	(5, 312)	(5, 1626)		

[a] F-Day tests whether the means across days are equal. F-Hour tests if all six hour means are equal.
[b] Standard deviations across days for each weekday and hour are given in parenthesis.

There is comparatively low volume during the first hour on Mondays. Therefore, the FV model indicating low trading volume on Mondays due to asymmetric information finds support in the second period of our data. However, an intraday interpretation of the FV model would imply *low* volumes at the beginning of each day contrary to our evidence.

Table 8

Trading Volume for Each Hour of the Week
Number of Contracts, Period 2

	Mond.	Tuesd.	Wednesd.	Thursd.	Frid.	Mean	F-Day[a]	p-value
10	2645[b]	3078	3619	4297	3126	3364	3.58	0.008
10	(1149)	(1387)	(1991)	(2516)	(1482)	(1842)		(4, 100)
11	2591	2634	3606	3520	2652	3009	2.27	0.067
11	(1327)	(1304)	(2765)	(1912)	(1113)	(1821)		(4, 100)
12	1776	1921	2134	2516	1588	1996	2.19	0.075
12	(1193)	(1471)	(1465)	(1569)	(705)	(1340)		(4, 100)
13	1917	1788	2436	2984	1779	2192	3.89	0.005
13	(1254)	(1221)	(1264)	(2075)	(858)	(1458)		(4, 100)
14	2169	2683	3142	3085	2241	2672	3.04	0.020
14	(1105)	(1660)	(1630)	(1429)	(900)	(1416)		(4, 100)
15	3202	3373	4516	3898	3538	3709	2.15	0.080
15	(1461)	(1687)	(2406)	(1757)	(1375)	(1805)		(4, 100)
Mean	2383	2580	3242	3383	2487	2815	13.07	0.000
Mean	(1322)	(1545)	(2108)	(1966)	(1291)			(4, 625)
F-Hour[a]	3.78	3.82	4.01	2.55	9.47	17.57		
p-value	0.003	0.003	0.002	0.030	0.000	0.000		
df	(5, 120)	(5, 120)	(5, 120)	(5, 126)	(5, 114)	(5, 614)		

[a] F-Day tests whether the means across days are equal. F-Hour tests if all six hour means are equal.
[b] Standard deviations across days for each weekday and hour are given in parenthesis.

6 Conclusion

One empirical conclusion of this essay is that the *intra*day trading volume pattern in the Swedish derivatives market is U-shaped and highly significant. This U-shape is in line with several other empirical studies from different stock exchanges and a few from U.S. derivatives markets. Another conclusion is that there is some statistically significant interday variation in derivatives trading volume. This is supportive of the Foster and Viswanathan (1990) model which predicts lower trading volumes on Mondays. An increased derivatives trading volume prior to the close of the stock exchange lends support to the Brock and Kleidon (1992) derived demand model of concentrated trading. Indeed, the concentration of volume at that time of the day disappears after the extension of the trading hours at the stock exchange, which again supports the Brock and Kleidon model.

Table 9

Trading Volume for Each Hour of the Week
Number of Transactions, Period 2

	Mond.	Tuesd.	Wednesd.	Thursd.	Frid.	Mean	F-Day[a]	p-value
10	118[b]	137	164	177	142	148	3.23	0.015
10	(49)	(55)	(83)	(83)	(64)	(70)		(4, 100)
11	106	106	133	149	105	120	3.54	0.009
11	(52)	(43)	(74)	(75)	(38)	(60)		(4, 100)
12	78	80	89	97	67	83	1.83	0.130
12	(49)	(51)	(47)	(54)	(32)	(48)		(4, 100)
13	76	79	103	121	78	92	4.08	0.004
13	(43)	(48)	(45)	(79)	(33)	(54)		(4, 100)
14	87	107	123	128	99	109	2.83	0.029
14	(43)	(63)	(61)	(61)	(38)	(56)		(4, 100)
15	127	140	180	159	154	152	2.55	0.044
15	(49)	(58)	(78)	(65)	(55)	(63)		(4, 100)
Mean	99	108	132	138	108	117	13.49	0.000
Mean	(99)	(108)	(132)	(138)	(108)			(4, 625)
F-Hour[a]	4.27	5.13	5.82	3.71	11.92	24.65		
p-value	0.001	0.000	0.000	0.003	0.000	0.000		
df	(5, 120)	(5, 120)	(5, 120)	(5, 126)	(5, 114)	(5, 624)		

[a] F-Day tests whether the means across days are equal. F-Hour tests if all six hour means are equal.
[b] Standard deviations across days for each weekday and hour are given in parenthesis.

References

Admati, A. R. and P. Pfleiderer, (1988), "A Theory of Intraday Patterns: Volume and Price Variability", *Review of Financial Studies*, 1, 3-40.

Biais, B., P. Hillion and C. Spatt, (1994), "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse", Working Paper, March 1994.

Brock, W. A. and A. W. Kleidon, (1992), "Periodic Market Closure and Trading Volume: A Model of Intraday Bids and Asks", *Journal of Economic Dynamics and Control*, 16, 451-489.

Easley, D., M. O'Hara and P. S. Srinivas, (1993), "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade", Working Paper, October 1993.

Foster F. D. and S. Viswanathan, (1990), "A Theory of the Intraday Variations in Volume, Variance and Trading Costs in Securities Markets", *Review of Financial Studies*, 3, 593-624.

Foster, F. D. and S. Viswanathan, (1993), "Variations in Trading Volume, Return Volatility, and Trading Costs: Evidence on Recent Price Formation Models", *Journal of Finance*, 48, 187-211.

Glosten, L. R and P. R Milgrom, (1985), "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics*, 14, 71-100.

Grossman, S. J. and J. E. Stiglitz, (1980), "On the Impossibility of Informationally Efficient Markets" *American Economic Review*, 70, 393-408.

Hamon, J. and B. Jacquillat, (1992), *Le marché français des actions*, Presses Universitaires de France, Paris.

Harris, L., (1991), "Stock Price Clustering and Discreteness", *Review of Financial Studies*, 4, 389-415.

Hedvall, K., (1994), "Trade Concentration Hypotheses - An Empirical Test of Information vs. Demand Models on the Helsinki Stock Exchange", Working Paper, Swedish School of Economics and Business Administration, Helsinki, September 1994, Forthcoming in Journal of International Financial Markets Institutions and Money.

Jain, P. C. and G.-H. Joh, (1988), "The Dependence between Hourly Prices and Trading Volume", *Journal of Financial and Quantitative Analysis*, 23, 269-283.

Merton, R. C., (1971), "Optimum Consumption and Portfolio Rules in a Continuous-Time Model", *Journal of Economic Theory*, 3, 373-413.

Niemeyer, J. and P. Sandås, (1993), "An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange", *Journal of Multinational Financial Management*, 3, No 3/4, 63-101.

Stephan, J. A. and R. E. Whaley, (1990), "Intraday Price Change and Trading Volume Relations in the Stock and Stock Options Markets", *Journal of Finance*, 45, 191-220.

Stoll, H. R., (1992), "Principles of Trading Market Structure", *Journal of Financial Services Research*, 6, 75-107.

Essay 3

Tick Size, Market Liquidity and Trading Volume: Evidence from the Stockholm Stock Exchange*

Abstract

The regulated tick size at a securities exchange puts a lower bound on the bid/ask spread. We use cross-sectional and cross-daily data from the Stockholm Stock Exchange to assess if this lower bound is economically important and if it has any direct effect on market depth and traded volume. We find a) strong support that the tick size is positively related to the bid/ask spread (market width) and b) support that it is positively correlated to market depth and c) some support that it is negatively related to traded volume. We identify different groups of agents to whom a lower tick size would be beneficial and to whom it would be detrimental.

1. Introduction and Definitions

Apart from the tick size, this essay also deals with the market liquidity and we therefore need a definition of that concept. In principle, liquidity refers to how quickly and how cheaply investors can trade an asset when they want to. However, liquidity is a complex term. There are, at least, four highly interrelated dimensions to market liquidity: width,

* This essay is joint work together with Patrik Sandås. We wish to thank the Stockholm Stock Exchange and *Stockholms Fondbörs Jubileumsfond* for providing the data set. We also wish to thank seminar participants at the Stockholm School of Economics and the Swedish School of Economics and Business Administration in Helsinki as well as participants at the European Finance Association Meetings in Copenhagen, August 1993 and at the First Annual Conference on Multinational Financial Issues in Atlantic City, June 1994 for helpful comments. We are especially indebted to Kaj Hedvall, Ragnar Lindgren, Atulya Sarin and Anders Warne, for their comments on earlier drafts. For all remaining errors, we absorb full culpability.

depth, immediacy and resiliency. Harris defines these in the following manner.[1]

> "Width refers to the bid/ask spread (and to brokerage commissions and other fees per share) for a given number of shares ... Depth refers to the number of shares that can be traded at given bid and ask quotes. Immediacy refers to how quickly trades of a given size can be done at a given cost. Resiliency refers to how quickly prices revert to former levels after they change in response to large order flow imbalances initiated by uninformed traders."

When discussing liquidity in this essay, we primarily refer to width or depth.[2]

When discussing the impact of the tick size, it is important to recognize that even when agents are free to choose their prices, discrete price schemes will emerge. For the trading in many assets, the discreteness is not regulated but the result of different customs. Why are real estate prices on odd dollars rarely found? There must be some positive effect of clustering prices to discrete values. In fact, there are several effects. The costs of negotiating may be lowered and a deal be struck faster when discrete prices are used. Furthermore, the risk of ex-post misunderstandings of the actual trading price will be lower using discrete prices.[3] The degree of discreteness depends on the assets' characteristics. When economic agents have similar reservation prices and available information sets, a fine price grid is likely to emerge.

Even on exchanges with a regulated tick size, prices of financial assets tend to cluster on round numbers. Harris notes that NYSE stock prices cluster on round fractions. "Integers are more common than halves; halves are more common than odd quarters; odd quarters are more common than odd eighths."[4] Recently, there has been increased interest in the reasons and consequences of clustering on a discrete set of rounded prices.

It should be noted that even if prices tend to cluster by themselves, a superimposed tick size may have an economically important effect. The purpose of this essay is to shed some light on the impact of the tick size on market liquidity, in the form of both width and depth, and on the volume of trading. Data from the Stockholm Stock Exchange is highly suitable since there are two price ranges with different nominal tick sizes for normally priced stocks. The essay extends the existing literature by examining some stocks where the nominal tick size has changed, or put differently where the price of the stock has moved from one tick size range to another.

---

[1] Harris (1990b) p. 3

[2] There is some confusion of terminology in the literature. Hasbrouck and Schwartz (1988) define depth essentially as the bid/ask spread (i.e. our width) and breath as the order volume (i.e. our depth).

[3] See Harris (1991) p. 390.

[4] Harris (1991) p. 389.

In a related paper using data from the NYSE and AMEX, Harris (1994) concludes that a lower tick size would reduce both the bid/ask spread and the quoted volume while it would increase traded volume. One purpose of our essay is to investigate whether these results can be generalized into another trading mechanism. We use data from the Stockholm Stock Exchange, a continuous auction market based on a consolidated electronic open limit order book with a high and *symmetric* transparency, without any specialist, and where strict price, display and time priorities are imposed.[5] The least obvious effect in Harris (1994) is the effect of the tick size on market depth. Harris explains his relationship between tick size and quoted volume with the quote matcher argument. It is possible to argue that this effect would be less pronounced at the Stockholm Stock Exchange since there is no designated specialist and all traders have similar information and strategy sets. The trading environment is symmetric. This symmetry combined with the high transparency of the limit order book might reduce the quote matcher problem. Interestingly, our results are similar to those of Harris (1994), despite the considerable differences in trading structure. Our results are also interesting since the completely electronic trading structure at the SSE does not facilitate combined trades to overcome the negative effect of the tick size.

The remainder of the essay is organized as follows. In Section 2, we present our data set. Section 3 gives some background to the problem and discusses earlier work. Section 4 contains our empirical results, using the cross-sectional sample, of the impact of the tick size on the bid/ask spread or width, on the quoted volume or depth and on trading volume. In section 5, we report our empirical findings using daily averages on some stocks which moved from one tick size regime during the period studied. The summary and conclusion are found in section 6.

2 The Data Set

Our data set consists of transactions and order book data from a number of stocks traded at the Stockholm Stock Exchange. The data include all quotes, quote revisions and transactions (excluding after hours trading) on some of Sweden's most traded stocks. The data set is divided into three samples. The first two samples are purely cross-sectional. The first cross-sectional sample, which is used for specification of the regression models, includes 52 stocks and the variables are simple averages using data for the time period between December 3, 1991 and January 17, 1992. The second cross-sectional sample, used to control for the model specifications includes 69 stocks and the variables are simple averages using data from January 20, 1992 to March 2, 1992. The

[5] For a detailed description of the trading structure of the Stockholm Stock Exchange, see Niemeyer and Sandås (1993) (Essay 1 in this dissertation).

third sample includes five stocks which, during the time period, moved from one tick size regime to another. Here, the variables are *daily* averages and we ran our regressions across days for all five stocks. For clarification, we want to stress that all our data are averages over time for each specific stock. We are therefore not able to estimate possible differences in trading costs, bid/ask spreads, etc. during the trading day.

The stock transaction data set contains the time, price and the number of stocks traded. The set from the electronic limit order book consists of the five best bid and ask prices, the associated quantities, and the number of orders at each bid and ask level in the electronic open limit order book. Stocks with fewer than 50 transactions were excluded from the samples. Using this criterion, three and nine stocks respectively were found to be too inactively traded to be included. The first sample thus included 49 and the second sample 60 stocks. The data from the second sample is included in Appendix 1. Only results from the second and third samples are reported below. In order to avoid some econometric problems, we also ran our test on some reduced versions of the second sample (see section 4).

It should be noted that different trading systems record transactions in a different manner. An example may clarify this issue. In a market maker based trading system, if investor A buys 3000 shares, one transaction between the market maker and investor A will be recorded. When the market maker later unwinds his position against investors B, C and D, there will be an additional three transactions recorded. In total, the transaction tape will include four transactions. In an order book driven trading system, investor A's 3000 shares will be matched directly with the standing limit orders of investor B, C and D. The total transaction record will therefore only contain three transactions. All variables averaged over the number of transactions will naturally be influenced by this phenomenon.[6]

In this study, we use order book data. These will be influenced by a similar phenomenon. When investor A's 3000 shares are matched against the three limit orders of investors B, C and D, we will automatically see three distinct changes in the order book occurring at the very same moment in time. When calculating variables such as the average relative bid/ask spread, we use the number of changes in the limit order book, for each distinct stock, as the denominator. It should further be stressed that not all changes in the limit order book occur at the best bid or ask prices. In our samples we record one change in the limit order book regardless of the level at which it has occurred (i.e. even if it occurred outside the five best bid or ask prices included in our sample).

[6] This raises the question of the differences between the definitions of a trade and a transaction. The question is whether we should consider investor A's purchase as one trade or three transactions. In this essay we view it as three transactions.

3 Background and Previous Studies

3.1 The Tick Size at the Stockholm Stock Exchange

Before we start discussing the different effects of the tick size at the Stockholm Stock Exchange (SSE), we first present an international comparison of the tick size at some other exchanges. Table 1 reports the tick sizes for the SSE, the NYSE, the Paris Bourse, and the Helsinki Stock Exchange.[7]

Table 1

Tick Size at Different Stock Exchanges in Respective Currency

Stock Price*	SSE	NYSE	Paris Bourse	Helsinki SE
0.00 - 0.10	0.01	0.03125	0.01	0.01
0.10 - 0.50	0.05	0.03125	0.01	0.01
0.50 - 1.00	0.05	0.0625	0.01	0.01
1.00 - 5.00	0.05	0.125	0.01	0.01
5.00 - 10.00	0.10	**0.125**	0.05	0.01
10.00 - 100.00	**0.50**	**0.125**	0.05	**0.10**
100.00 - 500.00	**1.00**	0.125	**0.10**	**1.00**
500.00 - 1000.00	1.00	0.125	**1.00**	1.00
1000.00 -	1.00	0.125	1.00	10.00

(Data sources: Stockholm Stock Exchange (1991), NYSE Rule 62, Biais, Hillion, and Spatt (1994), and Helsinki Stock Exchange (1991)).

* Stock prices are given in respective currency. SEK 1 is approximately equal to USD 0.14, FRF 0.72, and FIM 0.65 respectively.

The two price intervals where most shares are priced are printed in boldface. At one of the most important price ranges, the tick size at the Paris Bourse is one tenth of that at the SSE. Even the tick sizes at the Helsinki Stock Exchange, a less liquid stock exchange, are smaller than those at the SSE. Tick sizes are more difficult to compare between the SSE and the NYSE due to different stock price ranges. For average priced (in respective currency) stocks, the relative tick size is about the same at the NYSE and the SSE.[8] The tick sizes at the SSE clearly imply minimum spreads of between 0.5 per cent and one per cent for normally priced shares and a spread as high as five per cent for shares priced just above SEK 10.00 per share (an unusually low price level in our sample).

3.2 Theoretical Implications of the Tick Size

In principle, the numeric price of a stock should have no effect on its performance in the

[7] The tick size at the SSE has been reduced in two steps during 1994, (on March 4, and September 30). Presently, the tick size is 0.01 between 0.01 and 5.00, 0.05 between 5.00 and 10.00, 0.10 between 10.00 and 50.00, 0.50 between 50.00 and 500.00 and 1.00 above 500.00. Since the data set is from prior to the reduction, we only discuss the old tick size in this essay.

[8] Most NYSE stocks trade at prices between USD 10 and USD 100, implying a minimum relative spread (or relative tick size) of between 0.125 and 1.25 per cent. Most Swedish stocks trade at prices between SEK 50 and SEK 500, implying a relative tick size of between 0.2 and 1 per cent.

market. However, the discreteness of prices will. On most markets, the tick size (i.e. discreteness) is directly correlated with the price level. Therefore, the price level has an indirect effect on a stock's performance.[9] There are several effects of a tick size. First of all, if the tick size is large, it may form a binding bound on the bid/ask spread.

Appendix 2 presents the proportions (in percentage) of all observations where the bid/ask spread is one tick for the stocks in our sample. In addition we report the average price (midpoint quote) and the average daily traded volume (in SEK 1,000,000). For one third of all stocks, the tick size is binding in at least half of the observations. For one of the most liquid stocks Ericsson BF (denoted LME BF), the tick size is binding in 91 per cent of the observations. On average, the tick size rule can be expected to form a more binding restriction for actively traded stocks, as well as for low priced stocks and stocks priced slightly above SEK 100 (where the nominal tick size is changed). It is evident from Appendix 2 that the tick size is a binding restriction for the bid/ask spread, at least for some stocks. One hypothesis is therefore that the tick size is one major determinant of the spread.

A second effect of a mandatory large tick size is that it may preclude certain trades that would take place if the counterparts could freely choose the price. General micro economic theory implies that if the equilibrium price has to be rounded significantly to obtain a possible trading price, there will be some lost gains-from-trade. Rounding to discrete prices has the same effect as introducing a transaction cost. One of the first to model the influence of the spread and transaction costs on gains-from-trade was Demsetz (1968). Some transactions will not take place if the transaction costs are too large, or put differently if the tick size is too large.

Today, dealers cannot trade through the SAX-system at a price of SEK 101,5 even if they would like to. Thus, such transactions will either not be performed or will be rearranged into several transactions, resulting in higher handling and transaction costs.

Thirdly, if the tick size is too small, it may adversely affect the market's immediate

[9] There may also be other effects. In one study, Baker and Powell (1992) used a questionnaire to find the managers' reasons for stock splits. Out of the sample of 251 stock splitting NYSE and AMEX firms, 51 per cent of the managers argued that the most important reason was to move the stock into a better price range. 22 per cent argued that it would increase the stock's liquidity and only 14 per cent that it would signal optimistic managerial expectations. Clearly, in the view of a substantial part of the practitioners, there seems to exist an optimal stock price range, and therefore in practice an optimal relative tick size. Anshuman and Kalay (1993) is one attempt to model an optimal stock price range. Strangely enough a split would in most cases increase the relative tick size and thereby market width, i.e. possibly reduce market liquidity. In an empirical study, Copeland (1979) indeed concludes that splits increase the bid/ask spread. Still managers argue that a split would enhance liquidity. Is it possible that the managers believe that the positive effect is an increased depth on the market? However, the reasons for stock splits are not at issue here.

liquidity. To see this, consider the quote-matcher problem.[10] The quote-matcher's strategy is to try to use the information contained in existing orders. When a large limit order arrives on the market, traders have incentives to try to trade ahead of that order. The quote-matcher will try to get his order filled ahead of the large order and benefit from the reversal in the price subsequent to the execution of the large order. Traders committing to trade will, as a result of the risk of being by-passed by the quote-matcher, *ceteris paribus*, submit smaller limit orders to the market and thus the displayed market depth (and possibly also width) would be lower. One way to reduce the possibility for quote-matching is to enforce strict secondary priority rules (i.e. time priority).[11] The only way for a quote-matcher to gain priority over the large order is then through price. However, if the tick size is small, "traders can cheaply acquire precedence through price priority by setting a quote or limit order with a slightly better price"[12]. The combination of a considerable tick size and the time precedence rules protects traders who expose their limit orders. Only if both of these rules are enforced will the quote-matcher problem be substantially mitigated. To summarize, a small tick size could be detrimental to market depth and we might observe more displayed liquidity in a market in which a large tick size is imposed.

In our view the quote matcher argument is less compelling in a trading structure like the one at the SSE. There are several reasons. First, it is conceivable that the absence of a designated market maker and the fact that the liquidity is created by other traders at the SSE, make quoted volume more independent of the tick size. Furthermore, the quote matcher argument in Harris (1990b and 1994) rests implicitly on the assumption of anonymity. If a quote matcher has to reveal himself, he may ruin his reputation, which would be detrimental in a repeated game. Since the trading mechanism at the SSE is highly transparent, the quote matcher problem might be less severe.

Third, a relatively large tick size implies high round trip transaction costs for traders. At the same time, it means large compensations for providing market making service. In a market with no designated market makers, one would expect dealers to queue up to provide liquidity in stocks with comparatively large tick sizes. Harris (1992, 1994) discusses this effect and notes that dealers facing a price inelastic demand (retail traders) benefit from a large tick. However, for dealers facing price elastic demand, for example from institutional dealers, the disadvantage of a lower tick size could be off-set by the profits from an increased trading volume. It is possible that a large tick size together with a price-inelastic demand will make it attractive for traders to supply liquidity. Grossman and Miller (1988) argue that a minimum bid/ask spread may be necessary to

[10] The quote-matcher problem is extensively discussed in Harris (1990b).
[11] See Amihud and Mendelson (1991).
[12] Harris (1991), p. 391.

ensure that dealers recover their fixed costs of market making. The problem is to find a "tick size ... high enough to sustain a viable competitive supply of floor traders, but not so high as to give rise to the problems of rationing and queue discipline"[13].

From the analysis above, clearly the tick size is likely to have several effects. Firstly, if it is binding, it can directly affect the relative spread. Secondly, it can influence the depth of the market and thirdly, it may limit transaction volume.

3.3 The Effects of a Tick Size on Different Agents

There are several market participants who should be concerned with the tick size.

- The first obvious group of agents are the dealers. A large part of dealer profits comes from the bid/ask spread. If the tick size raises the bid/ask spread, dealer profits may rise. However, we saw in the previous subsection that the lower trading profits of a reduced tick size *may* be off-set by profits from increased trading, if a lower tick size results in larger trading volume.
- The traders are other market participants who should be interested in the tick size. Small traders are primarily interested in a narrow spread while larger traders might be more interested in depth. If a small tick size results in a lower spread and smaller depth, the latter group *may* prefer a larger tick size.
- Corporations may also be interested in the tick size. If trading costs are increased and trading volume lowered by a large tick size, the corporate cost of capital may be increased.
- Exchanges earn a substantial part of their income based on trading volume. Again, if trading volume is limited by a large tick size, the exchange is likely to lobby for lower tick sizes.

3.4 Previous Research

There exists an extensive literature attempting to explain the existence of the bid/ask spread. The early work focused on the inventory problem of the market maker, more or less assuming that he acted as a monopolist in search of an optimal inventory.[14] More recent work has focused on the asymmetric information as a reason for setting a bid/ask spread. This literature started off with a small intuitive article by Bagehot (1971), formalized in two important papers in the mid-80s, Copeland and Galai (1983) and Glosten and Milgrom (1985). Since then, the theoretical literature has exploded into a cascade of game theoretical models using an asymmetric information argument and strategic behavior by different market participants.

---

13 Grossman and Miller (1988) p. 630.

14 See Amihud and Mendelson (1980), Stoll (1978), Ho and Stoll (1980, 1981), O'Hara and Oldfield (1986) and Cohen, Maier, Schwartz and Whitcomb (1981).

The effect of discreteness on estimation of volatility and other moments of returns has been discussed by several authors.[15] Many other researchers mention the obvious influence of the tick size on observed market phenomena but few have explicitly studied the effect of the tick size on market *liquidity*. Harris (1991, 1992, 1994) finds that the tick size used at the NYSE and the AMEX has an economically significant impact on the inside spread and market liquidity. He also argues (1992, 1994) that a large tick size would make the provision of liquidity highly profitable. In (1994), he estimates equations for the relative spread, trading volume, and market depth. He then uses these estimates to project the effects of lowering the minimum tick size from $1/8 to $1/16. For a stock trading below $10 the lower tick size would result in a 36 per cent reduction in the relative spread, a 30 per cent increase in the trading volume, and a 15 per cent fall in displayed depth. Due to the reverse effects on the transaction costs and the depth, it is difficult to determine whether a smaller tick size would enhance overall welfare.

Another article studying the impact of tick sizes on liquidity is Anshuman and Kalay (1994). They argue that the firm increases the importance of the tick size by splitting. According to the model, this induces liquidity traders to strategically concentrate trading. Hence, transaction costs are reduced. Thereby, a high tick size will enhance liquidity by increasing depth, at least at certain moments in time.

One purpose of this essay is to extend Harris' analysis to a market, based on a limit order book. Data from the Stockholm Stock Exchange is exceptionally suitable for this purpose since the tick size is relatively important at this stock exchange (see Table 1). Since the nominal tick size is different for different stocks at the SSE, our data set is extremely suitable to study how the market width, depth and trading volume changes when a stock moves from one tick size regime to another.

4 Empirical Cross-Sectional Results

In this section, we empirically estimate simple heuristic reduced form equations for the spread, market depth and trading volume. First, we ran all our cross-sectional regressions on the first sample to find suitable specifications. Thereafter, we ran our specified models with the data from the second sample in order to control for the model specification and to avoid data mining. For brevity, we only report the results from the second sample. In this section, we consider regression models for both the relative bid/ask spread, the quoted volume and the traded volume.

[15] See Gottlieb and Kalay (1985), Ball (1988), Cho and Frees (1988) and Harris (1990a).

4.1 The Variables

For the empirical estimations, we define the following variables:[16]

$ISRNO_i$ = The inverse square root of the average aggregated number of limit orders across the five best bid and ask levels in the limit order book for share *i*.

$ISRNT_i$ = The inverse square root of the number of transactions[17] for share *i*.

$LnDVol_i$ = The natural logarithm of the average daily trading volume, in SEK, for share *i*.

$LnMVal_i$ = The natural logarithm of the total market value, in SEK, of share *i*.

$LnQSize_i$ = The natural logarithm of the average volume in SEK on the best bid and best ask price for share *i*.

$RSpr_i$ = The average bid/ask spread as a percentage of the quote midpoint for share *i*.

$RTick_i$ = The tick size divided by the average transaction price for share *i*.

$SD5R_i$ = Standard deviation of a five day rolling return series for share *i*, where the returns are calculated from the bid prices at noon every day.

It should be stressed that since the nominal tick size in our sample is either SEK 0.5 or SEK 1, the *relative* tick size, $RTick_i$, is highly dependent on the price. If the price level plays any other systematic role, we may be capturing this effect with the relative tick size variable. On the other hand, there are no clear theoretical market micro structure reasons why the actual price level should play any systematic role here.

The transformation of some variables into less obvious variables might seem strange at first glance. Why use a variable such as the Inverse Square Root of the Number of Transactions ($ISRNT_i$) instead of the number of transactions directly? Glosten and Milgrom (1985) conclude that "the average spread will be proportional to one over the root of the average volume."[18] They show that the inverse of the square root of the trading activity reflects the assimilation of the insider's information into the prices. Furthermore, the transformations can be seen as a means of controlling for heteroskedasticity.

Table 2 presents the summary statistics for the different variables and Table 3 contains the coefficients of correlation.

[16] A more extensive definition of the included variables is given in Appendix 3.

[17] When measuring the number of transaction, it is important to note the difference in the definition of a transaction at different stock exchanges, discussed in Section 2.

[18] Glosten and Milgrom (1985), p 87.

Table 2

Summary Statistics

Variable	Observ.	Mean	Median	Std Dev.	Minimum	Maximum
$ISRNO_i$	60	0.2933	0.2850	0.0840	0.0894	0.5423
$ISRNT_i$	60	0.0490	0.0410	0.0271	0.0114	0.1361
$LnDVol_i$	60	14.7559	15.0723	1.5521	10.3144	17.7866
$LnMVal_i$	60	22.2224	22.3810	1.0334	19.7243	24.4897
$LnQSize_i$	60	12.9750	12.9391	0.7618	10.9058	15.0108
$RSpr_i$	60	0.0182	0.0134	0.0120	0.0035	0.0467
$RTick_i$	60	0.0071	0.0060	0.0070	0.0017	0.0416
$SD5R_i$	60	0.0355	0.0328	0.0183	0.0109	0.0953

Table 3

Correlation Coefficients

	$ISRNO_i$	$ISRNT_i$	$LnDVol_i$	$LnMVal_i$	$LnQSize_i$	$RSpr_i$	$RTick_i$
$ISRNT_i$	0.809						
$LnDVol_i$	-0.612	-0.859					
$LnMVal_i$	-0.407	-0.570	0.593				
$LnQSize_i$	-0.712	-0.720	0.823	0.428			
$RSpr_i$	0.378	0.657	-0.773	-0.520	-0.513		
$RTick_i$	-0.405	-0.155	-0.059	-0.237	0.342	0.447	
$SD5R_i$	-0.195	-0.019	-0.197	-0.1915	-0.066	0.563	0.514

Figure 1

Relation Between Relative Tick Size and Relative Spread

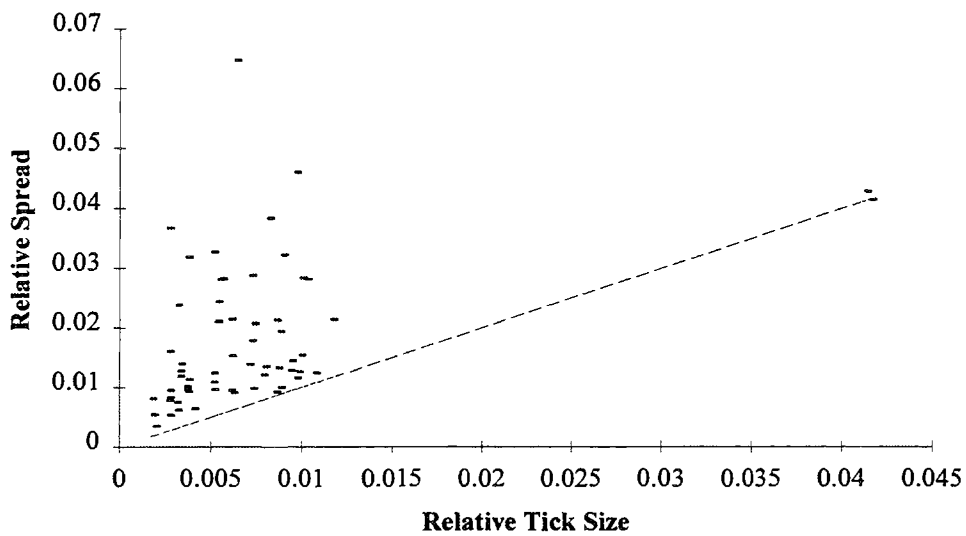


Figure 1 describes the relationship between the relative tick size and relative bid/ask spread. We have plotted the 45° line which evidently forms the lower-bound for the relative spread. From Figure 1, one data problem is evident. Our sample includes two stocks with average prices about SEK 12. However, we do not have any stocks with an average price of between SEK 12 ($RTick_i = 0.41$) and SEK 43 ($RTick_i = 0.12$). It is clear from Figure 1 that this lack of data is of paramount importance for the regression estimates using $RTick_i$. We will therefore run our regressions both with and without these observations.

