THESIS
3
2000

This is to certify that the

dissertation entitled

Three Essays on the Microstructure of the Turkish Stock Market

presented by

Sadettin Aydin Yuksel

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in Finance

Geoffrey Booth
Major professor

Date 7/26/00

MSU is an Affirmative Action/Equal Opportunity Institution

O-12771

LIBRARY
Michigan State
University

PLACE IN RETURN BOX to remove this checkout from your record.
TO AVOID FINES return on or before date due.
MAY BE RECALLED with earlier due date if requested.

DATE DUE	DATE DUE	DATE DUE

6/01 c:/CIRC/DateDue.p65-p.15

THREE ESSAYS ON THE MICROSTRUCTURE OF THE TURKISH STOCK MARKET

By

Sadettin Aydin Yuksel

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Finance

2000

ABSTRACT

THREE ESSAYS ON THE MICROSTRUCTURE
OF THE TURKISH STOCK MARKET

By

Sadettin Aydin Yuksel

This is the first study to use intraday data from the Istanbul Stock Exchange (ISE). The purpose of the study is to investigate short-term price dynamics in this emerging market. The data set covers the 30 most active stocks on the ISE over 14 months and contains about nine million transactions. The ISE is an order-driven market and its most distinguishing feature is the tick rule it employs. It appears that the ISE aims to keep a large relative tick constant for all price levels.

One goal of the study is to determine whether ISE's large tick restricts trader behavior more than do tick rules in other markets. The results suggest that traders on the ISE use predominantly one-tick and occasionally two-tick rounding. Perhaps due to the narrow tick regime width, no variation in clustering is found within a tick regime. In addition, the examination of spread and price change frequencies reveals they hardly ever exceed the tick size, which indicates that the tick size is binding.

The literature states that mean reversion in short-term price dynamics is necessary to make limit order trading an attractive strategy. A trading rule used in studies of the New York Stock Exchange (NYSE) and Paris Bourse is

employed here to compare the expected profitability of limit and market orders. Unlike the NYSE and the Paris Bourse, the ISE has excessive marketwide price movements and these hide the short-term mean reversion in price. The market-adjusted returns show that, on average, executed limit orders perform better than market orders, but the opposite holds for unexecuted limit orders. A comparison of the fraction of executed limit orders in these three markets reveals that prices are more volatile on the ISE than on the other two exchanges. This can be attributed to two factors. First, the absence of an opening call auction may negatively affect price discovery on the ISE. Second, there may be insufficient depth in the limit order book, which is unexpected, given the use of a large relative tick by the ISE. Therefore, one can hypothesize that the weak balance between limit and market order submission rates may be one reason for the ISE's choice of an unorthodox tick rule.

Finally, the short-term relationship between price and volume is examined. Both display strong intraday and weak interday variability on the ISE. Similar to other equity markets, the ISE displays an asymmetric contemporaneous relationship between volume and volatility. Moreover, there is a feedback relationship in the Granger sense between volume and volatility. This differs from Jain and Joh (1988), who found a unidirectional relationship (volatility causes volume) on the NYSE.

ACKNOWLEDGMENTS

I would like to thank my dissertation chair, Dr. G. Geoffrey Booth, for his guidance from start to finish. I have benefited immensely from our discussions. I am also grateful to him for his patience, for his strong moral support, and for exerting the right amount of pressure. Needless to say, this dissertation could not have been done without him. I also thank the other members of my committee, Dr. Kursat Aydogan, Dr. Kirt Butler, and Dr. Ted Fee, for their helpful comments throughout the process.

I am very grateful to Dr. S. Tamer Cavusgil for his enormous support in very difficult times. I thank my friend Umit Mersinli, of the Istanbul Stock Exchange, for providing data. I am grateful to my friend Yigit Kavurmacioglu for his help in improving my programming skills and to my friend Dr. Salim Hiziroglu for being there whenever I needed moral support. Finally, I am grateful to my parents, to whom this dissertation is dedicated.

TABLE OF CONTENTS

LIST OF TABLES viii

LIST OF FIGURES xi

LIST OF DETAIL TABLES xii

CHAPTER 1 Introduction 1

1.1 Purpose and Relevance of the Dissertation 7

1.2 Contributions of This Study 8

CHAPTER 2 The Istanbul Stock Exchange 12

2.1 History of the Securities Market in Turkey 12

2.2 Organization of the ISE 13

2.3 Trading Mechanism for Stocks 14

2.4 ISE Member Firms 19

2.5 Foreign Investment on the ISE 19

2.6 Data 20

CHAPTER 3 Price Clustering on the Istanbul Stock Exchange 25

3.1 Introduction 25

3.2 Literature Review 28

3.2.1 Early Evidence of Clustering 28

3.2.2 An Overview of Clustering Studies 29

3.2.3 The Extent of Clustering in Different Markets 30

3.2.4 Determinants of Clustering 31

3.2.5 The Effect of a Change in Tick Size 35

3.2.6 Relation to Other Microstructure Aspects 36

3.3 Empirical Analysis 40

3.4 Summary 49

CHAPTER 4 Limit Order Profitability on the Istanbul Stock Exchange ... 51

4.1 Introduction 51

4.2 A Comparison of the ISE with the Paris Bourse and the NYSE 54

4.3 The Viability of a Pure Limit Order Market 60

4.3.1 The Tradeoff between Market and Limit Order Strategies 60

4.3.2 The Method 61

4.3.3 The Experimental Design 66

4.3.4 Limitations of the Method 68

4.3.5 Empirical Evidence in Previous Studies 70

4.4 Empirical Analysis 73

4.4.1 Data 73

4.4.2 Results 75

4.5 Summary 87

CHAPTER 5 Relationship between Trading Volume and Price Change on the ISE 89

5.1 Introduction 89

5.2 Literature Review 91

5.2.1 Early Research on Price-Volume Relationship 93

5.2.2 More Recent Work 98

5.2.3 Intra and Interday Patterns in Volume and Return Volatility 102

5.3 Empirical Analysis 104

5.3.1 Introduction 104

5.3.2 Data 105

5.3.3 Time of Day and Day of Week Effects 108

5.3.4 Contemporaneous Price-Volume Relationship 110

5.3.5 Causality 113

5.4 Summary 116

CHAPTER 6 Summary 117

APPENDIX A Tables 123

APPENDIX B Figures 180

APPENDIX C Detail Tables 188

LIST OF REFERENCES 199

LIST OF TABLES

Table 1 Annual ISE Trading Activity, 1986-1998 124

Table 2 Monthly ISE Trading Activity during the Sample Period 124

Table 3 Comparison of Emerging Markets by Size, in Millions of Dollars 125

Table 4 Number of Stocks Listed on the ISE 126

Table 5 Types of Normal Order 126

Table 6 Minimum Trade Size for Special Orders 127

Table 7 Number of ISE Members Authorized to Trade on the Stock Market, 1986-July 1999 127

Table 8 Top 20 ISE Brokerage Houses Sorted by Total Transaction Value Generated, January-December 1998 128

Table 9 Top 20 ISE Brokerage Houses Sorted by Wholesale and Special Transactions, January-December 1998 129

Table 10 Equity Portfolio Holdings by Foreign Investors, 1995-1999, in Millions of Dollars 130

Table 11 Total Market Value of Companies Traded on the ISE, 1986-1999, in Millions of Dollars 130

Table 12 Some Characteristics of ISE Stocks in the Sample 131

Table 13 Weekdays without Trading during the Sample Period 132

Table 14 Number of Sessions Stocks were Traded during the Sample Period 133

Table 15 Monthly Volume Generated by Foreign Investors during 1998 among Stocks in the Sample 134

Table 16 Stock Split Adjustments for Sample Firms during the Sample Period 135

Table 17 Dividend Adjustments for Sample Firms during the Sample Period 136

Table 18 Number of Transactions for Sample Stocks 137

Table 19 Maximum Number of Shares Limit per Month for Sample Stocks during the Sample Period, in Lots 139

Table 20 Maximum Trade Size in Lots for Normal Orders (Type 1) 140

Table 21 Identification of Special Orders 140

Table 22 The Tick Rule on the ISE and Six Other Exchanges that Use Step Functions 141

Table 23 The Extent of Clustering in Different Markets 143

Table 24 Determinants of Clustering 144

Table 25 Distribution of Tick Size per Sample Stock 145

Table 26 Actual Frequencies 147

Table 27 Frequencies Adjusted for Serial Dependence in Price 150

Table 28 Distribution of Bid-Ask Spread as a Multiple of Tick Size for Sample Stocks 153

Table 29 Price Change in Consecutive Transactions 154

Table 30 Variation in Clustering within Tick Regimes 155

Table 31 Parameter Values and the Number Of Stock-Windows Used in the Experiment 159

Table 32 The Number of Stock-Windows Conditional on Execution and Nonexecution of Limit Orders 159

Table 33 Average Standardized Execution Price of Limit Orders 160

Table 34 The Difference between Execution and Triggering Prices for Executed Limit Orders 161

Table 35 Average Time to Execution in Hours for Naturally Executed Limit Orders 161

Table 36 Unconditional and Conditional Returns for Market and Limit Orders 162

Table 37 Differential Returns 163

Table 38 Standardized Price Following the Order Submission Day 165

Table 39 Sensitivity of Costs to the Choice of Investment Window Length 166

Table 40 Market-Adjusted Differential Limit Buy Order Returns 167

Table 41 Sensitivity of Market-Adjusted Differential Limit Buy Order Returns to the Choice of Investment Window Length 168

Table 42 The Experiment of Simultaneously Submitting Limit Buy and Sell Orders at ± k Ticks from the Equilibrium Price 169

Table 43 Frequency of Trade Sequences in Which Price Changed Consecutively 170

Table 44 Distribution of Intervals Based on Price Change and No Price Change Classification 172

Table 45 Stationarity of Price and Volume Series 173

Table 46 Average Turnover during 15 Minute Intervals by Weekday, in Percentage 174

Table 47 Average Return Volatility during 15 Minute Intervals by Weekday ($\times 10^{-4}$) 175

Table 48 Average Return during 15 Minute Intervals by Weekday 176

Table 49 Regression Results for the Test of a Contemporaneous Relationship between Volume and Return 177

Table 50 Granger Causality: Relationship between Return and Volume 179

Table 51 Granger Causality: Relationship between Return Volatility and Volume 179

LIST OF FIGURES

Figure 1	Standardized Price Level of ISE100 Index and Equal Weighted Portfolio of Sample Firms	181
Figure 2	Tick Rule on the ISE	182
Figure 3	Distribution of Nontrivial Spread over Time	182
Figure 4	Timing of Events	183
Figure 5	Standardized Price Following the Order Submission Day	183
Figure 6	Index Price Level over Time	184
Figure 7	Percentage Turnover over Time	184
Figure 8	Index Return over Time	185
Figure 9	Index Volatility over Time	185
Figure 10	Average Intraday Turnover	186
Figure 11	Average Intraday Volatility	186
Figure 12	Average Intraday Return	187

LIST OF DETAIL TABLES

Table 52 Unconditional and Conditional Returns for Market and Limit Orders, Investment Window of 5 Days 189

Table 53 Differential Returns, Investment Window of 5 Days 190

Table 54 Unconditional and Conditional Returns for Market and Limit Orders, Investment Window of 7 Days 192

Table 55 Differential Returns, Investment Window of 7 Days 193

Table 56 Market-Adjusted Differential Limit Buy Order Returns, Investment Window of 5 and 7 Days 195

Table 57 Details for the Experiment of Simultaneously Submitting Limit Buy and Sell Orders at ± k Ticks from the Equilibrium Price ... 196

Chapter 1

Introduction

During the last two decades many factors have contributed to increased competition in cross-border financial exchanges. The most important of these are improvement in information technology; elimination of foreign investment barriers; an increased supply of equities, partly fueled by the large number of privatizations; and investor demand for international diversification. To reduce the transaction costs of their stocks, world-class companies seek listings in all major markets. In addition to the international competition, exchanges in developed countries face domestic competition. For example the New York Stock Exchange (NYSE) competes with Nasdaq, regional exchanges, third-market firms that make over-the-counter markets in NYSE stocks, and crossing networks (such as POSIT, the Crossing Network, and Instinet) that allow investors to cut out the middlemen.

The increased competition forces organizers of these markets to reconsider the optimality of their design. Although there are similarities across exchanges, many significant differences can be observed. The trading mechanism may be either a call or continuous auction, or a market may open with one mechanism and switch to the other later in the trading day.[1] A market may be order or quote driven. It may use floor trading, electronic trading, or

[1] For example, the New York, Milan, and Helsinki stock exchanges.

both. Players in the market may differ. A continuous market may have a specialist (called a registered trader on the Toronto Stock Exchange) and floor traders, as does the NYSE, or it may simply match the order of public traders, as does the Stock Exchange of Singapore. Rules on transparency, short selling, maximum price change limit, and settlement date are all factors about which an exchange organizer must decide.

One feature of an exchange is the tick rule it employs. The minimum price increment (tick) determines what prices traders use. In most markets this increment is a decimal fraction, but for the NYSE and the American Stock Exchange (AMEX) it is based on negative powers of two (currently 1/16).[2] Some markets, such as the London Stock Exchange, have only informal customs that dictate the minimum price increment. Even among exchanges with a formal tick rule, there are differences. Some use single absolute tick size for all the listed stocks, whereas others employ a tick rule that is a step function of stock price. Among others, the London gold market and the major North American exchanges (NYSE, AMEX, and Toronto Stock Exchange, except for stocks with extremely low prices) have single absolute tick size; Helsinki, Hong Kong, Singapore, Sydney, and Tokyo stock exchanges are examples of markets that use step functions.

[2] It seems likely that the US stock markets will soon switch to decimal pricing. Some newspapers have already started to report prices in decimals.

The effect of tick size on trader behavior as well as the quality and competitiveness of markets has been the subject of academic and industry debate. Tick rules changed very infrequently in equity markets until the 1990s.[3] At least partially due to concerns about competitiveness and the increase in academic research in this area, owing to the availability of detailed trade data, stock exchanges have begun to experiment with tick rules. During the last decade, exchanges in Australia, Singapore, Hong Kong, Canada, and the United States have decreased tick size.

A stream of research analyzes how traders use the sets of discrete prices available to them. The existence of minimum price variation provides a natural benchmark in assessing trader behavior directly from prices. This literature dates back to Osborne (1962), and shows that asset prices deviate from random walk, and some prices are observed more frequently than others when underlying asset value is uniformly distributed over the range of feasible prices. The so-called clustering literature presents evidence of and explanations for this anomaly. Price clustering is shown to exist in all markets analyzed thus far, although its extent varies across markets.

An economic explanation of this anomaly comes from Ball et al. (1985) and Harris (1991). Ball et al. developed the price resolution hypothesis, that is, clustering is the manifestation of the haziness about asset values. In other

---

[3] In some other markets, such as commodity futures, rule changes have been quite common.

words, investors will use coarser discrete price sets than the set based on the regulated minimum price variation if they cannot determine the true price of an asset with enough precision. Harris took the argument a step farther and pointed out that even if investors can determine asset values with high precision, they may avoid using a fine price set if it is costly to do so. His negotiation hypothesis states that the use of a coarser grid arises from the incentive to lower negotiation costs, which include the time it takes to strike a bargain and the extra amount of information that traders need to track when they use a fine grid (such as close attention in recording). The extent to which traders use a coarse grid depends on the price resolution in the market. A high resolution will result in a small dispersion among traders' reservation prices, and if a coarse grid does not include a price acceptable to both parties in a trade, gains from trade may be lost. The negotiation hypothesis focuses on the tradeoff between lower negotiation costs and lost gains from trade.

Research on tick size and trader behavior emphasizes a market's liquidity and competitiveness as well as the reaction of issuing firms. Depending on market structure – whether quote driven, order driven or both – liquidity may be provided by exchange members as well as by public traders who submit limit orders. A market is quote driven if dealers announce the prices at which other market participants can trade; it is order driven if some investors, by placing limit orders, establish the prices at which other participants can buy or sell shares. In a quote-driven market, member firms, which provide market-making services, should earn a minimum amount of profit to cover their fixed costs. Anshuman and Kalay (1998) estimate annual discreteness-related profits and show that observed minimum tick size in U.S. exchanges is consistent with maximization of member profits.

In an order-driven market, public traders can choose to trade via limit order and supply liquidity to the market, or they can choose to trade via market order and demand liquidity from the market. In order for a public trader to forgo the immediate execution of his order, there should be some compensation for trading via limit order.

The problem with liquidity provision is that a limit order/dealer quote reveals part of the information owned by that trader and creates a free-rider problem. Without a minimum tick, given a strict price-time priority rule, competition among liquidity providers will result in front-running on existing limit orders/dealer quotes by other investors and/or dealers. The tick size poses a barrier to competing forces, thereby creating positive expected profits for market makers, as pointed out by Grossman and Miller (1988). In exchanges that use a sharing rule rather than enforce strict time priority, the effect of front-running may be attenuated, as suggested by Porter and Weaver (1997). To minimize this problem, some exchanges, such as the Paris Bourse, allow traders to display part of their limit orders, which decreases the transparency of the market.

Another issue is the effect of tick size on intermarket competition. A mandatory tick size may cause an exchange to lose part of the order flow to other trading mechanisms. The emergence of such nonprice competition practices as preferencing (also known as payment-for-order flow) and its extreme case, called internalization, are at least partially attributed to mandatory tick size. Brokers direct orders to other market makers off the floor and receive payments in return. Chordia and Subrahmanyam (1995) show that these practices may lead to inferior order execution. They argue that a decrease in tick size will make competition for order flow more transparent, and orders will flow to the least-cost liquidity provider.

All these issues affect transaction costs, and this will be of concern to the issuing firms. Amihud and Mendelson (1986) found that higher transaction costs as measured by bid-ask spreads are associated with higher rates of return. In general, however, firms have some flexibility in adjusting relative tick size of their stocks by using stock splits. Angel (1997) provides U.S. and international evidence in support of the view that one motive for splits is to move to the optimal relative tick size.

Various empirical studies examine the effect of tick size on trader behavior indirectly by measuring the change in a number of market quality variables caused by an event that alters relative tick size. These studies examine three events: the modification by an exchange of its tick rule; stock splits, and, in markets that use a step function, the transition of stocks into a different tick regime as their prices change. The market quality variables are the size of bid-ask spread, market depth at the best quotes or beyond those, and trade volume. The empirical results are mixed. All studies find a positive relationship between relative tick size and bid-ask spread, but there is limited evidence that the total depth in the limit order book decreases with an increase in relative tick size. However, no significant change in either the trading volume or dealer profits has been reported.

1.1 Purpose and Relevance of the Dissertation

Because of data limitations, most of the evidence in this area is from North American markets. In the United States, for instance, intradaily transaction data first became widely available in the mid-1980s, and access to quotation data was made possible at the beginning of the 1990s. In recent years, automation has expanded data accessibility, and evidence is starting to accumulate for other markets. Because some of these exhibit features that are not shared by the major markets, an examination of them advances the market microstructure literature by providing a different environment for analysis. This dissertation examines an emerging market that represents a polar case because of its apparently large tick size relative to stock price. On the Istanbul Stock Exchange (ISE), relative tick size is at least 120% and as much as 2,200% greater than that used by other exchanges. No previous analysis has examined the issues related to the ISE's tick size choice, and empirical evidence from this market may be of interest to policy makers there as well as to policy makers in other markets who question the optimality of their tick size. The purpose of this study is to investigate short-term price dynamics on the ISE.

Three issues that are related to the choice of tick size are addressed in this research. First, mandatory minimum price change rules should not restrict trader behavior. Clustering studies measure the effect of tick size on trader behavior directly from prices. This issue is of interest to regulators in order to assess the optimality of their tick rule.

Second, it is argued that mean reversion in short-term price dynamics is a necessary condition for the limit order trading strategy to be attractive (Handa and Schwartz 1996). Tick size is related to the magnitude of mean reversion due to its effect on the front-running practices of limit order submitters. Therefore, a tick rule can serve as a policy variable to market regulators for the purpose of affecting the extent of liquidity in a market.

Third, a large tick size causes observed prices to differ from underlying stock values. Consequently, the speed and precision of the price adjustment process is likely to be hampered, which may affect the short-term relationship between price and trading volume. This is important to investors.

1.2 Contributions of This Study

This dissertation advances the clustering literature by identifying and examining a market that uses a large relative tick for all price levels. The goal of Chapter 3 is to determine whether the tick size is as large as it appears to be. Depending on market conditions, a seemingly large tick may turn out to be an optimal choice.

One explanation for the ISE's large tick is that the price resolution in this market is low, and it is consistent with the typical precision required by investors. In this case, one would expect to see a level of price clustering comparable to those observed on other markets analyzed thus far. Alternatively, the minimum price variation may be binding. In this case, the choice of tick size may reflect other concerns of regulators.

Empirical examination supports the latter scenario. It shows very weak clustering on the ISE, which distinguishes it from all other markets examined thus far. Moreover, analysis of spread size and consecutive price changes indicates that these hardly ever exceed the tick size. Taken together, the evidence suggests that the extent of uncertainty in the market is not likely to dictate the choice of a large relative tick. Therefore, one wonders whether there is a rationale for the choice of a binding tick size.

This study also contributes to the order choice decision literature by applying a trading rule introduced by Handa and Schwartz (1996) in an emerging market, where liquidity provision is likely to be of greater importance than in the markets in which the rule has been applied previously. Tick size is likely to affect the balance between limit and market order submission rates and short-term price dynamics. A large relative tick attenuates the front-running problem, which means that it is likely to shift the balance in submission rates in favor of limit orders. Moreover, a large relative tick also makes price discreteness more restrictive, which is likely to affect short-term price dynamics.

The viability of an order-driven market depends on sufficient limit orders to provide liquidity at all times. For an order-driven emerging market, such as the ISE, temporary lack of liquidity is not uncommon. Therefore, the ISE tick rule may reflect an extra incentive to the providers of liquidity in this market. The performance and thus attractiveness of a limit order trading strategy require frequent deviation of the market price from its equilibrium value and its correction within a reasonably short period so that there is mean reversion in short-term price dynamics.

The last contribution this study makes to the finance literature is that it examines the price-volume relationship in a market where the speed and precision of the price adjustment process are hampered by extreme price discreteness as well as the absence of an opening call auction. The price-volume relationship is important because it reveals equilibrium dynamics in a market. The microstructure literature is concerned with the question of how equilibrium is reestablished following the arrival of new information, in particular the random rate of information arrival, the dissemination of private information to market participants, and the learning process of uninformed investors from informed trades. These are the respective focus of the mixture of distributions, the sequential information, and the asymmetric information model.

After the arrival of new information, an equilibrium will be attained at a new price, and no matter whether the information is private or public there will be increased trading activity during the adjustment period. Therefore, a positive relationship between price volatility and trading volume is predicted. Empirical observation of such financial market conditions as serial dependence in trades, lagged price adjustment, and the persistence in volatility suggest that this relationship is dynamic. Contemporaneous relationship and Granger causality between volume and volatility are examined in this analysis.

This dissertation is organized as follows. Chapter 2 describes the institutional rules of the ISE and the data used in the study. Chapter 3 examines the extent of price clustering in this market. Chapter 4 compares the profitability of limit and market order trading strategies. Chapter 5 presents univariate and bivariate analyses of price change volatility and volume on the ISE. Chapter 6 offers conclusions.

Chapter 2

The Istanbul Stock Exchange

2.1 History of the Securities Market in Turkey

An organized securities market in Turkey has roots in the second half of the nineteenth century. Following the Crimean War, the first such market in the Ottoman Empire was established in 1866, the Dersaadet Securities Exchange. It created a medium for European investors who were seeking higher returns in the vast Ottoman holdings. Following the proclamation of the Turkish Republic, a law was enacted in 1929 to reorganize the fledgling capital markets under the name Istanbul Securities and Foreign Exchange Bourse.

The bourse contributed substantially to the funding requirements of new enterprises across the country, but the 1929 Depression and World War II had serious consequences for the embryonic business world in Turkey. During the industrial drive of the postwar decades, there was a continuous increase in the number and size of joint stock companies, which began to open up their equity to the public. Those mature shares faced a strong and growing demand from mostly individual and some institutional investors.

By the early 1980s there was a marked improvement in Turkish capital markets, both in regard to the legislative framework and the institutions required to set the stage for sound capital movements. In 1981 the Capital Market Law was enacted. One year later, the main regulatory body responsible for supervision and regulation of the Turkish securities market was established, the Capital Markets Board, based in Ankara.

A new decree in October 1983 laid the groundwork for security exchanges in Turkey, and in October 1984, "Regulations for the Establishment and Functions of Securities Exchanges" was published in the Official Gazette. Operational procedures were approved in subsequent extraordinary sessions of the General Assembly, and the Istanbul Stock Exchange was formally inaugurated in late 1985. Turkey has one of the most liberal foreign exchange regimes in the world, with a fully convertible currency as well as a policy that allows foreign institutional and individual investment in securities listed on the ISE since 1989. There are no restrictions on foreign portfolio investors trading in Turkish securities markets. Decree No. 32, passed in August 1989, removes all restrictions on overseas institutional and individual investment in securities listed on the ISE. Hence, Turkish stock and bond markets are open to foreign investors, without any constraints on the repatriation of capital and profits. Decree No. 32 also allows Turkish citizens to buy foreign securities.

2.2 Organization of the ISE

The ISE is the only exchange in Turkey to provide trading in equities, bonds and bills, revenue-sharing certificates, private sector bonds, foreign securities, real estate certificates, and international securities. It is governed by the Executive Council, composed of five members elected by the General Assembly. The person who holds the posts of both chairman and chief executive officer is appointed by the government. The four other members of the council represent the three categories of ISE members: development banks, commercial banks, and brokerage houses. As an autonomous, professional, semipublic organization, the ISE is allowed a high degree of self-regulation. Its revenues are generated from fees charged on transactions, listing procedures, and miscellaneous services. The profits of the ISE are retained to meet expenses or undertake investments and are not distributed to any third parties. The ISE has its own budget. It is supervised by the Capital Markets Board (the regulatory and supervisory authority for Turkish capital markets), which not only ensures the proper operation of both the exchange and its members but also protects the interests of both the public and the investing community.

2.3 Trading Mechanism for Stocks

The ISE is a fully automated continuous auction market that matches buy and sell orders on a price and time priority basis. It was founded on December 26, 1985, and the first transaction was executed on January 3, 1986. Full automation occurred on October 21, 1994. This is a rapidly growing market, as revealed by various measures of total trading activity shown in Table 1 and Table 2. During the last five years, annual dollar volume tripled, share volume increased more than twentyfold, and the number of contracts quadrupled.

Table 3 compares the ISE to other emerging markets in terms of annual trading volume and market capitalization. One notable characteristic of the Turkish market is its high trading activity. The ISE generates more trading volume than most of the markets that have a larger market capitalization.

There are two trading sessions on the ISE: from 10:00 a.m. to noon and from 2:00 p.m. to 4:00 p.m. Unlike some other exchanges, the trading mechanism does not change during a trading day.

The national market has 262 firms listed (as of the end of 1998), and there are several much smaller markets. The regional market contains smaller stocks that cannot be listed in the national market. Young firms are listed in the new companies market . The so called wholesale market involves trades exceeding 10% of paid-in capital of a firm, and it is used for block trades of either existing shares to predetermined/unidentified buyers or public offerings. Trading in the wholesale market is conducted from 9:15 a.m. to 9:45 a.m., just before the other markets open. Unlike some other exchanges, the ISE does not have a parallel upstairs market that operates during the normal trading hours. Finally, the watch list companies market is reserved for firms under special surveillance and investigation due to extraordinary circumstances such as incomplete, inconsistent and/or untimely disclosure of information to the public; failure to comply with rules and regulations; or other situations leading to delisting and/or dismissal from the related market temporarily or permanently in order to protect investors' rights and the public interest. The number of stocks listed in those markets is shown in Table 4. During the last five years, the quantity listed in the national market has increased by 50%.

In the ISE all orders are submitted in the form of a limit order. The standard trade size, one lot, contains 1,000 shares. Investors place orders with brokers, who in turn enter these into the electronic limit order book. Brokers can see the aggregate order size at each price level in real time. In addition to that information, the member codes are also displayed for executed orders. Settlement occurs on the second day following a transaction.

At present, there are no fixed commissions for the trading of stocks. The fee an ISE member may charge clients ranges between 0.2% and 1% of the transaction value. Depending on the amount and frequency of trading, the fee is negotiable between the member and the client. For each transaction, members have to pay an exchange fee whether the order is for a customer or a trade on their own account. This fee amounts to 1.4 10^{-4} % of trade value, and it is paid separately by both members on each side of a transaction.

Short selling is allowed on the ISE. A customer must deposit cash or security with value equal to at least 50% of the short sale. If the most recent price is an uptick, the short sale can be made at the same price. Otherwise, it should be at a price higher than the most recent transaction price.

Both the tick size and the maximum price change limit to be used in a session depend on the stock price. For each stock, the weighted average price (WAP) as a result of filling normal orders during a trading session is used to calculate the base price and tick size for the next session. Base price is obtained by rounding the WAP to the nearest tick. Transaction prices during a session must be within a 20% band around the base price, again rounded to the nearest tick. Upper limits are rounded upward and lower limits downward, so the

±10% limit may be exceeded slightly.

Two examples show the calculation of base price and tick size in a session. First, a WAP of TL2,528 falls in the third interval (2,500 , 5,000]. Tick size in this interval is TL50. The base price for the next session is found by rounding the WAP up or down to the nearest permissible price, in this case TL2,550. Like the WAP, the base price also falls in the third interval (2,500 , 5,000]. Therefore, the tick size in the next session becomes TL50. Second, a WAP of TL10,083 falls in the fifth interval (10,000 , 25,000]. Tick size in this interval is TL250, so the base price for the next session is found by rounding the WAP to the nearest permissible price, which is TL10,000. The base price falls in the fourth interval (5,000 , 10,000]. Therefore, the tick size in the next session becomes TL100.

There are three different order types in the ISE: normal, special , and odd-lot. Each has its own limit order book. Normal orders have four different subtypes, for all of which a limit price is specified. The difference concerns the maximum trade size allowed and the status of the unfilled portion of the order. All normal orders are subject to a "maximum trade value" upper limit of TL500 billion. One category – ordinary limit orders – is subject to a lower "maximum number of shares" upper limit. This second limit is expressed in lots, and since it depends on prior trading activity, it differs among stocks.

The subtypes of a normal order are as follows. (1) Ordinary limit orders: Both the limit price and trade quantity are specified. If the order cannot be filled partially or completely, it waits in the limit order book. "Maximum number of shares" is the relevant upper limit. (2) Fill or kill: The unfilled portion is canceled immediately, and "maximum trade value" is the relevant upper limit. (3) Limit orders that do not restrict the transaction value: Order size is not fixed. It transacts with all the counter orders up to the specified price. "Maximum trade value" is the relevant upper limit. (4) Limit orders that restrict the transaction value: Order size is not fixed. It transacts with all the counter orders up to the specified total trade value. "Maximum trade value" is the relevant upper limit. Table 5 summarizes the differences among these four types of normal order.

Special orders are transactions that exceed the minimum trade size lower limit, expressed in lots (for normal orders, this is one lot), and fall below the block sale (10% of paid-in capital) upper limit. These orders need the approval of an exchange official and cannot be filled partially. For an earlier order to have time priority over a later order, both price and quantity of the two orders should be identical, so the time priority rule is of minor importance for these orders. The minimum trade size limit depends on the base price and is given as a multiple of "maximum number of shares", which is the upper limit for ordinary limit orders. Table 6 shows the rule used in determining the minimum trade size limit.

Odd-lot orders are for quantities less than a single lot. These are executed at the same price as the most recently traded round-lot order.

2.4 ISE Member Firms

All ISE members are incorporated banks and brokerage houses. According to an arrangement by the Capital Markets Board on August 15, 1996, banks that intend to operate in the stock market must transfer their relevant operations to the brokerage firms they control. Table 7 shows the number of ISE members over time. There were 140 brokerage houses executing customer orders at the end of 1998. Tables 8 and 9 list the decomposition of total transactions by brokerage house. In those tables, transactions are classified into three categories: primary market, executed wholesale and special orders, and other transactions. The last category contains executed normal orders as well as transactions in the rights coupon and the official auction markets.

Overall, the respective shares of primary market transactions, executed wholesale and special orders, and other transactions during 1998 were 0.07%, 2.42%, 97.51%.

Table 8 lists the top 20 brokerage houses in terms of total transaction volume. These accounted for 53.83% of volume in 1998. Table 9 lists these in terms of wholesale and special transaction volume. The top 5 brokerage houses captured 73.63% of volume in this category during 1998.

2.5 Foreign Investment on the ISE

As shown in Table 10, since December 1995, foreign investment in the ISE has more than tripled. As can be seen from Table 11, comparison of foreign investment to total market value of the companies traded on the ISE, assuming a float rate of 20%, suggests that about half the floating equity in this market is owned by foreigners.

2.6 Data

The sample used in this study consists of 30 stocks that made up the ISE30 index as of February 26, 1999. These are the most actively traded stocks on the ISE. The sample period covers 14 months, from January 1998 through February 1999. The data were provided by the ISE and included transaction number, time, session, day, price, size, and an indicator variable showing the type if two different types of the same stock were traded simultaneously.

Table 12 shows some characteristics of the sample. The median firm had been listed for about seven and a half years as of January 1998. The median stock price is TL 14,750 (U.S. dollar value of about four cents on March 12, 1999). The median firm has a market value of $467 million. The last column shows the fraction of shares kept in the ISE Settlement and Custody Bank, which is a proxy of the fraction of shares held by the public. The median float rate is 20%, a low figure. There are two reasons for that. First, most of the firms are controlled by families, as in Italy and some other countries. For example, nine of the 30 firms (Arcelik, Koc Holding, Migros, Otosan, Turk Otomobil Fab., Akbank, Akcimento, Aksigorta, and Sabanci Holding) are controlled by the Koc and Sabanci families. Their unwillingness to share control of these companies is likely a reason for the relatively low float rates. Second, some firms (Petkim, Petrol Ofisi, Tupras, and Turk Hava Yollari) were completely state-owned enterprises. In the first step of a privatization plan, the state reduced its holdings in these firms. However, it still has majority ownership.

During the sample period there were 302 weekdays. As Table 13 shows, 19 of these were weekday holidays. In addition, there was trade only during the first session on January 28, 1998, and October 28, 1998, which were the beginning of Ramadan and a national holiday, respectively. This leaves 564 trading sessions during the period. The total number of sessions available per firm and an explanation for differences are given in Table 14. With the exception of two stocks (Dogan Yayin Holding and Efes Yatirim) that were listed during the sample period, the minimum number of sessions per firm is 556.

The sample is representative of the entire market. Based on information in a local newspaper on August, 28 1998, the 30 firms generated 67.9% of total trading volume (TL27,890 billion) in the first session and 72.3% (TL28,471 billion) in the second. In relation to general market movement, Figure 1 compares the standardized price level of the sample and the ISE100 index over the 14 months. In calculating the index, the market value of shares held by the ISE Settlement and Custody Bank, rather than total market capitalization, is used, and only capital gains are considered. Over the sample period the correlation between the index and the equal weighted sample average is 0.976. These 30 most actively traded stocks reflect most of the trading and price change activity in the market.

The extent of foreign involvement in the 30 stocks during 1998 is revealed in Table 15. Using monthly data, the table allocates the volume of purchases and sales by foreign investors among the sample. On average, trading in sample stocks constituted 81.65% of total monthly foreign volume in 1998.

Based on a comparison of first trading prices with market prices at the close of market on March 12, 1999 (refer to Table 13), and recalling that the consumer price index in Turkey rose from 88.5 in January 1987 to 72,406.9 in March 1999 (average annual inflation of about 75%), it is fair to say that real stock prices have fallen considerably. An explanation is given in Table 16, which shows that there were stock splits in two-thirds of the sample firms, some as large as 12 to 1. Almost all involved a bonus issue, and some included a rights issue. The rights issue price was usually small in comparison to the presplit stock price. Table 16 also shows the price adjustment on split dates, which is important, since the adjusted presplit WAP determines the tick size used during the first session following the split. The adjusted WAP is calculated as follows:

$$\text{Adjusted WAP} = \frac{\text{WAP} + P^{*} S_{RI} - D}{1 + S_{BI} + S_{RI}} + D\,; \tag{1}$$

where:

WAP	=	weighted average price during the previous session;
P	=	price used in rights issue;
S_{RI}	=	shares issued in rights issue as a percentage of number of existing shares;
S_{BI}	=	shares issued in bonus issue as a percentage of number of existing shares; and
D	=	dividend to be paid to existing shares before the split.

Table 17 shows dividend payments of stocks in the sample and the adjustment on ex dividend dates. The formula for the adjusted WAP is as follows:

$$\text{Adjusted WAP} = \text{WAP} - \text{D}. \qquad (2)$$

The number of transactions per firm is given in the first part of Table 18. There were 8,751,940 transactions in the sample, and the number per firm ranges between 87,988 and 767,309. The second part of the table shows the periods over which the so-called new shares were traded and the total number of transactions involving these shares. When there is an increase in capital before dividend is paid in a given year, newly issued shares are not entitled to receive the next dividend payment. Until the payment of the next dividend, there is a separate market for "old" and "new" shares. In the sample, five stocks have the "new" shares traded.

As was shown in Table 8, combined wholesale and special order transactions accounted for less than 2.5% of aggregate transaction volume during 1998. The ISE data do not identify order type, so it is not possible to sort round-lot transactions in the sample into normal and special orders.

Distinguishing a normal order (types 2, 3, and 4) from a special order is problematic. An order value above TL500 billion clearly indicates a special order, but a transaction below that amount yet above the minimum trade size limit for special orders can be a normal order or special order. Two groups of transactions can be identified: those that exceed TL500 billion, and those transactions that exceed the minimum trade size for special orders (which contains the first group). All transactions in the first group are special orders, but cases in the second group may be either normal or special.

To find the minimum trade size for special orders, the maximum number of shares limit must be calculated. By the fifth day of each month, the ISE announces that information. This figure depends on the average trade size per transaction during the previous month. In calculating this quantity, the ISE uses all transactions except odd-lot orders. Once this quantity is found, the rule shown in Table 6 can be used to determine the minimum trade size for special orders.

The above procedure is followed to determine the number of transactions in the sample that are likely to be special orders. For all months, the average trade size is calculated for each stock after eliminating the odd-lot orders. This way, the relevant maximum number of shares limit is obtained for all months except the very first one. From Table 19 it can be seen that maximum number of shares limit is quite stable over time unless there is a rights or bonus issue. Therefore, it is assumed that the figure found for the second month is also correct for the first month in the sample period.

The number of identified special orders and gray cases per stock is shown in Table 21. Only 23 special orders can be identified, and there were 6,357 gray transactions. Even if all the latter are treated as special orders, the fraction of executed special orders in the sample is less than 0.1%.

Chapter 3

Price Clustering on the Istanbul Stock Exchange

3.1 Introduction

In this chapter, the ISE tick is evaluated by empirically examining the usage of different discrete price sets by traders.

According to Grossman et al. (1997 p. 26),

> The optimal minimum tick will be smaller than the unit of trade typically used during periods of normal trading activity. If market participants typically used the minimum tick as the unit of trade, then the market would lack the flexibility to reduce the minimum tick to allow for smaller units when appropriate. The minimum allowable increment is not chosen to be the typical degree of precision required but, rather, to reflect the most precision required, that is, the relatively rare event.

The minimum tick on the ISE is a step function of stock price. Table 22 compares it with step function rules used in six other equity markets: Helsinki, Hong Kong, Paris, Singapore, Tokyo, and Toronto stock exchanges. The relative tick on the ISE is at least 120% and as much as 2,200% larger than those on other exchanges.[4]

One reason for the ISE's apparently large relative tick size may be that price resolution in this market is low. The generation of information in the Turkish market is not the same as in developed markets. If uncertainty about the true value of stocks is higher due to inadequate information, then investors may

---

[4] Average relative tick is 1.36% in Istanbul, 0.61% in Hong Kong, and 0.06% in Paris.

avoid using a smaller tick size even if it is allowed. In this case, trader behavior would depend on the hypothesized tradeoff between price resolution and negotiation costs. Therefore, one would expect to observe a level of clustering comparable to that in other markets.

An extremely low level of clustering would be consistent with the view that the choice of a large tick reflects other concerns of the exchange. In this case, trader behavior would not depend on the above-mentioned tradeoff, simply because the enforcement of a large tick does not give traders the flexibility of choosing the desired tick. A consequence of this may be the slow evolution of prices in the market. If traders can resolve share values with a higher precision than is allowed by the tick size, then prices will be sticky. Until the true price moves significantly close to the next available discrete price, the transaction price will not change.

In markets where the minimum price variation does not limit the use of the desired tick, tick size is not a determinant of spread. Other than the concern that clustering may indicate anticompetitive behavior in dealer markets, the positive relationship between clustering and spread size found in Gwilym et al. (1998b) can be attributed to the overlap in their determinants. Yet, regarding the assets for which minimum price variation is binding, there is evidence about a positive relationship between tick size and spread. Low-priced stocks on the NYSE by definition have a large relative tick, and the spread equals tick size for a high fraction of these stocks. This accords with the Grossman and Miller (1988) argument that tick size puts a floor on spreads. If the ISE tick size is binding, then spreads may decrease after a reduction in tick size. Moreover, it is a common belief that lower spread is associated with higher volume, but empirical research provides limited support for this belief. Hameed and Terry (1998) report that a decrease in absolute tick size increases volume only for actively traded stocks. Therefore, it is arguable that a decrease in spread caused by a reduction in tick size necessarily increases trading volume in a relatively thin market such as the ISE. If the concern of the ISE is the liquidity provision, then market-making incentives may have high priority. Although there are no official market makers, it may be critical to keep profits of voluntary liquidity providers sufficiently high. The ISE is still in its infancy and market depth may be important for the viability of the exchange.

The experience of the Stock Exchange of Hong Kong (SEHK) may show the delicacy of this issue. In early 1994, the SEHK proposed to reduce the tick size by half, which the brokerage industry immediately opposed. The SEHK compromised and agreed to a four-month evaluation program; beginning on June 1, 1994, tick size was reduced by 50%. Volume dropped in the evaluation period, and the exchange reverted to the original tick size for stocks trading below HK$10. The decline in volume may partially have been caused by the gaming behavior of the brokerage industry.

The purpose of this chapter is to determine whether the ISE's relative tick size is so large that it deprives traders of flexibility. The next section reviews the literature on clustering. Then, additional details are presented about the ISE's tick rule. The following section contains an empirical analysis, and ends with a brief conclusion.

3.2 Literature Review

3.2.1 Early Evidence of Clustering

Osborne (1962) and Niederhoffer(1965, 1966) present empirical evidence of clustering on the NYSE and show that it depends on price level and variability. These studies do not give any economic justification for the anomaly, but rely instead on behavioral explanations.

Niederhoffer (1965) relates clustering to the behavior of limit order submitters. According to this explanation, traders place limit orders in numbers with which they are accustomed, that is, even rather than odd fractions. The argument is supported by using data from a specialist book. Given the congestion of limit orders at even fractions, it is hypothesized that one would expect a higher degree of clustering in high-priced issues, since a specialist would be reluctant to maintain price continuity by trading for his own account, which would result in a large dollar change in his inventory. The data confirmed this hypothesis and the examination of stocks with a closing price above $50 showed heavy clustering.

Another variable related to clustering was explored in Niederhoffer (1966). The hypothesis was that occurrences of consecutive fractional prices in a given stock on a single day are not independent. Thus, consecutive price changes of 1/8 would result in equal proportions of even and odd eighths. Niederhoffer used intraday transaction data for randomly selected stocks on seven days, to classify transaction prices into three groups according to the amount of consecutive price change: no change, a change of 1/8, and a change larger than 1/8. Given the way the groups were constructed, the first two were more likely than the third to contain stocks with lower price variability. The results showed moderate and high levels of clustering in the first and third groups, respectively, but no significant clustering in the second. The findings suggest that as price variability increases, so does clustering. The lack of clustering in the second group is consistent with the hypothesized negative effect of consecutive price changes on clustering.

3.2.2 An Overview of Clustering Studies

All of the previous studies display the extent of clustering and most of them examine its determinants. Two studies investigate the effect of a change in tick size on clustering More recent papers analyze whether clustering is related to other microstructure issues. Those studies give evidence from open outcry, continuous/call auction, and dealer markets. Depending on the market, analysts focus on single or multiple assets.

Single-asset studies look at variation in price over time. Researchers have examined gold, foreign exchange, long-term government bonds, and financial derivatives. Multiple-asset studies look at cross-sectional variation in equity markets. Table 23 shows the market(s) analyzed in each study.

All this research provides evidence about the nature of clustering. Harris (1991) shows its persistence through time. Transaction price distributions for the four most actively traded securities on the New York Stock & Exchange Board between March 22 and April 15, 1854, are qualitatively identical to the more recent Center for Research in Security Prices (CRSP) sample of daily closing stock prices for the period January 1963 to December 1987. Both Harris (1991) and Gwilym et al. (1998a) show clustering in quotes and transaction prices as well as in intradaily and closing prices for the same assets. Neither study reports any significant or consistent difference in clustering patterns. Harris (1991) and Booth et al. (2000) compare the clustering of same or similar assets across different market structures. Using NYSE/AMEX and Nasdaq transaction and quote data, Harris shows that Nasdaq has a higher degree of clustering in both transaction and quoted prices for similar stocks. Booth et al. examined the same stocks in terms of trading during continuous session and after hours on the Helsinki Stock Exchange (HSE). Transactions can be executed in either the downstairs or upstairs market during the continuous trading session and in the upstairs market after hours. It was found that clustering during these two periods is very similar.

3.2.3 The Extent of Clustering in Different Markets

The extent of clustering varies across markets. Extreme cases are financial derivatives on the London International Financial Futures and Options Exchange (LIFFE), silver futures on the Commodity Exchange (COMEX), and common shares on the Helsinki Stock Exchange. In the London case, about 98% of all trades occur on even ticks for the FTSE100 index futures, FTSE100 index options, and FTSE250 index futures. For silver futures, 92.2% of trade prices fall on zero and five out of ten available final digits. On the HSE, the share of transaction prices that fall on the same two digits varies between 55% and 78% in the three tick regimes analyzed. As suggested by Grossman et al. (1997), one possible measure of the extent of clustering is standardized range, that is, the range between the highest and lowest frequencies divided by the expected frequency per unit. The standardized range is an ordinal measure that can be used to rank the degree of clustering on different markets, but it cannot be used to assess the relative amount of clustering on those markets. The last column of Table 23 shows the standardized ranges reported in various studies or calculated for this study by using reported frequency distributions.

3.2.4 Determinants of Clustering

The attraction of round numbers explanation suggested by Goodhart and Curcio (1991) argues that discrete trading prices are obtained from continuously distributed true values by rounding to the nearest available final unit, but the attraction of each integer varies. Most studies do not provide evidence in favor of that hypothesis, which is supported only in Aitken et al. (1996); evidence in Harris (1991), Brown et al. (1991), and Goodhart and Curcio is inconsistent with the hypothesis.

Ball et al. (1985) put forward the price resolution explanation, which states that clustering manifests haziness about asset values. Building on that hypothesis by adding a counteracting force, Harris (1991) argues clustering is due to the incentive to lower negotiation costs, and its level is limited by the price resolution in the market. High price resolution will result in a small dispersion among traders' reservation prices, and if a large tick does not include a price acceptable to both parties in a trade, then gains from trade may be lost. Most empirical research adopts the price resolution hypothesis, perhaps because it is difficult to find measures of the level of negotiation cost in a market. In fact, even though Harris (1991) proposed the negotiation hypothesis, he does not rely upon it in developing explanatory variables.

The price resolution hypothesis suggests a number of variables that proxy the stock of information in the market. Ball et al. (1985) argue that high volatility is an indication that existing information is obsolete. Ball et al., Harris (1991), Gwilym et al. (1998a), Brown et al. (1991), and Booth et al. (2000) all report a positive relationship between volatility and clustering. The only exception is Hameed and Terry (1998) who find an insignificant relationship for the Singapore Stock Exchange. Aitken et al. (1996) differentiate between market and individual stock volatility, but both kinds display a significant positive association with clustering.

Harris (1991) justifies firm size as another proxy for the stock of information in the market on the premise that larger firms release more information and are also followed by a larger number of analysts. He finds evidence of a negative relationship between firm size and clustering, but Aitken et al.(1996), and Christie and Schulz (1994) could not detect any significant relationship.

Proxies to incorporate the ease of valuation of an asset are used by Harris (1991), Aitken et al. (1996), and Christie and Schulz (1994). Harris uses a dummy variable for close-end funds, and Aitken et al. use dummy variables for optioned stocks, and for those that can be sold short, since these two factors are believed to increase the efficiency of stock prices. Both studies find a negative relationship between these variables and clustering. In an analysis of Nasdaq, Christie and Schulz use dummies for dual listed stocks and stocks with listed options, but both of these prove to be insignificant.

Since frequent trading will lead to the incorporation of the most recent information into prices, variables that proxy trading activity, namely, volume and number of trades, are expected to increase price resolution. Aitken et al. (1996), Booth et al. (2000), and Harris (1991) all find a significantly negative relationship between transaction frequency and clustering, but Gwilym et al. (1998a) report a significant relationship in the opposite direction. This may be due to the open outcry trading mechanism used by LIFFE, which requires traders to stay in the pit for an order to execute. As suggested by Brown et al. (1991), pit traders have incentives to speed up trading by using a coarser price set to participate in a larger number of trades. Hameed and Terry (1998) find a negative relation between trading volume and clustering.

The only study that tests the negotiation hypothesis extensively is by Brown et al. (1991), who consider the implications of negotiation costs from the aspect of pit traders in COMEX silver futures. They test trade size as a variable, because a large trade increases both total surplus and benefits from negotiation.

This variable was suggested by Harris (1991) but not tested. Gwilym et al. (1998a), Booth et al. (2000), and Aitken et al. (1996) also include it in their analyses. The first two find, along with Brown et al., a negative relationship between trade size and clustering, but Aitken et al. report a relationship in the opposite direction for the Australian Stock Exchange. Based on the price resolution hypothesis, Aitken et al. argue that trade size may proxy the existence of new information, since larger orders are sometimes associated with informed traders. Two factors may weaken this effect, however. First, informed traders usually split their orders to hide themselves (stealth trading), so the association may be questionable. Second, even if a positive connection between large trades and informed trading is assumed, this may give rise to a negative relationship between clustering and trade size, since informed trading is expected to improve price discovery.

Brown et al. (1991) point out additional reasons for volume and volatility as determinants of clustering: lost trade opportunity and higher inventory variance from the aspect of pit traders. Because silver futures trading uses an open outcry mechanism, which requires face-to-face negotiation in the pit, it is a suitable setting for testing various implications of the negotiation hypothesis. Furthermore, detailed data about parties in trade and timing information are available. Brown et al. report that, in addition to such variables as volatility and trade size, whether a trader executes an order for a customer or on his own account makes a difference. Moreover, they show that odd tick orders take longer to consummate and create delay in clearing a trade.

The discussion in Ball et al. (1985) and the application in Harris (1991) both assume that, for a given price resolution, traders use discrete price sets based on minimum price variation that is a constant fraction of price. The relation between desired and mandated tick, both of which are expressed relative to price level, captures the effect of mandated tick size on clustering by using price level as a proxy. This implies more clustering for high-priced stocks in a market. The presumed relationship could be discontinuous in markets that use a step function tick rule. Aitken et al. (1996), Ball et al. (1985), Booth et al. (2000), Christie and Schulz (1994), Hameed and Terry (1998), and Harris (1991) all confirm the hypothesized positive relationship of clustering to price level.

3.2.5 The Effect of a Change in Tick Size

As discussed above, almost all studies use relative tick size to control for the effect of tick size on clustering. For example, Aitken et al. (1996) and Booth et al. (2000) examine stock exchanges that use step function tick rules, and they either consider a single regime or analyze different regimes separately; neither compares different tick regimes. Two studies estimate the use of discrete price sets if a lower tick is used. Harris (1991) bases his prediction on usage frequencies at the prevalent tick size. Hameed and Terry (1998) provide some evidence that absolute tick size may be a factor and that the method of prediction used by Harris (1991) overstates the use a of smaller tick. They examine the effect of a change in tick size by comparing the level of clustering in two adjacent regimes after controlling for cross-sectional determinants of clustering: price level, trading volume, and volatility. The results show that price clustering increases when the absolute tick size is reduced.

3.2.6 Relation to Other Microstructure Aspects

More recent studies examine the relationship of clustering to other microstructure aspects such as operating efficiency, transaction costs, collusion in the market, and the practice of preferencing.

Brown et al. (1991) show that low degree of rounding harms the **operating efficiency** of the market. Odd tick orders confuse pit traders, make them leave the pit temporarily, and take longer to execute. Emphasizing the tradeoff between anticompetitiveness and market viability, Brown et al. (1991 p. 68) argue,

> Intuition suggests that the optimal minimum tick size is a very small number, because a small tick maximizes the flexibility of traders in establishing transaction prices. However, there is no guarantee with a small tick size that the competitive solution is viable given the cost structure of those providing services to the market.

Gwilym et al. (1998b) analyze the relationship between clustering and **transaction costs**. They examined the intradaily pattern of the bid/ask spread and clustering in quotes. Spread is significantly higher when the market opens and significantly lower when it closes. Even after controlling for the effect of this intraday behavior, they found a significant positive relation between quoted spread and the level of clustering in quotes. Since volume is high both around opening and closing, they conclude that the use of odd ticks is driven more by the desired quoted spread than by volume of trading.

Hameed and Terry (1998) report limited evidence from Singapore about the effect of tick size on trading volume. They used data on four stocks for which tick size decreased from S$0.5 to S$0.1 on July 18, 1994. For actively traded stocks, they found that trading volume rose and volatility declined after a decrease in tick size, but no significant relationship was detected for thinly traded stocks.

Three studies explore the issue of whether **collusion** is a factor in clustering. Christie and Schulz (1994) examined the distribution of pooled inside bid and ask quotes and found that the lack of one-eighth spreads can be traced to an absence of either inside bid or ask quotes ending in odd eighths. Those stocks whose market makers rarely use odd eighth quotes have a mean duration of odd eighth quotes lower than that for even eighth quotes; for the remaining stocks, the mean duration of both is quite similar. Cross-sectional logistic regressions show that the factors which affect the width of spread have little power in identifying firms whose market makers avoid or use odd eighths. The authors argue that one explanation of this evidence is implicit agreement among market makers to keep spreads of at least at $0.25 by not posting quotes on odd eighths.

Bessembinder (1997) tests the implicit collusion hypothesis by examining the relationship between price/quote rounding frequencies and measures of both investors' trade execution costs and market maker profits. Cross-sectionally, after controlling for determinants of spread size (price level, firm size, and volatility), Bessembinder found that both quoted and effective spreads on the NYSE and Nasdaq are significantly and positively related to price and quote rounding frequencies. The decomposition of effective spread into price impact and realized spread shows, for NYSE stocks, the observed relation between price rounding and trade execution costs can be explained by similar variation in information costs. For Nasdaq, the significant and positive relationship between realized spread and rounding frequencies cannot be due to the information content of trades. This implies that larger trade execution costs associated with rounded prices can be justified by variation in observable market making costs for NYSE but not for Nasdaq stocks, which supports the collusion hypothesis. According to Bessembinder, a partial explanation for the positive relation between quote rounding and trading costs comes from the examination of price improvement probabilities. A comparison of these probabilities for spreads posted using odd and even eighths showed that trades are less likely to receive price improvement when even eighths are used on both NYSE and Nasdaq, but the differential for Nasdaq was more dramatic.

Grossman et al. (1997) indirectly examined the level of transaction cost for NYSE/AMEX and Nasdaq by using two different methods. The direct way to compare transaction cost would require the information on market depth, rather than spread size, but the former is difficult to measure. Since higher transaction costs will be passed to firms when they issue equity, comparable firms would find it advantageous to switch to the NYSE if it has lower transaction costs. A comparison revealed, however, that there are more secondary issues of Nasdaq stocks than NYSE/AMEX stocks. Also, transaction cost has implications for trading volume. One would expect the trading volume of comparable stocks to be higher in markets with lower transaction cost. Examination of comparable stocks showed that those on Nasdaq have higher trading volume than those on the NYSE, which is inconsistent with Nasdaq's higher transaction cost.

Godek (1996) hypothesizes an indirect link between **preferencing** and clustering through spread size. He argues that the focus on implicit collusion in Nasdaq understates the importance of preference trading as an institutional determinant of quoted spreads. A competing market maker who offers an unusually good price can be expected to receive less order flow from brokers and other market makers. Narrowing the spread below a certain level not only may fail to attract trades, but also could actually tend to repel them. Godek shows that even eighth spreads are quoted by using even eighth prices on both NYSE and Nasdaq. It is not the different quoting behavior but the higher spreads driven by the practice of preferencing that causes the low frequency of odd tick quotes for Nasdaq.

Godek uses the same exogenous economic factors as Christie and Schultz (1994) to identify firms whose market makers avoid or use odd eighths, but he reaches the opposite conclusion. Cross-sectional variation in clustering can be explained by factors that determine the spread size. Godek also gives evidence that in this large sample the bimodal distribution of clustering remained stable after the Christie and Schultz study data period.

Booth et al. (2000) provide evidence on the extent of internalization and its relation to price clustering by using trades of 73 issues listed on the Helsinki exchange during 1993-1995. Internalization, the extreme case of preferencing, is the practice of brokers executing orders in-house. Preferencing is believed to be an important institutional factor affecting price formation. The study compared the degree of clustering between internalized and noninternalized trades. After controlling for other factors, Booth et al. found that internalization is related positively to the level of clustering in continuous trading session, but its effect is small in comparison to that of control variables. In after-hours trading, internalization was found to be insignificant in explaining the level of clustering.