4.2 Regression Results

The purpose of this essay is to test some regression on market width, measured as $RSpr_i$, market depth, measured as $LnQSize_i$, and trading volume, measured as $LnDVol_i$. We define the following system of heuristic regression equations:

$$RSpr_i = \alpha_0 + \alpha_1\, RTick_i + \alpha_2\, ISRNO_i + \alpha_3\, ISRNT_i + \alpha_4\, SD5R_i + \varepsilon_{1i} \tag{1}$$

$$LnQSize_i = \beta_0 + \beta_1\, RTick_i + \beta_2\, LnDVol_i + \beta_3\, SD5R_i + \varepsilon_{2i} \tag{2}$$

$$LnDVol_i = \gamma_0 + \gamma_1\, RTick_i + \gamma_2\, LnMVal_i + \gamma_3\, LnQSize_i + \varepsilon_{3i} \tag{3}$$

Using the same explanatory variables and dependent variables as independent variables in other regressions, we actually have a simultaneous equation problem. We therefore estimate the regressions using the 3SLS-method. We explain the expected correlation between the independent variables and the dependent variables below.

If the tick size is an important determinant of the bid/ask spread, we expect to find a positive correlation between relative tick size and relative spread, that is a positive α_1. Furthermore, our conjecture is that trading interest, trading activity and information asymmetry will also affect the relative bid/ask spread. We measure the trading interest by the average total number of limit orders submitted at the five best bid and five best ask levels. Trading activity is measured by the number of transactions. Using the first sample, we found the number of transactions better approximating the pressure on the bid/ask spread than the trading *volume* and therefore chose to include the former rather than the latter. Due to the non linearity of the conjectured relationship, we transform both the variables for trading interest and trading activity by taking the inverse of the square root.[19] We thereby got the variables Inverse Square Root of Number of Orders ($ISRNO_i$) and Inverse Square Root of Number of Transactions ($ISRNT_i$). Both the variables $ISRNO_i$ and $ISRNT_i$ to some degree measure the competition between market participants. A stock with many limit orders in the order book, is likely to exhibit a high degree of competition and a lower relative bid/ask spread. We therefore expect both $ISRNO_i$ and $ISRNT_i$ to be positively correlated with $RSpr_i$. The standard deviation of the five-day return, $SD5R_i$, is included as a proxy for the riskiness of the stock and is also intended to capture the degree of asymmetric information. Since suppliers of liquidity

[19] See Glosten and Milgrom (1985).

services are likely to require larger compensation for riskier stocks, the correlation with $RSpr_i$ is also expected to be positive.

In the second equation, quoted volume is the dependent variable. If the quote matcher argument holds, the tick size will affect the quoted volume. An important tick size will then stimulate quotes. Therefore, our conjecture is that β_1 will be positive. In the absence of a formal model, our suspicion is that trading activity and price uncertainty will also affect quoted volume. Here, we measure trading activity by the log of the average daily trading volume, $LnDVol_i$. When the trading activity increases, quoted volume would probably increase. The variable $SD5R_i$ measures the uncertainty in the stock and is also a proxy for asymmetric information. Due to the free trading option[20] and the likely risk aversion of dealers, the relationship between $LnQSize_i$ and $SD5R_i$ will probably be negative.

In equation 3, we try to assess the impact of the relative tick size on traded volume, $LnDVol_i$. We expect that trading volume will fall when the tick size forms a binding restriction on the spread, i.e. raises the transaction costs. Our hypothesis is therefore that γ_1 is negative. We also include market value, $LnMVal_i$, and market depth, $LnQSize_i$, as explanatory variables. Companies with a large market value are normally more widely held and more actively traded. Furthermore, we expect the larger information coverage of large firms to induce an increased trading volume, resulting in a positive correlation between $LnDVol_i$ and $LnMVal_i$. We expect that market depth, $LnQSize_i$, and trading volume will be positively correlated. The regression results as well as the expected signs are summarized in Table 4.

We first concentrate on the regression results for the relative bid/ask spread. In Sample 2A, we use all observations and in Sample 2B we reduce the sample with our two outliers. In both regressions, we find a positive and significant relationship between $RTick_i$ and $RSpr_i$. All conjectured variables have the expected signs and they are all significant. The explanatory power of the models is substantial.

However, these two models have a problem. Any inference should be made with caution since the error terms clearly are non normal.[21] This could be the result of a miss-specified model. The outliers in these models turn out to be the most illiquid stocks. If we only include the stocks with more than 200 transactions (the earlier arbitrarily set cut-off value was 50 transactions), we reduce our sample to 47 stocks (45 if our two earlier outliers are also excluded).

[20] Among others, see Copeland and Galai (1983) and Stoll (1992) for discussions of free trading options.

[21] The significance levels for the Bera Jarque-test are: 5.99 and 9.21 for the 5% and 1% significance levels respectively. For an explanation of the Bera Jarque-test, see Judge et al (1988) p. 890-892.

Table 4
Simultaneous Regression Results

	Expected Sign	Sample 2A	Sample 2B	Sample 2C	Sample 2D
		Dependent Variable: Relative Bid/Ask Spread (RSpr)			
Intercept		-0.018	-0.018	-0.015	-0.015
		(-5.39)	(-5.26)	(-6.63)	(-6.09)
$RTick_i$	(+)	0.744	0.802	0.769	0.728
		(6.57)	(3.29)	(12.60)	(5.41)
t-test of α_j=1		(-2.26)	(-0.81)	(-3.79)	(-2.02)
$ISRNO_i$	(+)	0.033	0.034	0.026	0.025
		(2.40)	(2.46)	(2.53)	(2.36)
$ISRNT_i$	(+)	0.252	0.248	0.261	0.268
		(6.36)	(6.17)	(7.03)	(6.77)
$SD5R_i$	(+)	0.252	0.250	0.202	0.203
		(6.41)	(6.28)	(10.89)	(10.74)
Skewness of ε_1		0.71	0.78	0.23	0.26
Excess Kurtosis of ε_1		7.21	6.95	-0.29	-0.31
BJ normality test of ε_1		135.00	122.61	0.58	0.69
		Dependent Variable: Ln of Quoted Volume (LnQSize)			
Intercept		6.230	6.628	4.738	4.948
		(18.44)	(17.99)	(10.04)	(9.15)
$RTick_i$	(+)	43.895	16.373	48.829	36.920
		(7.43)	(1.10)	(8.29)	(2.20)
$LnDVol_i$	(+)	0.437	0.421	0.528	0.519
		(19.31)	(18.16)	(17.35)	(15.76)
$SD5R_i$	(–)	-0.512	-0.478	-0.259	-0.266
		(-0.51)	(-0.49)	(-0.31)	(-0.29)
Skewness of ε_2		0.02	-0.08	0.22	0.12
Excess Kurtosis of ε_2		-0.56	-0.30	-0.20	-0.17
BJ normality test of ε_2		0.79	0.28	0.46	0.16
		Dependent Variable: Ln of Traded Volume (LnDVol)			
Intercept		-14.277	-15.775	-8.916	-9.500
		(-8.88)	(-8.59)	(-5.91)	(-5.28)
$RTick_i$	(–)	-96.369	-35.940	-90.644	-68.994
		(-6.83)	(-1.05)	(-7.66)	(-2.20)
$LnMVal_i$	(+)	0.026	0.026	0.009	0.013
		(0.61)	(0.61)	(0.26)	(0.31)
$LnQSize_i$	(+)	2.246	2.335	1.873	1.903
		(17.63)	(16.80)	(15.83)	(14.85)
Skewness of ε_3		-0.05	0.06	-0.26	-0.16
Excess Kurtosis of ε_3		-0.59	-0.35	-0.16	-0.14
BJ normality test of ε_3		0.90	0.33	0.58	0.23
N		60	58	47	45
System Weighted R^2		0.831	0.817	0.835	0.815
System Weighted MSE		9.20	9.68	13.00	11.19

We now have four different sample sizes, with overlapping observations. Sample 2A included all 60 stocks, Sample 2B all except the two low-priced stocks. In Sample 2C, we raise the requirements on liquidity and exclude certain illiquid stocks reducing the number of observations to 47, and in Sample 2D, we also remove the two low-priced stocks. In Samples 2C and 2D, the problem of skewness and kurtosis disappears completely. Furthermore, all our included variables are still significant and with the expected signs.

We seem to have a reasonable model of the relative spread, at least for normally priced and actively traded stocks. The differences between the distribution of the error terms in Samples A and B on the one hand and Samples C and D on the other, indicate that any extrapolation of the results to less liquid stocks should be made with caution.

It should furthermore be noted that the coefficients are very stable across the different samples. Theoretically speaking, if the relative tick size variable would only capture the effect of the tick size (i.e. if the price level does not influence the estimates in any other way), α_1 should be equal to unity. In Samples 2A and 2C, α_1 is clearly less than unity (t-value of -2.26 and -3.79 respectively). When we omit the low-priced stocks, the situation becomes much more unclear. We, therefore conclude that our variable *might* catch something different from the tick size, at least for low priced stocks. A miss-specified model could possibly also explain why α_1 is not equal to unity. We have tested for non-linearities, by including $RTick_i^2$ as an extra explanatory variable, but it turns out highly insignificant.

It should be noted that Harris (1994), making similar estimations, gets a coefficient of 12.93, which is significantly *larger* than the tick size of 12.5. Our significant estimates are lower than our tick size. It is conceivable, but in our opinion unlikely, that this difference is due to the difference in trading structure. Further research on this topic using data from other exchanges is merited.

To summarize some of the most striking features of the regressions on the relative spread, we find that a) the parameter estimates are very stable across regressions and samples, that b) we are able to explain a substantial part of the bid/ask spread, that c) the price variable is highly significant throughout, indicating that the tick size has a significant influence on the relative spread and that d) the results should be interpreted with caution regarding low priced stocks and low liquidity stocks.

Turning to the results for the quotation size, β_1 is positive and mostly significant. Only if we add enough noise by excluding low priced stocks and including the low-liquidity stocks (i.e. Sample 2B) is the relationship between the tick size and quoted volume insignificantly positive. If we exclude the low liquidity stocks we get a significant relationship. If we include the low priced stocks the relationship becomes highly significant. Of course, the effect of the tick size is most pronounced for the low priced stocks. The other variables both have the expected signs but the uncertainty ($SD5R_i$) does not tend to influence the quoted volume to any significant degree. Furthermore, the Bera-Jarque test does not indicate any problem with non-normal error terms.

To summarize: a) We find evidence supporting the quote matcher argument especially if we include our low priced stocks. b) However, if we include low liquidity stocks, the relationship is no longer significant.

In reviewing the results in the regressions on trading volume, the first obvious reflection is that the coefficients for $RTick_i$ are all negative, as expected (although insignificant in Sample 2B). The relationship seems to hold better if we include the two low priced stocks. Once again the relationship seems to hold the best if we exclude the low liquidity stocks and if we include the low priced stocks. The other two explanatory variables also have the expected signs (although the market value is insignificant). The results are overall qualitatively similar across the different regressions. We should also note that in none of the regressions do we seem to have any problem with non normal residuals.

To summarize: we find some support for the hypothesis that the traded volume is lower when the relative tick size is high. This is likely to be a consequence of the increased trading costs a high tick size induces.

To get an idea of the importance of our estimates, a simple calculation, using estimated parameters from Sample 2D and average values, shows that if the nominal tick size would be reduced to half the current size for an average priced stock (SEK 211), the relative spread would fall from 1.21 to 1.03 per cent (i.e. a reduction of 14 per cent[22]), the quoted volume would fall from SEK 468 000 to SEK 428 000 (i.e. a reduction of 8 per cent[23]), and the traded volume would increase from SEK 4 856 000 to

[22] Using the estimates in Sample 2D and the average values of the explanatory variables give us the following estimate of the relative bid/ask spread:

Tick = 1: $-0.015 + 0.728 * 0.00474 + 0.025 * 0.2689 + 0.268 * 0.0375 + 0.203 * 0.0336 = 0.0121$

Tick = 0.5: $-0.015 + 0.728 * 0.00237 + 0.025 * 0.2689 + 0.268 * 0.0375 + 0.203 * 0.0336 = 0.0103$

[23] Using the estimates in Sample 2D and the average values of the explanatory variables give us the following estimate of the quoted volume:

Tick = 1: $e^{[4.948 + 36.920 * 0.00474 + 0.519 * 15.301 - 0.266 * 0.0336]} = 467\ 565$

Tick = 0.5: $e^{[4.948 + 36.920 * 0.00237 + 0.519 * 15.301 - 0.266 * 0.0336]} = 428\ 397$

SEK 5 718 000 (i.e. an increase of almost 18 per cent[24]). However in this context, we want to stress the inappropriateness of using our estimates for outright projections. This calculation is only tentative and an indication of the importance of the tick size.

5 Empirical Results on Cross-Daily Samples

In this section we use Sample 3, which consists of *daily averages* of five stocks, SKF BF, LME BF, SCA B, TREL B and TRYG B. The idea is to investigate if the relative spread, the quoted volume and the traded volume change depending on whether the same stock is in a range with a high or a low nominal tick size. Results from section 4 indicate that when stock trade in a range with a low nominal tick size the relative spread is lower, the quoted volume lower and the traded volume larger.

5.1 The Variables

In principle, we use the same variables and regression equations as in section 4. However, a certain number of modifications are necessary. The first is that we define a new variable, Ind_i, instead of $RTick_i$. Ind_i is simply a dummy being zero if the best ask price has been below SEK 100 the entire day and one if the best bid price has been above SEK 100 the entire trading day. To get a clear difference, all observations where the best bid or best ask have been fluctuating below and above SEK 100 have been excluded.

A second modification is that the daily trading volume is now the total number of stocks traded for that stock and day. Since all trades of these stocks are at prices around SEK 100, we do not have to use the prices as weights any more. In addition, the variable Ind_i captures the price effect. Furthermore, quoted volume is now *not* calculated from the best bid and ask levels only and not weighted by price. Instead, quoted volume is estimated as the number of stocks offered and demanded at prices within 1.5 per cent[25] of the quoted midpoint, and defined as $LnQproc_i$. A fourth difference is that the standard deviation of returns can no longer be defined based on prices from different days. We now define it at the standard deviation of the eight 30 minute returns (overnight returns excluded) during each trading day.

Running cross-daily regressions on individual stocks, the market value is not a very useful variable. If daily data are used, both quoted volume and traded volume are likely

---

[24] Using the estimates in Sample 2D and the average values of the explanatory variables give us the following estimate of traded volume:

Tick = 1: $e^{[-9.500\ -\ 68.994\,*\,0.00474\ +\ 0.013\,*\,22.459\ +\ 1.903\,*\,13.101]} = 4\ 855\ 804$

Tick = 0.5: $e^{[-9.500\ -\ 68.944\,*\,0.00237\ +\ 0.013\,*\,22.459\ +\ 1.903\,*\,13.101]} = 5\ 718\ 277$

[25] The figure ±1.5 per cent was arbitrarily chosen.

to be influenced by the overall activity at the stock exchange. In order to control this, the variable $Volport_i$ was created. This variable is defined as the ratio between the daily total traded volume of 51 other stocks and the average daily traded volume of the same stocks.[26] Finally we also create a new variable, $PDiff_i$, which is the difference between the highest and lowest trading price for each stock each day. The idea behind this is that if the prices move significantly, traded volume is likely to increase.

5.1 Regression Results

To summarize, we conjecture the following heuristic system of regression equations. Once again, we want to stress that we do not have any explicit theoretical model as base for our regressions.

$$RSpr_i = \alpha_0 + \alpha_1\, Ind_i + \alpha_2\, ISRNO_i + \alpha_3\, ISRNT_i + \alpha_4\, SD30R_i + \varepsilon_{4i} \tag{4}$$
$$LnQproc_i = \beta_0 + \beta_1\, Ind_i + \beta_2\, LnDVol_i + \beta_3\, SD30R_i + \beta_4\, VolPort_i + \varepsilon_{5i} \tag{5}$$
$$LnDVol_i = \gamma_0 + \gamma_1\, Ind_i + \gamma_2\, LnQproc_i + \gamma_3\, PDiff_i + \gamma_4\, VolPort_i + \varepsilon_{6i} \tag{6}$$

If the tick size is an important determinant of the bid/ask spread, we expect to find a positive correlation between Ind_i and $RSpr_i$, since Ind_i is unity when the tick size is SEK 1 and zero when the tick size is SEK 0.5. Our conjecture is therefore that α_1 is positive. As in the regressions in section 4, $ISRNO_i$ and $ISRNT_i$ capture the trading activity and the competition among the dealers. If there are many limit orders and many transactions in one day, we expect the spread to be lower. We therefore anticipate positive α_2 and α_3. The $SD30R_i$ is still a proxy for the riskiness of trading that particular stock that day. Since suppliers of liquidity are likely to require larger compensation during more volatile days α_4 is expected to be positive.

If the quote matcher argument is valid, a large tick size would be positively correlated with quoted volume, that is, β_1 would be positive. This implies that the quoted volume will be larger when the stock's price is just above SEK 100 than when it is below SEK 100. On days when the trading volume of stock i is large, the quoted volume of stock i is also expected to be large, resulting in a positive β_2. Due to the free trading option argument, we expect β_3 to be negative. Furthermore, on days when the rest of the stock exchange is active, we expect quoted volume to be large (i.e. a positive β_4).

[26] The trading volume of the 52 stocks represents a large portion of the trading volume at the SSE. In calculating the volport-variable for stock i, we first deleted the traded volume of stock i, used the traded volume of the remaining 51 stocks for each day in the nominator and the average daily trading volume for the same stocks in the denominator.

Table 5

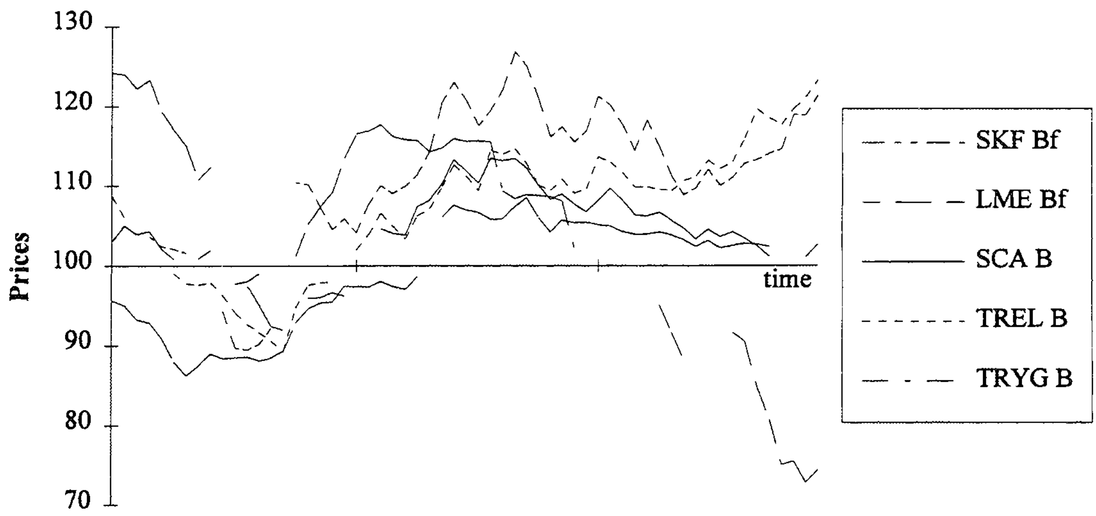
Simultaneous Regression Results

	Expected Sign	SKF Bf	LME Bf	SCA B	TREL B	TRYG B
No (p < 100)		27	5	8	14	14
No (p > 100)		28	50	43	39	33
Dependent Variable: Relative Bid/Ask Spread (RSpr)						
Intercept		0.002	0.005	0.005	0.002	-0.004
		(0.50)	(7.06)	(1.17)	(1.04)	(-0.26)
IND_i	(+)	0.002	0.003	-0.001	0.002	0.003
		(1.93)	(11.09)	(-0.76)	(4.97)	(0.76)
$ISRNO_i$	(+)	0.011	0.005	0.030	0.019	0.013
		(0.67)	(0.95)	(2.28)	(2.58)	(0.34)
$ISRNT_i$	(+)	0.016	0.0002	0.003	0.016	0.050
		(1.40)	(0.03)	(0.39)	(3.34)	(1.26)
$SD30R_i$	(+)	0.404	0.111	0.146	0.268	0.897
		(2.38)	(3.24)	(1.72)	(4.14)	(5.83)
Skewness of ε_4		1.27	0.08	0.49	0.51	1.48
Excess Kurtosis of ε_4		1.81	-0.68	0.36	2.89	3.58
BJ normality test of ε_4		22.29	1.12	2.32	20.74	42.26
Dependent Variable: Ln of Quoted Volume (LnQproc)						
Intercept		6.957	5.865	4.463	6.172	2.172
		(9.43)	(3.39)	(5.59)	(12.85)	(0.57)
IND_i	(+)	0.481	0.460	0.427	0.563	0.627
		(4.85)	(2.74)	(2.66)	(4.97)	(1.97)
$LnDVol_i$	(+)	0.279	0.372	0.468	0.299	0.646
		(3.69)	(2.77)	(5.00)	(6.62)	(1.68)
$SD30R_i$	(–)	-11.479	-25.769	-29.089	5.870	-18.535
		(-0.72)	(-1.22)	(-2.78)	(0.72)	(-1.68)
$Volport_i$	(+)	-0.194	0.306	-0.039	0.271	0.111
		(-1.09)	(2.25)	(-0.17)	(1.58)	(0.42)
Skewness of ε_5		0.03	0.73	0.46	0.17	-0.78
Excess Kurtosis of ε_5		-0.50	2.41	1.15	-0.32	1.78
BJ normality test of ε_5		0.58	18.20	4.61	0.48	10.97
Dependent Variable: Ln of Traded Volume (LnDVol)						
Intercept		-19.772	0.255	-4.262	-24.205	20.158
		(-1.96)	(0.09)	(-1.79)	(-7.74)	(1.10)
IND_i	(–)	-1.361	-0.570	-0.562	-2.339	-0.052
		(-2.37)	(-2.98)	(-1.52)	(-6.89)	(-0.07)
$LnQproc_i$	(+)	3.045	1.130	1.504	3.728	-1.185
		(2.98)	(4.47)	(5.26)	(11.01)	(-0.54)
$PDiff_i$	(+)	0.205	0.145	0.130	-0.029	-0.301
		(1.40)	(4.20)	(1.47)	(-0.85)	(-0.95)
$Volport_i$	(+)	0.602	-0.017	0.548	-1.008	-0.019
		(1.12)	(-0.10)	(1.42)	(-2.34)	(-0.03)
Skewness of ε_6		-0.11	-0.50	-0.14	-0.16	0.14
Excess Kurtosis of ε_6		-0.30	0.29	0.35	-0.14	0.03
BJ normality test of ε_6		0.32	2.48	0.43	0.27	0.05
N		55	55	51	53	47
System Weighted R^2		0.492	0.550	0.599	0.655	0.397
System Weighted MSE		1.59	1.27	1.59	5.81	0.66

Finally, we conjecture that days when the stock's price is above SEK 100 (i.e. high tick size) the traded volume will be low. We should therefore find a negative γ_1. The correlation between quoted volume and traded volume is expected to be positive. When trading prices have moved significantly during the day, we expect higher trading volume, that is, a positive γ_3. We also assume that when the activity of the rest of the stock exchange is high, the traded volume of stock i will be high (a positive γ_4). The regression results as well as the expected signs are summarized in Table 5.

The results for the cross-daily sample largely confirm the earlier findings. Although the significance differs between stocks, both the relative spread and the quoted volume seem to be larger and the traded volume lower when the stock's price is above SEK 100, that is, when the tick size is large. We should keep in mind that the sample here consists of only 59 days. A larger sample would be needed to draw any definite conclusions. Other factors may influence our results. There are relatively few days where the prices of the investigated stocks are below SEK 100, and they occur largely during the same time period for all stocks, see Figure 2. In view of all this, the independence of the observations can be questioned, and the results should therefore be interpreted with caution.

Figure 2
Average Daily Prices of the Five Included Stocks



6 Conclusions

We use cross-sectional and cross-daily data from the Stockholm Stock Exchange, a limit order driven market with a consolidated open limit order book, in trying to assess the importance of the tick size on the bid/ask spread, on the quoted volume and on traded volume. We draw three general conclusions. First, there is strong evidence that the tick size has an economically important effect by increasing the bid/ask spread. Thus, a high tick size is associated with a large market width, and is therefore detrimental to market liquidity. Second, on the other hand there is evidence that market depth increases with the relative tick size. The effect on overall liquidity of the observed tick size is therefore uncertain. Finally, there is evidence that a high tick size is associated with a lower traded volume. The results are similar to those of Harris (1994), using data from the NYSE, despite a different trading system. The trading system at the SSE is different in at least two respects. Firstly, the SSE is a fully order driven market without any designated market maker or specialist as at the NYSE. In other words, the liquidity is created by other traders on an equal footing. Secondly, there is a high degree of transparency, which means that everybody can see the entire order volume and identity of the different dealers. Both these differences could result in a less compelling quote matcher argument. However, our findings indicate that the tick size is as important in an order driven market without any designated market maker as in a mixed system with a specialist at the NYSE.

Our overall conclusion is that a reduction of the tick size would be beneficial for small traders, since they will benefit from the narrower bid/ask spread. However, the negative impact of a relatively large bid/ask spread might be offset by the positive effect of an increased market depth for traders who trade larger amount. A reduction of the tick size could be beneficial to corporations, by reducing the cost of capital (as a consequence of lower transaction costs) and to the stock exchange since traded volume would increase. The effect on the dealers is more ambiguous, since a lower tick size is likely to reduce their profits from the bid/ask bounce. On the other hand, their profits may also increase since traded volume is likely to increase with a lower tick size. To make any explicit projections of the effect of a changed tick size, a specific model of a discrete price pattern would have to be developed. However, this is not easy to achieve in view of the difficulty in modeling an investor's behavior over a discrete variable.

References

Amihud, Y. and H. Mendelson, (1980), "Dealership Market: Market Making with Inventory". *Journal of Financial Economics*, 8:31-53.

Amihud, Y. and H. Mendelson, (1991), "How (Not) to Integrate the European Capital Markets", December, (Paper prepared for the CEPR-IMI Conference on European Financial Integration, January 1990) in A. Giovannini and L. Mayer (eds.) *European Financial Integration.* Cambridge University Press 1991.

Anshuman, V. R., and A. Kalay, (1993), "A Positive Theory of Splits", Working Paper Presented at the European Finance Association in Copenhagen, August 1993.

Anshuman, V. R. and A. Kalay, (1994), "Can Splits Creat Market Liquidity? Theory and Evidence", Working Paper, August 1994.

Bagehot, W. (pseudonym), (1971), "The Only Game in Town", *Financial Analysts Journal*, 27:March-April:12-14,22.

Baker, H. K. and G. E. Powell, (1992), "Why Companies Issue Stock Splits", *FM Letters, Financial Management*, 21: No 2:11.

Ball, C. A., (1988), "Estimation Bias Induced by Discrete Security Prices", *Journal of Finance*, 43:841-865.

Biais, B., P. Hillion and C. Spatt, (1994), "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse", Working Paper, March 1994.

Cho, D. C. and E. W. Frees, (1988), "Estimating the Volatility of Discrete Stock Prices", *Journal of Finance*, 43:451-466.

Cohen, K. J., S. F. Maier, R. A. Schwartz and D. K. Whitcomb, (1981), "Transaction Costs, Order Placement Strategy, and Existence of the Bid-Ask Spread", *Journal of Political Economy*, 89:287-305.

Copeland, T. E., (1979), "Liquidity Changes following Stock Splits", *Journal of Finance*, 34:115-141.

Copeland, T. and D. Galai, (1983), "Information Effects on the Bid-Ask Spread", *Journal of Finance*, 38:1457-1469.

Demsetz, H., (1968), "The Cost of Transacting", *Quarterly Journal of Economics*, 82:33-53.

Glosten, L. R. and P. R. Milgrom, (1985), "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders",. *Journal of Financial Economics*, 14:71-100.

Gottlieb, G. and A. Kalay, (1985), "Implications of Discreteness of Observed Stock Prices", *Journal of Finance*, 40:135-153.

Grossman, S. J. and M. H. Miller, (1988), "Liquidity and Market Structure", *Journal of Finance*, 43:617-633.

Harris, L., (1990a), "Estimation of Stock Variances and Serial Covariances from Discrete Observations", *Journal of Financial and Quantitative Analysis*, 25:291-306.

Harris, L., (1990b), "Liquidity, Trading Rules, and Electronic Trading Systems", *New York University Salomon Center, Monograph Series in Finance and Economics 1990-4.*

Harris, L., (1991), "Stock Price Clustering and Discreteness", *Review of Financial Studies*, 4, 389- 415.

Harris, L., (1992), "Consolidation Fragmentation, Segmentation and Regulation", Working Paper, University of Southern California, March 1992.

Harris, L., (1994), "Minimum Price Variations, Discrete Bid-Ask Spreads, and Quotation Sizes", *Review of Financial Studies*, 7, 149-178.

Hasbrouck, J. and R. A. Schwartz, (1988), "Liquidity and Execution Costs in Equity Markets", *Journal of Portfolio Management*, 14:Spring:10-16.

Helsinki Stock Exchange, (1991), "Rules and Regulations of the Helsinki Stock Exchange, Vol. 2", The Helsinki Stock Exchange.

Ho, T. S. Y. and H. R. Stoll, (1980), "On Dealer Markets under Competition". *Journal of Finance*, 35:259-267.

Ho, T. S. Y. and H. R. Stoll, (1981), "Optimal Dealer Pricing Under Transactions and Return Uncertainty", *Journal of Financial Economics*, 9:47-73.

Judge, G. G., R. C. Hill, W. E. Griffiths, H. Lütkepohl and T.-C. Lee, (1988), *Introduction to the Theory and Practice of Econometrics*, John Wiley & Sons, 2nd edition.

Niemeyer, J. and P. Sandås, (1993), "An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange", Working Paper, Stockholm School of Economics, July 1993.

NYSE Rule 62, New York Stock Exchange Guide, Rules of Board, Rule 62

O'Hara, M. and G. S. Oldfield, (1986), "The Microeconomics of Market Making", *Journal of Financial and Quantitative Analysis*, 21:361-376.

Stockholm Stock Exchange, (1991), "Rules Governing Trading in Stocks and Convertible Participating Notes via the Stockholm Automated Exchange (SAX)". In Swedish Only. (in Swedish: "Regler för handel i aktier och konvertibla vinstandelsbevis via Stockholm Automated Exchange (SAX)".) Last revised May 7, 1991, Version 1.2.

Stoll, H. R., (1978), "The Supply of Dealer Services in Securities Markets". *Journal of Finance*, 33:1133-1151.

Stoll, H. R., (1992), "Principles of Trading Market Structure", Working Paper 90-31 Vanderbilt University, January 1992.

Appendix 1

The sample 2A (averages over the time period Jan. 20, 1992 to Mar. 2, 1992). Explanations for the variables are given in secion 4.1 and in Appendix 3. "2C" lists stocks in Sample 2C.