3.3 Empirical Analysis

The ISE tick rule was compared in Table 22 to the step function rules used on the Helsinki, Hong Kong, Paris, Singapore, Tokyo, and Toronto stock exchanges. One feature of the ISE rule is that the average relative tick is much larger than for the other six exchanges (1.36% for the ISE, versus 0.06% Paris, 0.18% Helsinki, 0.19% Tokyo, 0.40% Toronto, 0.55% Hong Kong, and 0.61% Singapore).[5] Moreover, the step function used by the ISE differs from the others. It has a larger number of tick regimes, and the width of each is narrow. On average, an increase by 114% or less would move a stock price into the next

[5] The first and last regimes are excluded in the calculation of average relative tick sizes.

regime.[6] Regime widths in Helsinki, Paris, Tokyo, and Toronto are several times as large as those in the ISE and this is true for at least some regimes in Singapore and Hong Kong.

The ISE tick rule limits both the time a stock may spend in a regime and the percentage decrease in relative tick size as stock price rises. As shown in Figure 2, relative tick size starts at 2% or 2.5% for each regime (left end) and falls to 1% (right end). This type of tick rule is exactly the kind that Angel (1997, p. 678) recommends not be employed by exchanges,

> If the exchange adopts a step function, however, it may find that it has set relative tick sizes either too high or too low, without giving firms a means to adjust them. For this reason, it seems prudent for an exchange to set a small number of absolute tick sizes and give firms the flexibility to modify their own relative tick sizes through stock splits.

The stability of nominal stock prices over time (refer to Table 12) and the frequency of stock splits and dividends during the sample period (refer to tables 16 and 17) raise an interesting question. Persistently high inflation has decreased real stock prices on the ISE over time. Moreover, the nature of the tick rule makes changing stock price through splits a less effective mechanism for firms to determine relative tick size. That being the case, it is not clear why splits have been a common practice of firms listed on the ISE at the expense of lowering real stock prices further. This is inconsistent with Angel's (1997) view that the motivation for stock splits is an adjustment of relative tick size through a

[6] Ignoring the first and last tick regimes, the maximum percentage change required is 96% (144%) in five (three) of the remaining eight regimes.

change in share price.

For each stock the distribution of tick size over the sample period is presented in Table 25.[7] Apparently due to the narrow tick regimes, persistently high inflation rate, and frequent use of stock splits, ISE stocks used multiple tick sizes during the sample period. The cross-sectional mean, median, and mode of the number of tick regimes used are 3.0, 3.0, and 2.0, respectively. The corresponding numbers for 18 firms that had stock splits are 3.6, 4.0, and 4.0.[8]

As was shown in Table 22, the ISE has ten tick regimes. For convenience in presentation, these are collapsed into three groups: (1) regimes 100, 1,000, and 10,000, (2) regimes 25, 250, and 2,500, (3) regimes 50, 500, and 5,000.[9] Based on the final digits of transaction prices, there are ten, four, and twenty price categories in these respective groups.

Table 26 reports actual frequencies of the final digits of intraday transaction prices for all stocks in the sample. Part A shows the frequencies for the first group. The null hypothesis that prices are uniformly distributed across the ten price categories in this group is rejected, but neither the individual tick regime nor combined distributions are consistent with the pattern of clustering

---

[7] As explained in Chapter 2, the tick size used during a trading session depends on the WAP in the previous session. Since special orders are not included in the calculation of WAP and it is not possible to identify these orders in the sample, WAP data were hand collected from daily Turkish newspapers.
[8] One of the firms, Migros, had a minor split during the sample period and is not included in this calculation.
[9] The first tick regime contains only 1,075 observations. Therefore it is excluded from the analysis.

that has been found elsewhere. The 00 and 50 price categories are not necessarily more common than the other categories. Moreover, the frequencies of even and odd final digits are almost identical.

Part B of Table 26 displays the frequencies for the second group. Both individual tick regime and combined results show weak clustering consistent with the pattern found elsewhere. First, the 00 price category is more common than the 50 category, which is more common than the other two price categories in this group. Second, even numbers are more frequent than odd numbers, which agrees with the observations in other studies.[10] Nonetheless, the standardized range measure calculated by using the combined frequencies is 0.18, implying a lower level of clustering than other markets as shown in Table 24.[11]

Part C of Table 26 displays the frequencies for the third group. Prices are not uniformly distributed, and the frequency of even final digits is larger than that of odd final digits. Moreover, the examination of combined frequencies shows that, for all the adjacent price categories, even categories are more frequent than odd categories. This last observation implies the existence of a weak form of clustering. To interpret the pattern, one can refer to the reasoning used in Ball et al. (1985) or in Harris (1991), both of which involve multiple classes of traders

---

[10] Since the tick regimes in the second group contain four price categories, this result follows directly from the first result.
[11] The standardized range is an ordinal measure that can be used to rank the degree of clustering in different markets, but cannot be used to assess the relative amount of clustering within those markets.

who use different types of rounding. The extent of clustering reflects the relative proportions of these trader classes in the market. Consider the TL50 regime. Traders can round the price using any one of the six available pricing grids: 50, 100, 200, 250, 500, and 1,000. For any pricing grid, it is assumed that the possible final three digits of the rounded price are equally likely to occur. For example, for the first grid in which prices are rounded to the closest TL 50, the occurrences of all the 20 possible final three digits (000, 050, 100, 150,...,800, 850, 900, 950) are equally likely. In this setting, the prediction that the final three digits are more likely to be 000 than 500 relies critically on the existence of traders who use TL1,000 rounding. By following this line of reasoning, the observed pattern of clustering can be explained as follows. If, due to a large relative tick, there are only two classes of investors on the ISE using either one-tick or two-tick rounding, then for all the adjacent price categories, even categories will be more frequent than odd categories. Moreover, if the proportion of traders who use two-tick rounding is much less than 50%, then the extent of clustering will be low. The pattern of clustering observed in the second and third groups (parts B and C of Table 26) are consistent with this scenario.

The observed prices depend on the initial price level, and for a stock with infrequent price change it may be the case that only part of the entire tick regime will be swept over time. To take this serial dependence into consideration, the adjustment discussed in Harris (1991) is used. In this method each price change creates domain events. A domain event occurs when prices change and price path passes over or arrives in a different price category. If prices do not often visit the region near a given category, then the frequency for that category is adjusted upward. If prices dwell in that region, then the frequency is adjusted downward. One property of this estimator is that the adjusted frequencies add up to one. Another property that makes this estimator desirable in the analysis of the ISE is that prices can cluster even if all price changes are equal to tick size.[12] This is because zero price changes are not counted as domain events. For each price category the adjusted frequency is given by the following expression:

$$f_{adjusted} = f_{actual} + f_{uniform} - f_{domain} \ ; \qquad (3)$$

where:

$f_{uniform}$ = the expected frequency given uniform distribution; and
f_{domain} = the frequency of domain events.

Three cases are discussed to understand the effect of the Harris (1991) adjustment: (1) If price does not pass over or arrive a price category, then for this category: $f_{actual} = f_{domain} \Rightarrow f_{adjusted} = f_{uniform}$. (2) If some price categories are skipped when price changes, then for those skipped categories: $f_{actual} < f_{domain} \Rightarrow f_{adjusted} < f_{uniform}$. (3) The effect of zero price change observations on corresponding price categories: $f_{actual} > f_{domain} \Rightarrow f_{adjusted} > f_{uniform}$.

The adjusted frequencies are shown in Table 27. Qualitatively the conclusions from this table are identical to those from Table 26. The only notable difference is, with the exception of the TL 5,000 tick regime, the pattern

[12] See Harris (1991, p. 401) for further properties of this estimator.

of clustering in the third group becomes more consistent with the above explanation. The standardized range measure, calculated by using the combined frequencies, is 0.26 for the third group.

To interpret the evidence provided by adjusted frequencies, univariate statistics are presented about bid-ask spread size and transaction price dynamics in the sample.

Bid and ask quotes at the close of the second trading session were compiled from *Dunya*, a daily Turkish financial newspaper. The data were screened for instances of no reported spread, missing bid or ask quotes, and days in which systematic errors were found in the newspaper. The resulting distribution of spread size in ticks is presented in Table 28 and Figure 3. Overall, in 7,486 of the 7,643 observations (98%) the size of bid-ask spread is at the minimum value of one tick. Hence, unlike other exchanges, the ISE can be considered a single-tick-spread market, which is consistent with the explanation that the tick size constraint on bid-ask spread is binding. Similar findings has been reported for low-priced stocks on the NYSE and AMEX. Harris (1994), for example, found a bid-ask spread equal to the tick size in 66.8% of the observations for stocks traded below $10, compared to 34% for stocks priced above $20.

The change in price from one transaction to the next, expressed as multiples of tick size, is presented in Table 29. In about 92% of the observations, there is no change. When price change occurred, it was equal to the tick size in more than 99% of the observations.[13] The evidence is consistent with the explanation that, due to large relative tick sizes imposed by the ISE, small changes in equilibrium price cannot be reflected in transaction price. Furthermore, since the price change in consecutive transactions rarely exceeds the minimum possible amount, the argument that the typical price change in the market justifies the enforced tick size is not supported. Taken together, the evidence about spread size and price change probabilities suggests that the tick rule may be constraining trader behavior to a greater extent on the ISE than in other markets.

As Table 29 shows, price changes predominantly by one tick on the ISE. Therefore, skipping a final digit category is not an issue in this market. This means $f_{actual} = f_{domain}$ and therefore $f_{adjusted} = f_{uniform}$ ignoring the zero price change cases. Hence, if there is any clustering, it will be driven by zero price change cases. Based on this interpretation, adjusted frequencies show that the time spent on each price category does not display significant variation on the ISE.

As discussed in the literature survey, clustering has been shown to increase with a decrease in relative tick size. Figure 2 reveals that the relative tick jumps at least 100% when a small increase in stock price moves the price into the next available tick regime. The weak clustering demonstrated in previous tables was attributed to a large relative tick size. On the ISE, relative

[13] Table 29 also shows that unconditional up and down movement probabilities are nearly identical during the sample period.

tick size never falls to a level comparable to those in other markets. In spite of that, one would expect to observe relatively more clustering at the right end of a tick regime, where relative tick size reaches its minimum of 1%. This can be explored by comparing the extent of clustering just before and after a stock moves into another tick regime. The advantage of this method is that observations will be taken during adjacent periods. Therefore, it is unlikely that a change in determinants of clustering will occur during the sampling period.

Alternatively, the possibility of a variation in clustering can be examined within a tick regime. If there is some clustering on the ISE, its extent should be highest (lowest) at high (low) price levels. This method enhances the comparison, since all observations are taken within the same tick regime. Table 30 reports the results by using this method.[14] Three price ranges within each regime are defined: low, medium, and high. The definition of each range is shown in the first part of the table.[15]

Although the results from these three groups do not display a consistent pattern, none of them supports the hypothesis that within regime variation in relative tick leads to a positive relationship between relative tick and the extent of clustering. For example, the extent of clustering is a U-shaped function of relative tick in the second and third groups as shown in Part C and Part D of

[14] Only combined frequencies are reported to increase the number of observations in each price range.
[15] The second range in some cases (tick=25, 250, and 2,500) does not contain the entire set because of narrow regime width.

Table 30. Therefore, it is fair to conclude that even a relative tick size of 1% may be too large to result in usage frequencies consistent with the pattern of clustering that has been found elsewhere.

3.4 Summary

It was shown that ISE's relative tick is up to 900% greater than that of other exchanges. The major purpose of this study was to examine whether large tick size restricts trader behavior in this market. It was found that prices show very weak clustering. It appears that traders use predominantly one- or two-tick rounding, and the proportion of the latter is small.

The examination of spread and consequent price change frequencies revealed that these hardly ever exceed tick size, which indicates that the tick size is binding. This suggests that the large relative tick in this market cannot be attributed to low price resolution. Given that price changes predominantly by one-tick, the only way prices will cluster in this market is if price is more likely to change when it falls on certain categories than others. The results show that this is not the case.

Based on the evidence from other markets, it was hypothesized that price clustering within a tick regime increases with an increase in stock price. Possibly due to the narrow regime width, it was found that within-regime variation in clustering is not consistent with this hypothesis.

Taken together, empirical findings in this analysis suggest that the large relative tick size on the ISE restricts trader behavior. Since a large relative tick applies to all price levels with little variation, it appears that tick size is used as a policy variable by the exchange.

Chapter 4

Limit Order Profitability on the Istanbul Stock Exchange

4.1 Introduction

The ISE is an order-driven market, and liquidity provision differs in this market structure from the other two types of continuous trading systems. In quote-driven and specialist systems, it is the responsibility of dealers or specialists to provide liquidity at all times, but in an order-driven market no party has such an obligation. Public traders provide liquidity by their use of limit orders.[16] From the perspective of individual traders, a limit order can be preferred when there is a need to rebalance their portfolios. Alternatively, they may find this a profitable strategy by itself and act voluntarily as market makers.

The extent of liquidity provision within continuous markets depends on a number of factors: the anonymity of trading, the informational advantage of liquidity providers, their ability to avoid trading with possibly informed traders, and the number of liquidity providers.

In a quote-driven market, trading is not necessarily anonymous. Preferencing and quote-matching practices create a certain kind of competition. Brokers direct uninformed customer orders to dealers with whom they have a close relationship. In effect, dealers do not routinely accept all incoming orders

---

[16] Brokerage houses also can submit limit orders when they trade on their own account.

but choose on a case-by-case basis. This is done by posting unattractive quotes initially and matching the best bid or offer when dealer wants to take the other side of a transaction. In an order-driven market, trading is anonymous, and priority rules make the completion of a trade automatic once a counterparty arrives. Therefore, liquidity providers cannot make case-by-case decisions.

Specialist market is a hybrid mechanism. The specialist as broker executes limit orders left with him by other brokers; as dealer, buys and sells for his own account. Because he observes the total order flow, he can use this advantage to decide when to step in ahead of the limit orders left with him for execution. Nevertheless, the specialist must optimize average profits, just as do liquidity providers in an order-driven market, due to the anonymity of arriving market orders.

The number of liquidity providers changes relatively infrequently in a quote-driven market, but may change substantially over time in an order driven system because there are no direct costs of entry. In the former there is a commitment to provide liquidity, but it may not necessarily be obtained at the minimum possible cost due to the nature of competition in the system. In the latter, although there is no such commitment, when the number of potential liquidity providers is large enough, the cost of liquidity may be driven down to the perfect competition level.

It is clear that market makers in specialist and quote-driven systems are given certain benefits that protect them from the problem of adverse selection in return for their commitment to provide liquidity. Although the viability of an order-driven market requires the use of limit orders, the lack of explicit protection from adverse selection is noteworthy.

A line of research that examines the order choice decision has emerged in recent years. Harris and Hasbrouck (1996) studied usage frequencies, execution rates, and profitability of limit and market orders on the NYSE. They found that trader behavior depends on the order size, the prevailing spread, and the side of the market, and they examined the ex post optimality of trader behavior. Handa and Schwartz (1996), who analyzed the rationale of limit order trading, argue that the viability of an order-driven market requires short-term price dynamics that follow a mean reverting process. They predict and test whether limit order trading is profitable only for traders with well-balanced portfolios due to their low opportunity cost of nonexecution. Hamon et al. (1995), drawing on findings in Handa and Schwartz (1996) and Hamon et al. (1993) compared the profitability of limit order trading on the NYSE and the Paris Bourse (the CAC system).

The balance between limit and market order submission rates is important for the ISE, because in an emerging market there is concern about the extent of liquidity provision. Therefore, the method used by Handa and Schwartz (1996) will be employed in this chapter to examine the profitability of limit and market order trading strategies.

The chapter is organized as follows. The next section compares the ISE to the Paris Bourse and the NYSE regarding certain aspects of their microstructure. The following section discusses the work of Handa and

Schwartz (1996), in particular the implementation and limitations of their one period model. It also describes the evidence given in Handa and Schwartz (1996) and Harris and Hasbrouck (1996) and compares the methods used in these two studies. Then limit order profitability on the ISE is analyzed empirically. The chapter concludes with a summary.

4.2 A Comparison of the ISE with the Paris Bourse and the NYSE

The ISE will be compared to the two exchanges in which the order choice decision has been studied. The aspects examined are market transparency, price change limits, the use of alternative trading mechanisms, and the settlement of transactions.

Transparency. The extent to which trading information is made available after each discrete market event can be classified as ex ante and ex post. The former is information available beforehand that enables the trade to take place, that is the information required to resolve transaction price uncertainty. Ex post transparency is the immediate publication of transaction prices and sizes to resolve uncertainty about future prices. Handa, Schwartz, and Tiwari (1998) argue that an increase in transparency helps traders better assess the execution probability of limit orders and thus improves market efficiency.

In Paris, the CAC system provides three levels of trading information. The first level that is available to everyone shows the last trade, current prices and quantities at the best ask and bid and other daily summary statistics. The second and third are available to brokers only. The second level consists of the last five transactions and the current state of the book; including broker identification numbers. The third level is similar to the second, but contains the entire transaction record for the day.

Under the rules of the NYSE, the content of the book of limit orders is known only to the specialist and may not be disclosed publicly. The specialist quotes best bid and ask prices along with maximum order sizes for which the execution is guaranteed at these quoted prices.

In Turkey, total quantities at each price level are disseminated to members in real time. Moreover, for executed orders the identity of both sides of the transaction are displayed.

Traders who supply liquidity but are concerned about the free option value of their orders are encouraged to supply such liquidity in some markets by allowing them to hide the full size of their order. Systems that incorporate this option almost invariably impose some cost regarding the execution priority of the hidden part.

In the CAC system, traders can hide part of their limit orders. This allows limit order submitters not to reveal their information or strategy to the public. The hidden part of the order preserves price priority but not time priority. On the ISE, hiding a limit order is not allowed.

On the NYSE, limit orders better than the current quote are not automatically posted as new quotes. The rationale is conjectured to be the desire of the NYSE to obscure true market prices. This action raises the marginal costs of non-dominant competitors by necessitating a search to discover true prices. Unlike the CAC procedure, the NYSE gives the specialist the discretion to hide a limit order unless he is instructed by the submitter to display it. Thus, it is easier for submitters to hide limit orders on the Paris Bourse than on the NYSE.

Price Change Limits. In Paris, stocks are traded in either the so-called forward or cash markets. In the forward market, for example, a trading halt of five minutes occurs if price exceeds the closing price of the previous session by more than 10%. If the price pressure continues, then a second halt occurs, and the maximum possible price change during a day is 20%.

The maximum price change regulation on the ISE is similar to that on the Bourse. Price cannot exceed the preannounced base price by more than 10% during a trading session.

On the NYSE, the whole market closes if the index trips a circuit breaker, but suspension of individual stocks is discretion based rather than rule based. Order imbalance halts are initiated by the specialist, after consulting with floor officials. A news halt may be initiated either by the exchange or by specialists.[17] To achieve a fair and orderly market, the NYSE provides price continuity-depth guidelines for specialists. These vary across stocks, since they depend on the price range and normal trading volume of each stock. Adherence to the

[17] Bhattacharya and Spiegel (1990) found that 49.1% of suspensions in their sample were brought by the announcement of news, and another 48.5% were caused when specialists observed a severe order imbalance. The typical price change during a suspension was 6.7% during 1974-1988.

guidelines is one of the several criteria by which NYSE specialists are evaluated, and those who perform poorly risk not being assigned more profitable stocks in the future or may even have their stocks reassigned to others. Trading suspensions can take the form of delayed openings or intraday suspensions.[18] NYSE policy concerning opening prices places particular emphasis upon minimizing subsequent price volatility and price reversals.

The treatment of large market orders in some pure limit order markets can be interpreted as an indirect way of imposing price continuity rules. In the CAC system, due to the concern for transaction price, large market orders may not get immediate and full execution. After consuming the entire depth at the best quote on the opposite side of the book, the unexecuted part of a large market order is converted into a limit order at the price of partial execution. This limit order waits the arrival of an opposing order.

On the ISE there are no market orders.[19] Helsinki Stock Exchange's HETI system has the same feature. In addition, HETI does not allow a limit price to exceed the best price level on the opposite side of the book. Whereas aggressive traders on the Paris Bourse can submit a suitably priced limit order

---

[18] Regardless of the cause, all trading delays that exceed 29 minutes for delayed openings and 14 minutes for intraday suspensions must be officially approved by a floor governor or a duly appointed floor official. Once trading has been halted, the suspension must continue for at least 15 minutes to permit the announcement of suspension on the exchange ticker and to provide time for investors to respond by changing outstanding orders and submitting new orders.
[19] This is not of any practical consequence. A trader has to use the best limit price on the other side of the market to get immediate execution.

rather than a market order to get immediate execution for large order sizes, this opportunity does not exist in the HETI system.

In the early 1990s, the competition from London's quote-driven dealer system, Stock Exchange Automatic Quotation (SEAQ), forced Paris to implement an innovation. Jacquillat, Schwartz, and Hamon (1995) give a description of and rationale for PIBAL (Programme d'Intervention en Bourse pour l'Amelioration de la Liquidité), which is used in the CAC system to add liquidity to the market and increase its efficiency. Companies listed on the Bourse use their own shares and cash to set up a fund to buy shares in a falling market and sell shares in a rising market. The fund trades in the opening call according to a prescribed formula. The idea is as follows. The higher the elasticity of the supply curve, the lower will be the price impact of a shift in the market demand curve. Thus, the fund dampens price volatility by adding liquidity to the market. The fund also has an indirect effect on liquidity. An improvement in liquidity is generally believed to attract additional order flow, which leads to further improvement. Since the use of the fund delays the adjustment of price to its new equilibrium value, the addition of liquidity cannot be done effectively in this way in a continuous market. In a call market, the fund will trade after observing the total imbalance in the market, but this is not possible in a continuous market, and the operation of such a fund would give some traders the opportunity to make unjustified profits.

Alternative Trading Mechanisms. Both the Paris Bourse and the NYSE have call auction at the opening of each trading day, a feature not shared by the

ISE. Whereas entire order flow information is disseminated in Paris before the call auction takes place, only some imperfect information about the extent of the order imbalance is given by the specialist on the NYSE.

A parallel upstairs market exists on both the NYSE and the Paris Bourse, but block trading on the ISE is conducted from 9:15 a.m. to 9:45 a.m. just before the other markets open. In the block trading of existing shares, if the trade leads to a change in the control of the corporation, there is no restriction on the transaction price. Otherwise, the transaction price should be within ± 20% of the average WAP during the past 15 days. In Paris, since 1989, blocks can be negotiated off the exchange. The procedure is similar to that on the NYSE. Blocks are negotiated by upstairs traders and then brought to the exchange. Unlike the procedure for small trades, block trades are allowed to occur outside the bid-ask spread on the Paris Bourse, but the limit orders triggered by the block price must be cleared at their limit prices. On the NYSE, limit orders are traded at the block price.

In Paris, small orders can trade off the exchange by following the rules on the transaction price. ISE members can execute transactions off the exchange for odd lots only.

Settlement of Transactions. French companies are listed in either the official list or the second market, the difference being that the official list contains stocks with high trading activity. The most active stocks on the official list are traded on a forward basis, and the settlement occurs at the end of each month.[20] Because the extended time to settlement introduces additional payment risk, there is a performance margin requirement on these forward contracts. Unlike the Bourse, all NYSE and ISE stocks are traded on a cash basis.

4.3 The Viability of a Pure Limit Order Market

4.3.1 The Tradeoff between Market and Limit Order Strategies

The following tradeoffs affect traders' order choice decision. Market orders receive certain and immediate execution at a cost equal to half the prevailing spread, assuming the quote midpoint represents the equilibrium value. Limit orders benefit when liquidity trading moves price temporarily so that they can be executed at a favorable price. There are two costs associated with trading via limit order: the risk of nonexecution and the risk of being picked up by informed traders due to the free option nature of limit orders. The first cost measures the risk of having to transact at a disadvantageous price if a limit order does not get executed. The second risk is costly, although the order is still executed nominally at a better price than would be the case for a market order submitted at the same time and in the same direction as the limit order.

The equilibrium of the limit order book has been examined in the literature (e.g. Glosten 1994 and Sandas 1999), but these studies ignore investor

[20] The remaining stocks in the official list and all stocks in the second market are traded on a cash basis.

eagerness to trade as well as other aspects of the order choice decision. Abstracting from these issues and assuming the presence of a large number of traders willing to place limit orders, the equilibrium of the limit order book at any given time can be modeled as follows. The book contains orders at different price levels. Execution probabilities and deviation of limit prices from the equilibrium value of the stock at the time of execution vary among the existing limit orders in the book. Since submitters cannot condition on the size of the order against which their limit order will transact, and there is competition among a large number of potential submitters, the depth at each price level is determined in a way to make the expected profitability of the marginal limit order equal to zero.

4.3.2 The Method

The Hypotheses. Handa and Schwartz (1996) inject hypothetical orders into the actual transaction data to measure performance of limit and market orders. That procedure will be used in this research to test of the following hypotheses.

Hypothesis 1: The expected total gain from limit order trading is negative.

Hypothesis 2: Traders who submit limit orders must be those for whom the opportunity cost of forgoing a trade is low.

Handa and Schwartz (1996) claim that there are two conditions necessary to maintain a balance between the limit and market order submission rates in an order-driven market. First, there should be enough mean reversion in short-term price dynamics. Second, there should be traders in the market for whom the opportunity cost of forgoing a trade upon the nonexecution of their limit orders is low. The second requirement describes a trader characteristic, and the first refers to the mechanism that reestablishes equilibrium after it is disturbed. The total cost of limit order trading can be decomposed into two parts: the execution cost and the nonexecution cost. Without mean reversion in short-term price dynamics, the first cost is positive, and the second is zero. Therefore, no one will want to submit a limit order. With mean reversion, however, the sign of the first cost is ambiguous, and the second cost is positive. Since the total of these two costs is positive, the only traders who may find limit order trading desirable are those who are "patient", that is, for whom the cost of forgoing a trade is low. These traders will submit limit orders if the cost of execution is nonpositive. This means that the deviations from the equilibrium price caused by liquidity shocks are systematically corrected in the short run.

When the equilibrium between order submission rates is disturbed, for example, when the share of limit orders in the market is disproportionally low, short-term price volatility will increase. That will increase limit order profitability and induce more limit orders to be submitted, which will reestablish the equilibrium in order submission rates.

To see whether an investor who wants to trade but needs to decide on the order type has an incentive to prefer a limit order strategy over a market order strategy, the relative performance of these two trading strategies needs to be examined. The expected value from the market order trading strategy is zero.[21] The expected value of the limit order trading strategy is derived by using a simple one-period model. The model makes predictions about the signs of the total cost of a limit order trading strategy and its components, with and without a mean reversion in stock price dynamics.

The Model. Consider the limit order book for a stock in a one-period model. Assume that stock price at the beginning of the period, P_0 reflects all the available information. A particular limit buy order, placed at the price $P_{lim} < P_0$, will be examined. This limit order is assumed to have the highest time priority at this price level. During the period, exactly one trader arrives at the market and submits a market buy or sell order. With the probability p he is informed (I), and with probability q=1-p he is a liquidity trader (L). The probability distribution of the end-of-period price, P_n, depending on the type of the arriving trader, is given by two marginal densities $f(P_n|I)$ or $f(P_n|L)$, regardless of whether the limit order under consideration is among those orders executed against the market order. If the market order submitted by the arriving trader does not execute the limit buy order under consideration, then it is converted into a market buy order and executed immediately at the price prevailing at the end of the period.[22]

---

[21] The bid-ask spread is ignored.

[22] This price depends on the size and direction of the market order submitted by the arriving trader.

Equation (5) in Handa and Schwartz (1996) gives the unconditional expected cost of this limit order trading strategy that will guarantee execution by the end of the period:

$$EC= \quad p \cdot \int_{-\infty}^{P_{lim}} (P_{lim} - P_n) f(P_n \mid I) dP_n \; + \; q \cdot \int_{-\infty}^{P_{lim}} (P_{lim} - P_0) f(P_n \mid L) dP_n \; +$$

$$q \cdot \int_{P_{lim}}^{\infty} (P_n - P_0) f(P_n \mid L) dP_n + p \cdot \int_{P_{lim}}^{\infty} (P_n - P_n) f(P_n \mid I) dP_n ;$$

with $E(P_n|L)=P_0$. (4)

The first term represents the expected cost when the limit order is triggered by an informed trader. The second term is the corresponding expectation when a liquidity trader takes the other side of the transaction. The third term is the expected cost when the limit order does not get natural execution after the arrival of a liquidity trader. The last term represents the expected cost when there is no natural execution after the arrival of an informed trader. In this case, the forced execution occurs at the price that equals the expected value of the stock, given all the available information in the market and thus the last term is equal to zero.[23, 24] Hereafter, the first two terms combined will be referred to as the bagging cost, and the third term will be called the nonexecution cost.

---

[23] It is assumed that market price adjusts immediately and completely to the new information.

[24] One problem with this model is that it incorporates a limit order book, but it uses a single market price by avoiding the spread.