Stock	2C	ISRNO	ISRNT	LnDVol	LnMVal	LnQSize	RSpr	RTick	SD5R
AGA A	*	0.28712	0.05893	13.5711	22.7321	12.7419	0.0128	0.003205	0.014145
AGA B		0.28318	0.07433	13.7717	21.9798	13.0738	0.0139	0.003267	0.012791
AGA BF	*	0.37242	0.05998	15.0729	21.8564	12.883	0.0119	0.00321	0.014239
ARGO B	*	0.25507	0.05256	13.5485	20.7914	12.4736	0.0213	0.011641	0.029691
ASEA A	*	0.27618	0.02974	16.2013	23.7902	12.8035	0.0075	0.003058	0.027251
ASEA AF		0.44856	0.13608	12.0261	19.7243	12.2198	0.0238	0.003072	0.030189
ASEA BF	*	0.25565	0.02665	16.399	22.7853	13.1818	0.0062	0.003096	0.029616
ASTR A	*	0.21522	0.01573	17.6685	24.4897	13.9188	0.0035	0.001857	0.023821
ASTR AF	*	0.28127	0.03503	16.4678	23.188	13.8316	0.0081	0.001707	0.024298
ASTR BF	*	0.27106	0.02435	16.7414	23.1507	13.7846	0.0055	0.001769	0.032947
ATCO AF	*	0.27629	0.03501	15.6716	22.6032	13.2929	0.0097	0.003588	0.024447
ATCO BF	*	0.31296	0.03522	15.9756	21.9142	13.4828	0.0102	0.003593	0.024213
ELUX BF	*	0.22954	0.02063	16.9565	23.6144	13.9162	0.0064	0.003953	0.045417
INCE A	*	0.28689	0.03841	15.0989	22.8222	12.4408	0.0153	0.006022	0.020406
INCE BF	*	0.26612	0.03079	15.7146	21.8091	13.1741	0.0091	0.006156	0.026208
INDU A	*	0.32898	0.06143	13.6505	22.2484	12.4489	0.021	0.00526	0.034993
INDU BF		0.42757	0.09853	13.5286	20.3804	12.3027	0.0281	0.005345	0.042419
INDU CF		0.44108	0.08805	12.5917	21.1022	12.1303	0.0282	0.005518	0.035231
INVE A	*	0.32427	0.04951	14.9368	22.8325	12.6092	0.0207	0.007289	0.040642
INVE AF		0.54233	0.08839	14.5406	21.1527	12.6085	0.0288	0.007135	0.0301
INVE BF	*	0.26707	0.03137	15.6956	20.9864	13.2154	0.0121	0.00777	0.043553
LME A		0.34199	0.12403	10.3144	21.3896	10.9058	0.0647	0.006269	0.063028
LME BF	*	0.1264	0.01136	17.7866	23.8175	14.7725	0.0092	0.008477	0.048727
LUND B	*	0.29527	0.06608	12.7121	21.6316	12.1131	0.0383	0.008089	0.095339
NOBL	*	0.08939	0.01965	15.268	22.2948	15.0108	0.0415	0.041597	0.077232
NOBL F	*	0.12977	0.02813	14.7536	20.5544	14.4345	0.0429	0.041288	0.08212
PROC A	*	0.25499	0.03774	14.4024	24.1756	12.6131	0.0124	0.005043	0.035858
PROC AF		0.45835	0.10153	12.544	20.8693	12.2879	0.0327	0.005056	0.041191
PROC B	*	0.25318	0.03306	15.333	23.0874	13.2566	0.0097	0.005089	0.039154
PROC BF	*	0.28083	0.03238	15.8614	22.6441	13.2174	0.0109	0.005056	0.044171
PROV A		0.42448	0.08839	12.2242	22.4383	12.2461	0.0283	0.009916	0.033353
PRTS B	*	0.21869	0.05278	13.3018	21.1663	12.7303	0.0127	0.00973	0.010924
SAND A	*	0.28748	0.04555	15.0024	23.4631	13.3039	0.0084	0.002659	0.01122
SAND BF	*	0.29298	0.04541	15.5835	22.2811	13.4103	0.0095	0.002657	0.014649
SCA A		0.43315	0.08111	12.7518	22.6207	12.2858	0.0322	0.008874	0.024622
SCA B	*	0.26509	0.0341	15.2992	22.3939	13.0673	0.0129	0.009264	0.02273
SCA BF	*	0.29173	0.03812	15.2901	22.6425	13.0573	0.0145	0.00933	0.018329
SDIA F	*	0.27462	0.03369	15.021	23.1187	12.8518	0.014	0.007011	0.040451
SEB A	*	0.15986	0.01736	16.2596	23.1583	13.841	0.0124	0.010663	0.071333
SEB CF	*	0.2963	0.04845	12.7294	20.2659	11.8258	0.0281	0.010206	0.076072
SHB A	*	0.24154	0.02522	15.6142	23.1604	13.0117	0.0095	0.006014	0.039635
SHB BF	*	0.37113	0.04704	13.4891	20.8674	11.965	0.0215	0.006009	0.032597
SKA B	*	0.23325	0.02864	15.3866	23.1429	13.1095	0.0133	0.008604	0.046733
SKA BF	*	0.30571	0.04623	14.3189	21.5679	12.4523	0.0194	0.008709	0.046007
SKF A		0.40791	0.07581	12.5326	22.3704	11.9704	0.0461	0.009583	0.050632
SKF B	*	0.31591	0.04903	15.5468	21.5535	13.2358	0.0155	0.009894	0.014449
SKF BF	*	0.20537	0.02889	16.259	22.1697	13.8484	0.0116	0.009635	0.01441
STOR A	*	0.26361	0.03392	15.8369	23.1675	12.8314	0.0093	0.003658	0.032619
STOR AF		0.37529	0.07906	13.9748	21.1558	12.6418	0.0319	0.003644	0.038703
STOR BF	*	0.28784	0.03742	15.6739	21.9005	12.8166	0.0114	0.003681	0.040139

Appendix 1
Cont.

Stock	2C	ISRNO	ISRNT	LnDVol	LnMVal	LnQSize	RSpr	RTick	SD5R
SYD A		0.32444	0.07433	13.8465	23.0921	12.9953	0.0179	0.007155	0.01898
SYD C	*	0.27298	0.04527	15.2657	22.4693	13.79	0.0099	0.007219	0.015353
TREL B	*	0.16514	0.0201	16.352	22.1322	14.0078	0.01	0.008746	0.034455
TREL BF	*	0.30905	0.04891	15.0716	21.107	13.1137	0.0212	0.008508	0.039948
TREL C	*	0.23557	0.04287	13.9568	20.8228	12.5306	0.0135	0.007876	0.026044
TRYG B	*	0.29867	0.03922	14.1081	22.3915	12.0702	0.0244	0.005282	0.064318
VOLV A	*	0.307	0.04903	14.1532	22.7205	12.7821	0.0161	0.002629	0.029563
VOLV AF		0.37113	0.09245	12.1342	21.5481	11.8559	0.0367	0.00262	0.034048
VOLV B	*	0.22942	0.01904	17.0769	23.0993	13.9214	0.0054	0.002655	0.025974
VOLV BF	*	0.25318	0.02566	16.4862	22.9364	13.7873	0.0078	0.002606	0.026196

Appendix 2

The number of observations for which the bid/ask spread equals one tick as a proportion of all observations. Average midpoint quote and average daily trading volume [in million SEK] (excluding after hours trading) is reported for each stock in sample 2A.

Stock	One Tick Spreads As %	Average Midquote	Average Daily Volume	Stock	One Tick Spreads As %	Average Midquote	Average Daily Volume
NOBL F	96	12	2.5	PROC A	36	199	1.8
NOBL	95	12	4.3	INVE A	35	138	3.1
LME BF	91	118	53.0	ATCO BF	34	278	8.7
TREL B	87	114	12.6	SYD A	30	140	1.0
SEB A	86	46	11.5	STOR BF	28	272	6.4
SYD C	76	138	4.3	VOLV BF	25	384	14.5
PRTS B	73	52	0.6	SAND A	25	376	3.3
SCA B	71	108	4.4	SEB CF	24	49	0.3
SKF BF	71	104	11.5	ASTR BF	23	565	18.7
INCE BF	69	162	6.7	INDU A	20	190	0.8
SKA B	66	116	4.8	SKF A	20	106	0.3
INVE BF	65	128	6.6	PROV A	20	102	0.2
SCA BF	64	107	4.4	SAND BF	18	376	5.9
ELUX BF	64	253	23.1	TRYG B	17	95	1.3
SHB A	61	83	6.0	SHB BF	16	84	0.7
TREL C	55	127	1.2	AGA BF	14	312	3.5
ARGO B	51	43	0.8	AGA A	13	312	0.8
VOLV B	51	377	26.1	INVE AF	12	140	2.1
ASTR A	51	539	47.1	AGA B	9	306	0.9
SDIA F	50	143	3.3	SCA A	9	114	0.3
ASEA BF	49	323	13.2	ASTR AF	9	586	14.2
PROC B	48	196	4.6	INDU BF	7	187	0.8
PROC BF	46	197	7.7	VOLV A	6	381	14.0
SKF B	45	101	5.6	PROC AF	4	197	0.3
SKA BF	42	116	1.7	INDU CF	3	181	0.3
INCE A	40	167	3.6	LUND B	3	62	0.3
STOR A	38	273	7.5	STOR AF	2	273	1.2
TREL BF	38	117	3.5	ASEA AF	1	325	0.2
ASEA A	37	327	10.9	LME A	1	157	0.0
ATCO AF	36	279	6.4	VOLV AF	0	383	0.2

Appendix 3

This Appendix contains a more explicit description how the different variables have been calculated:

$$ISRNO_i = \frac{1}{\sqrt{\frac{N\ Ord_i}{NO_i}}}$$ where $N\ Ord_i$ is the total number of limit orders across the ten different levels in the order book (i.e. the five best bid and five best ask levels) aggregated over all observations in the limit order book for share i. NO_i is the number of observations in the order book for share i.

$$ISRNT_i = \frac{1}{\sqrt{NT_i}}$$ where NT_i equals the number of transactions for share i.

$$LnDVol_i = \ln\left(\frac{\sum_{j=1}^{NT_i} transaction\ price_j \cdot transacted\ volume_j}{d}\right)$$ where d equals the number of trading days in the sample.

$$LnMVal_i = \ln\left(\text{Number of outstanding shares}_i \cdot \frac{\sum_{k=1}^{NO_i} midquote_{ki}}{NO_i}\right)$$ where NO_i equals the number of observations in the order book for share i.

$$LnQSize_i = \ln\left(\frac{\sum_{k=1}^{NO_i} \frac{(ask_{ki} \cdot ask\ volume_{ki}) + (bid_{ki} \cdot bid\ volume_{ki})}{2}}{NO_i}\right)$$ where NO_i equals the number of observations in the order book for share i.

$$RSpr_i = \frac{\sum_{k=1}^{NO_i} \frac{Ask_k - Bid_k}{MidQuote_k}}{NO_i}$$ where NO_i equals the number of observations in the order book for share i.

$$RTick_i = \begin{cases} \frac{1}{AP_i} & \text{if } AP_i \geq 100 \\ \frac{0.5}{AP_i} & \text{if } AP_i < 100 \end{cases} \quad where\ AP_i = \frac{\sum_{j=1}^{NT_i} Transaction\ price_{ji}}{NT_i}.$$

$$SD5R_i = \frac{(d-5)\sum_{k=6}^{d}\left[\ln(bid_k) - \ln(bid_{k-5})\right]^2 - \left(\sum_{k=6}^{d}\left[\ln(bid_k) - \ln(bid_{k-5})\right]\right)^2}{(d-5)(d-6)}$$ where d equals the number of trading days in the sample and bid_k is the bid price at noon.

In the third sample the following additional variables were (re-)defined

(where i refers to stocks and j to days)

$$IND_{ij} = \begin{cases} 1 & \text{if the best bid}_{ij} > 100 \text{ during the entire trading day} \\ 0 & \text{if the best ask}_{ij} < 100 \text{ during the entire trading day} \\ & \text{the rest of the observations were deleted} \end{cases}$$

$$LnDVol_{ij} = \ln\left(\sum_{k=1}^{NT_{ij}} traded\ number\ of\ stocks_{ijk}\right)$$

$$LnQproc_{ij} = \ln\left(\sum_{k=1}^{p_m \cdot 1.015} Number\ of\ shares\ quoted\ at\ ask_k + \sum_{k=1}^{p_m \cdot 0.985} Number\ of\ shares\ quoted\ at\ bid_k\right)$$

where ask_1 equals the best ask price, bid_1 the best bid price, ask_2 the second best ask price, bid_2 the second best bid price ... and p_m equals quote midpoint.

$$PDiff_{ij} = \text{maximum trading price}_{ij} - \text{minimum trading price}_{ij}$$

$$SD30R_{ij} = \frac{8 \cdot \sum_{k=2}^{9} \left[\ln\left(bid_{ijk}\right) - \ln\left(bid_{ij(k-1)}\right) \right]^2 - \left(\sum_{k=2}^{9} \left[\ln\left(bid_{ijk}\right) - \ln\left(bid_{ij(k-1)}\right) \right] \right)^2}{8 \cdot 7}$$ where

bid_{ij1} equals the bid price of stock i day j at 10:30 a.m, bid_{ij2} the bid price at 11:00 a.m and so forth.

$$Volport_{ij} = \frac{\sum_k \left(transaction\ price_{jk} \cdot transacted\ volume_{jk} \right)}{Avg\left[\sum_k \left(transaction\ price_{jk} \cdot transacted\ volume_{jk} \right) \right]}.$$ where both

summations are for 51 stocks excluding stock i, and the average is taken across days.

Essay 4

An Analysis of the Lead-Lag Relationship between the OMX Index Forwards and the OMX Cash Index*

Abstract

This essay investigates the intraday lead-lag structure in returns between on the one hand the OMX cash index and on the other hand the OMX index forwards and the OMX synthetic index forwards in Sweden. The data set includes 22 months of data, from December 1991, to September 1993. It is divided into three sub-periods. The main conclusion is that there is a high degree of bidirectional interdependence, with both series Granger causing each other. Using a Sims-test, we find that the forwards as well as synthetic forwards lead the cash index with between fifteen and thirty minutes, while the cash index leads the forwards with about ten to fifteen minutes. This implies a longer lead from the cash index to the forwards than in previous studies. The large interdependence could possibly be due to higher transaction costs, lower liquidity in the forward market and the specific trading environments used for Swedish securities.

1 Introduction

The dynamic relationship between the index futures and the cash market has been subject to an active discussion in many countries. If there exists a systematic lead-lag

* I wish to thank *Dextel Findata AB* and *OM Stockholm AB* for providing the data set. I also wish to thank seminar participants at the Stockholm School of Economics as well as participants at the Third Annual Conference on European Financial Management in Maastricht, July 1994 and at the Seventh Annual CBOT European Futures Research Symposium in Bonn, September 1994, and specially Ragnar Lindgren and Pradeep Yadav. I am further indebted to Sune Karlsson and Anders Warne who assisted with suggestions and solutions to countless computational and econometrical problems. The usual disclaimer applies.

relationship between the returns on the two securities, arbitrage opportunities might be present. Furthermore, index arbitrage has been blamed for excessive stock market price swings. A more academic question is which market is informationally the most efficient, or put differently which market impounds new information the fastest. Therefore, an academic analysis of the dynamic relationship from different markets might shed warranted light on the robustness of observed patterns.

Since stock index forward contracts[1] are usually priced using the cost-of-carry model, the returns on the cash index and on the forwards should have perfect contemporaneous correlation and zero cross-autocorrelation, assuming perfect capital markets and non-stochastic interest rates and dividends. Theoretically, all relevant new information should therefore be incorporated immediately in *both* the forward and cash prices. One implication of the model is that there should be *no* lead-lag relationship between the two markets. Furthermore, if one market systematically lags the other, there will be arbitrage opportunities, at least if transaction costs are small. However, market imperfections might result in a systematic lead-lag structure, where one market adapts quicker to new information and thus can be used to make projections on the other. This in turn might cast some light into the question of the relative efficiency of different market structures.

Using intraday data from the US, several empirical studies indicate that the index futures market leads the cash index market rather than the other way around.[2] Other studies have also taken the volatility of the different markets into account. Kawaller, Koch, and Koch (1990) find no systematic lead-lag relationship between futures volatility and index volatility. Chan, Chan and Karolyi (1991) find that "price innovations that originate in either the stock or futures markets can predict the future volatility in the other market".[3] Yet other studies investigate the relationship between the stock option market and the stock market.[4] Stephan and Whaley (1990) find that the stock market leads the option market while Chan, Chung and Johnson (1993) argue that this is due to technicalities in how the options and stocks are traded.

To summarize, the American studies indicate that the index futures market leads the cash index market while the lead-lag structure between the stock market and the stock options market is more uncertain. The interpretation of Chan (1992) is that if the market wide information first reaches the index derivative market and later the cash index

1 In this essay, we largely disregard the difference between a forward contract and a futures contract. Unlike in most countries, no futures are traded in Sweden. Instead, the standardized traded contract is of forward type. The difference is that there is no marking to market.
2 References include Kawaller, Koch, and Koch (1987), Stoll and Whaley (1990) and Chan (1992).
3 Chan, Chan and Karolyi (1991), p 657.
4 References include Stephan and Whaley (1990), Varson and Selby (1991) and Chan, Chung and Johnson (1993).

market. On the other hand, the stock specific information is likely to reach the stock market and the derivative market in a less systematic way. A possible alternative explanation is that there is a significant difference between the futures market and the options market.

Since most lead-lag papers so far have used US-data, an interesting question is if the empirical findings pertain to the special trading structure or any other specific feature of the American markets. In order to appropriately assess the importance of the trading structure on the lead-lag relation, evidence from other markets becomes crucial.

Recently, there has been a spur of research on the lead-lag relationship using data from European markets. Both Grünbichler, Longstaff and Schwartz (1994) and Booth, Broussard and Loistl (1994) use the German DAX index and futures on that index. Similarly to the US-studies, their overall conclusion is also that the futures market tends to lead the cash market. Since the DAX futures are traded on a computerized screen based market with a consolidated electronic limit order book, while the stocks included in the index are floor traded, Grünbichler, Longstaff and Schwartz (1994) claim that their results primarily are due to the difference in trading structure. However, since there is also a short term significant feedback from the index to the futures, Booth, Broussard and Loistl (1994) draws the conclusion "that an electronically based futures market does not completely dominate a traditional floor based system".[5] Furthermore, Abhyankar (1994) performs lead-lag tests on hourly UK data. The main conclusion is that the FT-SE 100 index futures lead the cash index.

Finally, Shyy and Vijayraghavan (1994) have access not only to transaction prices but also to bid/ask quotes from MATIF and the Paris Bourse in France. Their results indicate that although the futures lead the CAC-index when measured from transaction prices, there is a strong bidirectional causality when returns are calculated from bid/ask quotes. Since all earlier studies have used transaction prices only, their conclusion is that previous results "could be misleading because of nonsynchronous trading and the stale price problem".[6] Furthermore, since in France the cash market is electronic and the futures market employes an open outcry floor trading system, Shyy and Vijayraghavan draw the conclusion that "the automated trading system enhances the information flow efficiency but ... does not dominate the price transmission process over the traditional open outcry floor trading".[7]

---

[5] Booth, Broussard and Loistl (1994), p. 40.
[6] Shyy and Vijayraghavan (1994), p. 16.
[7] Shyy and Vijayraghavan (1994), p. 17.

Extending the knowledge of which market imperfection or market structure leads to a specific lead-lag structure might help regulators in identifying possible regulatory improvements and competing exchanges in identifying possible competitive advantages. To accurately address this question, results from many different markets are essential.

This essay extends the existing literature in several ways. First of all, it uses intraday data from another market, the Swedish one.[8] In this case, both the cash and derivative markets have very similar trading systems based on computerized open limit order books. The focus of the essay can therefore be on the actual lead-lag relation by minimizing the impact of differences in trading systems on the results. Furthermore, the trading structures on both of the Swedish markets are different from the ones in the USA. This could possibly lead to different results. Thirdly, with information on the bid and ask quotes of the component stocks in the index, we are able to control for any bid/ask bounce effect in the index. Finally, we investigate whether the same lead-lag relation holds for both forwards and synthetic forwards, i.e. whether the options market is as fast in incorporating new information as the forward market.

The essay proceeds with a discussion of the theoretical background in section 2. Section 3 gives some background information about the Stockholm Stock Exchange and the options and forwards exchange in Stockholm, OM. In section 4, we discuss some methodological problems. The data is presented in section 5. The empirical findings are reported in section 6 and we conclude with a summary in section 7.

2 Theoretical Background

The theoretical relationship between the index forward and the cash index can be expressed as the "Cost-of-Carry" relation,[9] i.e.:

$$F_t = I_t e^{(r-d)(T-t)} \tag{1}$$

where F_t is the forward price at time t, I_t is the index value at time t, r is the riskfree rate of interest, d is the dividend yield and T-t is the remaining maturity of the forward contract. Both r and d are assumed to be known and continuously compounded. Calculating logarithmic returns yields the following relation:

$$\ln\left(\frac{F_t}{F_{t-1}}\right) + (r-d) = \ln\left(\frac{I_t}{I_{t-1}}\right) \tag{2a}$$

[8] One pilot study on Swedish data, (Elmhammer and Trocmé (1993)), finds that the OMX index forwards *lag* the cash OMX index with between fifteen and thirty minutes.

[9] For references, see Hull (1993) p. 69 and Stoll and Whaley (1990) p. 442.

or expressed differently,

$$f_t + \left(r - d\right) = i_t \tag{2b}$$

If both the interest rate cost and the expected dividend yield are constant over time, at least over the short time horizon, there is a direct link between the return on the forwards and on the cash index. Indeed, most studies using intraday data make this assumption. It does not seem unreasonable to assume that the change, during say 15 minutes, in interest rates and in expected dividend yield is "small" compared to the change in forward prices and cash indices.

Apart from traded forwards, we use synthetic forwards[10] in this essay. These can be calculated using the well-known put-call parity.[11] By buying a call and selling a put with the same exercise price, it is possible to create a synthetic forward, in the following manner:

$$F_t^S = X + \left(C_t - P_t\right)e^{(r-d)(T-t)} \tag{3}$$

where X is the exercise price, C the call option price and P the put option price.

If both markets were fully efficient, there would not be any systematic lead-lag structure and the cost-of-carry relation would hold at all points in time. Any deviation from the cost-of-cary relation would then imply arbitrage opportunities. By assuming constant interest rates and dividend yields, as well as continuous, frictionless and efficient stock index, index forwards and index options markets the cost-of-carry relation has at least three interesting implications:

a) The contemporaneous rates of return of the forward contract and the underlying stock portfolio are perfectly positively correlated.
b) The non-contemporaneous rates of return of the forward contract and the underlying stock portfolio are uncorrelated.
c) It will not be possible to use one series to make forecasts on the other series.

However, empirical studies of the cost-of-carry relation document frequent violations of

10 See Grossman (1988) for a discussion of the problems of using synthetic instruments instead of traded instruments. However in this case, the problem of synthetic forwards is reduced since these can be traded as one instrument on the Swedish derivatives market, see section 3.

11 Under an assumption of asymmetric information, the put-call parity may not hold at every instant in time. Therefore, although arbitrage would ultimately make the relationship hold, the present formulation may induce noise into the lead-lag relationship, (see Easley, O'Hara and Srinivas (1993)).

this relation.[12] There might be several reasons for these violations. The primary problem is that the "true" return series are unobservable. Our empirical observations are based on a noisy signal of the "true" returns. This noise could have several distinct sources:

1) Noise caused by the bid/ask bouncing effect;
2) Infrequent trading and stale prices;
3) Delays in the computation and reporting of stock index values;
4) Non-synchronous trading and stale prices;
5) Short selling restriction in the cash market;
6) Transaction costs;
7) Liquidity differences; and finally
8) Lead-lag relation behavior of the stock index and the stock index forward returns.

The four first reasons impose certain econometrical problems, to which we will return in section 4. The fifth reason could induce a lead of the derivatives over the index in down periods.[13] The transaction costs will primarily induce noise by preventing complete arbitrage and thereby impairing full synchronization between the two return series. It is impossible to trade the cash index in *one* transaction. This liquidity aspect is likely to result in index forwards leading the cash index.

3 The Stockholm Stock Exchange and the Options and Forwards Exchange, OM

Internationally, the Stockholm Stock Exchange (SSE) is a small stock exchange. As a comparison, Table 1 lists the market values and turnover statistics from the NYSE, the London Stock Exchange and the SSE.[14]

Table 1
The Size of the Stockholm Stock Exchange

USD (1 000 000 000)	Year-End Market Value		Turnover*	
	1992	1993	1992	1993
NYSE	3 798	4 221	1 745	2 283
London	928	1 199	663	857
SSE	78	107	29	43

* Turnover figures are converted into USD at month-end exchange rates

12 References include Kawaller, Koch and Koch (1987, 1990), Stephan and Whaley (1990), Stoll and Whaley (1990), Varson and Selby (1991), Chan (1992), Chan, Chung and Johnson (1993), Grünbichler, Longstaff and Schwartz (1994), Booth, Broussard and Loistl (1994), Abhyankar (1994) and Shyy and Vijayraghavan (1994).

13 See Diamond and Verrecchia (1987) for a discussion of the consequences of short selling restrictions.

14 The market value and turnover statistics have been obtained from the FIBV statistics (1993).

The OMX index is a value-weighted index based on the 30 most traded stocks at the SSE. The derivatives on the OMX index[15] are traded at the options and forwards exchange, OM. The options on the OMX index are highly liquid. In contrast, the index forward market in Sweden is limited. Table 2 gives an idea of the size of index derivative trading at OM in 1993, compared to the US and UK trading volumes.[16]

Table 2

The Size of OM Stockholm's Index Derivative Trading (1993)

	Number of Contracts (1 000)				Notional Value (1 000 000 000)			
	Options		Futures/Forwards		Options		Futures/Forwards	
U.S.A.	87 443	(1)*	14 386	(1)	4 199	(1)	3 127	(1)
United Kingdom	3 439	(7)	3 120	(7)	151	(5)	342	(6)
OM	4 073	(6)	628	(12)	44	(10)	7	(13)

* Numbers in parenthesis refer to world ranking.

In order to understand the characteristics of the data, some aspects of the trading structures at the SSE[17] and OM[18] must be taken into account. The two trading systems are very similar. Both are highly transparent and based on a computerized open limit order book (OLOB).[19] It is a computer file registering the price and volume of all limit orders. Thus, liquidity is provided by the outstanding limit orders of other traders.[20] All orders are firm. Matching is *automatic* and fully computerized within the OLOB.[21] Therefore, all trades will take place either at the bid or ask level. There is no trading between the quotes such as on the NYSE. The tick size for individual stocks at the SSE is rather important, ranging from one half to one-and-a-half per cent at the most common stock price ranges.[22] Even if most of the tick size effect will be smoothed in an

15 The traded derivative contracts on the OMX index are call and put options and forward contracts.

16 The data have been obtained from the FIBV statistics (1993).

17 The trading system at the SSE is described in some detail in Niemeyer and Sandås (1993) (Essay 1 in this dissertation).

18 The trading system at OM is described in some detail in Niemeyer (1994) (Essay 2 in this dissertation).

19 There are a few differences between the OLOB:s at the Stockholm Stock Exchange and OM. At the SSE but not at OM, the identity of the dealers is presented (i.e., it is not anonymous). On the other hand at the SSE you cannot, but at OM you can, see the size of the individual orders. At the SSE all limit orders at the same price are consolidated and only the aggregated volume shown. To make the distinction, the OLOB at the SSE is normally referred to as a consolidated open limit order book or COLOB. Furthermore, at OM the dealer can see all limit orders, while at the SSE only the orders at the five best bid and ask prices respectively are shown.

20 At OM, there is a market making system, where some dealers have the obligation to post both bid and ask quotes, within the automatic system, and in return get a lower fee on transactions on their own account.

21 On both exchanges, there is also a possibility to match manually, off-the-exchange and within five minutes report the trade to the exchange.

22 The tick size is sometimes referred to as the minimum price variation. For an analysis of the importance of the tick size on the Stockholm Stock Exchange see Niemeyer and Sandås (1994) (Essay 3 in this dissertation). During 1994, after the end of the sample period, the tick size at the SSE has been reduced.

index, it is still possible that an index calculated from bid (ask) prices could have quite different statistical properties than an index calculated from transaction prices, due to the tick size effect. At OM the tick sizes are less important.

The list of stocks included in the OMX index is revised every six months. The index is calculated every minute, on the minute, by an independent company Dextel Findata AB. The only index transmitted to the dealers is based on transaction prices of the underlying stocks. Dextel Findata AB also calculates index-series based on ask and bid prices respectively.

The trading at the SSE starts with a sequential call auction. As a consequence, the trading is not opened simultaneously in all stocks. Before all stocks are opened, the OMX index therefore includes some prices from the previous trading day. Only when trading in all stocks has started, will the OMX index incorporate all new information. The trading hours at the SSE used to be from 10 a.m. to 2:30 p.m. On April 1, 1993, the trading hours were extended to 4 p.m. The trading hours at the OM are between 10 a.m. and 4 p.m.

One specific feature of the trading system at OM is the possibility to submit combination orders. Submitting a combination order, a dealer offers to buy (sell) two or more different types of contracts on the same underlying claim. Combination orders can be handled either manually or electronically. Only certain standardized combination orders can be traded within the automatic system. Presently, there are three types of standardized combination orders, "price spreads", "time spreads" and "synthetic forwards". Since all index options are standardized European style options, it is easy to construct a synthetic forward.

A standardized combination order is quoted as the net price of the two options and can be seen as a combination of on one hand a limit order and on the other hand a market order conditional on the limit order. Thereby, trading is simultaneous in all options constituting the combination order and the probability of getting both legs of the combination matched at the very same moment in time equals one. A trader using a standardized combination order will therefore not be subject to any additional execution risk. The fact that the trading in synthetic forwards is institutionalized and fully computerized, can be used as an argument for also using synthetic forwards when the real forward contracts are traded infrequently.

4 Methodological Issues

There are in principle two different ways to estimate a lead-lag relationship. The most common way, put forward by Sims (1972), is to estimate a model of the form:[23]

$$i_t = z + \sum_{k=-n}^{n} a_k f_{t+k} + e_t \tag{4}$$

where n is the number of lags in the regression model.

In principle, Sims showed that if *all* the a_k-coefficients are *in*significant and some of the a_{-k}-coefficients are significant, we can conclude that forwards lead the cash index. If some of the a_k-coefficients are significant and *all* the a_{-k}-coefficients are *in*significant, the cash index can be said to lead the forwards. If coefficients on both sides are significant, there is a feedback relation. Furthermore, it might be interesting to investigate the number of significant leading and lagging coefficients to see if the forwards lead the cash index *more* than the other way around. The joint test of the null hypothesis that all the a_k-coefficients (a_{-k}-coefficients) in equation (4), are equal to zero can be achieved by calculating an F-statistic from the restricted and unrestricted versions of each regression. Correcting for heteroskedasticity with the White (1980) asymptotically heteroskedasticity consistent covariance matrix, we instead get a χ^2-statistic.

The second way, proposed by Granger (1969), is to test for Granger causality with an equation model of the following form:[24]

$$i_t = z_1 + \sum_{k=1}^{n} a_{-k}\, i_{t-k} + \sum_{k=1}^{n} b_{-k} f_{t-k} + e_{1t} \tag{5a}$$

$$f_t = z_2 + \sum_{k=1}^{n} c_{-k}\, i_{t-k} + \sum_{k=1}^{n} d_{-k} f_{t-k} + e_{2t} \tag{5b}$$

In this formulation, the interesting coefficients are the b_{-k} and the c_{-k}-coefficients. If we can reject the joint hypothesis that *all* the b_{-k}:s equal zero, the forwards are said to

[23] References include Stephan and Whaley (1990), Stoll and Whaley (1990), Chan (1992), Chan, Chung and Johnson (1993), Grünbichler, Longstaff and Schwartz (1994) and Abhyankar (1994).

[24] See Kawaller, Koch and Koch (1987), Booth, Broussard and Loistl (1994) and Shyy and Vijayraghavan (1994). There is some debate whether f_t in equation (5a) and i_t in equation (5b) should be included as explanatory variables. Koch (1993) argues that they should, since the omission of the contemporaneous variables may lead to biased results and inaccurate conclusions. On the other hand, Granger (1988) argues that no contemporaneous variables should be included if the aim is really to focus on Granger causality. In the Granger formulation in this essay, we have therefore decided to only use lagged variables.

Granger-cause the cash index. On the other hand, if we can reject the joint hypothesis that *all* the c_{-k}:s are zero, the cash index Granger-causes the forwards. Once again, the appropriate test-statistic is a χ^2-test.

Before performing a test, an appropriate significance level should be chosen. Lindley (1957) argues that the significance should be kept low when the sample size is large. Therefore, and following earlier lead-lag studies,[25] this study uses the 0.1 per cent significance level. In addition, we report the results with the 0.01 per cent significance level.