A liquidity motivated trade leads to a deviation of market price from its equilibrium value. It is assumed that this deviation is corrected in the short run. The market price following an informed trade reflects the new equilibrium price. Consider two scenarios. In the first, all traders are informed. In other words, q=0 in the expected cost equation. In this case, there is no mean reversion in the price dynamic, and the bagging cost is positive, since trading against an informed trader results in a certain loss. The nonexecution cost is zero, since the market price equals the equilibrium value in this case. Therefore, the total cost of limit order trading is positive.

In the second scenario, there are both informed and liquidity traders in the market. In other words, q is positive in the expected cost expression. Since the price impact of liquidity trading fades quickly, there is mean reversion in the short-term price dynamics. The sign of the bagging cost is ambiguous, since the gain from trading with a liquidity trader may compensate the loss from trading with an informed trader. The sign depends on three factors: the likelihood that the market order submitter is informed, by how much his information will change the equilibrium price, and the likelihood that the transaction will change the price so that the limit order will be executed, given that the market order submitter is uninformed. The expected value of the nonexecution cost is positive. More specifically, if the arriving trader is informed, then the expected nonexecution cost is zero, since the market price at the end of the period equals the equilibrium value. Otherwise, P_0 is still the expected value of the true price, given all the available information. Moreover, the market price at the end of the period is expected to be higher than P_0, since the fact that there is no natural execution eliminates the possibility of this price being in the interval $[0,P_{lim}]$. Therefore, if there is sufficient liquidity trading in the market and prices are corrected in the short run , the bagging cost will be negative. Nonetheless, it can be shown that the expected total cost is positive even in this case. Therefore, only traders for whom the cost of nonexecution is lower than the one assigned by this analysis can have negative total cost from limit order trading.

4.3.3 The Experimental Design

In the experiment, hypothetical one-share limit and market buy orders are used to assess both the profitability of these two trading strategies and whether there is a mean reversion in price dynamics. The use of one-share orders has two implications. First, if these orders had actually been submitted, they would not have changed the transaction record. Second, since the hypothetical limit orders are assumed to be executed when price falls to or below the limit price, the results are only valid for small order sizes.

Timing of Events. Figure 4 describes the timing of events in the experiment. Following the order submission at time zero, if the price falls to or below the limit price by the end of the trading window, then the limit order is assumed to be executed naturally, as shown in part A of the figure. In the figure, the trading window is two days, and the execution occurs during the first day. After execution, the stock is held during a period called the investment window. In the figure, this period is three days, and the stock is sold at the end of the third day following the execution. The investment window represents the time allowed for the hypothesized mean reversion in price to take place.

If there is no natural execution during the trading window, as depicted in part B of Figure 4, then the limit order is converted into a market order and gets immediate execution. To be consistent with the natural execution case, the stock is held during an investment window of the same length before its sale.

Alternatively, as shown in parts A and B of Figure 4, a market order gets executed as soon as it is submitted, and the position is closed at the end of an identical investment window. Irrespective of any news arrival during the trading and investment windows, these naive strategies are strictly followed.

As Figure 4 shows, for each limit order there exists a corresponding market order. Both the start and the length of the investment window for market and limit orders do not match perfectly. Given the parameter values in the figure, there is a minimum lag of one day and a maximum lag of two days between the starting points. The length of investment window is exactly three days for market orders, and it may vary between three and four days for limit orders, depending on the time of execution. Any setup that arranges immediate and sure execution for market orders but postponed and risky execution for limit orders cannot use identical periods to compare the profitability of these two strategies. The nonidentical periods will introduce some noise but will not bias the reported values.

The Definition of Prices and Returns. Since the data set contains bid-ask prices at market close, the end of the trading day is chosen as the time of order submission. A trader can submit a market order and get immediate execution at the prevailing ask price, or he can use a limit order, for which the earliest time of execution is the next morning when the market reopens.

Returns are calculated as the difference in the logarithm of purchase and selling price. For market orders, the ask price at the time of order submission is the purchase price, and the selling price is the bid price at the end of the market order investment window. For limit orders, the selling price is the bid price at the end of the limit order investment window. For executed limit orders, the purchase price is the limit price, and for unexecuted limit orders it is the ask price at the time of forced execution.[25] Limit prices are defined with respect to the midpoint of bid and ask prices at the time of order submission. The limit price is chosen k ticks below the quote midpoint. In the four limit order test categories, k takes on the values 0.5, 1.5, 2.5, and 3.5.

4.3.4 Limitations of the Method

The trading rule is fairly successful in classifying hypothetical limit orders correctly as executed or unexecuted, but in a few situations it does not work. When quotes move so that the limit price equals the best ask price and no transaction occurs until the end of the trading window, the hypothetical limit buy

---

[25] Since the aim is to assess the profitability of hypothetical limit orders, when there is natural execution, the limit price is taken as the execution price, even though it may be greater than the price that triggers the trade.

order will incorrectly be classified as unexecuted. If the hypothetical limit buy order were actually displayed in the limit order book, then the trader who submitted the limit sell order at the best ask price would use a market sell order and trade against the limit buy order. The trading rule is also less reliable when used in a market with spreads typically larger than the tick size. In that case, the price of the hypothetical limit order might fall between the best bid and ask prices. If the hypothetical limit order were actually displayed in the limit order book, then the price of immediacy would decrease for sellers in the market. Therefore, if such a hypothetical limit order is labeled as unexecuted by the trading rule, then it is likely to be misclassified. Since spreads hardly ever exceed the tick size on the ISE, as was shown in chapter 3, only the first case can lead to misclassification.

Another problem with the trading rule is that it follows a naive strategy. An information event may occur before the natural/forced execution of a limit order, but the naive strategy does not allow the original limit order to be replaced with one that incorporates the change in equilibrium value brought about by that information event. Yet, since positive and negative information events are equally likely, their effects will cancel each other in the calculation of average returns. Therefore, the use of a naive limit order submission strategy should not bias the results.

4.3.5 Empirical Evidence in Previous Studies

The Handa and Schwartz (1996) method was used by Hamon et al. (1993) to examine the profitability of limit order trading in forward and cash markets on the Paris Bourse.[26] In a later work, Hamon et al. (1995) compare and contrast the evidence to test the validity of their conjecture that any viable order-driven market requires that prices follow a mean reverting process. They found that in Paris as well as on the NYSE bagging cost is negative and nonexecution cost is positive. Overall, the limit order trading strategy outperforms the market order trading strategy. Moreover, a limit order trader, who is not facing competition from a specialist performs better on the Paris Bourse than on the NYSE. In all the three markets (cash and forward markets in Paris and the NYSE), the higher the difference between limit price and equilibrium value of the stock at the time of order submission, the higher is the nonexecution cost. Intermarket comparison shows that a high nonexecution cost is associated with a high execution rate, which compensates the cost. The authors concluded that market structure can only lead to second-order effects on the basic compensation that traders require to supply liquidity to a securities market.

---

[26] The stocks in the forward market have higher transaction frequency, smaller relative spread, and higher maximum price change limit in comparison to stocks in the cash market.

Harris and Hasbrouck (1996) examined the profitability of limit and market order trading strategies using both transaction and quoted price data. Ex ante and ex post performance measures were employed to compare returns. The first measure compared execution price and the price at the best quote on the opposite side of the market at the time of order submission. The second measure looked at these prices on the same side of the market five minutes after execution. The former was computed for all limit orders, but the latter was calculated only for limit orders that were naturally executed. The sum of the ex ante and ex post measures gives the round-trip return for executed limit orders. Had the ex post measure been computed for all limit orders, both natural and forced execution, the sum would be analogous to the total return measure in Handa and Schwartz (1996). Harris and Hasbrouck (1996) report the results using prevailing spread, size and side of the order, and limit price position as control variables.

The comparison of limit order strategies that differ in terms of limit price position shows that those performing best are the most commonly used. Compared to market orders, at-the-quote limit orders achieve better average performance. Moreover, bettering the quote in markets where the prevailing spread is larger than one tick is a better strategy than placing at-the-quote limit orders. Harris and Hasbrouck (1996) also tried to infer the profit of a hypothetical public trader who acts as a dealer. In contrast to the finding of negative bagging cost in Handa and Schwartz (1996), they determined that the round-trip return for executed limit orders is negative, even without including commissions

To interpret these inconsistent findings regarding the sign of the bagging cost, the empirical methods and samples in the two studies need to be compared. First, the performance measures used are not the same. The ex post measure in Harris and Hasbrouck resembles the so-called bagging cost in Handa and Schwartz, but there are two differences. (1) Rather than use a closing trade, Harris and Hasbrouck compare the execution price to the same-side quote. This is like using a market order to close the position, but the price improvement factor is ignored. (2) The length of the investment window differs. In the Harris and Hasbrouck study, the closing trade occurs five minutes after natural execution, but this period varies between one and three days in the Handa and Schwartz study.

The ex ante performance measure in Harris and Hasbrouck is somewhat similar to the total expected gain from limit order trading in Handa and Schwartz. Yet, the former uses the opposite-side quote at the time of order submission rather than the price of the closing trade as the benchmark to compare the execution price. The computation period also differ. In Harris and Hasbrouck it is less than a trading day whereas in Handa and Schwartz it varies between four and six days.

Second, there are differences regarding the segment of the total NYSE order flow used in the two studies. Handa and Schwartz consider indirectly the total order flow by using the entire transaction tape, but Harris and Hasbrouck limit their sample to Superdot orders. Using their trading rule, Handa and

Schwartz examine only limit orders with the highest time priority at a given price level, whereas Harris and Hasbrouck analyze all the limit orders in their sample, which should result in a less attractive picture from the perspective of a limit order trader. Clearly, natural execution is more likely in Handa and Schwartz than in Harris and Hasbrouck.

In addition, recall that the derivation and empirical results in Handa and Schwartz show that bagging cost is less than the total cost of limit order trading. In other words, the nonexecution cost is positive. This implies that ex post performance should be better than ex ante performance in Harris and Hasbrouck, and this proved to be the case ignoring the problems caused by the choice of time interval in their analysis. Therefore, the two studies agree on the sign of the nonexecution cost.

4.4 Empirical Analysis

4.4.1 Data

The parameter values and number of stock-windows for each limit order test are shown in Table 31. 283 trading days in the sample period are divided into 10 subperiods of 28 days each, and every subperiod is further divided into windows. Depending on the limit order test, the window length varies from four days for the 0.5 and 1.5 tick categories to five and six days, respectively for the

2.5 and 3,5 ticks.[27] For these four limit order tests, the sample period contains 2,100, 2,100, 1,500, and 1,200 potential windows, respectively.[28]

There is one limit order and one market order observation per window. About 21% of potential observations were lost due to missing values for the bid-ask spread and another 2% were lost due to the omission of an observation if either a stock split or a dividend payment occurred during a window. When a stock-window was removed from the limit order sample, it also was removed from the market order sample, and vice versa. The final sample contains 1,546, 1,543, 1,181, and 953 windows in the four respective limit order test categories after eliminating the problem cases.

The subperiod average per stock is the basic unit of observation. Results are reported both as the cross-sectional average per subperiod and the overall average for all subperiods. Table 32 reports for each limit order test and subperiod the number of stock-windows and the number of stocks used to calculate the subperiod average in the subsequent tables. The figures are arranged into two categories based on whether execution of the limit buy order is natural or forced in windows within each subperiod.

---

[27] The last three and four days of every subperiod were not used for the 2.5 tick and 3.5 tick limit order tests, respectively.

[28] For example, for k=0.5 tick there are 30 stocks $\times$ 7 windows per stock and subperiod $\times$ 10 subperiods =2,100 windows.

4.4.2 Results

Descriptive Statistics. Table 33 shows the average execution prices standardized by the market price at the time of order submission. Part A of the table reports the results for all limit orders. Overall, the unconditional limit order execution price is not different from the market order execution price. Part B of the table displays similar figures for forced execution and reveals there is a penalty: Had a market buy order been used, the stock would have cost from 4.21% to 6.89% less, depending on the limit order test category.

Table 34 reports the difference between standardized execution price for limit orders and the triggering price. Overall, the latter is significantly less than the submitted buy price by about 0.55% for all limit order tests.

Table 35 reports the time to execution in hours for naturally executed limit orders. On average, about 22 minutes are required for the 0.5 tick, 58 minutes for the 1.5 tick, 172 minutes for the 2.5 tick, and more than one trading day (about five trading hours) for the 3.5 tick.

Overall Average Returns. Table 36 reports average returns for limit and market orders, along with two related statistics. On average, for the four test categories the limit price was set 0.779%, 2.310%, 3.861%, and 5.423%, respectively below the market price at the time of order submission. Out of all the limit orders submitted, the proportion naturally executed is 87.65% for the 0.5 tick, and the corresponding values are 66.36%, 58.00%, and 52.47% for the other test categories, respectively. Therefore, as the price concession required by a limit order increases, the probability of its execution declines.

The data on overall returns show the following picture. Unconditional returns are significantly negative for both market and limit orders, although limit orders show better average performance than market orders. Interestingly, for the two lowest categories the limit order returns are significantly lower in the case of natural rather than forced execution. As expected, limit order return conditional on execution is as good as or better than the unconditional market order return. Surprisingly, except for the highest test category, limit order return conditional on nonexecution is significantly better than unconditional market order return.

A regularity in Table 36 is the decrease in limit order return conditional on nonexecution as the limit order test value increases. Two factors depend on the value of limit order test. First, the upward tendency of stock price should rise as the limit order test value declines. The information that price never falls by 0.5 tick during the trading window implies a larger upward trend in price than suggested by the information that price has never fallen by 3.5 ticks during the trading interval. Second, delay in purchasing a stock is costly in a rising market. The time of forced execution is by design a nondecreasing function of the limit order test value. Therefore, an increase in limit order test value will make a limit order strategy less attractive in a period of rising stock prices. These two factors, together or individually, are consistent with the decrease in limit order return as the limit order test value increases.

Differential Returns. To measure the total, bagging, and nonexecution costs, the difference between limit order return (both unconditional and conditional) and unconditional market order return is used. Tables 37A, 37B, and 37C report the unconditional differential returns, differential returns conditional on execution, and differential returns conditional on nonexecution, respectively. Unconditional market order returns serve as a benchmark to assess the profitability of a limit order trading strategy.

Overall values for conditional differential returns, reported in Tables 37B and 37C, are not equal to the difference in corresponding values from Table 36. For example, if there are no forced execution observations for a stock in a particular subperiod, then the unconditional market order return of this stock will not affect the differential return conditional on nonexecution for this subperiod. The averages given in Table 36 do not reflect this constraint, which arises from the definition of differential return. The difference between the values reported in tables 36 and 37B-C can be quite significant. As was shown in Table 32, for the 0.5 tick category there were subperiods in which almost all limit orders were naturally executed.

Except for the 0.5 tick limit order test, bagging costs are significantly negative, which is consistent with the sufficient price mean reversion requirement suggested by Handa and Schwartz (1996). For the two lowest test categories, the nonexecution cost is negative; this result is inconsistent with the Handa and Schwartz model regardless of mean reversion requirement. The nonexecution cost increases with limit order test value but is significantly positive only for the 3.5 category. Total costs do not support the predictions of the model. These are negative for all the test categories and are significant only for ticks of 1.5 and 2.5. These results are qualitatively similar to those reported in Handa and Schwartz (1996) and Hamon et al. (1993) for the NYSE and the Paris Bourse, respectively.

Investment Window Length. The choice of a three-day investment window is arbitrary. It was selected so that results would be comparable to those in previous studies of the NYSE and the Paris Bourse. In general, there is a tradeoff in the choice of investment window length. On the one hand, it should be long enough to allow time for the hypothesized mean reversion to take place. On the other hand, it should be short enough to avoid picking up noise from another event that may follow the hypothesized liquidity event.

To determine whether the three-day window length is appropriate, the midpoint of closing bid and ask prices was tracked for 10 days following the order submission. Table 38 reports the average prices standardized by the spread midpoint at the time of order submission for both executed and unexecuted orders. Figure 5 graphs the data for executed orders. It appears that for the 2.5 and 3.5 test categories there is mean reversion in price, but a window of at least eight days is necessary for this process to be completed. For the 0.5 and 1.5 test categories, there is no reason for price correction following a small liquidity shock to take that long. Nonetheless, as Figure 5 shows, price rises, on average till the end of the seventh day, an observation for which no explanation is offered in this analysis.

The experiment was repeated twice, using investment windows of five and seven days. The definition of subperiods was not changed to maintain the comparability of results with those previously obtained. Details about the findings are reported in the Appendix. The number of valid observations for the four test categories falls to 980, 969, 975, and 636 when the investment window is five days. The corresponding figures are 621, 617, 710, and 478 when the investment window is seven days.

Table 39 summarizes the results by showing the overall average of the three costs for each choice of investment window. Except for the 3.5 tick test category, the bagging cost becomes significantly positive as the investment window lengthens from three to five days. Had the bagging cost decreased, it would mean that an investment window of three days is insufficient for the mean reversion to be completed. Because the bagging cost increases significantly in three of the test categories, it appears that the mean reversion cycle is shorter than five days. The bagging cost is significantly negative for all the categories when the investment window is extended to seven days. These sign changes most likely indicate the effect of new information or other liquidity events that follow the original shock. If for each stock new events are independent and equally likely to occur in positive and negative directions, then they should not bias the cross-sectional averages that are used to measure the effect of the original liquidity event. It is possible that marketwide events dominate firm-specific events. If so, then subsequent events will significantly distort the measurement of bagging cost associated with the original shock. This possibility will be examined in the next section by using a market adjustment to concentrate on firm-specific events.

Market Adjusted Returns. If prices in the market move together, in other words, if the marketwide information is the major factor that moves prices, then it is appropriate to test the predictions after making adjustment for marketwide events.

In order to find market-adjusted differential return for stock *k* during window *i* in subperiod *s*, the average market order return for stock *k* during windows in subperiod *s* is subtracted from limit order return for stock *k* during window *i* in subperiod *s*:

$$R_{kis}= r^{l}_{kis} - r^{m}_{k.s} \quad . \qquad (5)$$

In the same way, the differential return of a limit order strategy for a portfolio that includes all stocks except *k* is formulated by:

$$R_{pis}= r^{l}_{pis} - r^{m}_{p.s} \quad . \qquad (6)$$

The differential stock return is regressed on a constant and the differential portfolio return for all the stocks in the sample:

$$R_{kis}= \alpha_{k.} + \beta_{k} R_{pis} + \varepsilon_{kis} \quad \forall k \quad . \qquad (7)$$

The residuals e_{kis} from this regression are stacked into a vector, which contains the differential limit order returns after removing the effect of marketwide events. This vector of residuals is regressed on a constant and a dummy E, which equals one if the limit order is naturally executed, zero otherwise.

$$e_{kis} = \eta_1 + \eta_2 E_{kis} + \nu_{kis} . \tag{8}$$

The coefficients of the second-stage regression measure the effect of firm-specific events only. $-\eta_1$ shows the nonexecution cost, and $-(\eta_1 + \eta_2)$ indicates the bagging cost. The assumption of a mean reversion in price dynamics predicts negative and positive signs for η_1 and η_2, respectively.

The results of this second-stage regression are shown in Table 40. For all the test categories, whenever a coefficient is significant in a subperiod, its sign is consistent with the prediction. Therefore, this is evidence that, after removing the effect of marketwide information events, there is mean reversion on the ISE. It appears that marketwide information events affect short-term price dynamics to a greater extent on the ISE than on the NYSE or the Paris Bourse.

Table 41 compares the overall regression results for the three choices of investment window.[29] Unlike the unadjusted returns discussed in the previous section, the signs of the adjusted regression estimates are not sensitive to window length. Although the magnitudes of η_1 and η_2 vary, the bagging costs are fairly similar. These regression results also indicate that the bagging cost becomes more negative as the test category increases.

---

[29] The regression results for investment windows of five and seven days are given in Table 56 (Appendix C).

Profits from Voluntary Market Making. So far, it has been assumed that the problem is to determine the preferred trading strategy once the decision to trade has been made. Thus, the method of trading was part of a more complicated investment decision. In this section, limit order trading is examined as an independent strategy. The question is whether a trader who acts as a voluntary market maker can earn profits. Therefore, the market order trading strategy, no longer serves as a benchmark.

Consider another experiment in which a trader submits simultaneously both limit buy and limit sell orders. The orders are submitted at the price of $\pm$k ticks from the equilibrium price. Each time an execution occurs, the limit orders are renewed, and it is assumed that the most recent price that triggers execution is the new equilibrium price. This strategy is pursued for three subperiods, each 93 days long. At the end of each subperiod the accumulated stock inventory is eliminated. In this experiment, total loss during 93 days is decomposed into the bagging and the nonexecution costs. Total loss from roundtrip transactions measures the former cost, while the loss realized at inventory closing represents the latter.

The total gain from submitting a network of limit orders during the 93 days is:

$$\begin{aligned} \Pi &= (P_s N_s - P_b N_b) - P_c(N_s - N_b) && (9) \\ &= (P_s - P_b)\min(N_s, N_b) + (P_{av} - P_c)(N_s - N_b) \\ &= \text{gain per roundtrip*roundtrips +} \\ &\quad\ \text{per share gain from closing inventory* inventory imbalance} \\ &= \text{- bagging cost - nonexecution cost .} \end{aligned}$$

where:

P_s = average selling price;
P_b = average buying price;
P_c = inventory closing price;
N_s = total number of shares sold;
N_b = total number of shares bought; and
P_{av} = P_s if $N_s > N_b$ or
P_b if $N_b > N_s$.

The nonexecution cost is expected to be positive no matter in which direction price moves during the period in which a limit order strategy is used. More specifically: (1) If the market is bearish: Then $N_s>N_b$ therefore $P_{av}=P_s$, and $P_c > P_{av}$. (2) If the market is bullish: Then $N_s<N_b$, therefore $P_{av}=P_b$, and $P_c < P_{av}$. In both cases $(P_{av}-P_c)(N_s-N_b)$ is negative showing a positive nonexecution cost. The sign of the bagging cost is ambiguous. More specifically: (1) If trading occurs only with informed traders, then no matter whether the market is bearish or bullish $P_s<P_b$. (2) If trading occurs only with liquidity traders and there is sufficient mean reversion in short term price dynamics, then $P_s>P_b$. The first term in equation (9), $(P_s - P_b)\min(N_s,N_b)$ has opposite signs in these two cases; hence the sign of the bagging cost is ambiguous.

Therefore, if there is sufficient mean reversion in short term price dynamics then negative bagging cost can outweigh the positive nonexecution cost and voluntary market making may be profitable.

Adjustment for Split and Dividend. The splits and dividends of sample firms introduce a problem in using hypothetical one-share orders.[30] To give

[30] Other than adjusting the limit prices on ex-split and ex-dividend days.

equal weight to all the executions during the 93-day trading period, a share index is created for each firm. It shows for each day how many shares are equivalent to a share of stock at the beginning of the sample period. The index takes into consideration stock splits and dividends as well as cash dividends.[31] To find the transaction price for each execution, the actual transaction price is multiplied by the share index. The same adjustment is made to the price used to close the inventory. With this adjustment, the experiment examines outstanding limit orders for one equivalent share during the whole 93 days.

Two sets of experiments were conducted using a limit price of ± 2 and ±3 ticks around the equilibrium price. Table 57 (Appendix C) reports the number of shares bought and sold per firm, as well as the maximum and minimum values of the inventory. The number of purchases and sales are fairly similar.

Table 42 reports the results where stock-subperiod is the basic observation. Part A reports the results on TL basis. Part B expresses the result as a percentage of the price of one equivalent share at the close of each subperiod, which prevents higher weighting of higher priced stocks. The table shows negative bagging and positive nonexecution costs for both test categories. Since the absolute value of nonexecution cost is greater than that of bagging cost, the total cost is positive for the two cases, but it is significant only

---

[31] The money to participate in a rights issue is obtained by selling stock, and the cash dividend is used to purchase new stock.

for the ±3 tick category. Individual stock averages (not reported) show that the round-trip gain is always positive. Moreover, it is found that the per-share gain from closing inventory and share imbalance at the close always have opposite signs. In other words, the nonexecution cost is positive for individual stocks.

In the voluntary market making experiment there is no need to choose arbitrary parameter values for the trading and investment windows. Without imposing these constraints, the results are qualitatively consistent with those from the market-adjusted single limit order experiment. This strengthens the conjecture that the inconsistent results obtained from unadjusted differential returns arise because dominant marketwide events create a measurement problem when the investment window is chosen different from the true cycle length of the firm-specific mean reversion.

Intermarket Comparison. The fraction of executed limit orders may provide an opportunity to compare the balance between market and limit order submission rates on the ISE with those on the NYSE and the Paris Bourse. For the NYSE, these proportions are 46%, 39%, and 35% for orders placed 1%, 2%, and 3% from the equilibrium value at the time of order submission. For these same categories, the corresponding figures are 45%, 40%, and 34% on the Paris forward market and 21%, 25%, and 19% on the Paris cash market. For the ISE, the proportions per test category are: 88%, 0.5 tick; 66%, 1.5 tick; 58%, 2.5 tick; and 52%, 3.5 tick. These test categories represent a variation from equilibrium value between 0.8% and 5.5%.

These data imply that short-term volatility on the ISE is larger than on the NYSE. One possible reason for the ISE's volatility may be the absence of an opening call, a useful mechanism for price discovery. In addition, the opportunity to hide limit orders on the Paris exchange, and the existence of specialists as well as the limited disclosure of the limit order book on the NYSE may explain some of the difference. Because these features create transaction price uncertainty for informed traders, they protect limit order submitters to a certain extent, and may encourage the use of limit rather than market orders by uninformed traders. If so, then the depth at all price levels will increase, which reduces short-term volatility.

The choice of a large relative tick by the ISE may affect the balance of market and limit order submission rates. That is, it may be designed to enhance the attractiveness of a limit order trading strategy for small orders. A large relative tick sets a floor for relative spread. An increase in the relative spread increases both the cost of a market order trading strategy and the gains from a limit order trading strategy for small orders. The execution rates imply that – even with a large relative tick – the balance is weaker on the ISE than on the NYSE and the Paris Bourse.

4.5 Summary

A trading rule introduced by Handa and Schwartz (1996) was used to compare the performance of limit and market order trading strategies. This rule injects hypothetical orders into the transaction tape to estimate the expected round-trip returns from these two strategies.

It is conjectured that unconditional returns from limit order trading are negative. Only traders who can forgo trading when their limit orders are not executed can find limit order trading attractive. This requires sufficient liquidity trading and a mean reversion in short-term price dynamics.

The results show that average short-term returns from these naive strategies are negative. The method of using average differential limit order returns is not reliable, because results are highly sensitive to the choice of investment window length. The reason seems to be that marketwide rather than firm-specific events are the major factor in stock price movement in the short run. After adjusting the differential returns for marketwide events, the results are stable and generally consistent with predictions of the Handa and Schwartz (1996) model. There seems to be enough mean reversion in price so that when firm-specific events occur, limit order return conditional on execution is greater than unconditional market order return; in other words, the bagging cost is negative. Moreover, for return conditional on nonexecution, the relationship is in the other direction. Stated differently, the nonexecution cost is positive.

The results also show that a trader who acts as a market maker will make negative average profits on the ISE. This is consistent with findings in two other studies, which used the same trading rule to examine the NYSE and the Paris Bourse.

Compared to the NYSE and the Paris exchange, the fraction of executed limit orders is large on the ISE, which indicates higher short-term price volatility on the Turkish exchange. Two explanations can be given. First, unlike the ISE, trading on the NYSE and the Paris Bourse start with a call auction, which is thought to enhance price discovery in a market. Its absence is likely to result in high intraday volatility. Second, high volatility may reflect an imbalance in market and limit order submission rates. This suggests that even the use of a large tick size is not sufficient to bring the rates into balance.

Chapter 5

Relationship between Trading Volume and Price Change on the ISE

5.1 Introduction

In economics, changes in market equilibrium are thought to depend on information arrival. Once information is incorporated into prices, a new equilibrium is established. The mechanics of price formation can be modeled by using two approaches. According to the first, known as the rational expectations framework, investors use price information to find their equilibrium demand. The second employs the concept of a Walrasian auctioneer who aggregates the supply and demand schedules of individual investors and finds the price that clears the market. Although trading occurs continuously in actual markets, both approaches ignore the adjustment process and concentrate on the properties of the new equilibrium.

The adjustment process is a focus of the market microstructure literature. During the adjustment period, existing information becomes obsolete and uncertainty about the true asset value increases. It is reasonable to predict a positive association between asset price volatility and the strength of the new information. Furthermore, whether the information is private or public is likely to be important. Such public information as the announcement of earnings or a merger is believed to be incorporated into price quickly and directly without generating abnormal trading activity. In contrast, private information is revealed through the timing and size of informed trades. Depending on competition among informed traders and whether information is short or long lived, the price adjustment can take some time. Microstructure theory investigates the strategic behavior of informed traders and considers stealth trading a natural strategy. Nonetheless, it still relies on increased trading activity to model the learning process of uninformed traders. Although abnormal trading activity is not thought to be part of the price adjustment process following the arrival of public information, there is likely to be a period of high trading characterized by hedging and speculation.

Since both price volatility and trading volume are related to market information flow, a contemporaneous relation between them is likely.[32] Uncovering the relationship between these two variables is important to an understanding of how prices adjust to new information.

In most theoretical models in the microstructure literature e.g., Brown and Jennings (1989) and Grundy and McNichols (1989), price adjustment is not instantaneous. Empirically, transitory liquidity effects add noise to the measurement of permanent information effects. Because the price adjustment is not immediate, such market statistics as the price-volume sequences may be useful. Unfortunately, theory does not provide a definite answer about what traders can learn from market data beyond the current price. Yet, the fact that

[32] One should be careful in this argumentation. If the new information is a public signal and transaction level data is used, then this argument would be incorrect since the abnormal trading activity is believed to follow the price adjustment. For less frequent data sampling, this argument should be valid.

technical analysis is widespread in seemingly efficient markets indicates that there may be a dynamic relationship between price and volume.

The interaction between trading volume and price change has been an issue for almost 40 years (Granger and Morgenstern 1963). As pointed out in a survey article by Karpoff (1987), one benefit of investigating this relationship is the insight gained about the structure of financial markets. Relevant factors noted in the literature include the flow of information, its dissemination, the extent to which prices reflect information, and the effect of market frictions, such as the cost of taking a short position.

This chapter examines the intraday relationship between price and volume on the ISE. Empirical evidence is provided on both a contemporaneous and a dynamic relationship. An examination of the univariate temporal patterns in price and volume precedes bivariate analyses. The next section reviews the literature on the price-volume relationship and temporal patterns. It is followed by an empirical analysis and a brief conclusion.

5.2 Literature Review

According to Gallant et al. (1992, p. 201),

> Generally speaking, the empirical work on price-volume relation tends to be very data-based and not guided by rigorous, equilibrium models of market behavior. The models are more statistical than economic in character, and typically neither the optimization problem facing agents nor the information structure is fully specified. The intrinsic difficulties of specifying plausible, rigorous, and implementable models of volume and prices are the reasons for the informal modeling approaches commonly used.

The evolution of theoretical research in this area can be separated into two periods. The models in the early period saw the arrival of new information as the factor that generates trades, but they did not distinguish between private and public signals. The second period began with the introduction of the private information models, which is usually credited to Bagehot (1971), but the concept of trades themselves as signals of information was first developed by Glosten and Milgrom (1985) and Easley and O'Hara (1987). A new generation of work emerged after the concept of asymmetric information was introduced into the microstructure literature.

Empirical research has identified at least two characteristics of the price-volume relationship.[33] Trading volume is positively correlated with both price change and its absolute value. Moreover, the ratio of volume to price change for upticks exceeds the absolute value of the same ratio for downticks. To explain this difference, Karpoff (1987) argues that if the true relationship between the two variables is asymmetric, then incorrect specifications that force a functional and/or monotonic relation between them can lead to these somewhat inconsistent findings for upticks and downticks. Asymmetry has been confirmed in stock and bond markets, which Karpoff believes can be a consequence of the extra cost involved in taking a short position. His explanation is supported by Foster (1995), who reports a symmetric relationship in crude oil futures markets, where there is no difference in the cost of long and short positions.

[33] See the survey article by Karpoff (1987) for a list of empirical works.

5.2.1 Early Research on Price-Volume Relationship

The positive correlation between volume and the absolute value of price change is consistent with both the mixture of distributions hypothesis and the sequential information model. An important difference between them is the speed with which a market moves to the full information equilibrium. The former assumes that upon the arrival of new information the new equilibrium is reached immediately; the latter theorizes that the final equilibrium is attained after passing through a number of incomplete equilibria.

Mixture of Distributions Hypothesis. Work by Clark (1973), Epps and Epps (1976), and Tauchen and Pitts (1983) is consistent with the mixture of distributions hypothesis, which states that price changes over time are sampled from distributions with different variances.

The Clark (1973) study belongs to the body of research on the distribution of speculative prices. In an effort to explain the leptokurtis in the distribution of daily stock price changes, Clark points out the distinction between transaction and calendar time. He argues that although the price change process for individual transactions may be Gaussian with constant variance, the random rate of daily information arrival to the market makes the central limit theorem inapplicable. Total volume and price change over a fixed period are summations of statistics generated from individual transactions during this interval. Therefore, price change during a fixed period is a mixture of independent normals, with the number of new pieces of information flowing into the market being the mixing variable.

Clark (1973) conjectures that volume during a fixed period is related positively to the number of new pieces of information. Hence, volume is a proxy for the rate of information arrival, and this makes price change variability during a fixed period proportional to the volume generated. Clark uses the daily change in cotton futures prices to test this hypothesis. By grouping observations according to the level of volume, he shows that the kurtosis of the distribution is significantly reduced for each volume category relative to the kurtosis of the entire sample. In other words, the distribution of price change adjusted for operational time looks more like the normal distribution, which supports the hypothesis.

Another version of the mixture of distributions hypothesis is presented by Epps and Epps (1976), who examined volume-price changes from one market clearing to the next, rather than over a fixed interval. Therefore, although their model predicts the same relationship as Clark, their result is not driven by the random rate of information arrival. In the Epps and Epps model, after new information arrives, each investor updates his beliefs about the distribution of assets' end-of-period values. This updating changes means, but not variances or covariances of these distributions. The change in the equilibrium price is the average of changes in traders' reservation prices. The critical assumption in the model is that the higher the absolute value of the average change in traders' reservation prices, the higher is the disagreement among investors. Assuming that high disagreement among investors is associated with high volume, a positive correlation between the absolute value of price change and volume arises.

Tauchen and Pitts (1983) formalize Clark's idea by using an economic model in which the change in reservation prices of investors has a common and an investor-specific component. There is functional dependence between the first two moments of price change and trading volume at each market clearing, but the two variables are stochastically independent. During a fixed period, the relationship between volume and price change variability is due to their common positive connection to the number of new pieces of information arriving to the market.

One goal of Tauchen and Pitts (1983) is to explain the increase in volume and decrease in daily price change variability in the Treasury bill futures market over time. Their model shows that both price change variance and expected volume over a fixed interval depend on the mean arrival rate of information to the market, the extent to which traders disagree when they respond to new information, and the number of active traders in the market.

The mixture of distributions hypothesis implies that price change variance over a fixed interval is heteroskedastic. Lamoureux and Lastrapes (1990) relate the observation of persistent return volatility in financial markets to that hypothesis. They suggest that the GARCH effects in stock returns may reflect serial correlation in the number of information arrivals. Using daily stock return and volume data, they found strong support for this view. When contemporaneous volume was added to the conditional variance equation, its coefficient was significant. Moreover, the GARCH effects disappeared after the inclusion of volume.

A similar analysis by Najand and Yung (1991) used data from the Treasury bond futures market. Unlike Lamoureux and Lastrapes (1990), they did not find that the GARCH effects disappeared when contemporaneous volume was included to the variance equation, volume was not significant in explaining the variance. The suspicion of simultaneity then led them to use lagged volume as an instrument for contemporaneous volume, and it proved significant. Nevertheless, the GARCH effects remained significant even after solving the simultaneity problem. A later study by Foster (1995) of the market for crude oil futures supports the findings in Najand and Yung.

Sequential Information Model. A positive correlation between volume and the absolute value of price change is also predicted by Copeland's (1976) model, in which information is received sequentially by investors. They are classified as optimist or pessimist depending on the way they interpret the new information. Investors shift their demand curve up or down by a fixed amount after receiving the information. Since short selling is not allowed in the model, the volume generated by a pessimist in response to the information is lower than the volume generated by an optimist. Total volume and price change in this model depend on the composition of investors and on the amount of information. In addition, total volume depends on the order in which information is received. Expected total volume reaches its maximum when there is complete agreement among investors, a counterintuitive result caused by the no short selling constraint. Expected total volume and the absolute value of price change attain their minimum for the same fraction of optimists in the market, and the absolute value of price change increases with volume. This shows the positive correlation between the two variables.

To explain asymmetry in the volume-price change relationship, Karpoff (1986, 1987) pointed to the cost of short selling in most markets. Another model Epps (1975) that examines asymmetry arrives at a different explanation. Epps creates a portfolio selection model that classifies investors as optimist or pessimist depending on their beliefs about the end-of-period value of an asset. They accept a new piece of information that reinforces their beliefs and otherwise ignore it. Another critical assumption by Epps concerns the effect of new information. Each investor changes his belief about the end of period value of the asset in response to news shocks in such a way that the coefficient of variation remains constant. This assumption implies that optimists have a steeper demand function than pessimists, which leads to the result that the ratio of volume to absolute value of price change is higher for price upticks than for downticks.

In the models discussed thus far, the results are generally not driven by the maximization of objective functions of different investor groups. Instead, these models make strong assumptions that are hard to justify, such as ignoring information that contradicts beliefs, or the artificial classification of investors as optimists or pessimists. These features of early research affected the way empirical studies were conducted in this area.

5.2.2 More Recent Work

The informational role of volume is examined in more recent works that are not subject to the same criticisms as the early models. One approach analyzes the volume that emerges when traders with different information signals transact. Another approach focuses on what traders can learn from observing volume.

Informational Role of Volume. As an example of the first approach, Wang (1994) created a model of stock trading in which investors are heterogeneous with regard to information and private investment opportunities. Informed investors trade when they receive private information about the stock's future cash flows or to rebalance their portfolio when their private investment opportunity changes. The uninformed are willing to trade with the informed, since not all the trades from the informed traders are information motivated. Investors follow dynamic trading strategies to maximize lifetime expected utilities. Market clearing price does not fully reveal the informed investors' private information because they have two possible motives for trade. The effect of information asymmetry on the behavior of volume is Wang's major concern. As that asymmetry increases, uninformed investors demand higher price concessions in trading with informed investors. Therefore, trading volume is always positively correlated with absolute price changes, and the correlation increases with information asymmetry. Expected future returns conditional on current volume and return depend on the extent of information asymmetry. Thus, the dynamic return-volume relationship can reveal the nature of investor heterogeneity in the market.

The second approach is exemplified by Blume, Easley, and O'Hara (1994), who focus on the learning problem that arises when traders condition on the information conveyed by volume. If the process by which prices adjust to information is not immediate, then market statistics may contain information that has not been incorporated into the current market price. In this model, volume does not merely describe but affects market behavior. Therefore, Blume et al. give one explanation for the existence of technical analysis in seemingly efficient markets.

In this Walrasian model, informed and uninformed traders receive signals of different quality (precision). Both the level and the quality of the informed traders' signal is unknown to uninformed traders. Price incorporates the aggregated value of underlying signals, whereas volume conveys information about the signal quality of informed traders that can be used, together with price, to make inferences about the true value of the asset.

The relation between volume and information is not linear in the Blume et al. framework. Both low and high volume may indicate the arrival of new information. Volume is related to the dispersion of investor beliefs, and the link between dispersion and information is complex. In equilibrium, volume is strictly convex in price, and a V-shaped pattern emerges. Therefore, absolute price change and volume are positively correlated. Both information quality and the level of information dissemination affect the price-volume relationship. The dispersion of the distribution of the price changes decreases with an increase in information quality, while it increases with volume given a high level of information dissemination. The latter prediction is consistent with the empirical evidence given by Gallant et al. (1992). According to Blume, Easley, and O'Hara (1994), past volume and price sequences help to make inferences about the true value of a security. Thus, a dynamic relationship between volume and price is consistent with this model.

A number of studies (Cheung et al. 1993, Foster 1995, Gwilym et al. 1999 , Hasbrouck 1991, Jain and Joh 1988, and Stickel and Verrecchia 1994) give empirical evidence of the dynamic relationship between volume and price change.

Jain and Joh (1988) and Cheung et al. (1993) use intraday data to investigate the contemporaneous and causal links between price change and volume in equity markets. Both studies confirm a positive asymmetric contemporaneous relationship and find that return causes volume in the Granger sense.

Hasbrouck (1991) follows information-based theoretical models, which suggest that security prices respond to trading activity as a consequence of asymmetric information. He uses vector autoregression (VAR) modeling because he maintains that microstructure imperfections necessitate the use of lagged price, trade size, and trade direction terms in estimation. Factors related to public trader behavior, such as order fragmentation and price pressure, as well as dealers' concern for inventory control lead to serial dependence in transactions. Moreover, certain trading rules, such as price discreteness and exchange-mandated price smoothing requirements, result in lagged adjustment of price to new information.

The dynamic structure of the VAR system permits the measurement of price response to a single impulse in unanticipated trade size. The unanticipated trade size gauges the effect of private information. The use of impulse response function picks up the persistent price impact and thus eliminates the transient inventory control and liquidity trading effects. The unanticipated price change in the VAR model reflects the effect of public information.

Hasbrouck (1991) provides evidence that price impact is a positive, increasing, and concave function of trade size. Another finding is that Granger causality runs in both directions. Contemporaneous and past trades affect the current change in price, which suggests a lagged price adjustment process. The negative relation between current trade and past price changes is consistent with both inventory control effects and the price experimentation hypothesis, which maintains that market makers set quotes to extract information optimally from traders.

Stickel and Verrecchia (1994) examine how trading volume influences subsequent price change around earnings announcements. They hypothesize that price changes are more likely to reverse following weak volume support than strong volume support. It is argued that price changes reflect demand for a stock, and higher volume increases the likelihood that the demand originates from informed rather than uninformed trading. They give evidence that large price changes on days with weak volume support tend to reverse the next day, after controlling for the bid-ask bounce effect.

Foster (1995) reports a contemporaneous relationship between price volatility and volume, after controlling for lagged observations of these variables. This suggests that volume and volatility are both driven by the same factors, one of which may be information, as is assumed in the mixture of distributions hypothesis. The coefficient estimates of lagged volume and volatility are significant in Foster's study and support the prediction in the Blume, Easley, and O'Hara (1994) model that past volume can be used to explain future price volatility.

Gwilym et al. (1999) investigate the intraday relationship between volume and volatility in LIFFE futures markets and show a positive contemporaneous correlation between the two. Moreover, causality is bidirectional between volatility and volume. The authors argue that the latter finding supports the sequential dissemination of information in LIFFE futures markets. This is attributed to the potential for profitable trading due to short-lived informational advantages, which stem from the low transaction costs and margin requirements in this market.

5.2.3 Intra and Interday Patterns in Volume and Return Volatility

Empirical research provides evidence of temporal patterns in volume and return volatility. Wood, McInish, and Ord (1985) report that intraday volatility is U-shaped. A systematic pattern in interday returns is found in Harris (1986), who shows that significant interday differences in returns occur during the first 45 minutes after the market opens. Moreover, prices drop on Monday morning, but rise on other weekday mornings. Jain and Joh (1988) report that volume has a U-shaped intraday and an inverse U-shaped interday pattern.

Theoretical work on this issue consists mainly of the intraday model of Admati and Pfleiderer (1988) and the interday framework of Foster and Visvanathan (1990). Both use the concept of discretionary liquidity traders to derive temporal patterns. They differ primarily in their assumptions about the nature of private information (whether it is short or long lived) and the number of informed traders in the market.

In the Admati and Pfleiderer model, there are multiple informed traders, and they receive a private signal in each period. Their information is short-lived (becomes public at the end of the period). There also are discretionary liquidity traders, who have the flexibility of choosing the period in which they will trade. To minimize their trading cost, they concentrate their trades in the same period. The reaction of informed traders is to increase their trading in the same period, because they can hide better when liquidity trading is high. When information acquisition is endogenized, the period with the highest volume also has more informative price and high price change volatility.

In the interday model of Foster and Visvanathan (1990), unlike the Admati and Pfleiderer (1988) framework, private information is long-lived. A single informed trader receives a private signal on all days, and the other market participants get a public signal on weekdays only. The discretionary liquidity traders can postpone their trades by no more than one day. Given the structure of Foster and Visvanathan model, the largest informational asymmetry occurs on Monday. The public signal reduces the advantage of private information. With a highly informative public signal, there will be two days of high trading activity. With a less informative public signal, Friday is the only day with concentrated trading. Volume is predicted to be lowest on Monday. Moreover, when the public signal is very precise, price change volatility will be high on Monday. In contrast, Admati and Pfleiderer (1988) predict that volume and price change variability move together.

5.3 Empirical Analysis

5.3.1 Introduction

Due to lack of data, the intraday price-volume relationship on the ISE has never been examined. The analysis in this section is the first attempt to do so. The microstructure of the ISE is likely to affect this relationship.

The ISE is not different from most other markets regarding the rules on short selling, so the asymmetry documented in stock and bond markets is expected to exist there as well. As discussed earlier, serial dependence in trades and lagged price adjustment are features that Hasbrouck (1991) cites in a dynamic volume-price relationship. One factor that leads to serial dependence in trades, – the inventory control effect – does not exist on the ISE because there are no designated market makers. Moreover, the ISE's large relative tick implies that price discreteness is more important in this market, and there are no price smoothing rules other than the maximum price change limit. These last two points are related to the issue of lagged price adjustment: The former is likely to delay it and the latter to enhance it. Finally, the opening call auction accommodates a significant fraction of trading volume in many markets but is absent on the ISE. Therefore, the information collected during nontrading periods has to be acted upon during the continuous trading period.

5.3.2 Data

The Choice of Sampling Frequency. The relationship between price and trading activity can be analyzed in either transaction or clock time. With the former method, trade direction can be used as a control variable. Since the ISE data do not contain an identifier for trade direction, another method is required. One way to classify trades is to compare the trade price to the quote prices at the time of trade, but ISE quote data are not available. In similar situations, researchers have used the tick method: The trade direction is inferred by comparing the price of the current and preceding trade. Trades are classified into four categories: an uptick, a downtick, a zero-uptick, and a zero-downtick.[34]

To see whether the tick method is satisfactory in classifying consecutive transactions, Table 43 gives the frequency distribution of trades using only

---

[34] A trade is an uptick if the price is higher than in the previous trade. A zero and a downtick is defined analogously. A zero tick is classified as a zero-uptick if the previous trade is an uptick. A zero-downtick is defined analogously.

upticks and downticks.[35] As discussed in chapter 3, about 10% of transactions result in a price change. It is clear from the table that only a small fraction of transactions in the sample can be classified with this method. Therefore, the distinction between seller- or buyer-initiated trades is ignored in the analysis, which is based on clock time, by sampling price and volume information periodically.

Although the choice of sampling frequency is arbitrary, there is a tradeoff between the total number of sampled data points and the fraction of these for which the price changed during the sampling period. Table 44 shows frequencies using three interval lengths, that is, splitting a trading day into intervals of 15, 30, and 60 minutes. The 15-minute interval is used in the analysis.

The Price and Volume Series. To construct an equally weighted price and volume series, the following procedure was adopted. The use of nominal stock prices would assign larger weights to higher priced stocks. Therefore, the nominal price series are adjusted so that the price of each stock equals 100 at the beginning of the sample period. The final price index relies on these individual stock indexes.[36]

---

[35] Lee and Ready (1991) found that the tick method is 90% accurate, but Aitken and Frino (1996) found only 74% accuracy for the Australian Stock Exchange (more than 90% when zero ticks were excluded).

[36] Split and dividend adjustments were done for each stock. Five stocks had old and new shares trading simultaneously. The price of old shares was used in creating the price series. Since the new share volume could not be ignored, the volume series includes the trades of both kinds of shares. Refer to Chapter 2 for

For most stocks the number of outstanding shares changed during the sample period, so trading activity is measured by share turnover. Due to the large cross-sectional variation in the float rate, share turnover is defined as the ratio of shares traded to floating shares.

There were 283 trading days in the sample period, of which 277 were standard trading days with sixteen 15-minute intervals. On the remaining six days, either there was trading only during the first session or there were trading delays/halts. As a result, there are 4,500 intervals during the sample period.

Figures 6 and 7 plot the price and percentage turnover series over time. Figure 6 shows the effect on stock prices of the Russian crisis of August 1998, during which month average prices fell about 50%. A similar decrease in volume can be observed from Figure 7. The popular press emphasized the pressure on prices exerted by the sell orders of foreign investors.

Stationarity. To decide on the specification to model the relationship between price and volume, the stationarity of these two series needs to be examined. If the two are integrated on the order one, then it is possible that they are cointegrated. In this case, the short- and long-term relationship between the two series can be distinguished, and estimation methods that preserve the information about both forms of covariation should be employed. Table 45 shows formal stationarity tests for price, return, and percentage turnover. Both the augmented Dickey-Fuller and Phillips-Perron tests give consistent results. The

---

the definition of old and new shares.

hypothesis that the volume series contains at least one unit root is rejected at the 0.001 level of significance, so it is concluded that this series is stationary. Because neither test indicates rejection for the price series, differencing is appropriate in that case.

The return series is the difference of logarithmic prices at the end of consecutive intervals. Close-to-open returns (both overnight and midday) are excluded to eliminate any possible confounding effects from information that arrives when the market is closed. Figures 8 and 9 graph the return and return squared over time. As shown in Table 45, the unit root test is rejected for the return series at the 0.001 level of significance, which suggests it is stationary.

Intraday and interday variation in stock returns and trading volume has been shown in other markets. Since this is the first study to employ intraday transaction data from the ISE, a univariate analysis of systematic intraday patterns in these two variables is presented before investigating the bivariate relationship. To eliminate measurement error, the six days with fewer than 16 intervals were excluded, which leaves 277 trading days and 4,432 intervals in the final sample.

5.3.3 Time of Day and Day of Week Effects

Intraday Trading Volume. Table 46 and Figure 10 show average turnover for each interval and each weekday. The overall average turnover during a 15-minute interval is 0.467%. For each day of the week, turnover attains maximum value during the first interval and it is about twice the amount observed in the remaining intervals. Turnover is also high during the first and last intervals of the second trading session. High trading activity during the first interval of both sessions can be attributed to the effect of information flow during the nontrading periods, whereas the increase during the last interval of the day probably reflects the concern of traders to rebalance their holdings before the market closes.

Several analysis of variance tests were performed to measure the variability of mean turnover across intervals and days. Table 46 shows these F tests. F_{int} tests the hypothesis of equality of mean turnover during all intervals in a given weekday. F_{frst} (F_{ninth}, $F_{sixteenth}$) tests the hypothesis that mean turnover in interval 10:00-10:15 (14:00-14:15, 15:45-16:00) is not different from the mean turnover in the remaining intervals (excluding those three intervals). F_{day} tests the hypothesis that there is no interday difference in mean turnover during a given interval. Overall, the results suggest weak interday but strong intraday variation in turnover.

Intraday Volatility. Table 47 and Figure 11 show average return squared for each interval and each weekday. This measure is a proxy for return volatility during an interval. The volatility of return increases during the first interval of each session, but it is much higher during the first interval of the day. The definition of F_{int}, F_{frst}, F_{ninth}, $F_{sixteenth}$, and F_{day} in Table 47 are analogous to the F tests in Table 46. Combined with the turnover pattern, the variation in volatility suggests that the incorporation of new information into prices occurs during the first interval of both trading sessions, and the high turnover at the end of the day is due to portfolio rebalancing rather than the effect of information.

To complement the picture, Table 48 and Figure 12 show the time-of-day and day-of-week effects for average return. Similar to the behavior of the other two series, there seems more intraday than interday variation in average returns. A large positive return during the last interval of the second session is the most striking pattern. This may be caused by buyer-initiated trades to close short positions by the end of the trading day. Positive returns on Friday afternoon, and negative returns on Monday suggest that investors prefer to take long positions during the weekend and liquidate their holdings on the first day of the week.

The univariate analysis so far shows systematic temporal patterns in return, volatility, and turnover. The time-of-day rather than day-of-week effect seems to be the dominant source. To remove seasonality, the three series were standardized using time-of-day and day-of-week means and standard deviations. The analysis in the remainder of this chapter uses the standardized return, volatility, and volume series.

The link between price and volume will be examined, first, by investigating any contemporaneous association and, second, by testing for a causal relationship in the Granger sense.

5.3.4 Contemporaneous Price-Volume Relationship

To examine the contemporaneous relationship between price change and turnover, the Jain and Joh (1988) empirical model is used. Three specifications of this model are estimated:

$$\text{volume}_t = a + b\left|\text{return}_t\right| + c\text{Dneg}_t\left|\text{return}_t\right| + \sum_{i=1}^{20} e_i D_{it} + \sum_{i=1}^{19} f_i D_{it}\left|\text{return}_{t-i}\right| +$$

$$\sum_{i=1}^{19} g_i (D_{it}\left|\text{return}_{t-i}\right|\text{Dneg}_t) + u_t \ ; \qquad (10)$$

where

D_{neg} = a dummy variable that takes on the value of one when return is negative;

D_i = i=1-19, that is, four day-of-week and 15 time-of-day dummies. For example, D_1 equals one when the day of the observation is Tuesday, zero otherwise; D_5 equals one when the observation belongs to the 10:15-10:30 interval, zero otherwise; and

D_{20} = a dummy variable to incorporate the effect of Russian crises. Its value is zero before August 1, 1998, and is one otherwise.

The model allows the contemporaneous relationship to depend on the sign of return. As discussed in the introduction, the theoretical models of Epps (1975) and Karpoff (1986, 1987) predict an asymmetric relationship: Volume on price upticks will be larger than volume on downticks.

The first specification imposes the restriction that all the coefficients except a, b, and c are equal to zero. The second specification sets all f_i and g_i equal to zero. The last specification estimates the unrestricted model.

Table 49 reports the estimated coefficients and their p values for the three specifications. To account for heteroskedasticity and autocorrelation in disturbance terms, the current model and the following two models used to analyze causality are estimated with the Newey and West (1987) approach.[37]

The first specification shows a strong contemporaneous relationship between absolute value of return and volume. Moreover, the prediction of an asymmetric relation is also supported, although the extent of the asymmetry is small. Positive return has a coefficient of 0.491, compared to 0.429 for negative return.

The second specification includes time-of-day and day-of-week dummies. None of these are significant, which suggests that the standardization removed systematic intraday differences. The dummy denoting the down market after the Russian crises is highly significant and shows that volume decreased following the shock. The strong relation between volume and absolute value of return and the small asymmetry displayed in the first specification are robust to the inclusion of the above-mentioned control variables.

The third specification permits the relationship between volume and absolute value of return, as well as asymmetry to depend on the time-of-day and the day-of-week. In this specification, the coefficients b and c show the relation for the first interval on Monday. As in the second specification, all day-of-week dummies are insignificant. All time-of-day dummies that are significant have

[37] Newey-West estimator of the covariance matrix of the least squares estimator is: $\mathbf{S}=\mathbf{S}_0+\frac{1}{T}\sum_{l=1}^{L}\sum_{i=l+1}^{T} w_j e_i e_{i-l}[\mathbf{x}_i\mathbf{x}_{i-l}^{'}+\mathbf{x}_{i-l}\mathbf{x}_i^{'}]$ where $\mathbf{S}_0=\frac{1}{T}\sum_{l=1}^{T} e_i^2\mathbf{x}_i\mathbf{x}_i^{'}$ and $w_j=1-\frac{j}{L+1}$, e_i is the least squares residual, and autocorrelations greater than L are small enough to ignore.

negative coefficients. This probably reflects the fact that the first interval of the day has the highest volume, and standardization could not completely eliminate time-of-day differences in turnover. The relation between volume and return for the first interval on Monday is qualitatively similar to the results in the other two specifications, except that asymmetry is much greater in this interval. The general conclusion is that both the positive contemporaneous relation between volume and absolute return and asymmetry regarding the sign of the return exist at different levels in all intervals on all days. The few exceptions are that asymmetry disappears on Tuesday and its direction changes during the interval 14:45-15:00.

5.3.5 Causality

For the two jointly covariance stationary time series x and y, x is said to Granger cause y if knowledge of past x and y leads to better predictions of y than would result from knowledge of past y alone. Several Granger causality tests have been proposed in the literature.[38] Bivariate vector autoregression, as suggested by Granger (1969), is used in this study. Two specifications are estimated.

---

[38] See survey articles by Pierce and Haugh (1977) and Geweke et al. (1983).

Specification 1:

$$\text{return}_t = a + \sum_{i=1}^{4} b_i \text{return}_{t-i} + \sum_{i=1}^{4} c_i \text{volume}_{t-i} + \mu_t \, ; \tag{11}$$

$$\text{volume}_t = d + \sum_{i=1}^{4} e_i \text{return}_{t-i} + \sum_{i=1}^{4} f_i \text{volume}_{t-i} + \eta_t \, .$$

This specification uses signed return and presumes that two returns of the same magnitude but opposite signs have a different effect on future return and volume. Since there is no reason to impose this restriction, a second specification that uses absolute return is also estimated. This system can be interpreted as testing the causality between return volatility and volume.

Specification 2:

$$|\text{return}_t| = a + \sum_{i=1}^{4} b_i |\text{return}_{t-i}| + \sum_{i=1}^{4} c_i \text{volume}_{t-i} + \sum_{i=1}^{4} d_i \text{Dneg}_{t-i} + \mu_t \, ; \tag{12}$$

$$\text{volume}_t = e + \sum_{i=1}^{4} f_i |\text{return}_{t-i}| + \sum_{i=1}^{4} g_i \text{volume}_{t-i} + \sum_{i=1}^{4} h_i \text{Dneg}_{t-i} + \eta_t \; ;$$

where:

Dneg_k is a dummy that equals one if return is negative in interval k, zero otherwise.