The Sims formulation is a practical test of unidirectional causality. Sims also gives an interpretation of the actual sizes of the coefficients. If the leading coefficients are insignificant and the lagging coefficients are significant, bidirectional causality may still be very important in practice if the former are larger than the latter. A Sims test makes it easier to compare our results to those of earlier studies. However, in principle, the Sims formulation implies trying to explain todays index return with tomorrows forward return. Therefore, the Granger formulation is econometrically more appealing. Furthermore, if the index returns in equation (4) are serially correlated statistical problems might appear. Geweke, Meese and Dent (1983) have shown that the sampling distributions of tests *with* lagged dependent variables (i.e., Granger tests) are better than those of the tests *without* lagged dependent variables (i.e., Sims tests).

As mentioned in section 2, since our observed returns are noisy signals of the "true" returns, there are several aspects to consider when empirically testing any lead-lag structure between different financial markets. First of all, the bid/ask spread has several effects. The cash index based on transaction prices can be influenced by the bid/ask spread if stock movements are correlated. This might be important in a narrow index such as the OMX index, where the tick size for the component stocks is comparatively large.[26] Therefore, using transaction prices, we might get a bias that the cash index lags the forwards. One way to circumvent the problem of the bid/ask spread is to use the average of the bid and ask quotes, which we term the "spread index". However, the problem is really a problem of discreteness. If the tick size is rather important, the discreteness also affects the quotes, and thus their average. Still, a return series calculated on the spread index *might* be faster in incorporating new information than a series calculated on transaction prices.[27]

---

[25] See Chan (1992) and Booth, Broussard and Loistl (1994).

[26] See section 3.

[27] See Chan, Chung and Johnson (1993).

Furthermore, the bid/ask bounce on the forwards might influence the forward returns. This could result in a bias that the cash index leads the forwards. Unfortunately, we do not have access to data of the quotes on the forward, so in this essay only the transaction prices of the derivatives are used. Potentially, the problem with the bid/ask bounce is even more severe for the synthetic forward since it is based on two option prices, both with bid/ask spreads. Furthermore, it is far from sure that the spread is limited to one tick.

By infrequent trading, we mean the problem arising from the fact that not all securities are traded in every interval. Thus, the infrequent trading problem is dependent on the measured interval length. If some component stocks in the index trade less frequently than every interval (which is the case with some of the stocks in the OMX index), there will be a problem of infrequent trading. The result is that the cash index based on transaction prices will not incorporate all information in all intervals. The effect on the index of the stocks not traded will only appear when they are actually traded. This will induce a bias that the observed cash index lags the forwards.

One way to circumvent the problem of infrequent trading is to use the spread index, since it is likely to incorporate new information faster, even if there is no trading. Another way, suggested by Stoll and Whaley (1990), to cope with the problem of both the bid/ask spread and the infrequent trading is to use a pre-filter. Following a number of previous lead-lag studies,[28] we first use an ARMA(p,q)-model to estimate the effect of infrequent trading and the bid/ask spread.

$$i_t = \gamma + \sum_{j=1}^{p} \phi_j \, i_{t-j} + \sum_{k=1}^{q} \theta_k \, e_{t-k} + e_t \tag{6}$$

The return innovations are calculated as the deviations from this estimated ARMA(p,q)-model (i.e., the e_t:s). These return innovations are then used as instruments for the "true" cash index returns. The equation to be estimated is then:

$$e_t = z + \sum_{k=-n}^{n} a_k \, f_{t+k} + \eta_t \tag{7}$$

where e_t is the return innovation on the index (i.e., the residual from the ARMA-model).

[28] See Stephan and Whaley (1990), Stoll and Whaley (1990), Chan (1992), Grünbichler, Longstaff and Schwartz (1994) and Abhyankar (1994).

Furthermore, if the forwards are not traded every interval, the these returns will also be calculated with stale prices. The result is likely to be that the observed forward returns lag the index.

A possible third methodological problem, is that the actual computation and reporting of stock index values is systematically delayed. This should not be an important problem on the Swedish market since stock trading is fully automated and quotes and transaction prices are instantaneously and electronically transmitted to the market participants.

A fourth problem concerns non-synchronous trading. It arises since the forward transactions need not have taken place at the very same instant as the index was measured, even if the forwards are traded every interval. The OMX index is calculated every minute, and if we measure the lead-lag structure on five minute intervals, using the last forward transaction per interval, this transaction might have taken place very early in the interval while the index is always measured at the end. This effect of stale prices is likely to induce a bias that cash index leads the forwards rather than the other way around.

The problem of non-synchronous trading is even more evident for synthetic forwards. For these, we assume that both legs of the forward are traded within the same interval. Furthermore, we still assume they are traded at the end of each period, i.e. at the same time the index is calculated.

Short selling restrictions have been abolished in Sweden. Presently, there is a well-functioning market for stock loans why the short selling dilemma is not likely to be a major problem in this essay.

Transaction costs will limit the arbitrage opportunities and will therefore have an impact on the lead-lag structure between the forwards and the index. However, the exact impact of transaction costs is difficult to gauge. The average intraday bid/ask spread on the OMX-index ranges between 0.8 and 1.6 per cent.[29] An additional 0.2 per cent in spread cost on the forward leg is probably reasonable. Assuming early closing of the arbitrage position, the full spread cost would have to be paid in both markets. However, arbitrage opportunities will differ across traders due to differences in direct transaction fees.[30]

[29] See Niemeyer and Sandås (1993) (Essay 1 in this dissertation).

[30] Nordén (1994), investigating index arbitrage profitability in Sweden in 1993, reports frequent violations of the cost-of-carry model. However, he claims that arbitrage signals are risky, and on average give rise to *negative* realized profits partly due to the execution lags. This indicates a quick adjustment between the two return series. Nordén also puts forward another reason for the risk in index arbitrage. Since the OMX index is settled in cash at the *average* value of the index during the last day of trading in the forward contract, a replicating strategy will not necessarily be able to use

Internationally, the spread cost in Sweden is quite high. For the S&P 500 index in the U.S., Sofianos (1993) has estimated the sum of the cash and futures spread components of transaction costs to 0.2 per cent, and zero for the direct transaction costs.

Since it is impossible to trade in the stock index in one transaction, the index derivative markets provide, in a sense, higher immediacy to investors than the cash index.[31] Especially informed traders are therefore likely to trade in the forward market rather than in the cash market, at least if the information pertains to the entire market. On the other hand, Subrahmanyam (1991) demonstrates that *un*informed traders benefit from trading in the forward markets since the adverse selection costs typically are lower in these markets. This result rests largely on the assumption that traders with firm-specific information will tend to trade in the stock or stock derivative markets rather than in the index derivative market. In any case, there is some evidence that market wide information produces a lead-lag relation from the index derivative market to the cash market, with the possibility of an aggregation of firm-specific information inducing a lead from the cash to the index derivatives.[32]

5 The Data Set

This essay uses data between December 1, 1991, and September 30, 1993 from the Swedish market. There are two data sets. The first consists of three different OMX indices, using bid, ask and transaction prices respectively, obtained directly from Dextel Findata AB. All indices are calculated every minute during the trading day. The second data set consists of all transactions on forward and options on the OMX index for the same period. These data have been supplied directly by OM.

A proper analysis should take the interest rate component of equations (1) and (3) into account. Unfortunately, only daily interest rate data were available. For the traded forward contracts, they are completely useless. However, for the synthetic forwards an adjustment is not entirely fruitless, since the interest rate does not affect the exercise price component. With highly volatile interest rates in the studied period,[33] a correction using daily observations on the one month STIBOR[34] was deemed appropriate. However, the effect of this adjustment is minimal and regression coefficients only changed to the fourth decimal.

---

exactly these *average* prices.

[31] See Grossman and Miller (1988).

[32] See Chan (1992).

[33] Due to exchange rate uncertainties, the one month STIBOR varied from 8.05 to 70.00 per cent (annualized) in the studied period.

[34] STIBOR is the STockholm InterBank Offered Rate.

We divide the sample into three time periods, December 1991 to July 1992 (8 months), August 1992 to March 1993 (8 months), and April 1993 to September 1993 (6 months). In each time period, we look for any lead-lag structure measuring the returns on three different intervals, five, ten, and fifteen minute returns. In addition, for every time period and interval length, we measure the cash index in two different ways, using transaction prices and using the midquotes. In the OM data set, only the contracts closest to maturity have been used.[35]

The last transaction prices/quotes of each price series are used in each interval (five, ten or fifteen minutes). Returns are calculated by taking the first difference of the natural logarithm of each price/quote. If the forward contract has not been traded in one interval, we record a zero return. No overnight returns are included since they span a different return interval and since the focus of the essay is on the *intraday* lead-lag structure. Furthermore, due to the sequential opening procedure at the SSE, all observations from the first 15 minutes every trading day are omitted. Thus, the first return is calculated from 10:15 to 10:20, from 10:20 to 10:30, and from 10:15 to 10:30, for the five, ten and fifteen minute intervals respectively. Only returns from the *same* day are used in the regressions.[36] Thereby, each day is a separate subsample.

In the regressions using synthetic forwards, we have created a synthetic forward only if *both* the call and the put where traded that interval. To be conservative, if only one of them (or none) was traded, a zero return is recorded. In order to minimize the impact of the constant interest rate assumption, all synthetic forwards during one day have the same exercise price. We have selected the exercise price with the most liquid synthetic forward.

All data from 38 different days were excluded from the sample due to incomplete data or computer problems at the Stock Exchange or Dextel Findata AB. A list of the excluded days can be found in Appendix 1. We therefore have a remaining 154, 144 and 121 trading days in the three time periods respectively.

[35] The OMX derivative contracts expire each month on the fourth Friday. Trading stops the previous trading day. We switch to the new contract on the previous trading day in order to avoid any expiration day effects.

[36] This implies in the Granger formulation with five lags and five minute intervals, that the first estimated return is from 10:40 to 10:45 since this is the first return with at least five previous returns the same day.

6 Empirical Findings

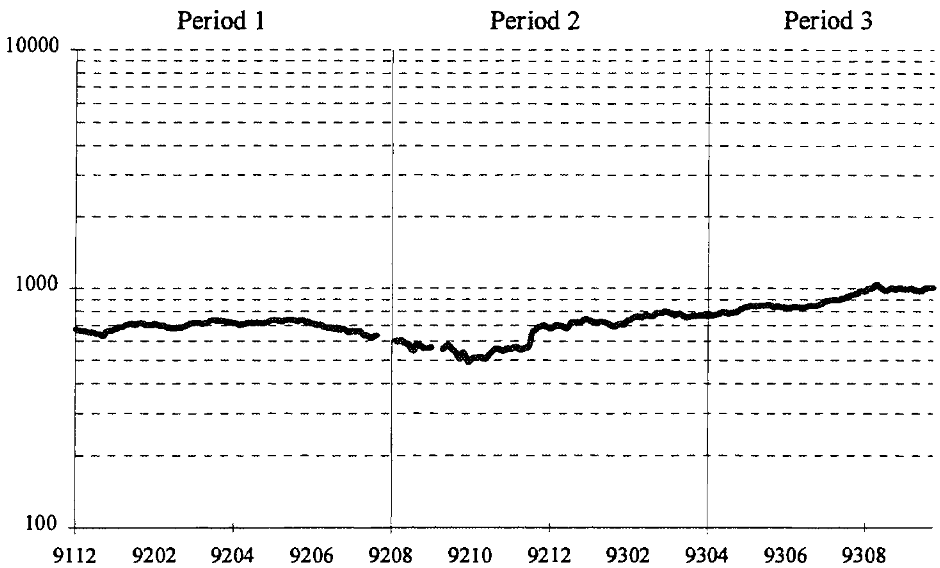
6.1 Descriptive Statistics

The purpose of this study is to examine the lead-lag structure in returns between the cash OMX index and the traded forward contracts and synthetic forwards on that index.

Since the data set has not been used earlier, we start by presenting some descriptive statistics. The development of the OMX cash index measured from transaction prices during the three periods is described in Figure 1.

Figure 1

OMX Index (December 1991 - September 1993)



We also calculate the daily standard deviation of the logarithmic returns (based on transaction prices), to get an idea of the variability of the cash index. Table 3 lists some descriptive statistics of these daily standard deviations of returns. In period 1, the standard deviations range from 0.042 to 0.284 per cent, with an average of 0.080 and a standard deviation of 0.036 per cent across days. Clearly, the second period has a higher volatility than the other two periods.

Table 3

Statistics of the Daily Standard Deviation of Five Minute Returns per Period

Period	Minimum	Average	Maximum	Std. Deviation
1	0.00042	0.00080	0.00284	0.00036
2	0.00056	0.00140	0.00875	0.00110
3	0.00045	0.00103	0.00277	0.00036

Since the Swedish market is comparatively small, the problem of infrequent trading might be serious. In Table 4, we record the number of intervals with trading in the derivative market. The infrequent trading problem is indeed severe. During the second period, forwards were not traded in 46 per cent of the total number (7,308) of five-minute intervals. Surprisingly in the first period, it is possible to construct synthetic forwards in more intervals than there was trading in the actual forward contract. In the later periods, the liquidity of the forward contract increased, compared to the synthetic forwards.

Table 4
The Number Intervals without Derivatives Trading per Period

	5-Minute Intervals			10-Minute Intervals			15-Minute Intervals		
Period	Total	Forw.	Synt.	Total	Forw.	Synt.	Total	Forw.	Synt.
1	7,818	73%	52%	3,832	57%	26%	2,606	44%	14%
2	7,308	46%	55%	3,582	26%	32%	2,436	16%	21%
3	8,277	58%	66%	4,078	39%	46%	2,759	29%	33%

Table 5 further emphasizes the infrequent trading problem. It lists the number of intervals without derivative trading following non-trading intervals. During the second period, forwards were not traded in two consecutive five minute intervals in 26 per cent of all observations. The results from the five minute intervals should therefore be interpreted cautiously. The consequence of the infrequent trading is an errors in variables problem. However, this problem is less severe for the ten and fifteen minute intervals.

Table 5
The Number Successive Intervals without Derivatives Trading per Period

	5-Minute Intervals			10-Minute Intervals			15-Minute Intervals		
Period	Total	Forw.	Synt.	Total	Forw.	Synt.	Total	Forw.	Synt.
1	7818	55%	31%	3832	34%	11%	2606	22%	4%
2	7308	26%	37%	3582	10%	16%	2436	5%	9%
3	8277	39%	50%	4078	21%	27%	2759	13%	17%

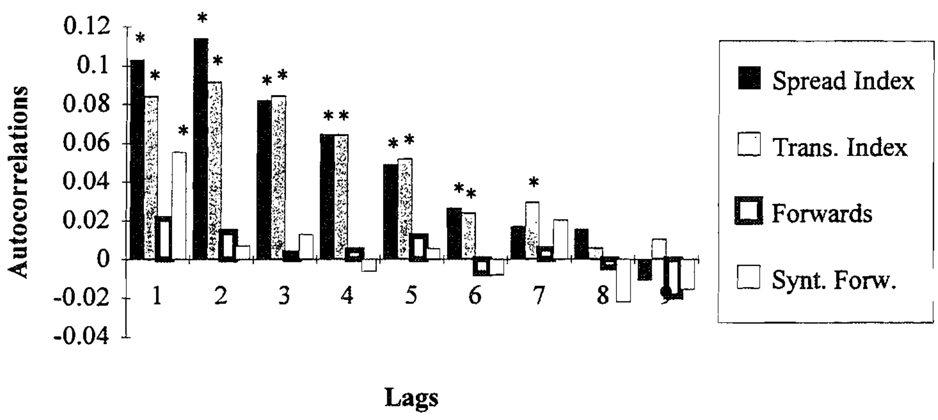
If the forward or synthetic forward is not traded in one interval, there is in a sense nothing to explain. In order to limit the impact of the errors in variables, we therefore modify equation (5b) in the following manner:

$$f_t = \delta_t \left[z_2 + \sum_{k=1}^{n} c_k \, i_{t-k} + \sum_{k=1}^{n} d_k f_{t-k} + e_{2t} \right] \tag{5c}$$

where δ_t=0 when the forward or synthetic forward is not traded in time interval t. Thereby, the number of observations is reduced. However, keeping the non-trading observations makes the variables clearly non-normal and induces extreme kurtosis in the error terms.

In any empirical lead-lag study, one important decision is how many leads/lags to include. To get an idea, the autocorrelations of the different variables can be calculated. Figure 2 plots the autocorrelation for the different return series.

Figure 2
Autocorrelations of Five Minute Returns
(December 1991 - September 1993)



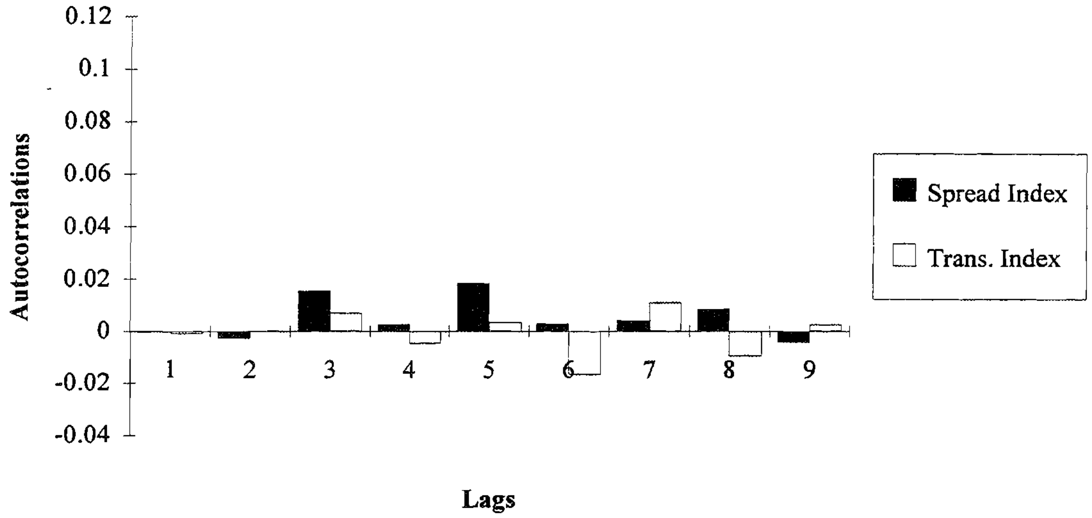
The cash indices have positive and comparatively long autocorrelations, probably due to the problem of infrequent trading. In contrast, the derivative returns have only one or no significant autocorrelation. For the cash index the autocorrelations are significant[37] (marked with an *) until about lag five. The autocorrelations calculated from the ten and fifteen minute returns (not shown) are very similar, with the exception that the number of significant autocorrelations for the cash indices is lower.

Figure 2 also clearly demonstrates the effects of the bid/ask bounce and infrequent trading problem within the stock indices. The combined effect is a long lag-structure with a number of significant autocorrelations. In order to acquire an estimate of the "true" returns and to control for the bid/ask bounce and infrequent trading problem, the indices have been filtered with an ARMA-process to obtain the return innovations. An

[37] The significance level used here is 0.1 per cent.

ARMA(2,0) and an ARMA(1,1) have been applied to the spread index and transaction index respectively. These processes efficiently purged the effect of the infrequent trading and the bid/ask spread bounce on the returns. The remaining non-significant autocorrelations are plotted in Figure 3.

Figure 3
Autocorrelations of Five Minute Return Innovations
(December 1991 - September 1993)



6.2 Empirical Results

The regression results in this essay are rather voluminous. We therefore focus on the case where returns are measured on 15 minute intervals and where the infrequent trading problem is less critical. Table 6 summarizes the χ^2-tests.[38] The equivalent summary tables for the five and ten minute cases can be found in Appendix 2. Tables 7 and 8 report the number of significant leading and lagging coefficients in the Sims regressions using raw returns and return innovations respectively. The entire results from all regressions are tabled in Appendix 3.

Table 6 lists the χ^2-statistics for the joint lead-lag tests following equations (4) and (5). We test two hypotheses. The first null hypothesis is that the (synthetic) index forwards do not lead the cash index (i.e., *f/s* $\nRightarrow$ *i*). In the Granger case, this amounts to a test of Granger causality. If the hypothesis is rejected, the cash index returns could partly be explained by lagged forward returns. To put it differently, it would indicate that forwards are leading the cash index. The second null hypothesis is that the cash index does not lead (or Granger cause) the (synthetic) index forwards (i.e., *i* $\nRightarrow$ *f/s*). In the case

[38] All χ^2- and t-statistics in this essay are all calculated with the White (1980) asymptotically heteroskedasticity consistent covariance matrix.

of rejection, we would be able to conclude that the index leads the forwards.

Table 6
Summary of Lead-Lag χ^2-tests, 15 Minute Returns

	Period 1		**Period 2**		**Period 3**	
	$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$
Granger						
Forw. Spr. Ind.	20.60 *	142.35 **	24.03 *	87.29 **	17.92	104.03 **
Forw. Tra. Ind.	33.89 **	167.39 **	45.12 **	79.02 **	46.42 **	125.39 **
Synt. Spr. Ind.	28.41 **	97.52 **	29.69 **	67.64 **	30.32 **	75.05 **
Synt. Tra. Ind.	76.29 **	70.23 **	52.91 **	48.18 **	56.62 **	87.76 **
Sims						
Forw. Spr. Ind.	25.11 *	106.42 **	87.61 **	37.91 **	24.37 *	67.67 **
Forw. Tra. Ind.	26.14 **	118.94 **	118.58 **	27.49 **	65.89 **	87.90 **
Synt. Spr. Ind.	52.13 **	65.95 **	117.03 **	59.82 **	33.41 **	46.02 **
Synt. Tra. Ind.	100.33 **	27.33 **	166.31 **	26.56 **	94.41 **	57.08 **
Sims, Return Innov.						
Forw. Spr. Ind.	20.13	102.51 **	58.75 **	38.10 **	12.35	63.16 **
Forw. Tra. Ind.	5.83	97.91 **	56.69 **	27.93 **	26.40 **	83.45 **
Synt. Spr. Ind.	42.98 **	64.43 **	75.64 **	58.68 **	19.23	41.20 **
Synt. Tra. Ind.	30.90 **	24.20 *	84.62 **	24.92 *	44.16 **	51.73 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

In virtually all cases, we reject both the hypotheses of no lead from forwards to cash *and* of no lead from cash to forward. In the Granger case using traded forwards and the spread index, the forwards lead the cash index, since with the significant χ^2-statistic of 20.60 we can reject the null of no Granger causality. Similarly, from the same data set we can reject the null of no Granger causality from the cash index to the forwards since the χ^2-statistic is significant at 142.35. To put it differently, we find that the (synthetic) forwards lead the cash index *as well as* that the cash index leads the (synthetic) forwards. This result holds regardless of if we use the spread cash index or the transaction cash index, if we use traded or synthetic forward or if we measure returns in five, ten or fifteen minute intervals. Furthermore, it holds for all subperiods. Thus, in contrast to earlier studies, the Swedish data reveal a high degree of interdependence between the index forwards returns and the cash index returns.

In only *one* case does the Granger-test indicate a unidirectional Granger causality. In period 3, the spread index leads the traded forwards while the converse is not true. Using the return innovations in period 1 and 3, again the spread index leads the forwards, while the opposite is not true. This time, the unidirectional Granger causality also holds for the synthetic forwards. Thus, contrary to all previous studies, in some cases we find evidence of the combination that the cash index (measured from quoted prices) leads the forwards, *and* that the forward returns do not lead the cash index. However, the main conclusion is that there exists an extensive feedback between the two return series. In the more volatile second period, the bi-directional interdependence is overwhelmingly evident.

Having established the high degree of interdependence between the cash index returns and the index forward returns, the Sims test can also be used to estimate the number of significant time intervals in order to assess if the first return series leads the second more than the second the first. Tables 7 and 8 summarizes the number of significant coefficients in the Sims regressions using returns and returns innovations respectively.

Table 7

Summary of Number of Significant* Lead-Lag Coefficients, Returns

		Period 1		Period 2		Period 3	
		Lags	Leads	Lags	Leads	Lags	Leads
5-Min. Returns							
Forw.	Spr. Ind.	-4	5	-5	2	-2	2
Forw.	Tra. Ind.	-5	5	-5	2	-4	2
Synt.	Spr. Ind.	-4	4	-5	2	-3	3
Synt.	Tra. Ind.	-5	3	-5	2	-3	3
10-Min. Returns							
Forw.	Spr. Ind.	-2	3	-3	1	-2	1
Forw.	Tra. Ind.	-2	2	-4	1	-2	1
Synt.	Spr. Ind.	-2	2	-3	1	-2	1
Synt.	Tra. Ind.	-4	1	-4	1	-2	1
15-Min. Returns							
Forw.	Spr. Ind.	-1	1	-2	1	-1	1
Forw.	Tra. Ind.	0	1	-2	1	-1	1
Synt.	Spr. Ind.	-2	1	-2	1	-1	1
Synt.	Tra. Ind.	-2	1	-3	1	-1	1

* A significance 0.1 per cent is used in this table.

In Tables 7 and 8, several both leading and lagging coefficients are significant in almost all time periods, regardless of measurement interval and type of cash index used. Furthermore, it is quite clear from Tables 7 and 8 that, in the second more volatile period, the lead from forwards (lag-coefficients) to the cash index extends for between twenty and thirty minutes. In the other two periods, the lead from forwards to the cash index is shorter, about fifteen to twenty minutes. On the other hand, the lead from the cash index to the forwards (lead-coefficients) is more limited and extends only to between ten and fifteen minutes. As expected, the number of significant coefficients falls when then return innovations, rather than the raw returns, are used.

Table 8
Summary of Number of Significant* Lead-Lag Coefficients, Return Innovations

		Period 1		Period 2		Period 3	
		Lags	Leads	Lags	Leads	Lags	Leads
5-Min. Return Innov.							
Forw.	Spr. Ind.	-3	4	-3	2	-2	2
Forw.	Tra. Ind.	0	4	-3	2	-1	2
Synt.	Spr. Ind.	-3	3	-4	2	-2	3
Synt.	Tra. Ind.	-2	3	-4	2	-2	3
10-Min. Return Innov.							
Forw.	Spr. Ind.	-2	3	-2	1	-1	1
Forw.	Tra. Ind.	-1	2	-2	1	-1	1
Synt.	Spr. Ind.	-2	2	-3	1	-2	1
Synt.	Tra. Ind.	-1	1	-2	1	-2	1
15-Min. Return Innov.							
Forw.	Spr. Ind.	-1	1	-1	1	0	1
Forw.	Tra. Ind.	0	1	-1	1	-1	1
Synt.	Spr. Ind.	-2	1	-2	1	-1	1
Synt.	Tra. Ind.	-1	1	-2	1	-1	1

* A significance 0.1 per cent is used in this table.

Our results confirm the findings in earlier empirical work that the derivative markets tend to lead the cash market rather than the other way around.[39] One difference with earlier studies is the comparatively long lead *from* the cash index *to* the forwards. Most earlier studies report that the cash index leads the forwards with at the most five minutes.

The longer lead from forwards to the cash index in the more volatile period is in accordance with the findings in Abhyankar (1994) who report the lead of forwards over the cash index to be more pronounced in more volatile periods. On the other hand and contrary to our results, Kawaller, Koch and Koch (1993) conclude that fewer lags become significant as volatility increases.

Furthermore, Table 7 unveils another interesting feature. Using the spread index, there are generally fewer significant lagging coefficients than when the index based on transaction prices is used. The conclusion in Shyy and Vijayraghavan (1994) that an index based on quotes, rather than on transaction prices, will be faster in incorporating new information therefore receives some support in our results.

A closer study of the Tables in Appendix 3 reveals another surprising regularity. In the Sims regressions, the first lagging coefficient is considerably larger than the first leading

[39] References include Stephan and Whaley (1990), Chan (1992), Grünbichler, Longstaff and Schwartz (1994) and Abhyankar (1994).

coefficient in almost all cases. This further emphasizes the conclusion of a highly significant bidirectional interdependences, since it indicates a significant feedback from the cash index (both measured as the spread index and transaction index) to the forwards.

A striking characteristic in Tables 7 and 8 is also that there are fewer significant coefficients in period 3 compared to earlier periods. One possible interpretation is that the market is maturing and incorporates new information faster in this period than in earlier periods.

Tables 6, 7 and 8 also demonstrates that the synthetic forwards are good substitutes for the traded forwards. Our results are largely *in*dependent on whether traded or synthetic forwards are used. Whether this also holds in a market structure without the facility of automatic trading in both legs of a synthetic forward, remains an open question for further research.

7 Summary and Conclusion

This essay investigates the lead-lag structure between the returns on the cash index market and the returns on the index forwards and synthetic index forwards in Sweden. The main conclusion is that the lead-lag structure between the OMX cash index and the OMX forwards is highly bidirectional. Coefficients are significant for a considerable number of both leads and lags.

With the Granger causality test, we are not able to say more than that there is a high degree of bidirectional interdependence between the forward returns and the cash index. With only a few exceptions, both series seem to Granger cause each other. Using the Sims tests, our results indicate that the forwards lead the cash index with between fifteen and thirty minutes while the cash index leads the forwards with a shorter ten to fifteen minutes. It is therefore possible to say that the forwards lead the cash index more than the other way around. This result is in accordance with earlier empirical results, although our results show a longer lead from cash index to forwards than earlier studies.

Another conclusion to be drawn from this essay is that it does not really matter if one uses the traded forwards or the synthetic forwards. A third conclusion is that in the more volatile period, the number of significant lagging forward coefficients increases. It indicates that the lead from forwards to the cash index is extended as volatility increases.

A fourth conclusion is that the bid/ask spread effect of an index could be important. Although the relation is does not hold systematically over the periods, we report that the cash spread index sometimes leads the forwards without the forwards leading the spread index. This reinforces the conclusion of Shyy and Vijayraghavan (1994) that the lead-lag relation might be different when quoted prices instead of traded prices are used. In contrast to their paper, we only have access to quoted prices from the cash market. An interesting extension would be to test the lead-lag relation using quoted prices also from the forward market.

However, our main conclusion is the long and significant bidirectional interdependence between the returns on the cash index and the forwards. There might be several reasons why our results diverge from empirical findings in earlier studies using data from other markets. First of all, the transaction costs are likely to be higher in Sweden than on more liquid markets, such as in the US. This will inhibit an efficient arbitrage, and thereby reduce the force which drives the prices together. In that sense, our results are an indication of less well functioning index markets in Sweden.

Secondly, we use the quotes on the index to construct a spread index. Preliminary results from the French markets (i.e., Shyy and Vijayraghavan (1994)) indicate a bidirectional lead-lag structure when quotes are used instead of transaction prices. However, we find similar lead-lag structure also when the transaction prices are used.

Furthermore, although hardly any other lead-lag study reports any details on the infrequent trading problem, it is likely to be more important in this essay than in previous studies. The lower liquidity of the Swedish market with a resulting high non-trading frequency could seriously affect the results. The comparatively low liquidity of the Swedish forward market implies that the observed forward prices to a large extent are stale. With stale forward prices, the cash index returns will probably be able to significantly explain subsequent forward returns. On the other hand, if the true forward returns really lead the true cash index returns, as previous studies have indicated, the *observed* forward returns are likely to lead the cash index, when the forwards actually trade. The consequence could easily be a significant bidirectional interdependence.

Finally, it is possible that the lead-lag structure indeed is different in Sweden. Unlike any other investigated country, investors trade in a computerized and centralized limit order market environment, with full ex ante transparency in both the cash and the forward markets in Sweden. Previous studies have concluded that the forwards lead the cash index rather than the opposite. In all cases (except the French case), the stocks have been traded in an open outcry floor trading system. Since we report a significant and long bidirectional interdependence with Granger causality in both directions, our results could be interpreted as support for the claim that a centralized automatic trading environment enhances price discovery. The possible effect of different trading structures on the lead-lag relationship between the cash and derivative markets definitely merits further research.

References

Abhyankar, A. H., (1994), "Return and Volatility Dynamics in the FT-SE 100 Stock Index and Stock Index Futures Markets", WP, University of Stirling, July 1994.

Booth, G. G., J. P. Broussard and O. Loistl, (1994), "Do Electronic Trading Systems Completely Dominate Floor Trading Systems In Information Processing Capability? - Evidence from Germany's Spot and Stock Index Futures Markets", WP, Louisiana State University, April 1994.

Chan, K., (1992), "A Further Analysis of the Lead-Lag Relationship between the Cash Market and Stock Index Futures Market", *Review of Financial Studies*, 5, 123-151.

Chan, K., K. C. Chan, and G. A. Karolyi, (1991), "Intraday Volatility in the Stock Index and Stock Index Futures Markets", *Review of Financial Studies*, 4, 657-684.

Chan, K., Y. P. Chung and H. Johnson, (1993), "Why Option Prices Lag Stock Prices: A Trading-based Explanation", *Journal of Finance*, 48, 1957-1967.

Diamond, D. W. and R. E. Verrechia, (1987), "Constraints on Short-Selling and Asset Price Adjustment to Private Information", *Journal of Financial Economics*, 18, 277-311.

Easley, D., M. O'Hara and P. S. Srinivas, (1993), "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade", Working Paper, Cornell University, October 1993.

Elmhammer, N. and J. Trocmé, (1993), "Tidssambandet mellan prisändringar på termins- och avistamarknaden för OMX-index; Viftar svansen på hunden eller tvärtom?", Masters Thesis, Stockholm School of Economics, September 1993. (In Swedish only).

FIBV Statistics, (1993), Statistical Supplement to the Fédération Internationale des Bourses de Valeurs, Annual Report 1993, Paris.

Geweke, J., R. Meese and W. Dent, (1983), "Comparing Alternative Tests of Causality in Temporal Systems: Analytical Results and Experimental Evidence", *Journal of Econometrics*, 21, 161-194.

Granger, C. W. J., (1969), "Investigating the Causal Relationship by Econometric Models and Cross-Spectral Methods", *Econometrica*, 37, 424-438.

Granger, C. W. J., (1988), "Some Recent Developments in a Concept of Causality", *Journal of Econometrics*, 39, 199-211.

Grossman, S. J., (1988), "An Analysis of the Implications for the Stock and Futures Price Volatility of Program Trading and Dynamic Hedging Strategies", *Journal of Business* 61, 275-298.

Grossman, S. J. and M. H. Miller, (1988), "Liquidity and Market Structure", *Journal of Finance*, 43, 617-633.

Grünbichler, A., F. A. Longstaff and E. S. Schwartz, (1994), "Electronic Screen Trading and the Transmission of Information: An Empirical Examination", *Journal of Financial Intermediation* 3, 166-187.

Hull, J., (1993), *Options, Futures, and Other Derivative Securities*, Second Edition, Prentice-Hall Inc., Englewood Cliffs, N.J., USA.

Kawaller, I. G., P. D. Koch, and T. W. Koch, (1987), "The Temporal Relationship between S&P 500 futures and the S&P 500 Index", *Journal of Finance*, 42, 1309-1329.

Kawaller, I. G., P. D. Koch and T. W. Koch, (1990), "Intraday Relationships between the Volatility in the S&P 500 Futures and the Volatility in the S&P 500 Index", *Journal of Banking and Finance* 14, 373-397.

Kawaller, I. G., P. D. Koch and T. W. Koch, (1993), "Intraday Market Behavior and the Extent of Feedback Betwen S&P 500 Futures Prices and the S&P 500 Index", *Journal of Financial Research* 16, 107-121.

Koch, P. D., (1993), "Reexamining Intraday Simultaneity in Stock Index Futures Markets", *Journal of Banking and Finance*, 17, 1191-1205.

Lindley, D. V., (1957), "A Statistical Paradox", *Biometrika*, 44, 187-192.

Niemeyer, J., (1994), "An Empirical Analysis of the Trading Structure at the Stockholm Options and Forwards Exchange, OM", WP, Stockholm School of Economics, November 1994.

Niemeyer, J. and P. Sandås, (1993), "An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange", *Journal of Multinational Financial Management*, 3, No 3/4, 63-101.

Niemeyer, J. and P. Sandås, (1994), "Tick Size, Market Liquidity and Trading Volume: Evidence from the Stockholm Stock Exchange", WP, Stockholm School of Economics, November 1994.

Nordén, L., (1994), "Stock Index Arbitrage Profitability: A Transactions Data Analysis of Swedish OMX-Index Cash and Forward Prices", WP, University of Lund, October 1994.

Shyy, G. and V. Vijayraghavan, (1994), "A Further Investigation of the Lead-Lag Relationship between the Cash Market and Stock Index Futures Market Using Bid/Ask Quotes: The Case of France", WP, October, 1994.

Sims, C. J., (1972), "Money, Income, and Causality", *American Economic Review*, 62, 540-552.

Sofianos, G., (1993), "Index Arbitrage Profitability", *Journal of Derivatives*, 1, (Fall), 1-11.

Stephan, J. A. and R. E. Whaley, (1990), "Intraday Price Change and Trading Volume Relations in the Stock and Stock Option Markets", *Journal of Finance*, 45, 191-220.

Stoll, H. R. and R. E. Whaley, (1990), "The Dynamics of Stock Index and Stock Index Futures Returns", *Journal of Financial and Quantitative Analysis*, 25, 441-468.

Subrahmanyam, A., (1991), "A Theory of Trading in Stock Index Futures", *Review of Financial Studies*, 4, 17-51.

Varson, P. L. and J. P. Selby, (1991), "Option Prices as Predictors of Stock Prices: Intraday Adjustments to Information Releases", Paper presented at the 18th EFA Meeting in Rotterdam, Holland.

White, H., (1980), "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", *Econometrica*, 48, 817-838.

Appendix 1

All data from the following days where omitted:

Jan.	8	1992	Sep.	3	1992
Apr.	16	1992	Sep.	4	1992
Apr.	24	1992	Sep.	8	1992
Jun.	5	1992	Sep.	9	1992
Jun.	26	1992	Sep.	10	1992
Jul.	7	1992	Sep.	11	1992
Jul.	29	1992	Sep.	14	1992
Jul.	30	1992	Sep.	15	1992
Jul.	31	1992	Oct.	5	1992
Aug.	3	1992	Nov.	2	1992
Aug.	4	1992	Dec.	29	1992
Aug.	5	1992	Dec.	30	1992
Aug.	6	1992	Jan.	25	1993
Aug.	7	1992	Feb.	16	1993
Aug.	10	1992	May	12	1993
Aug.	11	1992	May	13	1993
Aug.	26	1992	Jul.	14	1993
Sep.	1	1992	Aug.	11	1993
Sep.	2	1992	Sep.	1	1993

Appendix 2

Table 2A

Summary of Lead-Lag χ^2-tests, 5 Minute Returns

		Period 1		Period 2		Period 3	
		$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$
Granger							
Forw.	Spr. Ind.	58.58 **	175.24 **	77.05 **	242.98 **	83.24 **	234.81 **
Forw.	Tra. Ind.	64.26 **	211.69 **	138.43 **	320.20 **	142.88 **	322.99 **
Synt.	Spr. Ind.	107.08 **	286.09 **	87.61 **	182.94 **	48.48 **	292.20 **
Synt.	Tra. Ind.	140.30 **	277.63 **	158.94 **	271.63 **	103.23 **	275.35 **
Sims							
Forw.	Spr. Ind.	80.47 **	285.14 **	307.23 **	307.92 **	107.84 **	252.60 **
Forw.	Tra. Ind.	95.26 **	344.10 **	390.94 **	260.52 **	142.21 **	249.07 **
Synt.	Spr. Ind.	122.62 **	320.53 **	313.29 **	259.65 **	78.89 **	287.91 **
Synt.	Tra. Ind.	179.64 **	269.67 **	350.71 **	308.30 **	121.66 **	223.47 **
Sims, Return Innov.							
Forw.	Spr. Ind.	71.92 **	258.67 **	117.65 **	246.05 **	56.61 **	225.33 **
Forw.	Tra. Ind.	22.53 *	255.77 **	105.93 **	229.89 **	62.03 **	226.45 **
Synt.	Spr. Ind.	110.33 **	297.83 **	112.86 **	191.36 **	45.15 **	256.90 **
Synt.	Tra. Ind.	53.53 **	219.56 **	93.16 **	281.21 **	51.20 **	202.03 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 2B

Summary of Lead-Lag χ^2-tests, 10 Minute Returns

		Period 1		Period 2		Period 3	
		$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$	$f/s \nRightarrow i$	$i \nRightarrow f/s$
Granger							
Forw.	Spr. Ind.	33.55 **	162.35 **	31.55 **	110.28 **	39.47 **	188.61 **
Forw.	Tra. Ind.	59.54 **	181.94 **	62.84 **	105.88 **	93.13 **	136.99 **
Synt.	Spr. Ind.	75.63 **	170.77 **	42.52 **	104.58 **	21.48 *	164.66 **
Synt.	Tra. Ind.	116.71 **	179.83 **	76.80 **	120.21 **	67.29 **	111.50 **
Sims							
Forw.	Spr. Ind.	59.48 **	169.34 **	104.23 **	112.66 **	63.05 **	132.67 **
Forw.	Tra. Ind.	63.76 **	189.10 **	170.08 **	72.33 **	83.52 **	100.94 **
Synt.	Spr. Ind.	90.62 **	136.95 **	150.19 **	99.65 **	68.28 **	123.76 **
Synt.	Tra. Ind.	124.61 **	110.56 **	278.78 **	70.08 **	99.05 **	102.31 **
Sims, Return Innov.							
Forw.	Spr. Ind.	57.95 **	171.84 **	76.52 **	107.74 **	33.84 **	124.44 **
Forw.	Tra. Ind.	17.88	150.73 **	78.39 **	70.12 **	37.22 **	94.73 **
Synt.	Spr. Ind.	89.73 **	139.15 **	106.69 **	95.53 **	38.41 **	115.15 **
Synt.	Tra. Ind.	38.42 **	101.36 **	124.87 **	71.07 **	47.93 **	93.44 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Appendix 3

Table 3A
5-Minute Intervals, Granger Test, Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot f_{t-k} + e_{1t} \quad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00001	-0.00001	0.00001	0.00001	0.00001	0.00001
a_{-1}	-0.01533	0.01004	0.06980	0.08658 **	0.01504	-0.07980 **
a_{-2}	0.05280	0.01950	0.05017	0.01877	0.01001	-0.03108
a_{-3}	0.04972	0.05548 *	0.00718	-0.00755	0.00178	0.00422
a_{-4}	0.02173	0.00804	0.00133	0.00193	0.00353	-0.00734
a_{-5}	-0.00938	0.02517	0.00733	0.00726	0.00057	-0.00392
b_{-1}	0.06866 **	0.05660 **	0.11216 **	0.11535 **	0.09723 **	0.13838 **
b_{-2}	0.05235 **	0.05654 **	0.05051 **	0.07435 **	0.06763 **	0.07947 **
b_{-3}	0.05228 **	0.04618 *	0.02442	0.03255	0.01092	0.05241 **
b_{-4}	0.04203 *	0.03949	0.02969	0.04890 **	0.03261	0.04932 **
b_{-5}	0.00350	0.03400 *	0.03166	0.03375 *	0.00516	0.01863
N	6620	6620	6477	6477	7527	7527
Adj R^2 (%)	3.55	3.43	8.44	9.89	3.10	3.34
Skewness	0.02	-0.10	-0.03	0.23	-0.18	-0.15
Exc. Kurtosis	8.07	5.15	19.75	4.57	14.00	5.53
χ^2-test ($b_{-k}=0$)	58.58 **	64.26 **	77.05 **	138.43 **	83.24 **	142.88 **

Model: $$f_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot f_{t-k} + e_{2t} \right] \quad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00006	-0.00006	0.00004	0.00004	0.00002	0.00003
c_{-1}	0.66853 **	0.87249 **	0.85115 **	0.90613 **	0.69387 **	0.62369 **
c_{-2}	0.62217 **	0.58825 **	0.46063 **	0.29321 **	0.45085 **	0.44086 **
c_{-3}	0.42034 **	0.41411 **	0.19230 **	0.08602	0.27826 **	0.27174 **
c_{-4}	0.37967 **	0.26961 **	0.08040	-0.01214	0.19239 **	0.17128 **
c_{-5}	0.11584	0.06430	0.06274	-0.03982	0.10880	0.05177
d_{-1}	-0.28856 **	-0.37516 **	-0.25029 **	-0.23675 **	-0.27367 **	-0.24551 **
d_{-2}	-0.27246 **	-0.24054 **	-0.27739 **	-0.22765 **	-0.22283 **	-0.22308 **
d_{-3}	-0.20965 **	-0.19872 **	-0.19050 **	-0.15201 **	-0.23227 **	-0.21955 **
d_{-4}	-0.11077	-0.12756	-0.13239 **	-0.07010	-0.11437 **	-0.11945 **
d_{-5}	-0.09588	-0.07990	-0.06826	-0.04233	-0.10601 **	-0.10881 **
N	1673	1673	3343	3343	3060	3060
Adj R^2 (%)	19.31	23.01	17.14	16.01	17.07	16.29
Skewness	-0.17	-0.07	0.04	0.05	0.27	0.13
Exc. Kurtosis	4.44	4.19	8.21	7.79	3.29	2.64
χ^2-test ($c_{-k}=0$)	175.24 **	211.69 **	242.98 **	320.20 **	234.81 **	322.99 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3B
10-Minute Intervals, Granger Test, Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot f_{t-k} + e_{1t} \quad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00002	-0.00002	0.00003	0.00002	0.00001	0.00002
a_{-1}	0.08411	0.04841	0.06926	0.09503	0.06115	-0.05450
a_{-2}	0.07089	0.03985	-0.01338	-0.05894	-0.00863	-0.05667
a_{-3}	-0.00211	-0.02747	-0.01860	-0.00496	-0.01607	-0.06081
a_{-4}	-0.00141	0.00269	-0.05074	-0.05485	0.00396	-0.04629
a_{-5}	0.00998	0.00215	-0.03508	0.00426	-0.00972	-0.02244
b_{-1}	0.08956 **	0.11554 **	0.12265 **	0.12886 **	0.11286 **	0.18056 **
b_{-2}	0.07194 **	0.08039 **	0.05807	0.09781 **	0.05861	0.11139 **
b_{-3}	0.01914	0.05879 *	0.06186	0.05654	0.00562	0.07244 *
b_{-4}	-0.00890	0.02430	0.04375	0.04978	0.03989	0.07505 *
b_{-5}	0.01319	0.01391	0.03270	0.02250	-0.00053	0.01321
N	2881	2881	2819	2819	3417	3417
Adj R^2 (%)	5.34	5.13	6.86	9.22	4.14	4.26
Skewness	-0.15	-0.17	0.42	0.24	-0.18	-0.18
Exc. Kurtosis	5.04	4.46	10.46	4.24	5.10	3.78
χ^2-test ($b_{-k} = 0$)	33.55 **	59.54 **	31.55 **	62.84 **	39.47 **	93.13 **

Model: $$f_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot f_{t-k} + e_{2t} \right] \quad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00009	-0.00010	0.00005	0.00006	0.00002	0.00004
c_{-1}	0.75936 **	0.81150 **	0.70358 **	0.64621 **	0.68244 **	0.56431 **
c_{-2}	0.45876 **	0.52701 **	0.25111 *	0.06430	0.29486 **	0.25717 **
c_{-3}	0.38198 **	0.21421 *	0.10051	0.12816	0.25196 **	0.14166
c_{-4}	0.17900	0.14549	0.05622	0.02741	0.13640	0.09960
c_{-5}	0.04169	0.06273	0.02169	-0.00364	0.10170	0.05204
d_{-1}	-0.28964 **	-0.28926 **	-0.30048 **	-0.25046 **	-0.28189 **	-0.23603 **
d_{-2}	-0.17306 *	-0.18729 *	-0.24813 **	-0.17087 **	-0.23566 **	-0.19191 **
d_{-3}	-0.22102 **	-0.18586 **	-0.09355	-0.08717	-0.22940 **	-0.18211 **
d_{-4}	-0.14898 *	-0.13885	-0.11223	-0.08935	-0.07797	-0.05998
d_{-5}	-0.11056	-0.13308 *	-0.08705	-0.06767	-0.11282	-0.09384
N	1141	1141	2008	2008	1983	1983
Adj R^2 (%)	22.11	23.70	11.13	8.23	13.95	10.81
Skewness	-0.38	-0.39	0.17	0.14	0.11	0.14
Exc. Kurtosis	2.62	2.40	5.56	5.63	2.81	2.99
χ^2-test ($c_{-k} = 0$)	162.35 **	181.94 **	110.28 **	105.88 **	188.61 **	136.99 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3C
15-Minute Intervals, Granger Test, Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot f_{t-k} + e_{1t} \qquad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00003	-0.00002	0.00006	0.00006	0.00004	0.00004
a_{-1}	0.15463 *	0.11501	0.07934	0.08036	0.07058	0.02253
a_{-2}	-0.01273	-0.00999	-0.03084	-0.04517	0.01772	-0.06998
a_{-3}	0.06151	-0.01349	-0.08090	-0.06454	-0.05028	-0.08835
a_{-4}	-0.01089	-0.02372	0.02324	-0.02549	-0.05055	-0.07404
a_{-5}	-0.01037	0.02059	0.01702	0.00104	-0.05484	-0.08361
b_{-1}	0.10893 **	0.13304 **	0.13797 **	0.17508 **	0.08630	0.16412 **
b_{-2}	0.02873	0.09173 *	0.08098	0.08370	0.02810	0.08740
b_{-3}	0.03079	0.05196	0.04194	0.05302	0.06393	0.09877 *
b_{-4}	0.00063	0.01788	0.01270	0.05636	0.07470	0.09646 *
b_{-5}	0.03328	0.03040	0.01033	0.03038	0.02805	0.05395
N	1646	1646	1662	1662	2087	2087
Adj R^2 (%)	6.62	6.86	7.50	10.36	3.50	5.13
Skewness	0.04	-0.13	0.13	0.25	-0.23	-0.27
Exc. Kurtosis	4.38	3.70	4.81	3.14	6.09	3.05
χ^2-test ($b_{-k} = 0$)	20.60 *	33.89 **	24.03 *	45.12 **	17.92	46.42 **

Model: $$f_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot f_{t-k} + e_{2t} \right] \qquad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00010	-0.00014	0.00004	0.00004	0.00004	0.00003
c_{-1}	0.76497 **	0.88609 **	0.67758 **	0.61525 **	0.64468 **	0.66514 **
c_{-2}	0.43715 **	0.40411 **	0.31490 *	0.21783	0.34468 **	0.24652 **
c_{-3}	0.35896 **	0.23709 *	0.13466	0.11582	0.16042	0.09979
c_{-4}	0.18579 *	0.03888	0.13878	0.12754	0.11399	0.07639
c_{-5}	0.07070	0.11373	0.12543	0.05099	0.05027	0.02710
d_{-1}	-0.25493 **	-0.27809 **	-0.35692 **	-0.29994 **	-0.35094 **	-0.34129 **
d_{-2}	-0.33426 **	-0.31300 **	-0.24088 *	-0.19626	-0.26446 **	-0.23030 **
d_{-3}	-0.19186 **	-0.16721 *	-0.25580	-0.22837	-0.14133	-0.11613
d_{-4}	-0.18614 **	-0.13450	-0.15249	-0.12797	-0.11825	-0.08633
d_{-5}	-0.09622	-0.07853	-0.06978	-0.04332	-0.11913	-0.10159
N	832	832	1345	1345	1436	1436
Adj R^2 (%)	24.28	24.82	11.05	8.30	11.89	12.48
Skewness	-0.39	-0.41	0.08	0.14	0.14	0.16
Exc. Kurtosis	2.26	2.70	4.81	4.76	3.58	3.20
χ^2-test ($c_{-k} = 0$)	142.35 **	167.39 **	87.29 **	79.02 **	104.03 **	125.39 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3D
5-Minute Intervals, Granger Test, Synthetic Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot s_{t-k} + e_{1t} \qquad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00001	-0.00000	0.00001	0.00001	0.00000	0.00001
a_{-1}	-0.04704	-0.02363	0.06436	0.08150 **	0.02512	-0.06154 *
a_{-2}	0.02814	-0.01250	0.04935	0.02415	0.03436	-0.01732
a_{-3}	0.03412	0.02490	0.00178	-0.00658	0.01794	0.02098
a_{-4}	0.01748	-0.00111	0.00708	0.00362	0.01477	0.00710
a_{-5}	-0.01080	0.02672	0.01951	0.01890	0.00696	0.00672
b_{-1}	0.12015 **	0.11441 **	0.11281 **	0.11939 **	0.09310 **	0.10890 **
b_{-2}	0.07266 **	0.08106 **	0.05201 **	0.05455 **	0.02462	0.06450 **
b_{-3}	0.04491 *	0.05848 **	0.03295	0.04610 **	0.01608	0.05662 **
b_{-4}	0.03805	0.05315 **	0.03279	0.04298 **	0.02326	0.01702
b_{-5}	0.02886	0.03542	0.01391	0.03055 *	-0.00187	0.02655
N	6879	6879	6340	6340	7350	7350
Adj R^2 (%)	4.82	4.87	8.35	9.54	2.81	2.61
Skewness	0.05	-0.08	-0.02	0.23	-0.27	-0.21
Exc. Kurtosis	7.74	4.97	20.34	4.73	13.82	5.64
χ^2-test ($b_{-k} = 0$)	107.08 **	140.30 **	87.61 **	158.94 **	48.48 **	103.23 **

Model: $$s_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot s_{t-k} + e_{2t} \right] \qquad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00004	-0.00004	0.00006	0.00005	0.00005	0.00004
c_{-1}	0.47623 **	0.55873 **	0.81918 **	0.93136 **	0.84191 **	0.72360 **
c_{-2}	0.30593 **	0.31059 **	0.47025 **	0.31237 **	0.50218 **	0.43140 **
c_{-3}	0.20107 **	0.14127 **	0.16535	0.09980	0.35233 **	0.27608 **
c_{-4}	0.08467	0.08162	0.11457	-0.04303	0.13301	0.14120
c_{-5}	0.01757	-0.03485	0.01396	-0.00143	0.11456	0.02964
d_{-1}	-0.06893	-0.09791 *	-0.17636 **	-0.16944 **	-0.30431 **	-0.28517 **
d_{-2}	-0.13023 **	-0.13391 **	-0.24729 **	-0.21155 **	-0.33586 **	-0.27109 **
d_{-3}	-0.09746 **	-0.09284 *	-0.21197 **	-0.17248 **	-0.20118 **	-0.16763 **
d_{-4}	-0.05546	-0.05396	-0.13643 **	-0.09368	-0.19050 **	-0.19078 **
d_{-5}	-0.07435	-0.06556	-0.09929	-0.08158	-0.12580 *	-0.10241
N	3186	3186	2744	2744	2416	2416
Adj R^2 (%)	13.03	14.14	15.73	15.99	18.48	15.91
Skewness	0.07	0.08	0.07	0.13	0.22	0.26
Exc. Kurtosis	2.44	2.60	3.97	3.99	5.00	5.21
χ^2-test ($c_{-k} = 0$)	286.09 **	277.63 **	182.94 **	271.63 **	292.20 **	275.35 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3E
10-Minute Intervals, Granger Test, Synthetic Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot s_{t-k} + e_{1t} \quad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00002	-0.00001	0.00004	0.00004	0.00001	0.00001
a_{-1}	0.01671	-0.01705	0.04329	0.07849	0.07727	-0.04235
a_{-2}	0.00528	-0.02374	-0.02928	-0.06159	-0.00168	-0.03993
a_{-3}	-0.02564	-0.04327	-0.00690	0.00798	-0.01473	-0.04182
a_{-4}	-0.01361	-0.01746	-0.02182	-0.02746	0.01842	-0.02481
a_{-5}	0.00948	0.01076	-0.01595	0.01470	-0.01366	-0.02084
b_{-1}	0.15603 **	0.17344 **	0.14092 **	0.13898 **	0.09322 **	0.16460 **
b_{-2}	0.09383 **	0.11873 **	0.07131 *	0.10194 **	0.05121	0.10382 **
b_{-3}	0.04092	0.07684 **	0.06049	0.05784	0.01759	0.05640
b_{-4}	0.04770	0.08216 **	0.01542	0.02233	0.02109	0.04622
b_{-5}	0.01439	0.02096	0.02402	0.01911	0.02187	0.03778
N	3005	3005	2768	2768	3344	3344
Adj R^2 (%)	6.75	7.63	7.19	9.47	3.71	3.79
Skewness	-0.15	-0.16	0.43	0.29	-0.17	-0.16
Exc. Kurtosis	4.83	4.39	10.53	3.94	5.06	3.79
χ^2-test ($b_{-k} = 0$)	75.63 **	116.71 **	42.52 **	76.80 **	21.48 *	67.29 **

Model: $$s_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot s_{t-k} + e_{2t} \right] \quad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00006	-0.00007	0.00005	0.00005	0.00002	0.00003
c_{-1}	0.50514 **	0.51465 **	0.68446 **	0.67135 **	0.80265 **	0.60474 **
c_{-2}	0.23045 **	0.16745 **	0.22504	0.03258	0.29794 **	0.30346 **
c_{-3}	0.08181	0.01114	0.17922	0.19837	0.28397 **	0.23286 **
c_{-4}	0.05378	-0.01674	-0.00902	-0.06467	0.21356 **	0.18034 *
c_{-5}	0.02070	-0.04551	0.00061	-0.00950	0.16953	0.12290
d_{-1}	-0.12264 **	-0.12483 **	-0.23978 **	-0.20473 **	-0.33081 **	-0.26443 **
d_{-2}	-0.14319 **	-0.11600 *	-0.27817 **	-0.21825 **	-0.28546 **	-0.26477 **
d_{-3}	-0.12673 **	-0.07819	-0.13332	-0.12054	-0.27369 **	-0.26303 **
d_{-4}	-0.02950	0.00688	-0.10314	-0.07423	-0.22157 **	-0.20927 **
d_{-5}	-0.08625 *	-0.04955	-0.06384	-0.04546	-0.13594	-0.12276
N	2134	2134	1796	1796	1755	1755
Adj R^2 (%)	11.83	10.91	10.39	9.08	16.91	11.72
Skewness	-0.35	-0.39	-0.17	-0.12	0.28	0.24
Exc. Kurtosis	5.75	6.10	2.58	2.45	4.06	4.18
χ^2-test ($c_{-k} = 0$)	170.77 **	179.83 **	104.58 **	120.21 **	164.66 **	111.50 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3F
15-Minute Intervals, Granger Test, Synthetic Forwards

Model: $$i_t = z_1 + \sum_{k=1}^{5} a_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} b_{-k} \cdot s_{t-k} + e_{1t} \qquad (5a)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_1	-0.00002	-0.00001	0.00006	0.00007	0.00004	0.00004
a_{-1}	0.07613	-0.00507	0.06531	0.05554	0.03554	0.01404
a_{-2}	-0.04157	-0.08190	-0.04197	-0.05215	0.04008	-0.03406
a_{-3}	0.04672	-0.03906	-0.09520	-0.07850	-0.02818	-0.06122
a_{-4}	-0.01482	-0.02210	0.01058	-0.02693	-0.03279	-0.06112
a_{-5}	-0.01036	0.05397	0.03864	0.02128	-0.07059	-0.09248
b_{-1}	0.15444 **	0.21195 **	0.14229 **	0.17869 **	0.13621 **	0.19824 **
b_{-2}	0.08194	0.14322 **	0.11704 **	0.11522 **	-0.00776	0.04136
b_{-3}	0.03438	0.09587 **	0.05777	0.06688	0.06222	0.08212
b_{-4}	0.02819	0.06709	0.03121	0.06313	0.04297	0.07888
b_{-5}	0.02373	0.00900	-0.00213	0.02182	0.05487	0.05869
N	1767	1767	1628	1628	2045	2045
Adj R^2 (%)	7.55	9.40	8.46	10.65	4.29	5.85
Skewness	-0.05	-0.24	0.04	0.17	-0.15	-0.25
Exc. Kurtosis	4.01	4.31	4.54	2.75	5.80	2.98
χ^2-test ($b_{-k} = 0$)	28.41 **	76.29 **	29.69 **	52.91 **	30.32 **	56.62 **

Model: $$s_t = \delta_t \left[z_2 + \sum_{k=1}^{5} c_{-k} \cdot i_{t-k} + \sum_{k=1}^{5} d_{-k} \cdot s_{t-k} + e_{2t} \right] \qquad (5c)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z_2	-0.00008	-0.00009	0.00005	0.00007	0.00005	0.00005
c_{-1}	0.46016 **	0.42965 **	0.65403 **	0.54776 **	0.57286 **	0.60648 **
c_{-2}	0.13411	0.05683	0.27601 *	0.23927	0.36575 **	0.32195 **
c_{-3}	0.12501	-0.03315	0.02507	-0.00247	0.34167 **	0.19386
c_{-4}	0.03645	-0.03993	0.04905	0.09207	0.17172	0.12753
c_{-5}	0.00446	0.05249	0.13575	0.04440	0.01525	-0.04348
d_{-1}	-0.14221 *	-0.12642	-0.32769 **	-0.26822 **	-0.27298 **	-0.28150 **
d_{-2}	-0.09289	-0.03523	-0.22187 **	-0.20383 *	-0.36515 **	-0.36077 **
d_{-3}	-0.10595	-0.01702	-0.18220	-0.16565	-0.25354 **	-0.18262
d_{-4}	-0.08528	-0.03334	-0.07597	-0.07817	-0.14780	-0.10328
d_{-5}	-0.05750	-0.05461	-0.07721	-0.04010	-0.06007	-0.03199
N	1478	1478	1245	1245	1316	1316
Adj R^2 (%)	8.90	7.03	9.52	6.01	10.52	10.77
Skewness	-0.35	-0.34	-0.15	-0.19	0.22	0.24
Exc. Kurtosis	5.85	5.42	1.59	1.36	3.31	2.93
χ^2-test ($c_{-k} = 0$)	97.52 **	70.23 **	67.64 **	48.18 **	75.05 **	87.76 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3G
5-Minute Intervals, Sims Test, Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + e_t \qquad (4)$$