Before the results are analyzed, a few points deserve clarification. First, the results of causality tests can be extremely sensitive to the choice of lag length. Although the two specifications use p=4, the estimation was repeated for p=1-5 to confirm robustness, and the results are qualitatively the same as those reported. Second, interpretation of size, sign, and significance of individual lagged terms in a vector autoregression is often meaningless.[39] Inferences using their combined effects are valid, however, and this is sufficient for the purposes of this study, which is testing for causal relationships. Third, only the lagged observations contained in the same trading session as observation t are considered. The reason is to isolate the effect of information arrival during the preceding nontrading period. Therefore, the maximum lag length that can be used in the analysis is seven.

Table 50 reports the regression results for the first specification. The coefficients suggest that both return and volume are positively autocorrelated. The Wald statistics displayed in the last row of the table suggest that return causes volume in the Granger sense. Moreover, there is no feedback, since the coefficients of lagged volume terms as a group are not significant in the return equation.

Table 51 displays the regression results for the second specification. Both return volatility and volume are positively autocorrelated. The negative coefficients of dummies in the volatility equation show that positive autocorrelation in volatility is stronger when past volatility arises from an increase in price. The significant Wald tests for both equations suggest that there is a feedback relationship between volume and return volatility. Past return volatility has a negative effect on future volume. If return volatility arises from a decrease in price, then future volume falls farther. Past volume has a negative effect on

---

[39] See the discussion in Sims (1980).

future return volatility. In other words, an interval with high trading activity is followed by a period in which price stays relatively stable, ceteris paribus.

5.4 Summary

This chapter examined intraday trading on the ISE. The analysis of return, return volatility, and volume data indicates a strong time-of-day and weak day-of-week effect for all three variables in this market.

The evidence shows a strong positive contemporaneous relationship between the absolute value of price change and volume. As in equity markets elsewhere, the relation is asymmetric on the Turkish exchange. Positive price change has a larger influence on volume than negative price change. Moreover, asymmetry shows variability within a trading day.

Two causality tests were performed. The first found a unidirectional relationship between volume and return: Past return causes volume in the Granger sense. The second revealed a feedback relationship between volume and volatility: Past values of both variables help explain the current value of the other variable.

Overall, the evidence in this chapter shows that the large relative tick size does not result in any notable difference regarding the price-volume relationship on the ISE. Neither the univariate temporal patterns nor the asymmetric positive relationship between volatility and volume differ qualitatively from the evidence reported for other markets such as the NYSE and SEHK.

Chapter 6

Summary

Broadly speaking, market microstructure studies investigate the effect of trading mechanisms on the formation of prices. Most of the empirical research examines developed markets, mainly because of data availability. During the last decade, probably due to automation of the trading process, high frequency data have become available for emerging markets. This is the first study to use intraday data from one such market, the Istanbul Stock Exchange. The data set covers the 30 most active stocks on the ISE over 14 months and contains about nine million transactions.

The most distinguishing feature of this order-driven market is its tick rule, a step function with 10 regimes of narrow width. North American exchanges fix the absolute tick size, but the narrow regimes of the ISE indicate a desire to keep the relative tick size constant. Moreover, ISE's relative tick is up to 900% greater than that of other exchanges.

One goal of this study was to examine whether large tick size restricts trader behavior in this market. It was found that prices show very weak clustering. It appears that traders use predominantly one-tick and occasionally two-tick rounding. Possibly due to the narrow regime width, no within-regime variation in clustering is found. In addition, the examination of spread and consequent price change frequencies revealed that these hardly ever exceed tick size, which indicates that the tick size is binding. This suggests that the large relative tick in this market cannot be attributed to low price resolution.

This study also presents evidence about limit and market order profitability on the ISE. In an order-driven market, liquidity is provided by public traders via limit orders. To be an attractive strategy, limit order trading requires sufficient liquidity trading in the market, and the deviation of price from its equilibrium value should be corrected within a short period. A trading rule used in the literature to analyze this aspect of the NYSE and Paris Bourse was employed here.

The analysis in this study indicates that on the ISE, average round-trip returns are negative for both limit and market order strategies. This is not surprising, given the short investment horizon incorporated into the trading rule. The use of raw returns yielded inconsistent results. The choice of the period for observing how long it takes the temporary price effect to fade seems to distort return estimates, possibly because marketwide information events can intervene. These are likely to affect estimated returns systematically, so market-adjusted returns were used to measure performance of the two trading strategies. Because the results are not sensitive to the choice of the waiting period, they support the conjecture about marketwide information intervention. Unlike the NYSE and the Paris Bourse, the ISE has excessive marketwide price movements, and they hide short-term mean reversion in price.

The market-adjusted returns show that, on average, executed limit orders perform better than market orders, but the opposite holds for unexecuted limit orders. Therefore, patient investors who can forgo trading if their limit orders are not executed are likely to play the role of liquidity provider on the ISE.

Data on the fraction of executed limit orders allow comparison of the ISE to the NYSE and Paris Bourse. On the NYSE the fraction is 46%, 39%, or 35% depending on whether orders are 1%, 2%, or 3% from the equilibrium value at the time of submission. The corresponding figures are 45%, 40%, and 34% for the Paris forward market and 21%, 25%, and 19% for the Paris cash market. For the ISE, these figures are 88%, 66%, 58%, and 52% for orders placed in the 0.5, 1.5, 2.5, and 3.5 test categories expressed in ticks (0.8%-5.5% from equilibrium value). This comparison implies that prices are more volatile on the ISE, which can be attributed to two factors. First, the absence of an opening call auction may negatively affect price discovery on the ISE. Second, there may be insufficient depth in the limit order book, which is unexpected, given the use of a large relative tick in this market. Therefore, one can hypothesize that the weak balance between limit and market order submission rates may be one reason for the ISE's choice of an unorthodox tick rule. Unfortunately, a test of this hypothesis is not possible with the data available.

This study also presents evidence on the relationship between price change and trading volume on the ISE. Similar to the NYSE and the Hong Kong exchange, these two variables display strong intraday variability on the ISE. It appears that the incorporation of new information into prices occurs during the first fifteen minutes of both daily trading sessions, and the high turnover at the end of the day is due to portfolio rebalancing rather than information effects. Unlike the NYSE and Hong Kong situations, there is a weak day-of-week effect on the ISE.

Consistent with previous studies of bond, equity, and futures markets, there is a strong contemporaneous relationship between volume and price change on the ISE. The literature documents that this relation is asymmetric in bond and equity markets, which is attributed to the extra cost of taking a short position. The absence of asymmetry in futures markets, where there is no cost difference between taking a long and short position supports this hypothesis. Asymmetry was found on the ISE. The ratio of volume to price change for upticks is 1.52 times the absolute value of the same ratio for downticks on the NYSE , 1.39 for the Hong Kong exchange, and 1.15 on the ISE.

The study also provides evidence of a dynamic relationship between price change and volume. Both are positively autocorrelated. Moreover, there is a feedback relationship between volume and volatility. This differs from Jain and Joh (1988), who found a unidirectional relationship on the NYSE, that is, volatility causes volume in the Granger sense.

While this dissertation has contributed to our understanding of the Turkish stock market, with the help of increased data availability and some recent developments regarding Turkish stocks further work will be possible in at least two directions. First, in order to test the conjecture that tick size is used as a policy variable for the purpose of enhancing liquidity on the ISE, quotation and order flow data should be used to describe the dynamics of limit order book and the order choice decision of traders in this market.

Second, recent developments will enable to analyze the price discovery process for the Turkish stocks. Price discovery is the process by which markets

incorporate information available to market participants to arrive at equilibrium asset prices. If a single financial asset or multiple highly related financial assets are traded on more than one market, each market may be involved in the price discovery process. In a few months, futures and option trading will be introduced on the ISE. Moreover, the first Turkish stock, Turkcell, was listed on the NYSE on July 12, 2000. It is likely that the cross-listing decision of Turkcell be followed by other large Turkish companies.

APPENDICES

APPENDIX A

TABLES

Table 1
Annual ISE Trading Activity, 1986-1998

Year	Traded Value (Billion TL)	Traded Value (Million $)	# of Shares (Million)	# of Contracts (Thousand)
1986	9	13	3	
1987	105	118	15	
1988	149	115	32	112
1989	1,736	773	238	247
1990	15,313	5,854	1,537	766
1991	35,487	8,502	4,531	1,446
1992	56,339	8,567	10,285	1,681
1993	255,222	21,770	35,249	2,815
1994	650,864	23,203	100,062	5,085
1995	2,374,055	52,357	306,254	11,667
1996	3,031,186	37,737	390,917	12,446
1997	9,048,721	58,104	919,784	17,639
1998	18,029,967	70,396	2,242,531	21,571

Source: ISE Web Page

Table 2
Monthly ISE Trading Activity during the Sample Period

Month	Year	Traded Value (Billion TL)	Traded Value (Million $)	# of Shares (Million)	# of Contracts (Thousand)
January	1998	1,194,321	5,669	89,653	1,481
February	1998	1,304,672	5,859	93,343	1,706
March	1998	1,311,703	5,605	101,264	1,729
April	1998	1,856,735	7,578	133,636	1,800
May	1998	2,218,081	8,853	178,274	2,044
June	1998	1,927,839	7,425	184,447	2,060
July	1998	1,990,915	7,453	240,022	2,098
August	1998	1,367,528	5,009	195,863	1,697
September	1998	1,364,690	4,973	253,912	1,890
October	1998	1,050,364	3,788	237,235	1,538
November	1998	1,374,580	4,692	291,077	1,883
December	1998	1,067,539	3,492	243,806	1,645
January	1999	939,282	2,944	182,409	1,202
February	1999	2,043,121	5,981	377,032	2,165

Source: ISE Web Page

Table 3
Comparison of Emerging Markets by Size, in Millions of Dollars

Market	Traded Value			Market Capitalization		
	1996	1997	1998	1996	1997	1998
Taiwan	470,193	1,297,474	884,698	273,608	287,813	260,015
China	256,008	369,574	284,766	113,755	206,366	231,322
So. Africa	27,202	44,893	58,444	241,571	232,069	170,252
Brazil	112,108	203,260	146,594	216,990	255,478	160,887
Korea	177,266	170,237	137,859	138,817	41,881	114,593
India	26,599	53,954	64,498	122,605	128,466	105,188
Mexico	43,040	52,646	33,841	106,540	156,595	91,746
Greece	8,283	21,146	46,999	24,178	34,164	79,992
Chile	8,460	7,445	4,419	65,940	72,046	51,866
Argentina	4,382	25,702	15,078	44,679	59,252	45,332
Israel	8,045	10,727	11,291	35,934	45,268	39,628
Philippines	25,519	19,783	9,992	80,649	31,361	35,314
Thailand	44,365	23,119	20,734	99,828	23,538	34,903
Turkey	36,831	59,105	68,646	30,020	61,090	33,646
Egypt	2,463	5,859	5,028	14,173	20,830	24,381
Indonesia	32,142	41,650	9,709	91,016	29,105	22,104
Russia	2,958	16,362	6,805	37,230	128,207	20,598
Poland	5,538	7,977	8,921	8,390	12,135	20,461
Morocco	432	1,048	1,385	8,705	12,177	15,676
Hungary	1,641	7,684	16,135	5,273	14,975	14,028
Colombia	1,360	1,894	1,539	17,137	19,529	13,357
Czech Rep.	8,431	7,055	4,741	18,077	12,786	12,045
Peru	3,805	4,033	2,776	12,291	17,586	11,645
Venezuela	1,275	3,858	1,510	10,055	14,581	7,587
Jordan	297	501	653	4,551	5,446	5,838
Pakistan	6,054	11,476	9,102	10,639	10,966	5,418
Sri Lanka	134	311	281	1,848	2,096	1,705

Source: International Finance Corporation, Emerging stock markets factbook 1999.
Note: Markets are sorted in descending order of market capitalization at the end of 1998.

Table 4
Number of Stocks Listed on the ISE

Year	National Market	Regional Market	New Companies Market	Watch-List Companies Market
1986	80			
1987	82			
1988	79			
1989	76			
1990	110			
1991	134			
1992	145			
1993	160			
1994	176			
1995	193	12		
1996	213	11	1	3
1997	244	7	2	5
1998	262	7	1	7

Source: ISE Web Page

Table 5
Types of Normal Order

Type	Trader Specifies	Unfilled Portion	Maximum Trade Size
1	Price, Quantity	Waits	Expressed in lots
2	Price, Quantity	Canceled	Expressed in value
3	Price	Canceled	Expressed in value
4	Price, Maximum trade value	Canceled	Expressed in value

Source: ISE Publications, Capital Market and Securities Exchange Guide 1998

Table 6
Minimum Trade Size for Special Orders

Base Price (TL)			Minimum Trade Size[a]
0	-	25,000	10
25,500	-	50,000	6
51,000	-	100,000	3
102,500	and	above	1

Source: ISE Publications, Capital Market and Securities Exchange Guide 1998
Note: The size of an order expressed in lots should exceed a minimum level to be considered a special order. This lower limit depends both on the price level of a particular stock and its trading activity during the previous month.
[a] As a multiple of "maximum number of shares" limit.

Table 7
Number of ISE Members Authorized to Trade on the Stock Market, 1986-July1999

Year	Individual Broker- Dealers	Brokerage Houses	Commercial Banks	Investment & Development Banks	Total
1986	8	11	25	3	47
1987	15	16	39	3	73
1988	18	18	40	4	80
1989	22	20	44	8	94
1990	17	48	43	8	116
1991	---	110	46	9	165
1992	---	112	51	9	172
1993	---	112	53	11	176
1994	---	111	53	11	175
1995	---	103	50	12	165
1996	---	100	50	12	162
1997	---	140	2	0	142
1998	---	140	0	0	140
1999/7	---	137	0	0	137

Source: ISE Web Page
Note: Individual broker-dealers assumed corporate status in 1991 and now operate as brokerage houses. According to an arrangement by the Capital Markets Board on August 15, 1996, banks that intend to operate in the equities market must transfer their stock market operations to the brokerage firms they control.

Table 8
Top 20 ISE Brokerage Houses Sorted by Total Transaction Value Generated, January-December 1998

		Million TL				Percent		
							Member Trade	
							Market Trade	
Rank	Member Firm	Primary	Large Secondary	Other Secondary	Total	Total	Cumulative Total	Large Secondary
1	Global	117,700	63,704,196	1,477,742,017	1,541,563,913	4.28	4.28	7.29
2	Demir Yatirim	87,111	7,163,896	1,255,612,646	1,262,863,654	3.50	7.78	0.82
3	Inter Yatirim	124,486	3,238,622	1,162,490,588	1,165,853,696	3.23	11.01	0.37
4	Tacirler	214,370	-	1,062,294,926	1,062,509,296	2.95	13.96	0.00
5	Finans Yatirim	91,159	37,978,602	972,888,295	1,010,958,055	2.80	16.76	4.34
6	Tekstil	25,450	3,974,801	914,225,981	918,226,232	2.55	19.31	0.45
7	Meksa	135,016	160,269	916,333,132	916,628,417	2.54	21.85	0.02
8	Alfa	12,846	11,106,950	901,996,391	913,116,187	2.53	24.38	1.27
9	Garanti	49,477	89,940,241	803,698,501	893,688,219	2.48	26.86	10.29
10	Yapi Kredi Yatirim	768,128	5,782,049	805,339,857	811,890,033	2.25	29.11	0.66
11	Ata Yatirim	65,591	5,085,747	705,473,388	710,624,726	1.97	31.09	0.58
12	Alternatif	10,948	15,398,883	684,978,391	700,388,223	1.94	33.03	1.76
13	Erciyes	60,830	-	662,878,974	662,939,804	1.84	34.87	0.00
14	Is Yatirim	5,533,420	7,898,520	643,548,884	656,980,825	1.82	36.69	0.90
15	Teb Yatirim	3,490,935	27,973,586	595,250,643	626,715,164	1.74	38.43	3.20
16	Dis Yatirim	29,770	312,736	623,370,476	623,712,982	1.73	40.16	0.04
17	Yatirim Finansman	204,621	322,403,052	287,932,374	610,540,047	1.69	41.85	36.88
18	Koc	133,228	550,180	599,959,666	600,643,073	1.67	43.52	0.06
19	Gedik Yatirim	38,973	-	590,864,428	590,903,401	1.64	45.16	0.00
20	Eczacibasi	48,160	12,720,855	566,027,287	578,796,303	1.61	46.76	1.46
	Grand Total	24,856,444	874,245,063	35,155,665,146	36,054,766,652			

Source: ISE Web Page
Note: Primary denotes primary market transactions. Transactions in the wholesale market and those involving special orders are classified as large secondary. All remaining trading volume is shown as other secondary.

Table 9
Top 20 ISE Brokerage Houses Sorted by Wholesale and Special Transactions, January-December 1998

		Million TL				Percent		
							Member Trade / Market Trade	
Rank	Member Firm	Primary	Large Secondary	Other Secondary	Total	Large Secondary	Cumulative Large Secondary	Total
1	Yatirim Finansman	204,621	322,403,052	287,932,374	610,540,047	36.88	36.88	1.69
2	Ak	662,374	129,689,493	281,075,670	411,427,537	14.83	51.71	1.14
3	Garanti	49,477	89,940,241	803,698,501	893,688,219	10.29	62.00	2.48
4	Global	117,700	63,704,196	1,477,742,017	1,541,563,913	7.29	69.29	4.28
5	Finans Yatirim	91,159	37,978,602	972,888,295	1,010,958,055	4.34	73.63	2.80
6	Bender	459,674	30,501,078	420,985,334	451,946,086	3.49	77.12	1.25
7	Teb Yatirim	3,490,935	27,973,586	595,250,643	626,715,164	3.20	80.32	1.74
8	Ulus	17,527	23,126,320	108,855,240	131,999,087	2.65	82.96	0.37
9	Murad Kuran	42,663	20,210,736	53,148,350	73,401,748	2.31	85.28	0.20
10	Alternatif	10,948	15,398,883	684,978,391	700,388,223	1.76	87.04	1.94
11	Eczacibasi	48,160	12,720,855	566,027,287	578,796,303	1.46	88.49	1.61
12	Alfa	12,846	11,106,950	901,996,391	913,116,187	1.27	89.76	2.53
13	Strateji	1,530	9,570,200	366,542,488	376,114,218	1.09	90.86	1.04
14	Is Yatirim	5,533,420	7,898,520	643,548,884	656,980,825	0.90	91.76	1.82
15	Camis	232,853	7,246,457	31,213,990	38,693,300	0.83	92.59	0.11
16	Demir Yatirim	87,111	7,163,896	1,255,612,646	1,262,863,654	0.82	93.41	3.50
17	Ekinciler Yatirim	30,177	6,951,183	451,663,022	458,644,382	0.80	94.21	1.27
18	Abn Amro Yatirim	6,199	6,921,511	257,213,169	264,140,878	0.79	95.00	0.73
19	Genborsa	396,895	6,202,112	140,462,032	147,061,039	0.71	95.71	0.41
20	Yapi Kredi Yatirim	768,128	5,782,049	805,339,857	811,890,033	0.66	96.37	2.25
	Grand Total	24,856,444	874,245,063	35,155,665,146	36,054,766,652			

Source: ISE Web Page
Note:Primary denotes primary market transactions. Transactions in the wholesale market and those involving special orders are classified as large secondary. All remaining trading volume is shown as other secondary.

Table 10
Equity Portfolio Holdings by Foreign Investors, 1995-1999, in Millions of Dollars

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1995												1.936
1996	2,457	2,849	3,029	2,736	2,489	2,965	2,617	2,551	2,790	2,926	3,165	3,085
1997	4,655	4,564	3,997	3,577	3,793	4,456	4,728	4,938	5,970	5,881	5,465	6,018
1998	5,718	5,296	5,373	6,864	5,765	6,095	6,589	3,845	3,200	3,068	3,668	3,700
1999	3,429	5,196	5,554	6,741	5,853	5,555	6,603					

Source: ISE Web Page

Table 11
Total Market Value of Companies Traded on the ISE, 1986-1999, in Millions of Dollars

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1986	657	797	632	611	661	672	685	843	844	824	878	938
1987	1,195	1,505	1,326	1,329	1,913	2,353	4,895	5,479	4,692	3,440	4,417	3,125
1988	3,569	2,905	2,674	2,107	2,020	1,696	1,783	1,578	1,374	1,293	1,237	1,128
1989	1,100	1,384	1,267	1,450	1,790	2,205	2,134	2,487	4,254	4,781	4,459	6,756
1990	10,911	10,269	9,353	9,500	10,706	15,493	26,355	25,438	25,915	23,917	18,742	18,737
1991	21,391	23,147	18,624	15,136	15,145	14,556	12,800	12,745	11,632	10,560	14,945	15,564
1992	16,613	11,679	12,329	10,411	9,060	11,936	11,315	11,329	10,824	9,604	9,444	9,922
1993	10,784	14,266	13,668	19,443	18,728	22,689	20,274	24,345	30,488	28,529	34,248	37,824
1994	31,401	22,014	16,253	11,191	11,802	16,290	18,646	20,967	21,019	20,017	23,119	21,785
1995	19,360	21,575	28,196	31,315	31,879	32,433	34,304	27,949	26,151	29,038	22,597	20,782
1996	26,644	30,568	31,480	29,404	26,220	29,390	27,804	26,546	28,043	29,157	31,510	30,797
1997	45,595	44,374	44,891	37,093	39,632	43,846	45,221	44,334	55,702	56,415	54,540	61,879
1998	63,311	53,235	51,680	64,753	57,935	61,442	62,991	37,453	33,900	31,002	34,485	33,975
1999	31,863	45,034	50,223	55,124	50,741	47.425	56,188					

Source: ISE Web Page

Table 12
Some Characteristics of ISE Stocks in the Sample

Stock	Industry	Traded Since	First Price (TL)	Current Price (TL)	Current Price (Cents)	Market Capitalization (Million $)	Float (%)
Akbnk	Banking	7/26/90	13,000	10,100	2.80	3,496	15
Akcns	Cement	10/6/87	1,170	7,800	2.16	411	15
Akgrt	Insurance	12/5/94	10,100	17,500	4.85	273	29
Alark	Conglomerates	5/24/89	1,900	5,200	1.44	193	23
Alctl	Telecom	3/22/88	6,400	22,250	6.16	123	33
Arclk	Consumer Durables	1/21/86	1,900	9,700	2.69	544	19
Bagfs	Fertilizers	1/28/86	2,010	15,000	4.15	83	59
Cukel	Utilities	1/7/86	3,220	455,000	126.02	630	18
Dohol	Conglomerates	6/21/93	5,800	3,150	0.87	363	34
Dyhol	Conglomerates	8/6/98	4,000	2,275	0.63	274	15
Efes	Conglomerates	2/19/98	36,500	4,800	1.33	168	46
Enka	Conglomerates	1/24/86	1,200	57,000	15.79	373	15
Eregl	Iron & Steel	1/13/86	800	4250	1.18	522	41
Garan	Banking	6/6/90	4,500	14,500	4.02	2,007	20
Hurgz	Media	2/25/92	7,900	6000	1.66	320	18
Ihlas	Conglomerates	3/17/94	45,000	23,250	6.44	187	25
Isctr	Banking	11/16/87	325	14,250	3.95	5,007	33
Kchol	Conglomerates	1/10/86	2,850	41,000	11.36	1,819	13
Migrs	Retail	2/27/91	8,800	470,000	130.17	1,327	48
Nthol	Conglomerates	10/5/89	3,300	1,850	0.51	51	55
Otosn	Automotive	1/13/86	950	152,500	42.24	588	15
Petkm	Petroleum Products	7/9/90	2,400	232,500	64.39	1,931	4
Ptofs	Petroleum Products	5/30/91	4,000	69,000	19.11	1,337	7
Sahol	Conglomerates	7/8/97	6,200	8,600	2.38	2,977	12
Thyao	Airlines & Services	12/20/90	2,700	19,500	5.4	1,620	2
Toaso	Automotive	7/1/91	20,000	3,700	1.02	181	22
Tuprs	Petroleum Products	5/30/91	1,800	23500	6.51	4,865	4
Uzel	Automotive	8/5/97	20,000	32,000	8.86	204	15
Vestl	Consumer Durables	6/27/90	15,000	34,000	9.42	377	31
Ykbnk	Banking	5/28/87	1,200	6,700	1.86	2,473	39
Mean			7,831	58,896	16.31	1,157	24
Median		7/3/90	3,650	14,750	4.09	467	20

Source: ISE Publications, Capital, Dividend, And Monthly Price Data 1986-1997
Note: Column 1 reports the date each stock became listed. Column 2 shows the first trading price. Columns 3 and 4 give the share price on 3/12/99 in TL and dollars, respectively. Columns 5 shows the market value of each firm in dollars. Column 6 shows the percentage of shares kept in custody by the ISE Settlement Bank. All figures other than those in column 2 are as of the close of the second trading session on 3/12/99.

Table 13
Weekdays without Trading during the Sample Period

Date	Weekday	Reason
1/1/98	Thu	New Year
1/2/98	Fri	New Year
1/29/98	Thu	Religious Holiday (Ramadan)
1/30/98	Fri	Religious Holiday (Ramadan)
4/6/98	Mon	Religious Holiday
4/7/98	Tue	Religious Holiday
4/8/98	Wed	Religious Holiday
4/9/98	Thu	Religious Holiday
4/10/98	Fri	Religious Holiday
4/23/98	Thu	National Holiday
5/19/98	Tue	National Holiday
10/29/98	Thu	National Holiday
10/30/98	Fri	National Holiday
1/1/99	Fri	New Year
1/18/99	Mon	Religious Holiday (Ramadan)
1/19/99	Tue	Religious Holiday (Ramadan)
1/20/99	Wed	Religious Holiday (Ramadan)
1/21/99	Thu	Religious Holiday (Ramadan)
1/22/99	Fri	Religious Holiday (Ramadan)

Table 14
Number of Sessions Stocks were Traded during the Sample Period

Stock	# of Sessions	Date	No Trading in
Akbnk	564		
Akcns	562	08/06/1998	Both sessions
Akgrt	564		
Alark	563	02/23/1998	Session 1
Alctl	564		
Arclk	564		
Bagfs	564		
Cukel	564		
Dohol	564		
Dyhol	277 [a]	01/05/1998 - 08/05/1998	Both sessions
Efes	503 [a]	01/05/1998 - 02/18/1998	Both sessions
Enka	564		
Eregl	562	12/22/1998	Both sessions
Garan	563	12/24/1998	Session 2
Hurgz	564		
Ihlas	564		
Isctr	553 [b]	05/04/1998 - 05/08/1998	Both sessions
Kchol	563	11/16/1998	Session 1
Migrs	564		
Nthol	564		
Otosn	564		
Petkm	564		
Ptofs	556 [c]	06/29/1998 - 07/01/1998	Both sessions
		06/15/1998	Session 1
		12/24/1998	Session 2
Sahol	564		
Thyao	564		
Toaso	564		
Tuprs	564		
Uzel	564		
Vestl	564		
Ykbnk	564		

Note: Column 2 indicates the days on which there was no trading in at least one session for a particular stock. Column 3 reveals the session in which there was no trading.
[a] Became listed during the sample period.
[b] The state sold its 12.3% stake by public offering.
[c] The state reduced its ownership to 49% by selling 51% of the equity through a block transaction.

Table 15
Monthly Volume Generated by Foreign Investors during 1998 among Stocks in the Sample

Stock	Average ($)	Average (%)	Median (%)	Maximum (%)	Minimum (%)
Akbnk	62,875,461	6.94	6.67	14.77	3.20
Akcns	10,097,018	1.00	0.88	2.70	0.22
Akgrt	17,970,050	1.98	1.95	4.08	0.93
Alark	4,870,535	0.45	0.36	1.18	0.06
Alctl	9,822,791	0.88	0.85	1.97	0.15
Arclk	22,082,140	2.06	1.76	4.19	0.59
Bagfs	5,098,539	0.45	0.27	2.03	0.04
Cukel	17,162,671	1.70	1.52	4.39	0.33
Dohol	34,134,138	3.53	3.53	5.11	2.66
Dyhol	9,022,976	1.23	1.01	2.16	0.36
Efes	16,116,866	1.48	1.34	2.30	0.64
Enka	7,306,394	0.72	0.67	1.28	0.34
Eregl	47,712,272	4.47	4.40	7.37	1.81
Otosn	7,953,310	0.88	0.85	1.87	0.40
Garan	56,572,491	5.89	5.45	9.41	3.57
Hurgz	9,869,593	1.01	0.98	1.76	0.33
Ihlas	8,597,380	0.67	0.23	2.40	0.04
Isctr	81,947,593	9.14	9.55	15.83	1.45
Kchol	45,316,097	4.33	4.28	7.30	1.61
Migrs	35,379,111	3.98	3.92	8.02	1.17
Nthol	4,057,242	0.34	0.21	1.35	0.05
Petkm	4,799,491	0.46	0.30	1.38	0.04
Ptofs	13,842,697	1.35	1.00	3.14	0.37
Sahol	68,612,065	7.46	7.17	10.88	4.87
Toaso	22,186,943	2.11	2.28	4.58	0.30
Tuprs	37,177,303	3.67	3.64	6.60	1.99
Thyao	3,693,065	0.32	0.25	1.08	0.05
Uzel	4,932,315	0.45	0.32	1.70	0.04
Vestl	23,663,697	2.14	1.76	5.27	0.82
Ykbnk	89,445,803	10.55	8.13	19.65	5.03
Total	782,318,045	81.65	79.88	87.82	73.37

Source: ISE Web Page
Note: Foreign volume is defined as the sum of foreign purchases and sales. Columns 2-5 report statistics about the share of each firm in total foreign volume over this 12 month period. The last row shows aggregate figures for the sample firms.

Table 16
Stock Split Adjustments for Sample Firms during the Sample Period

Stock	% Rights Issue	% Bonus Issue	Split Date	TL Rights Issue Price	Dividend to be Paid	PreSplit WAP[a]	PreSplit Adj. WAP[a]	PostSplit Tick
Akbnk	90.00	60.00	5/8/98	1,000	1,000	20,829.50	9,291.80	100
Akcns	0.00	400.00	4/27/98			38,683.64	7,736.73	100
Alark	149.15	1096.00	2/8/99	1,000		49,165.83	3,765.93	50
Arclk	0.00	100.00	5/29/98		300	21,835.05	11,067.53	250
Bagfs	0.00	900.00	4/21/98		6,000	283,314.31	33,731.43	500
Dohol	0.00	250.00	10/7/98			9,188.38	2,625.25	50
Efes	0.00	600.00	8/3/98			57,336.69	8,190.96	100
Enka	0.00	125.00	12/30/98			69,850.41	31,044.63	500
Eregl	200.00	400.00	2/24/99	3,000		18,318.19	3,474.03	50
Garan	0.00	25.00	11/12/98			5,315.06	4,252.05	50
Hurgz	0.00	250.00	2/25/98		4,200	48,691.21	31,579.21	500
Hurgz	0.00	50.00	8/27/98			8,910.04	5,940.03	100
Isctr	37.62	112.87	5/15/98	1,000	400.8	31,332.70	12,899.48	250
Migrs	7.94	0.00	8/18/98	260,000		241,691.06	243,037.31	2,500
Nthol	94.00	10.00	6/22/98	1,000		5,579.52	3,195.84	50
Sahol	80.00	70.00	8/24/98	1,000		14,680.23	6,192.09	100
Thyao	100.00	100.00	1/23/98	1,000		49,315.89	16,771.96	250
Toaso	0.00	40.00	12/14/98			3,924.82	2,803.44	50
Tuprs	75.00	75.00	11/9/98	1,000		34,949.30	14,279.72	250
Ykbnk	40.00	39.00	5/15/98	1,000		10,515.09	5,874.35	100
Ykbnk	0.00	24.00	11/9/98			3,986.13	3,214.62	50

Source: Bayindir Menkul Degerler A.S., a brokerage house.
Note: The first two columns the amount of rights and bonus issues as a percentage of the number of outstanding shares before the split. Column 4 gives the price per share to be paid to participate in the rights issue. Column 5 shows the next dividend to be paid for stocks that exist before the stock split. Presplit base price is adjusted for stock splits. Column 8 gives the tick size to be used during the first session following the split.
[a] Weighted average price

Table 17
Dividend Adjustments for Sample Firms during the Sample Period

Stock	Total Cash Dividend (Million TL)	Stock Dividend[a] (%)	Exdiv. Date	Dividend per Share (TL)	New Shares[b] (%)	Old WAP[c] (TL)	New WAP[c] (TL)	Adj. WAP[c] (TL)	Exdiv. Tick[d] (TL)
Akbnk	50,000,000		5/20/98	1,000		9,300		8,300	100
Akcns	4,185,673		4/1/98	1,100		32,486		31,386	500
Akgrt	1,648,125		5/21/98	293		19,016		18,723	250
Alark	249,043		5/29/98	250		69,113		68,863	1,000
Alctl	1,000,000		5/29/98	500		33,527		33,027	500
Arclk	3,037,500		5/29/98	300		stock split on the same day			
Bagfs	1,200,000		5/25/98	6,000	90	31,306	24,602	24,672	250
Cukel	11,782,315		3/4/98	23,565		608,710		585,146	10,000
Dohol	2,375,100		9/3/98	200		8,836		8,636	100
Enka	525,000		5/28/98	500		135,263		134,763	2,500
Hurgz	14,217,840	300	3/31/98	4,200	75	26,368	5,522	9,683	100
Isctr	20,306,131		5/25/98	401	60	12,035	11,750	11,704	250
Kchol	3,205,110		5/25/98	200		57,851		57,651	1,000
Migrs	945,000		5/29/98	1,000		239,585		238,585	2,500
Otosn	15,317,500		4/20/98	11,000		194,730		183,730	2,500
Petkm	29,550,000		5/1/98	9,850		171,296		161,446	2,500
Ptofs	18,798,560		5/1/98	2,686		72,401		69,716	1,000
Sahol	6,500,000		5/21/98	130		16,707		16,577	250
Uzel	7,728,000		4/1/98	3,360		33,874		30,514	500
Ykbnk	24,026,587		5/15/98	400		stock split on the same day			

Source: Bayindir Menkul Degerler A.S., a brokerage house.
[a] As a percentage of outstanding old shares.
[b] The percentage of total outstanding shares that are not entitled to receive the current dividend payment.
[c] Weighted average price.
[d] Tick size used during the first session on the exdividend day.

Table 18
Number of Transactions for Sample Stocks

Panel A: Entire Sample

		Odd Lot		Round Lot	
Stock	All	Old	New	Old	New
Akbnk	402,768	2,155		400,613	
Akcns	222,929	584		222,345	
Akgrt	87,988	205		87,783	
Alark	124,742	186	709	110,153	13,694
Alctl	203,625	609		203,016	
Arclk	181,146	854		180,292	
Bagfs	224,314	277	24	204,051	19,962
Cukel	218,186	2,828		215,358	
Dohol	767,309	2,548		764,761	
Dyhol	273,484	15		273,469	
Efes	268,107	86		268,021	
Enka	136,523	2,410		134,113	
Eregl	228,869	3,005	1	221,519	4,344
Garan	301,731	1,816		299,915	
Hurgz	264,737	947	132	259,903	3,755
Ihlas	371,123	1,262		369,861	
Isctr	630,345	5,513	120	619,827	4,885
Kchol	298,753	1,634		297,119	
Migrs	116,241	1,137		115,104	
Nthol	160,424	1,525		158,899	
Otosn	115,323	265		115,058	
Petkm	283,342	1,575		281,767	
Ptofs	199,345	566		198,779	
Sahol	468,719	1,218		467,501	
Thyao	332,909	294		332,615	
Toaso	259,624	729		258,895	
Tuprs	686,182	2,438		683,744	
Uzel	225,331	68		225,263	
Vestl	138,861	600		138,261	
Ykbnk	558,960	4,266		554,694	
Total	8,751,940	41,615	986	8,662,699	46,640

Table 18-continued

Panel B: New Shares

Stock	All	Odd Lot	Round Lot	Period	Month
Alark	14,403	709	13,694	2/8/99 - 2/26/99	Feb.
Bagfs	8,638	10	8,628	4/21/98 - 5/22/98	Apr.
Bagfs	11,348	14	11,334		May
Eregl	4,345	1	4,344	2/24/99 - 2/26/99	Feb.
Hurgz	1,001	18	983	2/25/98 - 3/30/98	Feb.
Hurgz	2,886	114	2,772		Mar.
Isctr	5,005	120	4,885	5/15/98 - 5/22/98	May

Note: When there is an increase in capital before dividend is paid in a given year, newly issued shares are not entitled to receive the next dividend payment. Until the payment of the next dividend, there is a separate market for "old" and "new" shares.

Table 19
Maximum Number of Shares Limit per Month for Sample Stocks during the Sample Period, in Lots

	Month												
Stock	Feb.98	Mar.98	Apr.98	May98	Jun.98	Jul.98	Aug.98	Sep.98	Oct.98	Nov.98	Dec.98	Jan.99	Feb.99
Akcns	250	250	250	500	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Alark	250	250	250	250	250	250	250	250	250	500	500	250	500
Alctl	500	500	500	500	500	500	500	250	500	500	1,000	500	1,000
Arclk	500	500	500	500	500	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Bagfs	100	100	100	100	250	500	500	250	250	250	500	500	500
Dyhol	-	-	-	-	-	-	-	1,000	1,000	1,000	1,000	1,000	1,000
Efes	-	500	250	250	250	250	250	1,000	1,000	1,000	1,000	1,000	1,000
Enka	100	100	100	100	100	100	100	100	100	100	250	250	500
Hurgz	250	250	250	500	500	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Ihlas	500	500	500	1,000	1,000	1,000	500	500	500	500	500	500	500
Isctr	250	250	250	250	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Kchol	250	500	500	500	500	500	500	500	500	500	1,000	1,000	1,000
Otosn	100	100	100	100	100	100	100	100	100	100	100	100	250
Ptofs	250	500	500	250	250	250	250	250	250	100	250	100	250
Thyao	250	500	500	500	500	500	500	1,000	1,000	500	1,000	1,000	1,000
Uzel	250	250	250	250	500	500	250	250	250	250	500	500	250
Vestl	500	500	500	1,000	500	500	500	250	250	250	500	250	500

Note: Not shown are Akbnk, Akgrt, Dohol, Eregl, Garan, Nthol, Sahol, Toaso, Tuprs, and Ykbnk, for which the maximum trade size was 1,000 lots, and Cukel, Migrs, and Petkm, for which the maximum was 100 lots.

Table 20
Maximum Trade Size in Lots for Normal Orders (Type 1)

Average Trade Size in Lots	Maximum Trade Size in Lots
>= 61	1,000
31 - 60	500
16 - 30	250
0 - 15	100

Source: ISE Publications, Capital Market and Securities Exchange Guide 1998

Table 21
Identification of Special Orders

Stock	Eligible	Special
Akbnk	7	3
Akcns	3	0
Akgrt	7	0
Alark	1	0
Arclk	6	1
Bagfs	671	2
Cukel	887	0
Efes	10	0
Enka	716	1
Garan	6	2
Ihlas	7	4
Isctr	6	1
Kchol	1	1
Migrs	759	1
Nthol	4	0
Otosn	284	0
Petkm	2,970	0
Sahol	6	0
Toaso	1	0
Vestl	11	5
Ykbnk	17	2
Total	6,380	23

Note: Among eligible transactions, some can be identified as special orders, so the quantities in the first column include the quantities in the second column.

Table 22
The Tick Rule on the ISE and Six Other Exchanges that Use Step Functions

Exchange	Regime	Stock Price Low	Stock Price High	Absolute Tick (TL)	Relative Tick (%)	Regime Width (%)
Istanbul						
	1	10	1,000	10	1.98	
	2	1,025	2,500	25	1.42	144
	3	2,550	5,000	50	1.32	96
	4	5,100	10,000	100	1.32	96
	5	10,250	25,000	250	1.42	144
	6	25,500	50,000	500	1.32	96
	7	51,000	100,000	1,000	1.32	96
	8	102,500	250,000	2,500	1.42	144
	9	255,000	500,000	5,000	1.32	96
	10	510,000	and up	10,000		
Helsinki						
	1	0.01	9.99	0.01	0.20	
	2	10	99.9	0.10	0.18	899
	3	100	999	1.00	0.18	899
	4	1,000	and up	10.00		
Hong Kong						
	1	0.001	0.249	0.001	0.80	
	2	0.25	0.495	0.005	1.34	98
	3	0.5	1.99	0.010	0.80	298
	4	2	4.975	0.025	0.72	149
	5	5	29.95	0.050	0.29	499
	6	30	49.9	0.100	0.25	66
	7	50	99.75	0.250	0.33	100
	8	100		0.500		
Paris						
	1	0.01	4.99	0.01	0.40	
	2	5	99.95	0.05	0.10	1,899
	3	100	499.9	0.10	0.03	400
	4	500	4,999	1.00	0.04	900
	5	5,000	and up	10.00		

Table 22-continued

Exchange	Regime	Stock Price Low	High	Absolute Tick (TL)	Relative Tick (%)	Regime Width (%)
Singapore						
	1	0.005	1	0.005	1.00	
	2	1.01	3	0.010	0.50	197
	3	3.02	5	0.020	0.50	66
	4	5.05	10	0.050	0.66	98
	5	10.1	25	0.100	0.57	148
	6	25.5	100	0.500	0.80	292
	7	101	and up	1.000		
Tokyo						
	1	1	999	1	0.20	
	2	1,000	9,990	10	0.18	899
	3	10,000	99,900	100	0.18	899
	4	100,000	999,000	1,000	0.18	899
	5	1,000,000	and up	10,000		
Toronto						
	1	0.005	0.495	0.005		
	2	0.5	4.995	0.010	0.40	899
	3	5	and up	0.050		

Sources: Bacidore (1997), Booth et al. (2000), Chan and Hwang (1998), Hamao and Hasbrouck (1995), Hameed and Terry (1998), Harris(1996), and ISE Publications, Capital Market and Securities Exchange Guide 1998.
Note: Columns 2 and 3 report the lowest and highest prices within each tick regime. Column 4 gives the absolute tick size. The relative tick size is defined as the ratio of absolute tick size to the average of lowest and highest prices for a given regime. The last column shows the width of each tick regime expressed by the ratio of the difference between the highest and lowest prices to the lowest price in that regime.

Table 23
The Extent of Clustering in Different Markets

Study	Market	Price Type	Asset	Price Level	Std Range
Ball et al. (1985)	London Gold Market	clearing	gold		3.65
Brown et al. (1991)	COMEX	transaction	silver futures		5.37
Goodhard and Curcio (1991)	Foreign Exchange Market	quoted	dollar-mark		2.12
Aitken et al. (1996)	Australian Stock Exchange	transaction	stock	A$ 0.10-10.00	0.94
Grossman et al. (1997)	NYSE/AMEX	quoted	stock		0.24
	NASDAQ	quoted	stock		1.36
	London Stock Exchange	quoted	stock		0.70
	London Gold Market	clearing	gold		1.40
	Foreign Exchange Market	quoted	dollar-yen		4.80
			dollar-mark		4.00
Gwilym et al. (1998a)	LIFFE	transaction	FTSE100 futures		0.16
			FTSE250 futures		3.38
			FTSE100 options		2.08
Gwilym et al. (1998b)	LIFFE	transaction	German Bund		0.19
			Italian BTP		1.06
			Japanese JGB		1.31
			UK Long Gilt		0.13
Hameed and Terry (1998)	Stock Exchange of Singapore	transaction	stock	S$ 0.00-1.00	2.19
				1.01-3.00	0.87
				5.05-10.00	0.77
				10.10-25.00	0.53
Booth et al.(2000)	Helsinki Stock Exchange	transaction	stock	FM 1.00-9.99	7.30
				10.00-99.90	4.40
				100.00-999.00	3.60

Table 24
Determinants of Clustering

Variable	Ball et al. (1985)	Brown et al. (1991)	____	Harris (1991)	____	Christie and Schulz (1994)	Aitken et al. (1996)	Hameed et al. (1998)	Gwilym et al. (1998a)	Booth et al. (2000)
Price Level	+	na	+	+	+	+	+	+	0	+
Trade Size	na	-	na	na	na	na	+	na	-	-
Asset Volatility	+	+	+	+	+	+	+	0	+	+
Market Volatility	na	na	na	na	na	na	+	na	na	na
Trade Frequency	na	na	na	-	-	na	-	na	+	-
Volume	na	na	na	na	na	na	na	-	na	na
Firm Size	na	na	-	-	0	0	0	na	na	na
Ease of Valuation[a]	na	na			na	0		na	na	na
Close-End Fund			0	-						
Options/Futures							-			
Short-Selling							-			
Absolute Tick Size	na	na	na	na	na	na	na	-	na	na
Open	na	na	na	na	na	na	na	na	+	na
Close	na	na	na	na	na	na	na	na	-	na
Dealer Market	na	na	na	na	+	na	na	na	na	na
Absolute Tick	fixed	fixed	fixed	fixed	fixed	fixed	step	step	fixed	step
Asset	single	single	multiple	multiple	multiple	multiple	multiple	multiple	single	multiple
Analysis	TS	TS	TSCS	TSCS	TSCS	TSCS	TSCS	TSCS	TS	TSCS

[a] Ease of valuation of assets is proxied by the dummy that the asset analyzed is a close-end fund, the availability of options or futures of the asset examined and the possibility of short selling the asset.
[b] Denotes time-of-day effect on the extent of clustering
[c] TS denotes time-series and TSCS denotes time-series and cross-sectional analysis

Table 25
Distribution of Tick Size per Sample Stock

Part A: All Transactions

	Tick										
Stock	10	25	50	100	250	500	1,000	2,500	5,000	10,000	Total
Akbnk			103,624	239,072	60,072						402,768
Akcns			42,725	140,805	1,515	37,884					222,929
Akgrt				37,898	50,090						87,988
Alark			20,145	1,800		65,954	36,843				124,742
Alctl					66,531	137,094					203,625
Arclk			864	102,342	60,923	17,017					181,146
Bagfs					111,650	55,881		50,784	5,999		224,314
Cukel									76,207	141,979	218,186
Dohol		163,463	125,936	255,442	222,468						767,309
Dyhol		223,233	50,251								273,484
Efes		52,555	126,010	23,116		11,376	55,050				268,107
Enka						28,891	36,553	71,079			136,523
Eregl			8,966		106,284	113,619					228,869
Garan			38,435	168,821	94,475						301,731
Hurgz			105,116	61,142	73,420	22,574	2,485				264,737
Ihlas					176,077	195,046					371,123
Isctr				312,040	161,210	157,095					630,345
Kchol					34,193	192,510	72,050				298,753
Migrs								64,638	51,603		116,241
Nthol	1,075	62,617	37,621	59,111							160,424
Otosn							58,617	56,706			115,323
Petkm							37,027	246,315			283,342

Table 25-continued

	Tick										
Stock	10	25	50	100	250	500	1,000	2,500	5,000	10,000	Total
Ptofs						106,761	92,584				199,345
Sahol			229,500	79,442	159,777						468,719
Thyao					252,026	75,356	5,527				332,909
Toaso		5,989	63,580	73,482	116,573						259,624
Tuprs					360,911	325,271					686,182
Uzel					74,800	110,157	40,374				225,331
Vestl					73,779	65,082					138,861
Ykbnk		34,460	341,179	171,235	12,086						558,960
Total	1,075	542,317	1,293,952	1,725,748	2,268,860	1,717,568	437,110	489,522	133,809	141,979	8,751,940

Part B: Transactions Involving New Shares

Stock	Tick	Total
Alark	50	14,403
Bagfs	250	8,193
Bagfs	500	11,793
Eregl	50	4,345
Hurgz	100	3,887
Isctr	250	5,005

Table 26
Actual Frequencies

Part A: Tick Sizes 100, 1,000,10,000

Category	100	1,000	10,000	Combined
0	10.43	10.36	11.39	10.48
100	9.84	11.32	11.07	10.20
200	10.97	11.30	9.91	10.97
300	11.00	10.81	10.28	10.92
400	9.95	10.72	9.97	10.10
500	10.19	9.63	9.96	10.07
600	9.57	8.85	9.27	9.41
700	9.52	8.64	8.57	9.30
800	9.72	9.51	9.74	9.68
900	8.80	8.87	9.84	8.88
Total	1,725,748	437,110	141,979	2,304,837
$\chi^2(9)$	0.000	0.000	0.000	0.000
Even	50.65	50.73	50.28	50.64
Odd	49.35	49.27	49.72	49.36
$\chi^2(1)$	0.000	0.000	0.036	0.000

Part B: Tick Sizes 25, 250, 2,500

Category	25	250	2,500	Combined
0	26.79	27.43	26.88	27.24
25	24.73	24.55	23.71	24.45
50	25.61	25.35	25.84	25.47
75	22.87	22.68	23.57	22.84
Total	542,317	2,268,860	489,522	3,300,699
$\chi^2(3)$	0.000	0.000	0.000	0.000
Even	52.40	52.78	52.72	52.71
Odd	47.60	47.22	47.28	47.29
$\chi^2(1)$	0.000	0.000	0.000	0.000

Table 26-continued

Part C: Tick Sizes 50, 500, 5,000

Category	50	500	5,000	Combined	Expected[a]
0	6.82	6.15	5.13	6.38	6.00
50	5.14	4.36	4.53	4.69	4.00
100	5.17	4.52	5.34	4.82	4.00
150	4.30	3.77	6.09	4.09	4.00
200	4.44	4.31	5.01	4.39	4.00
250	4.40	3.56	5.12	3.98	4.00
300	4.51	3.77	5.55	4.15	4.00
350	4.09	3.42	4.86	3.76	4.00
400	5.01	4.04	4.65	4.46	4.00
450	4.58	3.48	5.40	4.01	4.00
500	5.04	4.53	5.21	4.77	4.00
550	4.98	4.42	6.46	4.74	6.00
600	5.36	5.57	6.48	5.52	6.00
650	4.97	5.97	4.31	5.49	6.00
700	5.22	7.33	4.00	6.32	6.00
750	5.23	6.83	4.22	6.06	6.00
800	5.92	6.42	4.16	6.12	6.00
850	4.87	5.71	4.17	5.30	6.00
900	5.24	6.11	4.83	5.70	6.00
950	4.69	5.73	4.47	5.25	6.00
Total	1,293,952	1,717,568	133,809	3,145,329	
$\chi^2(19)$	0.000	0.000	0.000	0.000	
Even	52.74	52.74	50.38	52.64	
Odd	47.26	47.26	49.62	47.36	
$\chi^2(1)$	0.000	0.000	0.006	0.000	

Table 26-continued

Note: Tick size 10 has only 1,075 observations and is excluded from the table. Depending on the tick regime, the frequency of the last two to five digits of transaction prices are shown. For example, Part A uses the last three, four, and five digits of transaction prices for regimes 100, 1,000, and 10,000, respectively. The last column reports combined results for the three regimes. All transactions in the sample were used to prepare the table. The total row gives the total number of transactions in each tick regime. $\chi^2(9)$, $\chi^2(3)$, and $\chi^2(19)$ report the p value for the hypothesis that each final-digits category has equal probability of occurrence in parts A, B, and C, respectively. Even and odd rows report the frequencies of even and odd final-digit categories. $\chi^2(1)$ reports the p value for the hypothesis that even and odd final digits have an equal probability of occurrence.

[a] By definition expected frequencies vary across price categories for tick regimes 50, 500, and 5000.

Table 27
Frequencies Adjusted for Serial Dependence in Price

Part A: Tick Sizes 100, 1,000,10,000

Category	100	1,000	10,000	Combined
0	10.56	10.71	10.71	10.62
100	9.59	10.15	10.85	9.78
200	10.53	10.23	10.36	10.45
300	10.39	10.52	10.30	10.39
400	9.96	10.44	9.56	10.04
500	10.33	9.73	9.28	10.17
600	9.71	9.51	8.85	9.63
700	9.71	9.44	8.85	9.60
800	9.88	9.83	10.79	9.90
900	9.33	9.43	10.46	9.42
Total	1,725,748	437,110	141,979	2,304,837
$\chi^2(9)$	0.000	0.000	0.000	0.000
Even	50.65	50.73	50.27	50.64
Odd	49.35	49.27	49.73	49.36
$\chi^2(1)$	0.000	0.000	0.045	0.000

Part B : Tick Sizes 25, 250, 2,500

Category	25	250	2,500	Combined
0	26.90	27.24	27.84	27.25
25	24.10	23.72	23.40	23.72
50	25.51	25.54	24.89	25.47
75	23.49	23.49	23.87	23.56
Total	542,317	2,268,860	489,522	3,300,699
$\chi^2(3)$	0.000	0.000	0.000	0.000
Even	52.41	52.79	52.73	52.72
Odd	47.59	47.21	47.27	47.28
$\chi^2(1)$	0.000	0.000	0.000	0.000

Table 27-continued

Part C: Tick Sizes 50, 500, 5,000

Category	50	500	5,000	Combined	Expected[a]
0	7.20	6.60	6.49	6.84	6.00
50	3.50	3.62	4.07	3.61	4.00
100	4.03	4.33	4.72	4.25	4.00
150	3.67	3.57	5.51	3.71	4.00
200	4.10	4.33	4.51	4.26	4.00
250	3.87	3.90	4.35	3.94	4.00
300	3.91	4.13	4.01	4.07	4.00
350	3.48	3.53	3.46	3.54	4.00
400	4.36	4.01	3.92	4.18	4.00
450	3.76	3.35	4.60	3.59	4.00
500	3.90	4.15	3.62	4.05	4.00
550	5.83	5.77	5.42	5.81	6.00
600	6.23	6.30	5.51	6.25	6.00
650	5.84	5.98	5.12	5.86	6.00
700	6.13	6.40	5.38	6.18	6.00
750	5.86	5.80	5.79	5.75	6.00
800	6.64	6.28	6.01	6.38	6.00
850	5.76	5.97	5.55	5.84	6.00
900	6.24	6.22	6.21	6.19	6.00
950	5.69	5.76	5.75	5.70	6.00
Total	1,293,952	1,717,568	133,809	3,145,329	
$\chi^2(19)$	0.000	0.000	0.000	0.000	
Even	52.74	52.75	50.38	52.65	
Odd	47.26	47.25	49.62	47.35	
$\chi^2(1)$	0.000	0.000	0.005	0.000	

Table 27-continued

Note: $f_{adjusted} = f_{actual} + f_{uniform} - f_{domain}$, where $f_{uniform}$ shows the expected frequency given uniform distribution, and f_{domain} denotes the frequency of domain events. A domain event over a price category occurs when prices change and the price path passes over or arrives in a different price category. Depending on tick regime, the frequency of the last two to five digits of transaction prices are shown. For example, Part A uses the last three, four, and five digits of transaction prices for tick regimes 100, 1,000, and 10,000, respectively. The last column reports combined results for the three tick regimes. All transactions in the sample were used to prepare the table. The total row gives the total number of transactions in each tick regime. $\chi 2(9)$, $\chi 2(3)$, and $\chi 2(19)$ report the p value for the hypothesis that each final-digits category has an equal probability of occurrence in parts A, B, and C, respectively. Even and odd rows report the frequencies of even and odd final-digit categories. $\chi 2(1)$ reports the p value for the hypothesis that even and odd final digits have an equal probability of occurrence.

[a] By definition expected frequencies vary across price categories for tick regimes 50, 500, and 5000.

Table 28
Distribution of Bid-Ask Spread as a Multiple of Tick Size for Sample Stocks

Tick	1	2	3	4	6	8	Total
Akbnk	258	9	0	0	0	0	267
Akcns	259	10	0	0	0	0	269
Akgrt	262	4	1	1	0	0	268
Alark	262	5	0	1	0	0	268
Alctl	265	3	0	0	0	0	268
Arclk	265	4	0	0	0	0	269
Bagfs	245	11	4	0	0	1	261
Cukel	265	2	0	0	0	0	267
Dohol	265	2	0	0	0	0	267
Dyhol	124	3	0	0	0	0	127
Efes	215	4	0	0	0	0	219
Enka	254	6	2	1	0	0	263
Eregl	262	4	0	0	0	0	266
Garan	263	6	1	0	0	0	270
Hurgz	262	6	0	0	0	0	268
Ihlas	260	5	1	0	0	0	266
Isctr	262	2	0	0	0	0	264
Kchol	266	4	1	0	0	0	271
Migrs	262	3	1	1	0	0	267
Nthol	260	8	0	0	0	0	268
Otosn	264	5	0	0	0	0	269
Petkm	177	2	0	0	0	0	179
Ptofs	176	2	0	0	0	0	178
Sahol	266	1	1	0	0	0	268
Thyao	266	2	0	0	0	0	268
Toaso	264	3	1	0	0	0	268
Tuprs	263	4	0	0	0	0	267
Uzel	263	2	0	0	1	0	266
Vestl	256	9	0	0	0	0	265
Ykbnk	255	6	0	1	0	0	262
Total	7,486	137	13	5	1	1	7,643

Source: *Dunya*, a daily Turkish newspaper.
Note: Bid and ask prices at the daily close of the market are used to calculate spread size.

Table 29
Price Change in Consecutive Transactions

Change	Frequency	Percent
-12	1	0.00
-11	1	0.00
-10	1	0.00
-8	3	0.00
-7	9	0.00
-6	18	0.00
-5	29	0.00
-4	73	0.01
-3	176	0.02
-2	1,039	0.15
-1	355,552	49.75
1	356,569	49.89
2	1,027	0.14
3	143	0.02
4	58	0.01
5	24	0.00
6	16	0.00
7	2	0.00
8	5	0.00
11	1	0.00

Note: Transactions of old shares only (there were 47,626 transactions in which new shares were traded). After removing the 16,546 first transaction of each trading session, the remaining 8,687,768 transactions were examined. Price did not change in 7,973,021 transactions. For the remaining 714,747, the frequencies are expressed in multiples of tick size.