	Period 1		**Period 2**		**Period 3**	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	-0.00001	-0.00000	-0.00000	-0.00001	0.00001	0.00000
a_{-5}	0.00804	0.03862 **	0.04030 **	0.03635 **	0.01550	0.02240
a_{-4}	0.03902 *	0.03488 *	0.03514 **	0.05414 **	0.02930	0.03651 *
a_{-3}	0.05823 **	0.05109 **	0.03953 **	0.04051 **	0.01276	0.04045 **
a_{-2}	0.05205 **	0.05633 **	0.07640 **	0.09229 **	0.05990 **	0.05451 **
a_{-1}	0.06995 **	0.05270 **	0.13315 **	0.13426 **	0.09125 **	0.09571 **
a_0	0.11661 **	0.14668 **	0.22149 **	0.22736 **	0.25876 **	0.26423 **
a_1	0.11550 **	0.15240 **	0.15636 **	0.16091 **	0.16862 **	0.17743 **
a_2	0.09317 **	0.08574 **	0.06226 **	0.04007 **	0.07108 **	0.07504 **
a_3	0.06566 **	0.06309 **	0.02723	0.00162	0.02866	0.03160
a_4	0.07972 **	0.05574 **	0.00400	-0.00205	0.02697	0.02255
a_5	0.03698 *	0.03816 *	0.01919	0.01097	0.01922	0.00432
N	5850	5850	5757	5757	6922	6922
Adj R^2 (%)	11.65	13.39	29.53	30.65	21.59	18.17
Skewness	0.10	-0.09	-0.16	0.08	-0.13	-0.04
Exc. Kurtosis	7.52	4.76	22.86	4.55	15.63	4.92
χ^2-test ($a_k = 0$)	285.14 **	344.10 **	307.92 **	260.52 **	252.60 **	249.07 **
χ^2-test ($a_{-k} = 0$)	80.47 **	95.26 **	307.23 **	390.94 **	107.84 **	142.21 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3H
10-Minute Intervals, Sims Test, Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + e_t \qquad (4)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	-0.00001	-0.00001	-0.00001	-0.00003	0.00001	0.00001
a_{-5}	0.02138	0.01961	0.01696	0.02184	0.00614	0.00214
a_{-4}	-0.00360	0.01628	0.03076	0.04227 *	0.03476	0.03613
a_{-3}	0.02782	0.04590	0.04401 *	0.04216 *	0.00724	0.02696
a_{-2}	0.06642 **	0.05386 *	0.05508 **	0.08413 **	0.05732 **	0.06261 **
a_{-1}	0.09625 **	0.09808 **	0.15486 **	0.16869 **	0.10656 **	0.12123 **
a_0	0.20538 **	0.20595 **	0.34882 **	0.34925 **	0.39083 **	0.40554 **
a_1	0.17657 **	0.19642 **	0.15650 **	0.12386 **	0.16507 **	0.16755 **
a_2	0.10909 **	0.12157 **	0.01519	-0.00972	0.03347	0.02782
a_3	0.06686 *	0.03758	0.02033	0.02654	0.03788	0.01714
a_4	0.03584	0.04274	0.00017	0.01323	0.00711	0.00697
a_5	0.01960	-0.00163	0.01884	0.00805	0.02195	0.01088
N	2111	2111	2099	2099	2812	2812
Adj R^2 (%)	21.64	20.67	40.06	41.60	36.03	31.85
Skewness	-0.34	-0.17	0.08	0.01	0.00	0.04
Exc. Kurtosis	4.17	4.14	15.82	3.28	4.82	2.79
χ^2-test ($a_k = 0$)	169.34 **	189.10 **	112.66 **	72.33 **	132.67 **	100.94 **
χ^2-test ($a_{-k} = 0$)	59.48 **	63.76 **	104.23 **	170.08 **	63.05 **	83.52 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3I
15-Minute Intervals, Sims Test, Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + e_t \quad (4)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	-0.00002	-0.00000	0.00003	0.00001	0.00002	0.00001
a_{-5}	0.02037	0.03431	0.00273	-0.00105	0.00941	0.01612
a_{-4}	0.00142	-0.00367	-0.01043	0.02002	0.04333	0.03368
a_{-3}	0.03681	0.03768	0.03174	0.04239	0.03894	0.03585
a_{-2}	0.04236	0.06391	0.05978 *	0.06929 **	0.03422	0.04957
a_{-1}	0.09773 **	0.07080	0.16721 **	0.19075 **	0.09674 *	0.13366 **
a_0	0.25957 **	0.29597 **	0.43659 **	0.43396 **	0.46167 **	0.45109 **
a_1	0.24872 **	0.23935 **	0.12832 **	0.09888 **	0.15267 **	0.18725 **
a_2	0.06817	0.07039	0.02187	0.01167	0.04487	0.02034
a_3	0.04831	0.03114	-0.02402	-0.00019	0.01254	-0.00843
a_4	0.06598	-0.00057	0.01892	0.01993	0.01535	0.00094
a_5	-0.00880	0.03189	0.01293	0.01559	-0.01406	-0.01572
N	876	876	942	942	1482	1482
Adj R^2 (%)	29.26	29.03	46.54	50.12	43.81	41.63
Skewness	-0.00	0.14	0.32	0.23	-0.23	-0.07
Exc. Kurtosis	3.36	1.89	10.75	1.56	3.91	1.32
χ^2-test ($a_k = 0$)	106.42 **	118.94 **	37.91 **	27.49 **	67.67 **	87.90 **
χ^2-test ($a_{-k} = 0$)	25.11 *	26.14 **	87.61 **	118.58 **	24.37 *	65.89 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3J
5-Minute Intervals, Sims Test, Synthetic Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k \, s_{t+k} + e_t \qquad (4)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	-0.00000	0.00000	-0.00000	-0.00000	0.00000	0.00000
a_{-5}	0.03472 *	0.04200 **	0.02604 *	0.04330 **	0.00715	0.03031
a_{-4}	0.03690	0.04971 **	0.04762 **	0.05088 **	0.04002 **	0.02934
a_{-3}	0.04498 **	0.05113 **	0.04660 **	0.05686 **	0.02436	0.05480 **
a_{-2}	0.06458 **	0.06755 **	0.06857 **	0.07279 **	0.03960 *	0.05745 **
a_{-1}	0.09406 **	0.08041 **	0.12780 **	0.13076 **	0.09532 **	0.07681 **
a_0	0.18049 **	0.20886 **	0.21845 **	0.21847 **	0.23311 **	0.25392 **
a_1	0.16195 **	0.16808 **	0.13565 **	0.14822 **	0.15102 **	0.16264 **
a_2	0.07775 **	0.07785 **	0.06754 **	0.04115 **	0.07232 **	0.06253 **
a_3	0.05917 **	0.04051 **	0.01189	0.00416	0.04272 **	0.03846 *
a_4	0.04105 *	0.02492	0.01934	-0.00970	0.00898	0.01368
a_5	0.01188	-0.00208	0.01454	0.02226	0.00726	0.00021
N	6109	6109	5620	5620	6745	6745
Adj R^2 (%)	16.82	18.24	27.18	28.17	18.46	16.21
Skewness	0.11	-0.09	-0.17	0.25	-0.13	-0.01
Exc. Kurtosis	7.87	4.41	23.41	4.77	15.94	4.45
χ^2-test ($a_k = 0$)	320.53 **	269.67 **	259.65 **	308.30 **	287.91 **	223.47 **
χ^2-test ($a_{-k} = 0$)	122.62 **	179.64 **	313.29 **	350.71 **	78.89 **	121.66 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3K
10-Minute Intervals, Sims Test, Synthetic Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k\, s_{t+k} + e_t \qquad (4)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	-0.00001	0.00000	0.00002	-0.00000	-0.00001	-0.00001
a_{-5}	0.02747	0.03030	0.02309	0.03220 *	0.01380	0.00959
a_{-4}	0.02993	0.04616 *	0.02108	0.02713	0.03747	0.04158
a_{-3}	0.03907	0.04391 *	0.05246 **	0.05693 **	0.03454	0.03531
a_{-2}	0.07615 **	0.07841 **	0.07746 **	0.10491 **	0.07217 **	0.08843 **
a_{-1}	0.11710 **	0.12086 **	0.14350 **	0.15783 **	0.10136 **	0.11799 **
a_0	0.28145 **	0.31905 **	0.35276 **	0.35172 **	0.37485 **	0.40279 **
a_1	0.18483 **	0.17201 **	0.12309 **	0.10795 **	0.16833 **	0.14853 **
a_2	0.06834 **	0.04269	0.01396	-0.01954	0.03577	0.04376
a_3	0.00471	-0.01887	0.03044	0.03869	0.03253	0.01336
a_4	0.02079	0.01844	-0.00558	-0.00336	0.01969	0.02422
a_5	0.00004	-0.03373	0.01917	0.00255	0.03117	0.02234
N	2235	2235	2048	2048	2739	2739
Adj R^2 (%)	28.34	29.43	40.58	43.68	34.13	31.11
Skewness	-0.38	0.03	0.42	0.33	-0.18	-0.01
Exc. Kurtosis	4.42	2.72	16.98	2.09	5.09	3.07
χ^2-test ($a_k = 0$)	136.95 **	110.56 **	99.65 **	70.08 **	123.76 **	102.31 **
χ^2-test ($a_{-k} = 0$)	90.62 **	124.61 **	150.19 **	278.78 **	68.28 **	99.05 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3L
15-Minute Intervals, Sims Test, Synthetic Forwards

Model: $$i_t = z + \sum_{k=-5}^{5} a_k \, s_{t+k} + e_t \qquad (4)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00000	0.00001	0.00005	0.00003	-0.00001	-0.00001
a_{-5}	0.02220	0.02020	-0.00263	-0.00378	0.01327	-0.00355
a_{-4}	0.02934	0.04276	0.01719	0.04047	0.00359	0.02334
a_{-3}	0.04634	0.07885 **	0.04527	0.04801 *	0.04480	0.03094
a_{-2}	0.08239 *	0.05475	0.10581 **	0.10575 **	0.02617	0.03719
a_{-1}	0.12223 **	0.13391 **	0.15664 **	0.19343 **	0.12194 **	0.16673 **
a_0	0.40414 **	0.42753 **	0.41453 **	0.41459 **	0.48206 **	0.46911 **
a_1	0.16404 **	0.10877 **	0.11360 **	0.07987 **	0.11282 **	0.13228 **
a_2	0.00669	0.01591	0.04596	0.02570	0.03955	0.04072
a_3	0.01803	0.01299	-0.02130	-0.01187	0.06034	0.01718
a_4	0.04523	-0.00752	-0.02947	-0.00071	0.01315	0.02511
a_5	-0.01543	0.00147	0.01804	0.01470	-0.01376	-0.03052
N	998	998	908	908	1440	1440
Adj R^2 (%)	37.57	37.10	47.22	51.35	45.17	42.52
Skewness	-0.01	0.24	0.07	0.23	-0.38	-0.31
Exc. Kurtosis	3.21	2.77	11.32	1.21	5.28	1.83
χ^2-test ($a_k = 0$)	65.95 **	27.33 **	59.82 **	26.56 **	46.02 **	57.08 **
χ^2-test ($a_{-k} = 0$)	52.13 **	100.33 **	117.03 **	166.31 **	33.41 **	94.41 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3M
5-Minute Intervals, Sims Test, Return Innovations, Forwards

Model: $$e_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00000	0.00000	-0.00002	-0.00002	-0.00002	-0.00002
a_{-5}	0.00701	0.01753	0.03170 **	0.01448	0.01314	0.00977
a_{-4}	0.03696	0.01237	0.02703	0.03613 **	0.02596	0.02039
a_{-3}	0.05689 **	0.02684	0.02228	0.00773	0.00490	0.01936
a_{-2}	0.05161 **	0.03329	0.04823 **	0.05116 **	0.04329 **	0.02856
a_{-1}	0.06583 **	0.02064	0.08077 **	0.07087 **	0.06524 **	0.07401 **
a_0	0.11247 **	0.11890 **	0.18487 **	0.18563 **	0.24284 **	0.25258 **
a_1	0.11127 **	0.13641 **	0.14094 **	0.15082 **	0.16199 **	0.17201 **
a_2	0.09088 **	0.07395 **	0.05585 **	0.03922 **	0.06830 **	0.07201 **
a_3	0.06144 **	0.05341 **	0.02728	0.00166	0.02609	0.03012
a_4	0.07876 **	0.04918 **	-0.00148	-0.00412	0.02517	0.02170
a_5	0.03370	0.03414	0.02396	0.01080	0.01786	0.00442
N	5850	5850	5757	5757	6922	6922
Adj R^2 (%)	10.71	8.53	19.86	19.43	18.46	15.63
Skewness	0.08	-0.05	-0.55	-0.02	-0.03	-0.03
Exc. Kurtosis	7.67	4.51	28.59	4.20	16.04	4.83
χ^2-test ($a_k = 0$)	258.67 **	255.77 **	246.05 **	229.89 **	225.33 **	226.45 **
χ^2-test ($a_{-k} = 0$)	71.92 **	22.53 *	117.65 **	105.93 **	56.61 **	62.03 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3N
10-Minute Intervals, Sims Test, Return Innovations, Forwards

Model: $$e_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00000	0.00001	-0.00006	-0.00007	-0.00005	-0.00004
a_{-5}	0.02081	-0.00011	0.01432	0.00443	0.00357	-0.00464
a_{-4}	-0.00417	-0.00855	0.02758	0.02016	0.03342	0.02760
a_{-3}	0.02702	0.02124	0.03832 *	0.01297	0.00219	0.01107
a_{-2}	0.06441 **	0.02680	0.04220	0.04843 *	0.04280	0.03519
a_{-1}	0.09682 **	0.06088 *	0.13404 **	0.12515 **	0.07702 **	0.08665 **
a_0	0.20751 **	0.17418 **	0.34050 **	0.33680 **	0.37892 **	0.39286 **
a_1	0.17752 **	0.17807 **	0.15565 **	0.12475 **	0.16199 **	0.16453 **
a_2	0.11015 **	0.11279 **	0.01411	-0.01220	0.03104	0.02593
a_3	0.06706 *	0.03086	0.02028	0.02596	0.03636	0.01641
a_4	0.03487	0.03906	-0.00042	0.01237	0.00545	0.00630
a_5	0.02037	-0.00613	0.01723	0.00731	0.02224	0.01213
N	2111	2111	2099	2099	2812	2812
Adj R^2 (%)	21.81	14.54	37.61	36.27	33.25	28.54
Skewness	-0.35	-0.17	-0.00	0.08	0.01	0.05
Exc. Kurtosis	4.16	4.00	16.60	3.03	4.86	2.73
χ^2-test ($a_k = 0$)	171.84 **	150.73 **	107.74 **	70.12 **	124.44 **	94.73 **
χ^2-test ($a_{-k} = 0$)	57.95 **	17.88	76.52 **	78.39 **	33.84 **	37.22 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 30
15-Minute Intervals, Sims Test, Return Innovations, Forwards

Model: $$e_t = z + \sum_{k=-5}^{5} a_k f_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00001	0.00001	-0.00004	-0.00005	-0.00006	-0.00007
a_{-5}	0.01977	0.01290	0.00124	-0.01374	0.00573	0.01270
a_{-4}	-0.00023	-0.02892	-0.01605	-0.00315	0.04027	0.02999
a_{-3}	0.03379	0.01113	0.01884	0.00838	0.03310	0.02875
a_{-2}	0.03407	0.03053	0.02773	0.02313	0.01106	0.02495
a_{-1}	0.08869 *	0.02454	0.14238 **	0.14486 **	0.06322	0.08512 **
a_0	0.25524 **	0.26140 **	0.42903 **	0.42326 **	0.45026 **	0.43276 **
a_1	0.24771 **	0.22833 **	0.12972 **	0.10063 **	0.14858 **	0.18442 **
a_2	0.06578	0.06353	0.02230	0.01191	0.04307	0.02057
a_3	0.04753	0.02520	-0.02639	-0.00199	0.01246	-0.00784
a_4	0.06520	-0.00564	0.01951	0.01994	0.01691	0.00316
a_5	-0.00852	0.02857	0.01590	0.02106	-0.01646	-0.01786
N	876	876	942	942	1482	1482
Adj R^2 (%)	28.19	22.36	43.91	45.46	41.13	37.47
Skewness	-0.00	0.09	0.28	0.27	-0.19	-0.05
Exc. Kurtosis	3.35	1.73	10.83	1.67	4.00	1.25
χ^2-test ($a_k = 0$)	102.51 **	97.91 **	38.10 **	27.93 **	63.16 **	83.45 **
χ^2-test ($a_{-k} = 0$)	20.13	5.83	58.75 **	56.69 **	12.35	26.40 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3P
5-Minute Intervals, Sims Test, Return Innovations, Synthetic Forwards

Model: $$e_t = z + \sum_{k=-5}^{5} a_k \, s_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00001	0.00001	-0.00002	-0.00002	-0.00003	-0.00002
a_{-5}	0.03365	0.01918	0.01523	0.02153	0.00376	0.01798
a_{-4}	0.03613	0.02819	0.03591 *	0.02807 *	0.03675 *	0.01366
a_{-3}	0.04401 **	0.02691	0.03040 *	0.02936 *	0.01746	0.03529 *
a_{-2}	0.06503 **	0.04101 *	0.04229 **	0.03332 *	0.02340	0.03323
a_{-1}	0.08665 **	0.04388 *	0.07705 **	0.07238 **	0.07208 **	0.05661 **
a_0	0.17144 **	0.18382 **	0.18633 **	0.18034 **	0.21907 **	0.24356 **
a_1	0.15837 **	0.15661 **	0.11856 **	0.13812 **	0.14378 **	0.15772 **
a_2	0.07490 **	0.07229 **	0.06568 **	0.03992 **	0.06917 **	0.05965 **
a_3	0.05683 **	0.03704 *	0.00811	0.00509	0.04190 **	0.03626 *
a_4	0.04034	0.02479	0.01593	-0.01381	0.00737	0.01091
a_5	0.01252	-0.00250	0.01538	0.02226	0.00434	-0.00254
N	6109	6109	5620	5620	6745	6745
Adj R^2 (%)	15.38	12.81	18.12	17.68	15.79	14.00
Skewness	0.07	-0.06	-0.58	0.10	-0.02	-0.00
Exc. Kurtosis	8.13	4.25	29.25	4.43	16.79	4.40
χ^2-test ($a_k = 0$)	297.83 **	219.56 **	191.36 **	281.21 **	256.90 **	202.03 **
χ^2-test ($a_{-k} = 0$)	110.33 **	53.53 **	112.86 **	93.16 **	45.15 **	51.20 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3Q
10-Minute Intervals, Sims Test, Return Innovations, Synthetic Forwards

Model:

$$e_t = z + \sum_{k=-5}^{5} a_k \, s_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00001	0.00001	-0.00003	-0.00004	-0.00006 *	-0.00006
a_{-5}	0.02700	0.00906	0.02056	0.01596	0.01067	0.00150
a_{-4}	0.02952	0.02189	0.01699	0.00525	0.03419	0.03162
a_{-3}	0.03809	0.01661	0.04655 **	0.02879	0.02843	0.01782
a_{-2}	0.07279 **	0.04598	0.06517 **	0.07159 **	0.05812 *	0.06180 **
a_{-1}	0.11951 **	0.07683 **	0.12290 **	0.11479 **	0.07252 **	0.08421 **
a_0	0.28430 **	0.29620 **	0.34580 **	0.34028 **	0.36286 **	0.39082 **
a_1	0.18596 **	0.16565 **	0.12244 **	0.10956 **	0.16525 **	0.14434 **
a_2	0.06827 **	0.04220	0.01250	-0.02390	0.03316	0.04130
a_3	0.00479	-0.02410	0.03082	0.03956	0.03051	0.01076
a_4	0.02076	0.01849	-0.00600	-0.00352	0.01734	0.02277
a_5	0.00060	-0.03520	0.02027	0.00445	0.03012	0.02297
N	2235	2235	2048	2048	2739	2739
Adj R^2 (%)	28.65	23.26	38.24	38.53	31.45	27.89
Skewness	-0.37	-0.01	0.28	0.29	-0.17	0.02
Exc. Kurtosis	4.37	2.48	17.73	1.94	5.17	2.96
χ^2-test ($a_k = 0$)	139.15 **	101.36 **	95.53 **	71.07 **	115.15 **	93.44 **
χ^2-test ($a_{-k} = 0$)	89.73 **	38.42 **	106.69 **	124.87 **	38.41 **	47.93 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Table 3R
15-Minute Intervals, Sims Test, Return Innovations, Synthetic Forwards

Model: $$e_t = z + \sum_{k=-5}^{5} a_k \, s_{t+k} + \eta_t \qquad (7)$$

	Period 1		Period 2		Period 3	
	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.	Spread Ind.	Trans Ind.
z	0.00003	0.00002	-0.00003	-0.00003	-0.00009	-0.00009
a_{-5}	0.02085	-0.00409	-0.00579	-0.01939	0.01140	-0.00626
a_{-4}	0.02648	0.01219	0.01056	0.01710	0.00059	0.01991
a_{-3}	0.04210	0.04922	0.03221	0.01285	0.03928	0.02535
a_{-2}	0.07145 *	0.01701	0.07533 **	0.06260 *	0.00054	0.00872
a_{-1}	0.11436 **	0.08634 **	0.13389 **	0.15226 **	0.08766 *	0.11730 **
a_0	0.40277 **	0.41074 **	0.40896 **	0.40642 **	0.47320 **	0.45457 **
a_1	0.16389 **	0.10447 **	0.11452 **	0.07938 **	0.10860 **	0.12770 **
a_2	0.00586	0.01555	0.04785	0.02639	0.03543	0.03851
a_3	0.01714	0.01095	-0.02162	-0.01156	0.05943	0.01565
a_4	0.04521	-0.00984	-0.03078	-0.00271	0.01361	0.02842
a_5	-0.01510	-0.00528	0.01841	0.01659	-0.01500	-0.03166
N	998	998	908	908	1440	1440
Adj R^2 (%)	36.64	31.07	44.64	46.76	42.75	38.64
Skewness	-0.01	0.15	-0.01	0.21	-0.31	-0.25
Exc. Kurtosis	3.19	2.47	11.37	1.19	5.37	1.60
χ^2-test ($a_k = 0$)	64.43 **	24.20 *	58.68 **	24.92 *	41.20 **	51.73 **
χ^2-test ($a_{-k} = 0$)	42.98 **	30.90 **	75.64 **	84.62 **	19.23	44.16 **

* indicates significance on the 0.1 per cent level and ** significance on the 0.01 per cent level.

Essay 5

Order Flow Dynamics: Evidence from the Helsinki Stock Exchange*

Abstract

This essay investigates the dynamics of the order flow in a limit order book. In contrast to previous studies, our data set from the Helsinki Stock Exchange encompasses the entire order book structure, including the dealer identities. This enables us to focus on the order behavior of individual dealers. We classify the events in the order book and study the structure of subsequent events using contingency tables. In specific, the structure of subsequent events initiated by the same dealer is compared to the overall event structure. We find that order splitting is more frequent than order imitation. Furthermore, if the spread increases as a result of a trade, other dealers quickly restore the spread, by submitting new limit orders. One conclusion is therefore that there exists a body of potential limit orders outside the formal limit order book and that there is a high degree of resiliency in our limit order book market. As a logical consequence, a large dealer strategically splits his order, in order for the market to supply additional liquidity. One interpretation of our results is that a limit order book market can accommodate larger orders than is first apparent by the outstanding limit orders. Another interpretation is that a limit order book structure gives room for informed traders to successively trade on their information. A third interpretation is that prices only slowly incorporate new information.

* This essay is joint work together with Kaj Hedvall. We wish to thank the Helsinki Stock Exchange for providing the data set. We are also grateful for valuable comments and suggestions by seminar participants at the Swedish School of Economics and Business Adminstration and by participants at the 21st Annual EFA conference in Brussels and the international market microstructure workshop in Vaasa, September 1994, and in particular by Piet Sercu, Lars Nordén. Furthermore, we are especially indebted to Gunnar Rosenqvist for valuable suggestions. The usual disclaimer applies.

1. Introduction

Although there exists a vast body of market micro structure models depicting the behavior of individual agents possessing heterogeneous information, most empirical research has been performed on aggregated transaction data. Furthermore, previous studies from the U.S. have, almost without exception, been conducted on data, which allow the description of order flow dynamics only indirectly. Hasbrouck (1991a, b), for instance, has studied the time series properties of the midquote and transaction prices. From his data, he measures the length of the effects of an informational event and draws conclusions about the informativeness of an event from the permanent change component. Handa (1991) tries to capture the order flow dynamics by explicitly studying the past movements of the bid/ask midpoint between a fixed number of quote revisions. Harris and Hasbrouck (1992) does study the order flow but they focus on the performance of limit versus market orders at the New York stock exchange.

Recently, the introduction of automated exchanges has enabled the collection of data, which to a greater extent match the information set available to the market agents. This data set is not limited to transactions or even to quotes but also includes binding limit orders. The anatomy of limit order book trading encompasses the provision of liquidity in the form of limit orders as well as the consumption of liquidity in the form of submissions of matching orders. The setting is a highly dynamic environment in which bids and offers are constantly revised to reflect the current supply and demand. In order to understand the structure of the order book, and fundamentally the viability of a limit order book environment, the nature and dynamics of limit order trading has to be understood.

Several studies[1] have described and analyzed a wide set of properties of the limit order book on different exchanges. These studies have provided detailed descriptions about the structures of the different limit order books, but primarily in a static sense only. Biais Hillion and Spatt (1994) extend the existing literature into a dynamic analysis, examining the differences between the conditional and unconditional probabilities for certain classes of events in the limit order book. With their data, they can study the aggregated dynamics of order placement.

However, in all of these studies, the behavior of individual agents cannot be extracted from the aggregated quote statistics presented. At best, the *average* agent behavior can be approximated. Biais Hillion and Spatt (1994) explain some of their results by putting

[1] Aitken, Brown and Walter (1993), Niemeyer and Sandås (1993) (Essay 1 in this dissertation), De Jong, Nijman and Röell (1994), Lehmann and Modest, (1994) and Hedvall (1994) have described the limit order book at the Australian, Stockholm, Paris, Tokyo and Helsinki stock exchanges respectively.

forth a number of hypotheses of individual agent behavior. With our data, which includes the dealer codes, we are not only able to examine the probabilities of a certain event conditional on the previous event but also conditional on the identity of the agent. In doing so, we are able to explore some of the hypotheses put forward in Biais Hillion and Spatt (1994). In our view, the approach of extracting the individual agent's behavior and tracing the lives of individual orders is more in line with the suggestions of Easley, Kiefer and O'Hara (1993). They point to the importance of evaluating the empirical validity of market micro structure models that depict the behavior of stock market agents. Our data enable us to investigate some dealer strategies explicitly.

A dealer, wanting to trade a large amount of stocks in a limit order book market, can either trade directly or split the order in several trades. In the latter case, he attempts to reduce the price impact of his trade by hoping that the market will provide additional liquidity before the rest of the trade is executed. In the first case, we will observe a single large trade. On the other hand, in the second case we will observe the following sequence of events: One dealer (dealer A) trades against an outstanding limit order, other dealers might submit new limit orders to replace the old ones, and dealer A trades again. With our data set, we are able to identify if dealer A actually splits his order into several successive trades. Our results indicate that traders often split their orders over time. Often, but not always, the market provides additional liquidity so that the price impact of dealer A's trade is reduced.

In this study, we focus on the relation between informational events and the order flow behavior. In many studies,[2] exogenous circumstances like earnings' announcements form the informational events. In other studies,[3] the informational events consist of block trades. In our study, the information set is not limited to one pre-specified class of events. We extend the analyzed informational events to the dynamics of individual order flow events in the limit order book. Some of the limit order book revisions may result in completed transactions but much of the reaction comes in the form of new quote revisions. In this way, we also capture one central aspect of liquidity, resiliency, i.e. the speed at which the market recovers after an informationless trade.[4] Since the essay focuses on the dynamics of the quote revisions, it will provide valuable information on the nature of liquidity in general, and of resiliency in particular, of limit order book markets.

[2] References include, but are not limited to, Patell and Wolfson (1981), Jain (1988), Monroe (1992) and Lee, Mucklow and Ready (1993).

[3] References here include among others Kraus and Stoll (1972), Karpoff (1987), Holthausen, Leftwich and Mayers (1987, 1990), Keim and Madhaven (1991) and Chan and Lakonishok (1993).

[4] Many authors discuss liquidity in different terms. Harris (1990) defines it in four terms, width, depth, immediacy and resiliency. Bernstein (1987), Black (1991) and Glosten (1994) also discuss the importance of liquidity in general and resiliency in particular.

The essay proceeds with a short description of the trading system at the Helsinki stock exchange in section 2 and a description of our data set in section 3. Section 4 includes our empirical findings where all observations are taken into account. In section 5, we limit our study to the observations where the same dealer acts in two (or more) subsequent "events" in the limit order book. We also discuss a certain number of two-lag reaction functions where dealer A reacts to the *reactions* of dealer B to dealer A's initial action. Section 6 includes some tests through Poisson regressions. We conclude in section 7.

2 The Trading System at the Helsinki Stock Exchange

The Helsinki Stock Exchange (HeSE) is a Limit Order Book (LOB) market. The trading system, called HETI, closely resembles other LOB markets (e.g. CATS in Toronto, CAC in Paris and SAX in Stockholm). In an LOB market, the immediate liquidity[5] is provided by limit orders submitted by individual traders. Priority is given according to price and time of submission. The content of the LOB for a particular stock is shown on a computer screen to all members of the exchange. Customer and dealer orders are treated equal and cannot be distinguished from each other. The dealers have no obligations to provide liquidity nor any trading privileges. The liquidity of the market is thus solely provided by the limit orders in the LOB.

Continuous trading in the HETI starts with a closed call auction (Pre Trading[6]) and the unmatched orders from it form the basis of the continuous trading. The continuous trading session (Free Trading) is followed by after hours trading (After Market Trading) in which trades can be crossed at prices determined in the continuous trading. Bilaterally negotiated trades can also be crossed at the current LOB price level during the continuous trade (Contract Transaction Phase). Odd lots are matched at regular intervals to current prices of the continuous trading. Table 1 lists the sizes of the different trading modes in our sample.

In contrast to other LOB markets, only limit orders are allowed.[7] Furthermore, a limit order cannot exceed the best price level at the opposite side in the book. In effect, this prohibits impatient market orders or marketable limit orders that simultaneously match

[5] We use the term immediate liquidity to describe the liquidity provided by the LOB at any given moment in time, and distinguished from the "total liquidity" which also includes potential orders that traders do not want to make public but which would enter the LOB if market conditions change.

[6] The official terminology and regulations are stated in Helsinki Stock Exchange (1991), Rules and Regulations of the Helsinki Stock Exchange, Vol. 2, 1991.

[7] There exists a complementary matching system for odd lots, where market orders indeed are allowed. In all of the following we will limit ourselves to the "normal" matching system, where market orders are not admitted.

against orders on several price levels. Thus, matching can only occur at one price level at a time.

Table 1
The Importance of Different Trading Modes

Trading Mode	# of Trans.	Per cent	Volume*	Per Cent
Pre Trading	144	(0.25)	4.36	(0.06)
Free Trading	28 470	(49.31)	1 899.43	(27.95)
Odd Lot Trading	14 794	(25.62)	83.63	(1.23)
Pre-Arranged Trading	6 894	(11.94)	2 525.73	(37.17)
After Hours Trading	7 439	(12.88)	2 281.63	(33.58)
Total	57 741	(100.00)	6 794.77	(100.00)

* Volume is measured in million FIM.

When we study the dynamics of the order book we are specifically interested in the reactions of dealers and traders to different "events" in the LOB. A general feature of LOB trading is the distinction between transactions and trades. When prices match in the LOB, the order submitted by the active part (the submitter who placed an order across the inside spread) will be matched against one or, frequently, several limit orders at the best level on the opposite side. Thus in some cases, there will be more than one transaction per trade. Our data set includes all changes in the LOB, including all transactions and other changes necessary to reflect the new state of the LOB. Therefore, all events that are automatically induced by the trading system, such as the individual transactions, have to be excluded from a sample studying the behavior of the agents on the market.

The HETI is a strict market-by-order system in which every limit order and the identification of its submitter are displayed individually on the trading screen. This combination of order size and submitter visibility gives the HETI a high degree of ex ante transparency.[8] The disclosure of individual order volumes and submitter identities adds several new features to this study. An advantage of the market-by-order design[9] from a research perspective is that the order flow information set of the agent trading on the market and the researcher is identical. We are therefore able to study the strategic reactions of a trader to changes in the order flow information. Thus, this trading structure allows a trader to condition his actions upon the individual actions of other participants. In such an environment the opportunities for trade negotiation and repeated trading are greater. If the transparency of the system also induces a reluctance to show

[8] For a discussion of ex ante and ex post transparency, see Domowitz (1993). All orders are displayed in the HETI-system and there is no "hidden volume".

[9] Though a market-by-order design is beneficial for the research process, it does not imply that this particular design is in any sense more efficient than less transparent designs.

the true volumes offered and bid in the book, the result may be that the dynamics of the trading are different from what may be the case in less open designs. It is thus of interest to study the extent to which this kind of market structure results in strategic order splitting behavior and bilateral, repeated trading. Our data provide us a novel opportunity to study such multi period dynamics somewhat less myopically than previously conducted studies.

3 The Data Set

Our sample consists of all changes in the limit order book of 66 stocks trading at the Helsinki Stock Exchange. Each observation consists of a stock identification code, the side of the market (bid or ask), the time to the second, a code for the acting dealer, the price, the quantity, and the position in the limit order book. A list of the stocks can be found in Appendix A. The total sample has been collected during several subperiods from February 9, 1990, to February 27, 1993.[10] In total, we use data from 147 trading days. Since we disregard any overnight intervals, each day can be seen as a separate subsample. Furthermore, since almost all conclusions also are valid for each of the subsamples, we only report the results from the entire sample of 147 trading days.

In estimating the relevance of our data, it should be noted that the amount of off-book trading, in the form of prearranged transactions and after hours trades, is extensive on the HeSE. In our sample, two thirds of the trading volume is off book trading. The focus of this study is exclusively on the free trading section. We observe in total 128 806 order book "events" and 22 641 trades.

4 Empirical Findings

In this section and the following sections, we study the structure of the order flow. The flow of orders is measured in "event time", i.e. we disregard the time in seconds or minutes between different "events". In subsection 4.1, we classify the "events" into several categories, among other things according to their aggressiveness. First, we focus on the reaction to "events" consuming liquidity (i.e. trades) in subsection 4.2. In subsection 4.3, we then extend the analysis to include different types of non-trade "events" such as submission of new, and removals of outstanding, limit orders.

[10] The subperiods are: from February 9, 1990 to March 29, 1990; from November 1, 1990, to December 28, 1990; from March 1, 1991, to March 27, 1991; from December 1, 1992, to December 30, 1992; and from January 4, 1993, to February 27, 1993. While the first three subperiods exhibit falling prices and low liquidity, the latter two subperiods are up markets with relatively high liquidity.

4.1 Definitions of Order Flow Events

After having identified and removed all "events" directly induced by the trading system itself, we define nine different order flow "events". The types of events differ in their aggressiveness and impatience as well as whether they increase or reduce the immediate liquidity of the market. All nine categories can occur either at the bid or at the ask level. We therefore have, in total, eighteen different types of order flow events. The definitions are perfectly symmetric. In the following definitions, we therefore limit ourselves to the ask side of the market.

The first three types of order flow "events" refer to trades. In all cases, an impatient trader submits a marketable limit order to buy at the existing best ask price, i.e. he consumes immediate liquidity. The categories differ in the aggressiveness of the trader. In the first category, the trader submits a marketable limit order to buy an amount larger than the total volume existing at the best ask level. In doing so, the best bid changes. We term this an aggressive trade. In the second type of trade, the trader consumes all existing volume at the best ask level. We term this a full trade. The third category refers to trades consuming less than the full volume at the best ask level, which we term an ordinary trade. The example in Table 2 might clarify the definitions further.

Table 2

Classification of Trades: An example

LOB at time *t-1*		LOB at time *t*					
		Alternative Trade Forms					
		Aggr. trade		Full trade		Ord. trade	
Price	Volume	Price	Volume	Price	Volume	Price	Volume
ask 113	2 000	ask 113	2 000	ask 113	2 000	ask 113	2 000
ask 112	600					ask 112	400
		bid 112	900				
bid 110	1 000	bid 110	1 000	bid 110	1 000	bid 110	1 000
Submission of order:		buy 1 500 at 112		buy 600 at 112		buy 200 at 112	
Traded volume:		600		600		200	

Furthermore, we define three different types of order submissions, i.e. order flow events supplying immediate liquidity to the market. The first type of submission reduces the bid/ask spread. It is a submission of an order at a price level below the best ask quote and above the best bid offer. This order flow creates a new ask level in the order book. The second type involves a submission of additional depth at the existing best ask level. The third type of event is a submission of an order at a new or existing ask level, which is not the best level. This category refers to provision of immediate liquidity for future use, after a possible price increase.

Finally, we define three different types of order removals, where a trader removes an existing limit order to sell. In the first case, the removal of the ask order results in an increase in the spread. It involves the removal of the only order at the best ask level. The second type of removal or change reduces the depth at the best ask level and the third type reduces liquidity away from the best ask level. To summarize, we have the types of "events" described in Table 3.

Table 3

Classification of Order Flow Events

Type of Event	Ask	Bid
A trade implying the subm. of a new limit order	Aggr. trade at ask	Aggr. trade at bid
A trade consum. all exist. volume at the best level	Full trade at ask	Full trade at bid
A trade not consum. all volume at best level	Ord. trade at ask	Ord. trade at bid
A submission, reduc. the spread	Ask subm. within	Bid subm. within
A submission, increasing depth at best level	Ask subm. at	Bid subm. at
A submission, away from the best level	Ask subm. above	Bid subm. below
A removal, increasing the spread	Ask rem. within	Bid rem. within
A removal or change, reduc. depth at the best level	Ask rem. at	Bid rem. at
A removal or change, away from the best level	Ask rem. above	Bid rem. below

4.2 Correlation in Trading Events

In our main sample, we observe a total of 128 806 different order flow events. We classify these into all the types defined in Table 3. To simplify the exposition, we start by concentrating on the description of the six types of trade events. Table 4 reports the empirical frequencies of the trade events together with the respective unconditional probabilities.

Table 4

Frequency of Different Types of Trades

Type of Event	Frequency	Unconditional Probability (%)
Aggr. trade at ask	1 009	0.78
Aggr. trade at bid	959	0.74
Full trade at ask	6 893	5.35
Full trade at bid	6 336	4.92
Ord. trade at ask	3 547	2.75
Ord. trade at bid	3 897	3.03
Other	106 165	82.42
Total	128 806	100.00

In our sample, we can also observe the conditional probabilities. We tabulate these in Table 5, where: *P(Aggr. trade at ask at t | Aggr. trade at ask at t-1)* = 1.29 % and *P(Aggr. trade at ask at t | Aggr. trade at bid at t-1)* = 8.24 %.

Table 5
Conditional Probability Matrix in Per Cent

time *t-1* \ time *t*	Aggr. trade at ask	Aggr. trade at bid	Full trade at ask	Full trade at bid	Ord. trade at ask	Ord. trade at bid	Other
Aggr. trade at ask	1.29	7.33	4.26	19.52	1.39	7.43	58.77
Aggr. trade at bid	8.24	0.52	20.33	3.23	5.84	1.67	60.17
Full trade at ask	0.68	0.06	8.47	0.61	2.93	0.32	86.93
Full trade at bid	0.14	0.49	0.68	7.35	0.52	3.05	87.77
Ord. trade at ask	2.71	0.31	15.93	2.59	11.53	1.61	65.32
Ord. trade at bid	0.67	2.57	2.72	13.06	1.54	10.14	69.31
Other	0.74	0.72	5.18	4.93	2.82	3.30	82.32
Unconditional Prob.	0.78	0.74	5.35	4.92	2.75	3.03	82.42

Comparing the conditional probabilities with the unconditional probabilities in Table 5, several interesting phenomena can be noted about the time pattern of the order flow events in the LOB.

First of all, following an aggressive trade, the probability of a non-trading event is lower than the unconditional probabilities. There is clear indication that trades are serially correlated. Following an aggressive trade, there is an increased probability of all three types of trades. Most of the time, this trade is on the *other* side of the market. The conditional probability of an aggressive trade at bid (given an aggressive trade at ask) is almost ten times the unconditional probability. An aggressive trade at ask is ten times likelier after an aggressive trade at bid as unconditionally. We conclude that the immediate liquidity created by the aggressive marketable limit order is often quickly consumed by other traders. The aggressive trades often induce more trading. One interpretation is that the aggressive trades to some degree are informationless or transitory in Hasbrouck's (1991a, b) terminology. A probable interpretation is that these price reversals are part of the short term volatility inherent in an order driven market. An impatient liquidity order results in a temporary shift of the price level, which is subsequently corrected by additional orders. According to Handa and Schwartz (1991), this short-run volatility is a necessary condition for traders to use limit orders. It can be viewed as an equilibrium property of an order driven market. Without it, the submitters of limit orders would face a winner's curse where, ex post, all executions of the orders would be undesirable.

There is evidence of some autocorrelation in full trades at the *same* side of the market. In addition there is, after full trades, an extremely low probability of any form of trade on the other side of the market. A full trade at ask (bid) is more likely to be followed by yet another full trade at ask (bid). This would imply successively increasing spreads following full trades and could be due to new information arriving to the market. The market is simply moving. The information is first incorporated by trading off the existing levels, before new bid (ask) limit orders are inserted. The rule prohibiting market orders is certainly, at least partly, one explanation. Is it the same aggressive order that is split up in several trades or are there several, possibly informed, dealers who compete to trade away stale limit orders? We will return to this question in section 5 when we examine at the behavior of individual dealers.

There is also clear evidence of autocorrelation in ordinary trades at the *same* side of the market. After an ordinary trade at ask (bid), all three types of trades at ask (bid) are more common, than unconditionally. This could be the result of several traders reacting similarly to new information or of one dealer strategically splitting his orders over time to minimize the price impact. We will return also to this question in section 5.

4.3 Correlation in Non-Trading Events

As seen in Table 5, most of the events in the LOB do not result in trades. It is also of interest to examine these patterns of non-trade events in the LOB. The full table with the conditional probabilities can be found in Table B1 in Appendix B.

After an aggressive trade, there are more removals within the spread on the trade initiating side of the market. One possible explanation is that if the submitter of an aggressive marketable limit order does not get the rest of his limit order filled within a specified time interval, he withdraws his new bid (ask) order. Furthermore, after an ask (bid) removal within, there is increased probability of an aggressive trade at bid (ask). One explanation could be that the dealer gets impatient and subsequently changes his order from a limit order to a marketable limit order. We would then get two order flow events by the same dealer. We study this hypothesis in more detail in section 5. Quite expectedly, there is a significantly lower probability of an order submission within the spread, after an aggressive trade.

There is weak evidence that the submission of a new limit order within the spread induces trading directly. Table B1 in Appendix B indicates that after a submission of a new ask (bid) limit order within the spread, this order is more likely to consumed by a full trade than unconditionally. On the other hand, after a full trade at ask (bid), the probability of a submission of a new limit order at ask (bid) is enhanced. Thus, we find some support for the claim that immediate liquidity is provided and the spread reduced again after a spread-increasing trade.

Biais, Hillion and Spatt (1994) (henceforth BHS) find strong support for a mean-reversion in the spread, i.e. that new limit orders to reduce the spread are especially frequent when the spread is "large". This is supported in our study. After an ask (bid) removal within (i.e. a removal that increases the spread) an ask (bid) submission within is more likely than unconditionally. Furthermore, the reverse is also true. After an ask (bid) submission within, an ask (bid) removal within is more likely than unconditionally. More interestingly, there also seems to be considerable positive correlation between ask (bid) removals at and ask (bid) submissions at as well as between ask (bid) removals above (below) and ask (bid) submissions above (below). There seems to be a tendency to submit a new order to replace a just removed order as well as to remove an order after a new order has been submitted. The strong tendency for mean reversion in both spreads and depth provides evidence that the traders who expose their limit orders in the LOB are remunerated. Following Handa and Schwartz (1991), this could be sufficient to make limit order trading profitable.

So far, we have not used the dealer identity information. Our results are in line with those of BHS. When we now turn to the section using dealer identity codes, we will be able to investigate some hypothesis put forward in BHS.

5 Events Conditional on Individual Behavior

5.1 One Lag Analysis

In this section, we use the same set up as in section 4, but now we also condition on the fact that it is the same dealer acting in several successive events. There were 20 different dealers active on the HETI during the entire period under study.[11] In order to get an idea of the concentration in the dealer business, Table 6 lists the distribution of activity among the dealers. Although the dealer market in Finland is concentrated, no single dealer accounts for more than one fifth of the events in the sample. There seems to be enough number of dealers to draw conclusions on autocorrelation in individual dealer activity. If there is no autocorrelation in dealer "events", the probability is 8.9 per cent that the same dealer acts twice in a row.[12]

[11] We have omitted any dealers not active during the entire period. This is thus a conservative estimate of the total number of dealers in each period.

[12] Following Table 6, there is 17 per cent chance that dealer 1 acts. Therefore if there is no autocorrelation, we would unconditionally expect that dealer 1 acts in two successive events in 2.8 per cent of the observations. The unconditional probability of dealer 2 acting in two subsequent events is 2.5 per cent. Adding the figures for all dealers, there is an unconditional probability of 8.9 per cent that two successive events will be performed by the same dealer.

Table 6 (93)

Distribution of Activity Across Dealers, Per Cent

Ordering	Relative share of all events in the LOB	Relative share of LOB trades	Ordering	Relative share of all events in the LOB	Relative share of LOB trades
1	16.79	13.93	11	3.28	5.82
2	15.91	16.01	12	3.17	2.87
3	10.42	9.82	13	3.01	2.9
4	6.97	8.93	14	2.91	5.54
5	6.83	4.77	15	2.44	1.83
6	5.17	4.53	16	2.44	2.38
7	4.1	2.7	17	2.11	2.78
8	4.03	4.27	18	1.97	1.96
9	3.96	4.46	19	0.61	0.74
10	3.52	3.54	20	0.35	0.24

In 46 328 events, the *same* dealer initiates two successive order flow events, i.e. in 36 per cent of all observations the same agent is acting in two successive events. Table 7 lists the conditional probabilities of different trade events, conditional on other trades by the same dealer, together with two types of "unconditional" probabilities. In fact these "unconditional" probabilities are conditional in the sense that they are calculated only from the observations where the same dealer acts in two subsequent order flow events. We have 46 328 pair of events. The "Uncond. Prob. (*t-1*)" refers to the distribution across the eighteen different events in time t-1, regardless of which action that dealer takes in time t. In the same manner and more interestingly, "Uncond. Prob. (*t*)" refers to the distribution in time t, regardless of which action that dealer has taken in time t-1. When comparing the conditional with the unconditional probabilities, it is to our view more relevant to compare with the "Uncond. Prob. (*t*)".

Table 7

Conditional Probabilities in Per Cent (The Same Dealer)

time *t* / time *t-1*	Aggr. trade at ask	Aggr. trade at bid	Full trade at ask	Full trade at bid	Ord. trade at ask	Ord. trade at bid	Other
Aggr. trade at ask	4.15	0.46	7.37	2.76	0.92	2.76	81.57
Aggr. trade at bid	0.00	0.54	9.68	3.76	1.08	1.61	83.33
Full trade at ask	1.40	0.00	20.77	0.05	6.64	0.05	71.11
Full trade at bid	0.00	1.02	0.00	18.90	0.00	6.97	73.11
Ord. trade at ask	3.67	0.00	19.87	0.83	13.69	0.50	61.44
Ord. trade at bid	0.31	2.31	0.62	14.35	0.31	12.04	70.06
Other	0.54	0.66	2.62	3.19	2.58	3.30	87.12
Uncond. prob. (*t*)	0.61	0.65	3.61	3.87	2.76	3.38	85.12
Uncond. prob. (*t-1*)	0.47	0.40	4.78	4.43	1.29	1.40	87.23

Given that the previous event was an aggressive trade at ask, the probability of another aggressive trade at ask is considerably larger than unconditionally. This finding is contrary to our result when we did not condition on the identity of the dealer, where instead an aggressive trade at *bid* was likelier. We conclude that if there are two successive aggressive trades at ask, they are likely to be done by the same dealer. One explanation could be that we here capture the cases when a dealer possesses new or inside information and successively capitalize on that information. Caution has to be used with the interpretation here. The number of observations in this "cell" is small.

The auto-, and cross-correlations in full trades and ordinary trades are more pronounced when we condition on the identity of the dealer than in Table 5. This is probably a consequence of the rule prohibiting orders to walk up (down) the LOB. If this would be desired, the dealer would have to act in several steps, and we would observe several events. However, the high correlation between ordinary trades at ask (bid) and both aggressive and full trades at ask (bid) indicates that there is more to it than trading system induced order splitting. One alternative explanation is that certain dealers strategically split their orders. In that case, one dealer decides to trade only part of his total order now and to wait with the rest, thereby increasing the possibility that more depth will be provided and the impact of his trade on the equilibrium prices will be minimized. However, in this subsection we will observe the correlation pattern only when the strategy is unsuccessful and no extra depth is provided. In subsection 5.2 we will analyze the question further.

The full table with the conditional probabilities of the different order book events of the same dealer can be found in Table B2 in Appendix B, defined in exactly the same way as Table B1.

At first sight, Table B2 in Appendix B demonstrates that dealers tend first to withdraw an order and then to submit a new one in the subsequent event. The unconditional probabilities of removals in time t-1 are substantially higher than in time t, while the unconditional probabilities of submissions in time t are higher than in time t-1. This is not surprising since a dealer wishing to increase the quoted volume or change the price of an outstanding limit order, will have to submit a new order. To limit the exposure, the tendency seems to be to first withdraw and then submit. From the conditional probabilities, we see that if one dealer removes a limit order within/at/away from the spread, the very same dealer is likely to provide liquidity again by replacing the order with a new limit order within/at/away from the spread. There is also some evidence of first a removal and then a submission closer to (or within) the spread. Furthermore, the conditional probability of a removal within/at/away the spread following a submission within/at/away is higher than expected. Since the trading system prohibits any dealer from having more than one order at each level, this is clearly an indication of dealers testing the market. You submit an order to see if somebody jumps on it. If not, you withdraw it again. All of this supports our earlier finding in Table B1 in Appendix B of strong mean reversion in spread and depth.

According to Table B1 in Appendix B, a full trade at ask (bid) is often followed by a submission of a new order within at ask (bid). From Table B2 in Appendix B, we see that after a full trade at ask (bid) there is increased probability of a *bid (ask)* submission within by the same dealer. If one dealer trades away all volume at ask, thus increasing the spread and raising the midquote, the same dealer is very likely to submit a new order reducing the spread from under, i.e. raising the midquote even further. If the subsequent event is made by another dealer, he is more likely to submit a limit order at *ask*, i.e. lowering the midquote, rather than at bid after a full trade at ask. This demonstrates that order splitting might reduce the price impact of the trade. It is further an indication that a dealer with information is able to profit from the free trading options inherent in the outstanding limit orders of other dealers.

There is also evidence of impatience. The probability of all types of trade at bid (ask) after an ask (bid) removal at (or within) is considerably higher in the "same dealer" case than in the "total" case. That is to say; dealers with outstanding limit orders sometimes get impatient and first withdraw their limit orders to sell (buy) and instead hit the outstanding limit orders on the other side of the market. Furthermore, removals away from the spread lead to submissions on the same side of the market more frequently than directly to a trade. We conclude that a trader, with a limit order away from the trading prices, rather changes his quoted price gradually, than to change it immediately to a marketable limit order. Quite expectedly, after all types of trades at ask (bid), there is increased probability of a bid (ask) removal. If a dealer has new good (bad) information he also wants to get rid of his outstanding sell (buy) orders.

In Table B3 in Appendix B, we list the correlation frequencies given the same agent acting in subsequent events, relative to the total correlation frequencies. The first column of Table B3 gives the total relative frequencies of our 18 events that are followed by another event initiated by the same dealer. Not surprisingly removals and changes are often followed by events initiated by the same dealer. Of more interest are however the frequencies of the individual events.

BHS find that new orders within the quotes on the ask side were frequent after a large sale (and vice versa). They claim that this could reflect information effects and that these submissions are a result of a negative signal from the large sale. Table B3 in Appendix B sheds some additional light on these hypotheses. BHS's prediction assumes that the orders submitted from the same side are reactions by other dealers. An example may best explain the interesting features in Table B3. Table 8 summarizes the earlier discussion. In contrast to the prediction in BHS, Table 8 demonstrates that in most cases (53 %), the *same* dealer first sells (buys) away a price level and then submits the subsequent order within the spread on the ask (bid) side. This 53 per cent is considerably higher than the expected 32 per cent (i.e. the proportion of events following a full trade in time t-1 where the same dealer acts in time t compared to the total number of observations following a full trade in time t-1).

Table 8

Order Splitting vs Order Imitation

	From Table B1 in Appendix B Total Cond. Prob.		From Table B3 in Appendix B Proportion with Same Dealer		
	Ask Subm. Within	Bid Subm. Within	Total	Ask Subm. Within	Bid Subm. Within
Full Trade at Ask	26.55	23.02	32	5	53
Full Trade at Bid	18.73	30.03	32	53	5
Uncond. Prob.	13.26	16.55			

Thus, we find strong support for order splitting and only weaker support for order imitation. This is confirmed in Table B4 in Appendix B, where we list the conditional probabilities for observations where the two subsequent events are performed by *different* dealers. Order imitation would here appear as autocorrelation in events. However, if the first dealer trades aggressively at ask (bid), the second dealer is most likely to trade on the *other* side of the market, i.e. to consume the liquidity created by the first dealer. If the first dealer submits a full trade at ask (bid), the second dealer is most likely to replace the limit order consumed by the first dealer's trade on the ask (bid) side. Only following ordinary trades, is there evidence of order imitation. When the first dealer performs an ordinary trade at ask (bid), the conditional probability of all types of trades at ask (bid) by the second dealer is at least twice the unconditional probabilities.

5.2 Two Lag Analysis

In this section, we concentrate on a few very specific series of events. One purpose is to further compare the hypotheses of strategic order splitting behavior and dealer imitating behavior. In order to properly investigate if there is evidence of strategic order splitting behavior, we need to give other market participants the chance to react before the first dealer submits the second part of his order. We therefore need to extend the analysis beyond the one lag model.

Another purpose is to check for a bidding behavior. Since the spread normally is several ticks, there is potential room to strategically bid in order to split the spread cost with your counterpart. We check if there is evidence of two dealers successively reducing the spread from each side before one of the dealers jumps on the quote of the other. Once again, this requires an analysis of more than one lag.

One problem with extending to a two lag analysis is that the number of observations in each "cell" falls drastically. Another problem is that the number of possible outcomes in the two lag model becomes exorbitant. Therefore, we limit ourselves to a few cases.

For the order splitting or order imitating behavior, we only use observations where one dealer, say A, performed a full trade at ask (bid) in time t-2, and where a *different* dealer, say B, acts in the subsequent event, in time t-1. We then analyze the 18 possible actions taken in time t, conditional on how B reacted in time t-1. Thus, these frequencies in time t are conditioned on that there is a full trade at ask in time t-2 and that a different dealer acts in time t-1. We compare this table of frequencies with the frequencies where A acted again in time t. We then get the proportion of actions where A acted strategically compared to the total number of observations.

Table 9
Order Splitting Behavior: An example

LOB at time *t-3*		LOB at time *t-2* after full trade at ask		LOB at time *t-1* after ask subm within		LOB at time *t* after ord. trade at ask	
Price	Volume	Price	Volume	Price	Volume	Price	Volume
ask 114	2 000	ask 114	2 000	ask 114	2 000	ask 114	2 000
ask 112	1 600			ask 113	900	ask 113	500
bid 109	1 000	bid 109	1 000	bid 109	1 000	bid 109	1 000

The aim is to see if a dealer waits for the market to submit additional liquidity (depth) before putting through the entire trade. The example in Table 9 clarifies how order splitting behavior would turn up in our results. In this example, we assume that dealer A wants to buy 2 000 shares. Instead of submitting two orders, with a short interval, first buying 1 600 shares at 112 and 400 shares at 114, he performs the first part, waits until someone else submits additional volume at ask and then buys the rest. If order splitting is common, we would have a high frequency of trades at time t performed by dealer A.

If order imitating is more common, most of the trades at time t would be done by another dealer.

From the substantially reduced two lag sample, it is difficult to draw any statistically meaningful inferences. Still, some interesting conclusions can be drawn from Table 10. In total, we observe 4 465 sequences where a full trade at ask is followed by two events and the dealers are different in times t-2 and t-1. In 756 out of the cases, dealer A responded again. Since our sample is limited to 756 observations, we do not calculate any conditional probabilities, but report the actual frequencies in Table 10. Trader B typically submits a new order in time period t-1. A's response to B's ask submission within is mostly yet another full trade at ask. Furthermore, when a full trade at ask is followed by an ask submission within and another trade at ask, in 61 per cent of the cases, the two trades are performed by the same dealer, dealer A. Other common reactions to B's ask submission within in t-1 is a bid submission within or at in time t. In these cases, the new ask order might not have been attractive enough. If dealer A hopes to be able to split the existing spread through a bidding behavior, a high frequency of bid submissions within in time t is exactly what we would expect.

Table 10

Frequencies Assuming:
1) Full Trade at Ask in t-2
2) Different Dealers Acting in t-2 and t-1
3) Same Dealer Acting in t-2 and t

Frequencies in Parenthesis Refer to Observations Using Assumption 1 and 2 only.

t / *t-1*	Total freq.	Full trade at ask	Ord. trade at ask	Bid subm within	Bid subm. at
All 6 types of trades	37 (252)	4 (24)	0 (3)	19 (56)	1 (6)
Ask subm. within	414 (1652)	197 (324)	29 (81)	73 (199)	24 (55)
Bid subm. within	102 (697)	23 (50)	3 (7)	21 (71)	22 (67)
Ask subm. at	38 (245)	3 (4)	5 (9)	18 (53)	3 (12)
Bid subm. at	15 (111)	3 (6)	1 (3)	3 (15)	0 (0)
Ask subm. above	44 (289)	2 (9)	3 (5)	23 (65)	2 (11)
Bid subm. below	17 (125)	0 (5)	0 (1)	10 (31)	2 (11)
All 6 types of rem.	89 (1094)	3 (14)	5 (20)	40 (314)	9 (61)
Total	756 (4465)	235 (436)	46 (129)	207 (804)	63 (223)

The analysis is very similar if we instead assume that dealer A performed a full trade at bid in time t-2. For brevity, we do not report these findings. The overall conclusion is that order splitting is much more common than order imitation.

We now turn to another case, assuming that dealer A submits a new order within in time t-2, and analyze the response of another dealer, dealer B, in time t-1 as well as A's reaction to B's response. We limit ourselves to when A submits a new *bid* order within in t-2. The analysis is parallel when A submits a new *ask* order within in t-2. If dealer A's new bid order within in time t-2 is interpreted as positive information by the market, dealer B would logically respond by further increasing the quote midpoint in time t-1. This could be done by either, a trade at ask, a bid submission or an ask removal. As can be seen from the last column of Panel A in Table 11, A's most common response in time t is to withdraw his original bid order. If B responds by submitting a new bid order within (the most common response), A often (in 60 out of the 421 cases) goes further by submitting yet a new bid order within. Another possible answer is a full trade at ask.

If dealer A's new bid order within in time t-2 is interpreted as liquidity motivated and without information, a natural response by dealer B is to lower the quote midpoint again. This could be done by either a trade against A's limit order, an ask submission or a bid removal. Our results are summarized in Panel B of Table 11. If dealer B chooses an aggressive trade at bid (i.e. creating more immediate liquidity), A mostly responds by a full trade at ask (i.e. by completely exhausting the new immediate liquidity). If dealer B chooses a full trade at bid, A's response is almost always to submit a new order at bid within. Once again, we find clear evidence of an order splitting behavior. On the other hand, if dealer B chooses to submit an ask order, the most common response by A is to withdraw his original bid order. He is not prepared to go further and nobody hits his improved bid price. Another possibility is that A either trades away that ask order or submits a new bid order within. This suggests a bidding behavior, where the spread is successively reduced in a few steps before trading actually takes place.

One conclusion from this section is therefore that there is some evidence of a successive bidding behavior, where the dealers are testing each other by successively improving the quotes before one of them hits the outstanding limit order. In this way, the dealers reduce the spread cost of transacting.

Table 11

Frequencies Assuming:
1) Bid Submission Within in t-2
2) Different Dealers Acting in t-2 and t-1
3) Same Dealer Acting in t-2 and t

Frequencies in Parenthesis Refer to Observations Using Assumption 1 and 2 Only.

PANEL A

If A's bid order within (t-2) is seen as new good information, B's response will be:

	Total	Full trade at ask	Ask subm. within	Bid subm. within	Bid rem. below
Agg. trade at ask	8 (62)	0 (1)	0 (5)	1 (1)	3 (7)
Bid subm. within	421 (2186)	30 (103)	23 (300)	60 (308)	239 (366)
Total	1900 (15533)	166 (735)	107 (2240)	366 (2518)	295 (1127)

	Total	Full trade at ask	Ask subm. within	Bid subm. within	Bid rem. at
Bid subm. at	114 (1005)	11 (52)	12 (131)	12 (128)	46 (117)
Total	1900 (15533)	166 (735)	107 (2240)	366 (2518)	100 (233)

	Total	Full trade at ask	Ask subm. within	Bid subm. within	Bid rem. within
Full trade at ask	79 (765)	3 (79)	8 (178)	5 (170)	39 (39)
Ord. trade at ask	67 (313)	14 (48)	0 (12)	1 (19)	26 (26)
Bid subm. below	129 (1141)	7 (38)	15 (204)	18 (157)	49 (49)
Ask rem. within	20 (652)	2 (3)	3 (332)	2 (25)	9 (9)
Ask rem. at	25 (527)	0 (15)	0 (127)	0 (28)	14 (14)
Ask rem. above	21 (772)	2 (17)	1 (142)	4 (29)	7 (7)
Total	1900 (15533)	166 (735)	107 (2240)	366 (2518)	468 (666)

PANEL B

If A's bid order within (t-2) is seen as a liquidity trade and without information, B's response will be:

	Total	Full trade at ask	Bid subm. within	Bid subm. at	Bid rem. within
Agg. trade at bid	34 (173)	10 (37)	5 (11)	2 (6)	1 (3)
Full trade at bid	302 (1526)	1 (9)	212 (443)	17 (45)	10 (59)
Ord. trade at bid	75 (503)	7 (18)	2 (19)	0 (37)	40 (40)
Ask subm. within	351 (2261)	56 (191)	27 (308)	0 (84)	162 (162)
Ask subm. at	93 (764)	6 (21)	8 (101)	0 (43)	36 (36)
Ask subm. above	125 (1174)	13 (59)	9 (156)	0 (66)	56 (56)
Total	1900 (15533)	166 (735)	366 (2518)	37 (1058)	468 (666)

6 Assessing the Significance of the Event Patterns

6.1 Total Sample

Our one lag tables above, describing the conditional events in the LOB, are contingency tables. In order to study the statistical significance of the structures found, we treat our events as count data and apply the Poisson regression model[13] for discrete random variables. The Poisson distribution function is given by:

$$prob(y_i = k) = e^{-\lambda_i} \frac{\lambda_i^k}{k!} \qquad , \ k = 0,1,2,3,... \tag{1}$$

where λ_i is the parameter to be estimated.

If the observed frequencies of the dependent variable Y are $y_i,\ i = 1,2,\dots,N,\ and y_i \geq 0$ and we have a set of explanatory variables x_i, the Poisson regression model can be stated as:

$$\lambda_i = e^{\beta' x_i} \tag{2}$$

To study the extent to which the structure in our table deviates from an assumption of that the distribution at time t is independent of the distribution at time t-1, we regress the observed frequencies on a set of column and row dummies. Our baseline model (corresponding to our unconditional probabilities) is thus:

$$\lambda_i = \exp\{\alpha_0 + \alpha_2 R_2 + \alpha_3 R_3 + \cdots + \alpha_{18} R_{18} + \beta_2 C_2 + \beta_3 C_3 + \cdots + \beta_{18} C_{18}\} \tag{3}$$

where $$R_2, R_3, \dots R_{18} = row\ dummies \tag{4}$$

and $$C_2, C_3, \dots C_{18} = column\ dummies \tag{5}$$

From the fitted values, we then calculate the Pearson residuals as:

$$e_i = \frac{y_i - \hat{y}_i}{\sqrt{\hat{y}_i}} \tag{6}$$

The Pearson residuals are approximately standardized variables with mean 0 and variance approximately 1 (the variance is approximate due to the estimation of α_i and β_i in the linear model). We then use these standardized residuals as a measure of the deviation from the assumption of an "equal distribution".

Using these standardized Pearson residuals, we may assess the significance of our earlier tentative findings. In order to get a measure of the whether the distribution differs

[13] The model is a non-linear regression model where the error terms are assumed to follow the Poission distribution. For a reference, see McCullagh and Nelder (1989).

from an "equal" distribution, it can be noted that the sum of all the squared Pearson residuals will be equal to the Pearson goodness-of-fit statistic, which is χ^2-distributed with degrees of freedom equal to the number of rows minus one, times the number of columns minus one. Furthermore, from the individual standardized residuals it is possible to draw inferences of where the large deviations are to be found. We begin by examining our basic set of events, then we study the events conditioned on the dealer being the same.

Table B5 in Appendix B lists the Pearson residuals where all events are taken into account. Our empirical Pearson goodness-of-fit statistic is 66 930 with 289 degrees of freedom. This is of course significant at any reasonable significance level.[14] However, of more interest are the individual residuals. In general, the results of Table B5 are in line with our previous findings. The mean reversion of the price after an aggressive trade has high deviations as expected. The probability that an aggressive trade is followed by another trade from the opposite side is clearly higher than expected. Furthermore, while the probability of a trade at bid (ask) after an aggressive trade at ask (bid) is not substantially lower than expected, the expectation of a more patient limit order within at bid is much lower.

Our impression that a large portion of the trading takes the form of sequences of trades is also supported by the residuals. We get high positive residuals both for successive full trades and especially for full trades followed by a submission within the spread on both sides of the market.

Removals and changes followed by submissions have high residuals as do submissions followed by removals. These patterns are part of the dynamics of LOB trading in which bids and offers are revised in response to changing market conditions.

Permanent price reactions in the form of removals at ask (bid) as a result of aggressive trading at ask (bid) receive only weak support in our analysis. The residuals are positive for removals within or at the best level but the magnitudes are hardly significant. It is likely that permanent price reactions, of substance, occur after a sequence of full trades. Such longer term effects cannot be identified in our approach. A decomposition of the events in the book in transitory and permanent effects would call for an approach like Hasbrouck (1991a, b) in which time series analysis methods are employed.

[14] The critical values are 338 and 354 at the five and one per cent significance levels respectively.

6.2 Events Conditioned on the Dealer Being the Same

The analysis of events conditioned on the same dealers follow the same approach as above. Table B6 in Appendix B shows the standardized residuals from the Poisson regression on the two sets of dummy variables. The findings from Table B6 support our discussion based on comparing the conditional probabilities with the unconditional. We can safely reject the hypothesis of no overall serial correlation in events (i.e., an "equal" distribution). The empirical Pearson goodness-of-fit statistic is 97 856 with 289 degrees of freedom, which is highly significant.

Turning to the individual residuals, the serial correlation in full trades, indicating a sequence of trades that walk up (down) the book, gets high positive residuals. Thus, these events are more often initiated by the same dealer. In our sample, the "diagonal effect" discussed by BHS results from order splitting and not from imitation. BHS put forward the notion that the diagonal effect may result from dealers reacting similarly to events. By studying the time lag between their events they try to distinguish between order splitting and herding. Our dealer specific data allow us study this directly.

The time lag examination by BHS resulted in that correlation in large trades was assumed to result from "imitation" (different dealers) while small trade autocorrelation was a result from order splitting. Our full trades are not as large because of the rules prohibiting orders that cross several price levels. There are however strongly positive residuals in the diagonal for both full and ordinary trades. In our data the imitation hypothesis is clearly not supported.

Submissions within the spread followed by submissions within on the same side was by BHS assumed to arise from price undercutting between different dealers. Our residuals are in line with this interpretation. There are less such sequences than unconditionally expected in our same dealer data.

There is evidence that dealers are testing the market. An ask (bid) submission within/at/above (below) is very likely to be followed by the same dealer withdrawing that very order. Dealers often seem willing to give the market a chance on a "better" order but this better order is only outstanding for a short period of time. The order revision hypothesis put forward in our previous section also gets support here. The residuals for removals followed by submissions by the same dealer are very high. Here, there is clear evidence that dealers often change their price. Since the lower diagonals also are significant, there is evidence that these changes are primarily to better the price and our hypothesis that the dealers are testing the market is supported. These significant diagonal elements are thus a result from the dynamic nature of the order book in which orders submitted are revised in reaction the changing market conditions.

7 Conclusions

The main conclusion of the essay is that the unconditional probabilities of different event occurring in the LOB are different from the conditional probabilities. The recent history of events can be informative, especially if you also know *who* did what. Among other things, we show that there is considerable auto-correlation in trades. The hypothesis put forth in Biais, Hillion and Spatt (1994) that different dealers are imitating each other find no support in our data. Instead, we find that the dealers are likely to strategically split their orders. Our results also indicate that there exists a body of potential limit orders outside the LOB. These limit orders may be submitted, or existing orders changed, if market conditions change. Therefore, the LOB does not give a full picture of the real demand and supply functions. Furthermore, we find that the spread is mean-reverting, indicating that limit order trading can be profitable. We also show that dealers tend to successively better the quotes before trading takes place. Thereby the cost of the spread is reduced. Finally, we shed some light to how liquidity is provided in an LOB-market.

References

Aitken, M., P. Brown and T. Walter, (1993), "The Bid/Ask Schedule Under an Automated Trading Regime", Working Paper, University of Sydney, July 1993.

Bernstein, P., (1987), "Liquidity, Stock Markets and Market Makers", *Financial Management*, 16:54-62.

Biais, B., P. Hillion and C. Spatt, (1994), "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse", Working Paper, March 1994.

Black, F., (1991), "Exchanges and Equilibrium", Working Paper, Goldman Sachs & Co. New York.

Chan, L. K. C. and J. Lakonishok, (1993), "Institutional trades and intraday stock price behavior", *Journal of Finanical Economics*, 33:173-199.

Domowitz, I., (1993), "Financial Market Automation and the Investment Services Directive", Working Paper, Northwestern University, September 1993.

Easley, D., N. M. Kiefer and M. O'Hara, (1993), "One Day in the Life of a Very Common Stock", Working Paper, Cornell University, February 1993.

Glosten, L. R., (1994), "Is the Electronic Open Limit Order Book Inevitable?", *Journal of Finance*, 49, 1127-1161.

Handa, P., (1991), "Order Flow and Bid-Ask Dynamics: An Empirical Investigation". Working Paper, Stern School, New York University, July, 1991.

Handa, P. and R. A. Schwartz, (1991), "Dynamics of Price Discovery in a Securities Market", Working Paper, Stern School, New York University.

Harris, L., (1990), "Liquidity, Trading Rules, and Electronic Trading Systems", Monograph Series in Finance and Economics, 1990-4, (New York, New York University, Salomon Brothers Center, 1990).

Harris, L. and J. Hasbrouck, (1992), "Market versus Limit Orders: SuperDOT Evidence on Order Submission Strategy", Working Paper, NYSE, April 1992.

Hasbrouck, J., (1991a), "Measuring the Information Content of Stock Trades", *Journal of Finance*, 46:179-207.

Hasbrouck, J., (1991b), "The Summary Informativeness of Stock Trades: An Econometric Analysis", *Review of Financial Studies*, 4:571-595.

Hedvall, K., (1994), "The Anatomy of a COLOB During High- and Low-liquidity Periods - Empirical Market Microstructure Evidence From the Helsinki Stock Exchange", Working Paper, Swedish School of Economics and Business Administration, September 1994.

Helsinki Stock Exchange, (1991), "Rules and Regulations of the Helsinki Stock Exchange", Vol 2, 1991.

Holthausen, R. W., R. W. Leftwich and D. Mayers, (1987), "The Effect of Large Block Transactions on Security Prices: A Cross-sectional Analysis", *Journal of Financial Economics*, 19:237-267.

Holthausen, R. W., R. W. Leftwich and D. Mayers, (1990), "Large-block transactions, the speed of response, and temporary and permanent stock price effects ", *Journal of Financial Economics*, 26:71-95.

Jain, P. C., (1988), "Response of Hourly Stock Prices and Trading Volume to Economic News", *Journal of Business*, 61:219-231.

De Jong, F., T Nijman, A. Röell, (1994), "Price Effects of Trading and the Components of the Bid-Ask Spread on the Paris Bourse", Working Paper, Tilburg University, August 1994.

Karpoff, J. M., (1987), "The Relation between Price Changes and Trading Volume: A Survey", *Journal of Financial and Quantitative Analysis*, 22:109-126.

Keim, D. B. and A. Madhaven, (1991), "The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects", Working Paper, University of Pennsylvania, June 1991.

Kraus, A. and H. R. Stoll, (1972), "Price Impacts of Block Trading on the New York Stock Exchange". *Journal of Finance*, 27:569-588.

Lee, C. M. C., B. Mucklow and M. J. Ready, (1993), "Spreads, Depths and the Impact of Earnings Information: An Intraday Analysis", *Review of Financial Studies*, 6, 345-374.

Lehmann, B. N., and D. M. Modest, (1994), "Trading and Liquidity on the Tokyo Stock Exchange: A Bird's Eye View", *Journal of Finance*, 49, 951-984.

McCullagh, P. and J. A. Nelder, (1989), *Generalized Linear Models*, Monograph on Statistics and Applied Probability, Chapman & Hall, 2nd Edition.

Monroe, M., (1992), "The Profitability of Volatility Spreads around Information Releases", *Journal of Futures Markets*, 12:No 1:1-9.

Niemeyer, J. and P. Sandås, (1993), "An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange", *Journal of Multinational Financial Management*, 3, No 3/4, 63-101.

Patell, J. M. and M. A. Wolfson, (1981), "The Ex Ante and Ex Post Price Effects of Quarterly Earnings Announcements Reflected in Option and Stock Prices", *Journal of Accounting Research*, 19:434-458.

Appendix A

The Stocks in the Sample.

The stocks in the sample have been continuously listed on the exchange between January, 1990, and February, 1993. Some continuously listed stocks were excluded from the sample on the basis of major restructuring in their line of business.

1	Amer A	34	OKO A
2	Asea B	35	OP-Sijoitus
3	Asko A	36	Outokumpu
4	Asko B	37	Partek
5	Birka Line K	38	Pohjola A
6	Birka Line E	39	Pohjola B
7	Citycon	40	Raision Margariini
8	Cultor I	41	Raision Tehtaat
9	Cultor II	42	Rautakirja A
10	Enso A	43	Rautakirja B
11	Enso R	44	Rautaruukki K
12	Finnair	45	Sampo A
13	Fiskars A	46	Spontel
14	Fiskars K	47	Starckjohann B
15	Fazer Musik A	48	Stromsdal
16	Ford	49	Stockmann A
17	Huhtamäki K	50	Stockmann B
18	Huhtamäki I	51	Suomen Kiinteistöinv.
19	Instru A	52	SYP-Invest B
20	Instru B	53	SYP-Invest C
21	Interavanti	54	Tamfelt K
22	Investa B	55	Tamfelt E
23	Itikka-Lihapolar	56	Tampella
24	Kesko	57	Tietotehdas
25	Kone B	58	Unitas A
26	KOP	59	Unitas B
27	Kymmene	60	Unitas C
28	Lassila&Tikanoja	61	Valmet
29	Lännen tehtaat	62	WSOY A
30	Metsä-Serla A	63	WSOY B
31	Metsä-Serla B	64	YIT-Kiinteistöt
32	Nokia K	65	Ålandsbanken K
33	Nokia E	66	Ålandsbanken E

Appendix B

Table B1

Conditional Probabilities, Per Cent

time *t-1* / time *t*	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	1.29	**7.33**	4.26	**19.52**	1.39	**7.43**	6.44	1.49	3.77	6.24	4.56	5.45	4.36	**9.61**	4.96	0.89	3.17	7.83
Aggr. trade, bid	**8.24**	0.52	**20.33**	3.23	**5.84**	1.67	1.04	6.15	8.55	3.34	6.57	4.80	**8.45**	4.17	1.77	2.71	9.38	3.23
Full trade, ask	0.68	0.06	8.47	0.61	2.93	0.32	**26.55**	23.02	4.06	2.89	5.11	2.31	3.67	3.73	3.26	3.45	3.93	4.95
Full trade, bid	0.14	0.49	0.68	7.35	0.52	3.05	18.73	30.03	3.00	3.06	4.01	4.53	4.75	3.16	4.61	2.37	6.64	2.87
Ord. trade, ask	**2.71**	0.31	**15.93**	2.59	**11.53**	1.61	3.38	7.27	12.09	3.16	6.77	3.38	4.45	4.71	3.52	3.81	5.78	6.99
Ord. trade, bid	0.67	**2.57**	2.72	**13.06**	1.54	**10.14**	5.31	4.00	3.67	9.93	5.59	5.85	6.06	6.59	**6.59**	2.39	8.13	5.18
Ask subm. within	1.38	0.47	10.54	3.93	2.62	2.00	9.51	12.72	6.52	3.54	10.77	5.59	**8.30**	4.27	0.98	2.45	10.42	4.01
Bid subm.within	0.40	0.90	4.92	8.12	1.94	2.88	14.26	13.04	4.42	5.18	7.15	8.20	3.48	7.39	2.81	0.91	4.32	9.68
Ask subm. at	0.64	0.56	4.21	4.70	4.83	3.37	10.15	13.01	8.39	4.46	10.90	6.33	0.01	3.21	**10.70**	2.71	7.57	4.26
Bid subm. at	0.51	0.62	5.75	4.28	3.05	5.61	11.75	12.21	5.70	6.64	8.31	6.85	3.09	0.00	3.33	**10.94**	4.95	6.40
Ask subm. above	0.72	0.52	4.63	3.41	2.18	2.45	9.45	14.04	6.04	4.14	**21.93**	6.47	3.13	2.76	2.55	2.03	9.98	3.57
Bid subm. below	0.56	0.62	3.60	5.27	1.96	2.20	13.88	12.02	5.42	5.59	11.14	**14.33**	2.37	3.57	2.83	1.68	4.66	8.30
Ask rem. within	0.11	**1.92**	0.64	8.31	0.17	**9.93**	**56.94**	7.35	2.63	1.05	2.31	1.13	1.58	1.09	1.32	0.85	1.09	1.58
Bid rem. within	1.53	0.02	4.32	0.47	**6.69**	0.35	4.58	**68.51**	1.09	2.06	1.20	2.15	1.26	1.55	1.01	0.78	1.40	1.01
Ask rem. at	0.41	**1.84**	3.14	8.18	2.04	**10.89**	22.05	7.31	**19.04**	2.63	6.01	1.89	2.99	1.64	2.73	1.28	3.96	1.97
Bid rem. at	1.45	0.51	7.00	2.70	**9.50**	2.26	6.45	28.22	2.97	**14.94**	2.91	5.61	1.96	2.94	2.33	2.13	3.45	2.67
Ask rem. above	0.32	1.09	2.11	3.83	0.84	4.56	16.08	4.67	**18.81**	1.72	**31.83**	1.49	2.06	1.11	1.47	0.63	6.00	1.40
Bid rem. below	1.00	0.31	3.80	1.96	4.75	0.74	3.78	24.97	1.76	**20.33**	2.13	**22.61**	1.26	1.99	1.30	1.03	1.64	4.66
Uncond. prob.	0.78	0.74	5.35	4.92	2.75	3.03	13.26	16.55	6.41	5.15	10.36	6.89	3.63	3.76	3.04	2.30	6.01	5.07

Table B2

Conditional Probabilities, Given the SAME Dealer, per Cent

time *t* / time *t-1*	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	**4.15**	0.46	**7.37**	2.76	0.92	2.76	4.61	0.46	1.84	0.00	1.84	6.91	0.92	**44.70**	3.23	4.15	3.69	**9.22**
Aggr. trade, bid	0.00	0.54	**9.68**	3.76	1.08	1.61	0.54	3.76	0.00	0.54	9.68	1.61	**43.55**	1.08	**9.14**	1.08	10.22	2.15
Full trade, ask	**1.40**	0.00	**20.77**	0.05	**6.64**	0.05	3.84	**37.88**	0.95	3.66	2.08	1.35	1.35	4.74	1.67	**5.28**	1.63	6.68
Full trade, bid	0.00	1.02	0.00	**18.90**	0.00	**6.97**	**30.39**	5.02	2.83	0.58	2.00	1.95	7.89	1.46	**8.09**	1.41	9.89	1.61
Ord. trade, ask	**3.67**	0.00	**19.87**	0.83	**13.69**	0.50	0.50	13.52	2.34	3.51	4.51	4.34	1.67	5.01	0.50	**7.18**	5.01	**13.36**
Ord. trade, bid	0.31	**2.31**	0.62	**14.35**	0.31	**12.04**	9.26	1.08	4.17	2.47	6.64	4.78	9.57	1.85	**10.03**	1.54	**15.43**	3.24
Ask subm. within	0.22	0.31	2.34	3.76	1.11	1.03	4.59	4.81	0.00	1.42	14.56	4.06	**39.44**	2.06	4.65	1.64	**11.55**	2.45
Bid subm.within	0.44	0.15	5.37	1.78	1.60	1.27	11.03	6.69	2.50	0.00	6.05	11.42	1.62	**34.52**	1.34	4.25	2.92	7.06
Ask subm. at	0.06	0.32	1.41	3.66	0.32	1.16	6.68	5.78	0.00	2.76	19.38	5.13	0.00	1.09	**34.92**	2.18	**12.58**	2.57
Bid subm. at	0.16	0.16	4.12	1.24	1.17	0.08	6.14	8.63	4.74	0.00	9.18	10.58	1.87	0.00	2.80	**35.93**	4.04	**9.18**
Ask subm. above	0.41	0.26	1.97	1.50	0.82	1.09	3.62	6.32	2.62	1.44	**43.00**	5.82	2.53	1.50	**1.88**	1.09	**22.06**	2.06
Bid subm. below	0.21	0.34	1.35	2.32	0.88	0.72	10.58	5.94	4.76	3.12	17.57	**24.44**	1.64	2.49	1.69	1.10	3.33	**17.53**
Ask rem. within	0.00	**2.32**	0.08	**9.39**	0.03	**11.63**	**64.88**	2.78	2.39	0.42	1.61	0.34	1.22	0.18	1.07	0.26	0.73	0.68
Bid rem. within	**1.74**	0.00	4.57	0.20	**7.70**	0.02	2.20	**75.68**	0.42	2.03	0.17	1.71	0.46	1.10	0.44	0.59	0.46	0.51
Ask rem. at	0.07	**2.34**	1.33	**9.60**	1.11	**14.57**	27.62	3.15	**23.47**	1.04	6.08	0.59	2.34	0.41	1.82	0.67	2.97	0.82
Bid rem. at	**1.74**	0.10	**7.48**	1.35	**12.35**	1.35	3.42	**34.54**	1.40	**17.75**	0.77	6.66	1.11	3.42	1.25	1.59	2.12	1.59
Ask rem. above	0.03	1.10	0.59	3.40	0.17	4.92	17.78	1.21	**22.65**	0.36	**38.85**	0.42	1.56	0.32	1.00	0.19	5.01	0.44
Bid rem. below	1.11	0.08	2.74	0.79	4.94	0.10	1.05	29.25	0.18	**24.81**	0.44	**27.37**	0.32	1.37	0.69	0.58	0.48	3.71
Uncond. prob. (*t*)	0.61	0.65	3.61	3.87	2.76	3.38	14.05	16.46	5.64	4.57	12.60	7.44	4.85	4.91	3.10	2.48	5.42	3.62
Uncond. prob. (*t-1*)	0.47	0.40	4.78	4.43	1.29	1.40	7.76	9.85	3.36	2.78	7.34	5.12	8.30	8.83	5.82	4.47	12.71	10.88

Table B3

Proportion of Events by the Same Dealer for Each Conditional Probability, Per Cent

time t / time t-1	Total	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	22	69	1	37	3	14	8	15	7	11	0	9	27	5	100	14	100	25	25
Aggr. trade, bid	19	0	20	9	23	4	19	10	12	0	3	29	7	100	5	100	8	21	13
Full trade, ask	32	66	0	79	2	73	5	5	53	8	41	13	19	12	41	16	49	13	43
Full trade, bid	32	0	68	0	83	0	74	53	5	31	6	16	14	54	15	57	19	48	18
Ord. trade, ask	17	23	0	21	5	20	5	3	31	3	19	11	22	6	18	2	32	15	32
Ord. trade, bid	17	8	15	4	18	3	20	29	4	19	4	20	14	26	5	25	11	32	10
Ask subm. within	21	3	14	5	20	9	11	10	8	0	8	28	15	100	10	100	14	23	13
Bid subm.within	21	24	4	23	5	18	9	17	11	12	0	18	30	10	100	10	100	14	16
Ask subm. at	19	2	11	6	15	1	6	12	8	0	12	34	15	0	6	62	15	31	11
Bid subm. at	19	6	5	14	6	7	0	10	14	16	0	21	30	12	N/A	16	64	16	28
Ask subm. above	25	15	13	11	11	10	11	10	11	11	9	50	23	21	14	19	14	56	15
Bid subm. below	27	10	15	10	12	12	9	20	13	23	15	42	46	19	19	16	17	19	56
Ask rem. within	82	0	99	10	93	13	96	94	31	75	33	57	25	64	14	66	25	55	35
Bid rem. within	84	96	0	89	35	97	6	41	93	32	83	12	67	31	60	37	63	28	43
Ask rem. at	69	13	88	29	81	38	92	86	30	85	27	70	22	54	17	46	36	52	29
Bid rem. at	70	84	13	75	35	91	42	37	86	33	83	19	83	40	82	38	52	43	42
Ask rem. above	76	8	77	21	68	15	82	84	20	92	16	93	22	58	22	52	22	64	24
Bid rem. below	77	86	20	56	31	80	10	21	90	8	94	16	93	20	53	41	43	22	62

Table B4

Conditional Probabilities, Given DIFFERENT Dealers, per Cent

time t / time t-1	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	0.51	**9.22**	3.41	**24.12**	1.52	**8.71**	6.94	1.77	4.29	7.95	5.30	5.05	5.30	0.00	5.43	0.00	3.03	7.45
Aggr. trade, bid	**10.22**	0.52	**22.90**	3.10	**6.99**	1.68	1.16	6.73	10.61	4.01	5.82	5.56	0.00	4.92	0.00	3.10	9.18	3.49
Full trade, ask	0.34	0.09	2.65	0.88	1.18	0.45	**37.30**	15.99	5.54	2.52	6.54	2.76	4.77	3.25	4.02	2.59	5.02	4.13
Full trade, bid	0.21	0.23	1.00	1.82	0.77	1.17	13.14	**42.03**	3.08	4.25	4.97	5.77	3.25	3.97	2.94	2.83	5.09	3.48
Ord. trade, ask	**2.51**	0.37	**15.13**	2.95	**11.09**	1.83	3.97	6.00	**14.08**	3.09	7.23	3.19	5.02	4.65	4.14	3.12	5.94	5.70
Ord. trade, bid	0.74	**2.62**	3.14	**12.80**	1.79	**9.76**	4.52	4.59	3.57	11.42	5.39	6.06	5.36	**7.54**	5.91	2.55	6.68	5.57
Ask subm. within	1.68	0.51	12.73	3.97	3.03	2.26	10.82	14.83	8.25	4.10	9.76	6.00	0.00	4.86	0.00	2.66	10.11	4.43
Bid subm.within	0.39	1.10	4.80	9.85	2.03	3.32	15.14	14.77	4.95	6.60	7.44	7.32	3.99	0.00	3.21	0.00	4.70	10.39
Ask subm. at	0.78	0.61	4.86	4.94	5.88	3.88	10.95	14.70	10.34	4.85	8.92	6.61	0.01	3.70	5.07	2.83	6.40	4.66
Bid subm. at	0.60	0.73	6.14	5.02	3.50	**6.94**	13.10	13.07	5.93	8.24	8.11	5.95	3.39	0.00	3.46	**4.92**	5.17	5.73
Ask subm. above	0.82	0.60	5.54	4.06	2.64	2.92	11.44	16.68	7.21	5.07	14.73	6.69	3.33	3.19	2.78	2.35	5.85	4.08
Bid subm. below	0.69	0.72	4.43	6.35	2.35	2.74	15.08	14.24	5.66	6.49	8.79	10.64	2.63	3.97	3.24	1.89	5.15	4.94
Ask rem. within	0.60	0.12	3.22	3.34	0.84	2.15	20.53	28.28	3.70	3.94	5.49	4.77	3.22	5.25	2.51	3.58	2.74	5.73
Bid rem. within	0.40	0.13	2.93	2.00	1.20	2.13	17.58	29.43	4.79	2.26	6.79	4.53	5.59	3.99	4.13	1.86	6.52	3.73
Ask rem. at	1.15	0.74	7.15	5.02	4.11	2.71	9.70	16.53	9.21	6.17	5.84	4.77	4.44	4.36	4.77	2.63	6.17	4.52
Bid rem. at	0.79	1.47	5.87	5.87	2.82	4.40	13.54	13.43	6.66	8.35	7.90	3.16	3.95	1.81	4.85	3.39	6.55	5.19
Ask rem. above	1.25	1.03	6.93	5.20	2.98	3.41	10.67	15.70	6.55	6.06	9.47	4.87	3.63	3.63	2.98	2.06	9.15	4.44
Bid rem. below	0.61	1.08	7.40	5.92	4.10	2.89	13.06	10.43	7.13	5.11	7.87	6.46	4.44	4.10	3.36	2.56	5.59	7.87
Uncond. prob. (*t*)	0.93	0.83	6.50	5.79	3.02	3.27	13.48	15.65	6.72	5.57	8.68	6.36	2.87	3.02	3.00	2.17	6.27	5.86
Uncond. prob. (*t-1*)	0.96	0.94	5.67	5.19	3.57	3.94	16.35	20.31	8.13	6.48	12.06	7.89	1.02	0.91	1.47	1.07	2.24	1.80

Table B5

Standardized Residuals from the Poisson Regression, All Observations

time *t* / time *t-1*	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	1.7	23.8	-1.6	20.3	-2.9	7.2	-6.2	-11.5	-3.2	1.4	-5.5	-1.6	1.3	9.8	3.5	-2.9	-3.6	3.9
Aggr. trade, bid	25.4	-0.9	19.7	-2.6	5.3	-2.8	-10.6	-7.6	2.7	-2.5	-3.4	-2.3	8.0	0.8	-2.2	0.9	4.3	-2.5
Full trade, ask	-1.2	-6.7	10.7	-16.5	0.0	-13.6	28.9	14.7	-7.5	-8.4	-13.0	-14.2	0.4	0.1	1.1	6.4	-6.9	-0.4
Full trade, bid	-5.9	-2.5	-16.3	7.9	-11.2	-1.1	10.9	28.1	-10.5	-7.5	-15.2	-6.8	4.9	-2.2	7.2	0.5	2.2	-7.7
Ord. trade, ask	12.5	-3.1	26.7	-6.6	30.0	-5.6	-16.6	-12.9	13.6	-5.3	-6.2	-7.7	2.7	3.1	1.7	6.0	-0.4	5.1
Ord. trade, bid	-1.0	12.8	-7.3	22.0	-5.1	23.4	-14.1	-18.7	-6.6	12.9	-8.8	-2.2	8.2	9.4	12.7	0.4	5.6	0.4
Ask subm. within	8.1	-4.5	28.4	-6.8	-2.3	-9.4	-14.8	-10.5	1.0	-9.6	2.8	-5.8	32.5	3.9	-15.4	1.4	23.8	-6.1
Bid subm.within	-6.7	2.2	-3.4	19.5	-8.4	-3.4	2.3	-10.6	-11.1	-0.1	-13.5	8.1	-0.8	28.0	-1.9	-13.3	-9.8	30.0
Ask subm. at	-1.8	-2.2	-4.9	-1.6	10.1	0.3	-8.7	-6.7	7.4	-3.0	2.3	-1.5	-17.1	-2.3	40.0	2.6	6.0	-3.2
Bid subm. at	-2.7	-1.4	1.0	-2.9	0.6	10.3	-4.2	-7.6	-2.0	5.1	-4.5	0.3	-2.1	-15.7	1.4	46.7	-3.4	4.9
Ask subm. above	-1.2	-3.3	-4.1	-8.6	-5.0	-5.5	-13.2	-5.5	-1.3	-5.4	43.1	-1.3	-2.8	-5.7	-3.2	-1.9	19.0	-7.6
Bid subm. below	-2.6	-1.6	-7.5	0.7	-5.3	-5.8	0.5	-9.2	-3.4	1.6	3.1	27.5	-6.1	-0.6	-1.1	-3.8	-5.0	13.6
Ask rem. within	-5.4	9.0	-14.1	9.7	-11.0	24.9	80.0	-14.7	-10.1	-12.5	-16.8	-14.8	-7.2	-9.3	-6.7	-6.5	-13.7	-10.6
Bid rem. within	5.5	-5.9	-3.4	-14.3	15.3	-11.3	-17.1	91.6	-14.5	-9.6	-19.5	-12.3	-8.5	-7.8	-8.1	-6.9	-13.0	-12.5
Ask rem. at	-2.8	7.6	-6.2	8.5	-3.2	26.1	14.2	-13.5	31.6	-7.1	-8.0	-11.7	-2.0	-6.7	-1.1	-4.2	-5.1	-8.6
Bid rem. at	3.8	-1.6	3.6	-5.8	20.9	-3.1	-10.6	16.7	-7.3	23.2	-12.3	-2.4	-4.7	-2.1	-2.2	-0.5	-5.6	-5.8
Ask rem. above	-4.8	3.2	-12.6	-5.0	-10.7	6.1	5.7	-24.8	43.6	-13.4	60.2	-17.8	-7.1	-11.8	-7.9	-9.6	0.1	-14.3
Bid rem. below	1.6	-4.3	-5.7	-11.2	8.6	-11.4	-21.6	18.3	-14.7	53.5	-20.2	49.3	-9.9	-7.2	-8.0	-6.7	-14.3	-1.4

Table B6

Standardized Residuals from the Poisson Regression, Given the Same Dealer

time *t* / time *t-1*	Aggr. trade ask	Aggr. trade bid	Full trade ask	Full trade bid	Ord. trade ask	Ord. trade bid	Ask subm. within	Bid subm. within	Ask subm. at	Bid subm. at	Ask subm. above	Bid subm. below	Ask rem. within	Bid rem. within	Ask rem. at	Bid rem. at	Ask rem. above	Bid rem. below
Aggr. trade, ask	6.7	-0.4	2.9	-0.8	-1.6	-0.5	-3.7	-5.8	-2.4	-3.1	-4.5	-0.3	-2.6	26.5	0.1	1.6	-1.1	4.3
Aggr. trade, bid	-1.1	-0.2	4.4	-0.1	-1.4	-1.3	-4.9	-4.3	-3.2	-2.6	-1.1	-2.9	24.0	-2.4	4.7	-1.2	2.8	-1.1
Full trade, ask	4.8	-3.8	42.5	-9.1	11.0	-8.5	-12.8	24.9	-9.3	-2.0	-14.0	-10.5	-7.5	-0.4	-3.8	8.4	-7.7	7.6
Full trade, bid	-3.5	2.1	-8.6	34.6	-7.5	8.8	19.8	-12.8	-5.4	-8.4	-13.5	-9.1	6.3	-7.1	12.8	-3.1	8.7	-4.8
Ord. trade, ask	9.6	-2.0	20.9	-3.8	16.1	-3.8	-8.8	-1.8	-3.4	-1.2	-5.6	-2.8	-3.5	0.1	-3.6	7.3	-0.4	12.5
Ord. trade, bid	-1.0	5.2	-4.0	13.6	-3.8	12.0	-3.3	-9.6	-1.6	-2.5	-4.3	-2.5	5.5	-3.5	10.0	-1.5	10.9	-0.5
Ask subm. within	-3.0	-2.6	-4.0	-0.3	-5.9	-7.7	-15.1	-17.2	-14.2	-8.8	3.3	-7.4	94.1	-7.7	5.3	-3.2	15.8	-3.7
Bid subm.within	-1.5	-4.2	6.2	-7.2	-4.7	-7.7	-5.4	-16.3	-8.9	-14.4	-12.5	9.8	-9.9	90.3	-6.8	7.6	-7.3	12.2
Ask subm. at	-2.7	-1.6	-4.6	-0.4	-5.8	-4.8	-7.8	-10.4	-9.4	-3.3	7.5	-3.3	-8.7	-6.8	71.4	-0.7	12.1	-2.2
Bid subm. at	-2.1	-2.2	1.0	-4.8	-3.4	-6.4	-7.6	-6.9	-1.4	-7.7	-3.5	4.1	-4.9	-7.9	-0.6	76.2	-2.1	10.5
Ask subm. above	-1.5	-2.8	-5.0	-7.0	-6.8	-7.3	-16.2	-14.6	-7.4	-8.5	49.9	-3.5	-6.1	-9.0	-4.0	-5.1	41.7	-4.8
Bid subm. below	-2.5	-1.9	-5.8	-3.8	-5.5	-7.1	-4.5	-12.6	-1.8	-3.3	6.8	30.4	-7.1	-5.3	-3.9	-4.3	-4.4	35.6
Ask rem. within	-4.8	12.7	-11.5	17.4	-10.2	27.8	84.1	-20.9	-8.5	-12.0	-19.2	-16.1	-10.2	-13.2	-7.2	-8.7	-12.5	-9.6
Bid rem. within	9.3	-5.2	3.2	-11.9	19.0	-11.7	-20.2	93.4	-14.1	-7.6	-22.4	-13.4	-12.7	-11.0	-9.7	-7.7	-13.6	-10.4
Ask rem. at	-3.6	10.8	-6.2	15.2	-5.1	31.6	18.8	-17.0	39.0	-8.6	-9.5	-13.0	-5.9	-10.5	-3.8	-6.0	-5.5	-7.6
Bid rem. at	6.6	-3.1	9.3	-5.8	26.3	-5.0	-12.9	20.3	-8.1	28.1	-15.2	-1.3	-7.7	-3.0	-4.8	-2.6	-6.4	-4.8
Ask rem. above	-5.6	4.3	-12.2	-1.8	-12.0	6.4	7.6	-28.9	54.9	-15.1	56.8	-19.7	-11.5	-15.9	-9.1	-11.2	-1.4	-12.8
Bid rem. below	4.6	-5.0	-3.3	-11.1	9.3	-12.7	-24.6	22.4	-16.3	67.3	-24.3	51.9	-14.6	-11.3	-9.7	-8.6	-15.1	0.3