Table 30
Variation in Clustering within Tick Regimes

Part A: Classification Rule

Tick	Price Range Low	Price Range High	Low	High	Medium[d]
25	1,025-1,100	2,450-2,525	4	4	53
50	2,550-3,500	4,100-5,050	20	20	11
100	5,100-6,000	9,300-10,200	10	10	32
250	10,250-11,000	24,500-25,250	4	4	53
500	25,500-35,000	41,000-50,500	20	20	11
1,000	51,000-60,000	93,000-102,000	10	10	32
2,500	110,000-112,500	245,000-252,500	4	4	53
5,000	255,000-350,000	410,000-505,000	20	20	11

Part B: Tick Sizes 100, and 1,000 Combined[a]

Category	Low	Medium	High	Expected Medium[d]
0	9.99	9.11	11.23	12.50
100	7.96	12.04	6.52	12.50
200	9.88	13.00	4.78	9.38
300	10.90	10.79	12.41	9.38
400	10.91	9.95	10.48	9.38
500	11.19	9.51	10.09	9.38
600	9.71	9.55	9.77	9.38
700	9.96	8.97	11.88	9.38
800	10.16	9.12	12.48	9.38
900	9.34	7.96	10.37	9.38
Total	497,883	1,387,592	193,105	
$\chi^2(9)$	0.000	0.000	0.000	
Even	50.65	50.73	48.73	
Odd	49.35	49.27	51.27	
$\chi^2(1)$	0.000	0.000	0.000	
$\chi^2(2)$	0.000			

Table 30-continued

Part C: Tick Sizes 25, 250, and 2,500 Combined[b]

Category	Low	Medium	High	Expected Medium[d]
0	39.53	26.28	25.82	26.42
25	13.00	25.94	17.44	24.53
50	21.93	25.20	31.39	24.53
75	25.54	22.58	25.34	24.53
Total	192,182	2,880,770	128,256	
$\chi^2(3)$	0.000	0.000	0.000	
Even	61.45	51.48	57.22	
Odd	38.55	48.52	42.78	
$\chi^2(1)$	0.000	0.000	0.000	
$\chi^2(2)$	0.000			

Table 30-continued

Part D: Tick Sizes 50, 500, and 5,000 Combined[c]

Category	Low	Medium	High	Expected Medium[d]
0	5.76	11.00	3.88	9.09
50	4.54	7.94	2.47	9.09
100	4.92		7.79	
150	4.71		5.99	
200	4.86		6.95	
250	4.55		6.24	
300	5.40		5.90	
350	4.94		5.19	
400	5.64		6.17	
450	4.89		5.35	
500	5.55		5.38	
550	2.88	8.35	4.98	9.09
600	4.14	9.32	4.91	9.09
650	4.51	8.57	4.92	9.09
700	5.38	10.18	5.06	9.09
750	5.85	9.45	4.04	9.09
800	5.49	10.20	4.10	9.09
850	5.36	7.96	3.42	9.09
900	5.69	8.39	3.97	9.09
950	4.93	8.64	3.27	9.09
Total	1,369,268	809,330	845,289	
$\chi^2(19)$	0.000	0.000	0.000	
Even	52.84	49.08	54.12	
Odd	47.16	50.92	45.88	
$\chi^2(1)$	0.000	0.000	0.000	
$\chi^2(2)$	0.000			

Note: Transactions within each tick regime are sorted into three price classifications, shown in Part A. Only one set of final-digit categories is assigned to the low and high price classification. Tick sizes 10 and 10,000 are not included; in the former, all transactions fall into the high price classification, and in the latter the high price classification is undefined. The remaining 8,608,886 transactions are included in the table.

Panels B-D report actual frequencies, analogous to Table 26. Due to the small number of observations in the low and high price classifications, the table reports combined frequencies. Depending on tick regime, the frequency of the last two to five digits of transaction prices are shown. For example, Part B of the table uses the last three, and four digits of transaction prices for tick regimes 100, and 1,000, respectively. The total row gives the total number of transactions in each price classification. $\chi 2(9)$, $\chi 2(3)$, and $\chi 2(19)$ report the p value for the hypothesis that each final digits category has an equal probability of occurrence in parts B, C, and D of the table respectively. Even and odd rows report the frequencies of even and odd final digit categories. $\chi 2(1)$ and $\chi 2(1)$ report the p values for the hypotheses that even and odd final digits have an equal probability of occurrence and that the occurrence of even final digits does not depend on the price level, respectively.

[a] 84,278 transactions had prices too low(high) to be included in the low(high) price classification, and these were excluded from the analysis.
[b] 99,491 transactions had prices too low(high) to be included in the low(high) price classification, and these were excluded from the analysis.
[c] 121,442 transactions had prices too low(high) to be included in the low(high) price classification, and these were excluded from the analysis.
[d] Expected frequencies vary across price categories for the medium price range.

Table 31
Parameter Values and the Number Of Stock-Windows Used in the Experiment

Test	Trading Window (Days)	Investment Window (Days)	# of Windows Before Filtering	# of Windows After Filtering
0.5	1	3	2,100	1,546
1.5	1	3	2,100	1,543
2.5	2	3	1,500	1,181
3.5	3	3	1,200	953

Note: The limit order test gives the discount from the equilibrium price expressed in ticks used to calculate the limit buy price in the experiment.

Table 32
The Number of Stock-Windows Conditional on Execution and Nonexecution of Limit Orders

			Subperiod										
Test	Status	Observation	1	2	3	4	5	6	7	8	9	10	Overall
0.5	Unexecuted	Stocks	2	26	16	23	12	14	2	24	12	3	134
		Windows	3	43	22	27	16	17	2	46	12	3	191
	Executed	Stocks	28	28	28	29	29	30	28	28	28	30	286
		Windows	183	141	58	111	183	164	156	124	124	111	1,355
1.5	Unexecuted	Stocks	20	28	24	29	29	29	12	28	26	25	250
		Windows	34	91	49	50	84	53	13	77	28	40	519
	Executed	Stocks	28	28	22	29	29	30	28	28	28	29	279
		Windows	152	93	31	88	114	128	143	93	108	74	1,024
2.5	Unexecuted	Stocks	28	26	21	25	29	2	20	28	25	30	234
		Windows	73	60	29	46	74	2	24	66	42	80	496
	Executed	Stocks	28	27	29	28	23	30	28	28	28	28	277
		Windows	60	72	49	58	44	124	99	63	81	35	685
3.5	Unexecuted	Stocks	20	27	24	29	28	21	24	27	13	30	243
		Windows	32	73	36	43	66	22	37	48	16	80	453
	Executed	Stocks	28	22	13	25	28	30	27	28	27	28	256
		Windows	71	33	14	35	44	88	59	53	66	37	500

Note: These data are used to compute the subperiod averages in the following tables. The limit order test gives the discount from the equilibrium price expressed in ticks used to calculate the limit buy price in the experiment.

Table 33
Average Standardized Execution Price of Limit Orders

Part A: Unconditional

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	99.362 [a]	98.684 [a]	99.918	97.025 [a]
2	101.448 [a]	101.795 [a]	99.311 [b]	102.089 [a]
3	101.188 [a]	102.401 [a]	99.632	105.621 [a]
4	100.416 [b]	100.045	99.685	102.436 [a]
5	99.565 [a]	99.625 [b]	100.512	100.435
6	99.750	99.222 [a]	96.298 [a]	96.107 [a]
7	99.410 [a]	98.383 [a]	98.243 [a]	100.664
8	101.565 [a]	101.606 [a]	102.416 [a]	101.777 [b]
9	99.595 [a]	98.678 [a]	98.198 [a]	96.320 [a]
10	99.446 [a]	99.746	102.681 [a]	103.011 [a]
Overall	100.173 [b]	100.024	99.689 [b]	100.558 [c]

Part B: Conditional on Nonexecution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	109.428	103.922 [a]	103.203 [a]	102.447 [b]
2	109.187 [a]	105.981 [a]	103.215 [a]	105.925 [a]
3	106.713 [a]	105.643 [a]	105.825 [a]	110.690 [a]
4	105.744 [a]	104.600 [a]	104.830 [a]	109.710 [a]
5	103.518 [a]	102.281 [a]	102.935 [a]	104.713 [a]
6	103.957 [a]	102.610 [a]	100.043	102.390
7	113.446 [c]	105.402 [a]	106.113 [a]	110.198 [a]
8	107.944 [a]	106.307 [a]	108.236 [a]	109.378 [a]
9	103.377 [a]	102.578 [a]	102.188 [a]	103.066 [a]
10	108.133 [c]	103.481 [a]	105.770 [a]	106.872 [a]
Overall	106.547 [a]	104.208 [a]	104.625 [a]	106.886 [a]

Note: Execution prices are standardized by using the equilibrium price at the close of the day preceding the order submission day. Part A reports these prices for all limit orders, and Part B reports these prices for limit orders that are not naturally executed during the trading window.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 34
The Difference between Execution and Triggering Prices for Executed Limit Orders

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.208 [a]	0.049 [b]	0.022	0.000
2	0.667	2.197	2.745	3.245
3	0.800	0.746	1.008	2.058
4	0.161 [a]	0.000	0.008	0.000
5	0.029 [b]	0.000	0.014	0.169
6	0.278 [a]	0.059 [c]	0.154 [a]	0.008
7	0.827 [a]	0.395 [a]	0.185 [b]	0.104
8	0.630 [a]	0.196 [a]	1.371 [a]	0.000
9	2.159 [a]	1.545 [a]	0.292 [a]	0.843 [a]
10	0.268 [c]	0.159	0.131	0.145
Overall	0.595 [a]	0.522 [b]	0.594 [b]	0.519 [c]

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 35
Average Time to Execution in Hours for Naturally Executed Limit Orders

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.24	0.62	1.96	5.80
2	0.32	0.92	2.79	6.95
3	0.14	0.61	1.10	8.88
4	0.71	1.38	4.89	7.69
5	0.52	2.29	4.29	5.42
6	0.75	1.07	1.90	3.16
7	0.25	0.34	1.83	2.07
8	0.14	0.46	1.55	4.49
9	0.26	0.32	3.93	2.18
10	0.32	1.40	4.71	6.14
Overall	0.37	0.96	2.86	5.01

Note: Four hours is equal to a trading day.

Table 36
Unconditional and Conditional Returns for Market and Limit Orders

	Test			
	0.5	1.5	2.5	3.5
Discount	0.779	2.310	3.861	5.423
Fraction Executed	87.65	66.36	58.00	52.47
Limit Orders				
All	-0.841 [a]	-0.696 [a]	-0.731 [b]	-1.803 [a]
Executed	-1.176 [a]	-0.853 [a]	-0.314	-1.495 [a]
Unexecuted	1.191 [b]	-0.495	-0.763 [c]	-2.807 [a]
Market Orders				
All	-1.104 [a]	-1.149 [a]	-2.111 [a]	-2.071 [a]

Note: The first row reports average percentage discount from the equilibrium price at the close of the day preceding the order submission day used to determine limit buy order prices. The second row reports the fraction of limit buy orders that are naturally executed during the trading window. Rows 3-5 report unconditional, conditional on natural execution, and conditional on forced execution overall returns for limit buy orders. Row 6 reports the unconditional overall returns for market orders.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 37
Differential Returns

Part A: Unconditional

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.531 [c]	1.242 [a]	-1.856 [a]	2.348 [a]
2	0.397	0.080	3.774 [a]	0.876
3	-1.636 [a]	-2.789 [a]	2.323 [b]	-7.749 [a]
4	1.430 [a]	1.829 [a]	0.985	-0.597
5	1.584 [a]	1.545 [a]	0.109	0.876
6	-0.058	0.491	1.044 [b]	0.042
7	-4.035 [a]	-2.865 [a]	1.036	-2.857 [a]
8	-0.121	-0.132	-1.896 [a]	2.235 [a]
9	-0.609 [a]	0.330	5.666 [a]	3.889 [a]
10	4.816 [a]	4.552 [a]	2.574 [a]	3.679 [a]
Overall	0.263	0.454 [a]	1.380 [a]	0.267
Wilcoxon p	0.061	0.001	<.0001	0.004

Part B: Conditional on Execution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.319	1.515 [a]	-2.728	3.959 [a]
2	0.025	0.447	3.291 [a]	5.447 [a]
3	-1.091 [c]	-1.711 [c]	5.668 [a]	-0.803
4	0.283	0.976	3.757 [a]	-1.238
5	1.837 [a]	2.880 [a]	2.856 [a]	4.195 [a]
6	-0.385	1.618 [a]	1.221 [a]	0.835
7	-4.118 [a]	-3.407 [a]	0.106	-3.298 [a]
8	-1.594 [b]	-3.236 [a]	1.196	0.327
9	-0.944 [a]	-0.024	4.585 [a]	5.571 [a]
10	4.750 [a]	4.539 [a]	-0.913	-1.072
Overall	-0.052	0.439 [c]	1.890 [a]	1.454 [a]
Wilcoxon p	0.822	0.021	<.0001	<.0001

Table 37-continued

Part C: Conditional on Nonexecution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	5.393	-1.449	-2.186	-1.680
2	1.820 [b]	-0.415	5.042 [a]	-1.277 [c]
3	-3.704 [b]	-3.479 [a]	-4.078 [a]	-10.753 [a]
4	6.466 [a]	4.096 [a]	-3.443 [a]	0.627
5	-1.751	-0.415	-1.015 [c]	-1.153
6	0.866	-2.148 [c]	-10.227	-3.542 [a]
7	-1.827	-0.390	2.977 [b]	-3.313
8	2.386 [b]	3.494 [a]	-4.396 [a]	2.521 [a]
9	2.439 [b]	2.338 [b]	7.492 [a]	-4.029 [a]
10	1.244	3.594 [a]	3.845 [a]	5.134 [a]
Overall	1.681 [a]	0.657 [c]	0.373	-1.335 [a]
Wilcoxon p	0.001	0.048	0.455	0.009

Note: For each firm the difference between subperiod average firm limit buy order return and unconditional market order return forms the basic observation.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 38
Standardized Price Following the Order Submission Day

		Day									
Test	Status	1	2	3	4	5	6	7	8	9	10
0.5	Executed	99.550 [a]	100.153	99.723	99.288 [b]	99.847	99.729	100.479	100.310	100.635	100.333
1.5	Executed	98.557 [a]	99.139 [a]	98.503 [a]	98.041 [a]	98.735 [a]	98.770 [a]	99.811	99.843	99.780	99.298
2.5	Executed	97.840 [a]	96.416 [a]	96.430 [a]	96.882 [a]	96.715 [a]	96.613 [a]	96.837 [a]	97.541 [a]	97.326 [a]	97.393 [a]
3.5	Executed	97.443 [a]	96.426 [a]	93.751 [a]	94.379 [a]	94.877 [a]	93.518 [a]	95.322 [a]	95.204 [a]	95.736 [a]	96.450 [a]
0.5	Unexecuted	105.752 [a]	106.957 [a]	108.363 [a]	108.940 [a]	108.492 [a]	107.990 [a]	105.686 [a]	105.173 [a]	107.382 [a]	106.864 [a]
1.5	Unexecuted	103.418 [a]	104.238 [a]	104.647 [a]	104.899 [a]	104.665 [a]	103.798 [a]	102.486 [a]	101.723 [c]	104.459 [a]	104.209 [a]
2.5	Unexecuted	102.708 [a]	103.805 [a]	104.885 [a]	104.877 [a]	104.992 [a]	104.733 [a]	104.909 [a]	105.331 [a]	106.093 [a]	108.151 [a]
3.5	Unexecuted	102.708 [a]	105.353 [a]	106.062 [a]	107.136 [a]	107.322 [a]	105.116 [a]	104.810 [a]	104.529 [a]	105.021 [a]	104.562 [a]

Note: Reported are the overall averages of standardized bid-ask spread midpoints at the close of each day during the ten days following the order submission. Bid and ask midpoints were standardized by using the equilibrium price at the close of the day preceding the order submission. The investment window equals 3 days.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 39
Sensitivity of Costs to the Choice of Investment Window Length

		Investment Window		
Test	Cost	3 Days	5 Days	7 Days
0.5	Bagging	0.052	1.181 [a]	-1.358 [a]
	Nonexecution	-1.681 [a]	-0.355	3.638 [a]
	Total	-0.263	0.916 [a]	-0.590 [b]
1.5	Bagging	-0.439 [c]	0.793 [b]	-3.604 [a]
	Nonexecution	-0.657 [c]	1.119 [b]	3.490 [a]
	Total	-0.454 [a]	0.706 [a]	-0.745 [a]
2.5	Bagging	-1.890 [a]	1.494 [a]	-0.951 [c]
	Nonexecution	-0.373	-0.564	0.088
	Total	-1.380 [a]	0.411	-0.506 [c]
3.5	Bagging	-1.454 [a]	-1.689 [a]	-2.415 [a]
	Nonexecution	1.335 [a]	0.739	-3.583 [a]
	Total	-0.267	-0.887 [c]	-2.340 [a]

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 40
Market-Adjusted Differential Limit Buy Order Returns

	Test							
	0.5		1.5		2.5		3.5	
Subperiod	η_1	η_2	η_1	η_2	η_1	η_2	η_1	η_2
1	5.017	-5.211	-1.111	1.279	-1.647 [c]	2.706 [c]	-2.670 [b]	3.906 [a]
2	-0.944	1.258	-1.039 [b]	1.993 [a]	-0.319	0.818	-1.234 [c]	4.421 [a]
3	-4.016 [a]	5.570 [a]	-2.480 [a]	6.334 [a]	-4.356 [a]	7.007 [a]	-2.840 [b]	8.707 [a]
4	-0.854	1.308	-0.240	0.746	-0.946	1.653 [c]	-0.271	1.420
5	-2.105 [b]	2.332 [b]	-1.093 [b]	1.973 [a]	-1.896 [a]	5.076 [a]	-0.013	0.542
6	-0.481	0.745	0.19	-0.006	0.552	-0.467	-1.159	1.337
7	-10.498 [b]	10.189 [b]	-6.766 [a]	6.964 [a]	-3.962 [a]	4.718 [a]	-3.876 [a]	5.756 [a]
8	-1.747 [b]	2.351 [b]	-0.639	1.047	-1.152	2.536 [b]	-1.896 [b]	3.182 [b]
9	-1.827	1.855	-0.893	1.013	-0.858	1.663 [c]	-5.476 [a]	6.975 [a]
10	-0.152	0.413	-1.773 [b]	3.123 [a]	0.167	-0.038	-0.235	1.376
Overall	-1.573 [a]	1.793 [a]	-1.123 [a]	1.693 [a]	-1.297 [a]	2.249 [a]	-1.461 [a]	2.800 [a]

Note: For each firm the difference between window limit order return and average market order return during the corresponding subperiod was regressed on a constant and the difference between portfolio window limit order return and portfolio average market order return during the corresponding subperiod. The residuals from these 30 regressions were stacked to form a vector and were then regressed on a constant and a dummy that takes on the value 1 for natural execution, 0 otherwise. η_1 is the intercept, and η_2 is the coefficient of execution dummy. Subperiod and overall results are reported for each limit order test.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 41
Sensitivity of Market-Adjusted Differential Limit Buy Order Returns to the Choice of Investment Window Length

Test		Investment Window		
		3 Days	5 Days	7 Days
0.5	η_1	-1.573 [a]	-2.050 [a]	-1.725 [b]
	η_2	1.793 [a]	2.385 [a]	1.964 [b]
1.5	η_1	-1.123 [a]	-1.276 [a]	-0.812
	η_2	1.693 [a]	1.887 [a]	1.287 [b]
2.5	η_1	-1.297 [a]	-0.998 [a]	-0.639
	η_2	2.249 [a]	1.848 [a]	1.359 [b]
3.5	η_1	-1.461 [a]	-1.010 [b]	-1.300 [b]
	η_2	2.800 [a]	1.929 [a]	2.442 [a]

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 42
The Experiment of Simultaneously Submitting Limit Buy and Sell Orders at ± k Ticks from the Equilibrium Price

Part A:

Test	RTGAIN	RTRIPS	DC	IMB	BC	NEC	Profit	LOS	N
2	1,889.65 [a]	230.45 [a]	-2,611.47	5.78 [b]	-379,387.67 [a]	456,375.58 [a]	-76,987.91	-277.59	86
3	2,796.22 [a]	73.43 [a]	-3,054.64	3.67 [b]	-191,221.10 [a]	298,101.45 [a]	-106,880.35 [c]	-1,007.88	86

Part B:

Test	RTGAIN(%)	RTRIPS	DC(%)	IMB	BC	NEC	Profit	LOS	N
2	3.381 [a]	230.45 [a]	8.897 [c]	5.779 [b]	-8.047 [a]	9.178 [a]	-1.131	-0.357	86
3	4.766 [a]	73.43 [a]	7.028	3.674 [b]	-3.708 [a]	5.876 [a]	-2.168 [a]	-1.997 [a]	86

Note: RTGAIN gives the average gain from buying and selling the stock and vice versa. RTRIPS is number of times the inventory imbalance is corrected by the execution of limit order during the trading period. DC is the difference between the average price received (paid) for stocks sold (purchased) during the trading period and the selling(purchasing) price when the inventory is closed. IMB is inventory imbalance at the end of trading period expressed in equivalent shares. BC is the bagging cost. NEC is the nonexecution cost. Profit is total gain from the strategy. LOS is limit order spread, which is obtained by dividing the total TL profit (including the profit from closing transactions) by the total number of roundtrips (including the closing trades). Part A expresses RTGAIN, DC, BC, NEC, Profit, and LOS in TL. Part B reports the same figures by standardizes the TL values by the price at the end of the trading period. RTGAIN and DC are expressed in percentages, and BC, NEC, and Profit are multiples of price.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 43
Frequency of Trade Sequences in Which Price Changed Consecutively

	Lag												All
Stock	0	1	2	3	4	5	6	7	8	9	10	Total	Transactions
Akbnk	21,536	10,021	2,202	929	287	120	45	18	6	4	7	35,175	400,613
Akcns	14,361	5,804	1,261	481	155	68	26	11	5	-	1	22,173	222,345
Akgrt	5,154	1,569	289	91	18	6	1	1	-	-	1	7,130	87,783
Alark	6,371	2,115	428	127	32	9	1	-	-	-	1	9,084	110,153
Alctl	12,102	5,382	1,185	481	143	64	24	13	2	1	2	19,399	203,016
Arclk	11,373	4,461	885	292	84	27	7	3	1	1	1	17,135	180,292
Bagfs	11,070	4,368	951	344	114	29	11	5	2	1	5	16,900	204,051
Cukel	8,378	3,281	720	244	65	18	6	2	-	-	1	12,715	215,358
Dohol	36,475	18,653	4,217	1,955	610	287	104	51	18	11	20	62,401	764,761
Dyhol	11,702	4,696	902	344	123	52	17	9	5	2	3	17,855	273,469
Efes	12,988	5,367	1,073	426	109	44	12	5	-	-	1	20,025	268,021
Enka	6,936	2,421	528	159	37	7	2	-	-	-	1	10,091	134,113
Eregl	10,852	4,875	1,095	435	130	58	24	12	8	6	22	17,517	221,519
Garan	16,909	7,516	1,681	699	216	79	26	13	4	3	8	27,154	299,915
Hurgz	14,975	5,860	1,212	434	126	41	13	4	1	1	2	22,669	259,903
Ihlas	17,931	8,259	1,781	756	247	119	33	15	7	4	6	29,158	369,861
Isctr	38,561	19,241	4,421	2,028	620	292	113	51	28	16	10	65,381	619,827
Kchol	14,777	6,721	1,510	620	182	73	28	12	4	2	5	23,934	297,119
Migrs	6,346	2,249	442	138	47	19	6	1	1	-	1	9,250	115,104
Nthol	10,372	4,170	857	321	99	40	11	5	2	1	8	15,886	158,899
Otosn	6,317	2,100	425	122	32	11	3	-	-	-	1	9,011	115,058
Petkm	12,418	5,291	1,097	433	138	50	23	6	2	1	1	19,460	281,767
Ptofs	10,306	3,872	831	281	86	29	11	4	1	-	1	15,422	198,779
Sahol	23,759	11,550	2,660	1,152	374	167	60	32	8	5	8	39,775	467,501

Table 43-continued

	Lag												
Stock	0	1	2	3	4	5	6	7	8	9	10	Total	All Transactions
Thyao	16,057	7,331	1,568	616	175	62	29	7	5	3	2	25,855	332,615
Toaso	14,888	6,642	1,548	660	198	75	28	10	4	1	1	24,055	258,895
Tuprs	31,573	16,651	3,801	1,764	551	270	107	53	22	13	32	54,837	683,744
Uzel	13,097	5,310	1,110	412	114	42	16	7	-	-	1	20,109	225,263
Vestl	8,768	3,127	656	220	59	20	6	2	2	2	11	12,873	138,261
Ykbnk	25,353	11,897	2,389	951	278	101	39	12	4	2	2	41,028	554,694
Total	451,705	200,800	43,725	17,915	5,449	2,279	832	364	142	80	166	723,457	8,662,699

Note: Each transaction is assigned into categories based on the behavior of previous prices. For example, consider the following sequence: {5,100, 5,100, 5,200, 5,300}. Transactions that occurred at prices 5,200 and 5,300 are assigned into the lag=0 and lag=1 categories, respectively. The difference between the last two columns shows the number of transactions in which price did not change.

Table 44
Distribution of Intervals Based on Price Change and No Price Change Classification

	15 min		30 min		60 min	
Stock	No Change	Change	No Change	Change	No Change	Change
Akbnk	2,284	2,216	942	1,308	364	762
Akcns	2,131	2,353	893	1,349	316	806
Akgrt	2,533	1,967	1,021	1,229	380	746
Alark	2,427	2,065	961	1,285	363	761
Alctl	2,373	2,127	1,016	1,234	364	762
Arclk	2,318	2,182	955	1,295	376	750
Bagfs	2,439	2,061	970	1,280	389	737
Cukel	2,551	1,949	1,075	1,175	387	739
Dohol	2,169	2,331	900	1,350	361	765
Dyhol	1,002	1,202	415	687	143	409
Efes	2,136	1,876	888	1,118	309	695
Enka	2,569	1,931	1,072	1,178	419	707
Eregl	2,378	2,106	988	1,254	359	763
Garan	2,203	2,289	916	1,330	352	772
Hurgz	2,216	2,284	909	1,341	346	780
Ihlas	2,311	2,189	974	1,276	382	744
Isctr	2,279	2,141	970	1,240	330	776
Kchol	2,290	2,202	965	1,281	364	760
Migrs	2,561	1,939	1,045	1,205	422	704
Nthol	2,276	2,224	967	1,283	393	733
Otosn	2,542	1,958	1,046	1,204	395	731
Petkm	2,414	2,086	982	1,268	399	727
Ptofs	2,147	2,289	842	1,376	301	809
Sahol	2,217	2,283	946	1,304	359	767
Thyao	2,348	2,152	998	1,252	360	766
Toaso	2,263	2,237	950	1,300	367	759
Tuprs	2,240	2,260	915	1,335	333	793
Uzel	2,234	2,266	948	1,302	387	739
Vestl	2,334	2,166	966	1,284	341	785
Ykbnk	2,134	2,366	867	1,383	311	815
Total	68,319	63,697	28,302	37,706	10,672	22,362

Table 45
Stationarity of Price and Volume Series

	Dickey-Fuller		Phillips-Perron	
	Tau	Pr < Tau	Tau	Pr < Tau
Price				
Zero Mean	0.07	0.7060	0.07	0.7050
Single Mean	-1.01	0.7519	-1.07	0.7310
Trend	-0.84	0.9605	-0.94	0.9510
Return				
Zero Mean	-31.26	0.0000	-66.26	0.0010
Single Mean	-31.26	0.0001	-66.26	0.0010
Trend	-31.27	0.0001	-66.25	0.0010
Turnover				
Zero Mean	-12.59	0.0000	-29.19	0.0010
Single Mean	-22.20	0.0001	-45.14	0.0010
Trend	-22.54	0.0001	-45.35	0.0010

Table 46
Average Turnover during 15 Minute Intervals by Weekday, in Percentage

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00-10:15	1.018	0.876	0.986	0.970	0.911	0.952	0.40
10:15-10:30	0.534	0.536	0.636	0.565	0.535	0.561	0.57
10:30-10:45	0.371	0.425	0.414	0.484	0.415	0.422	0.74
10:45-11:00	0.304	0.350	0.368	0.351	0.371	0.349	0.38
11:00-11:15	0.286	0.308	0.338	0.310	0.350	0.318	0.49
11:15-11:30	0.278	0.321	0.311	0.285	0.278	0.295	0.27
11:30-11:45	0.242	0.225	0.379	0.300	0.333	0.295	2.30 [c]
11:45-12:00	0.298	0.365	0.351	0.353	0.334	0.340	0.34
14:00-14:15	0.566	0.667	0.634	0.644	0.662	0.634	0.20
14:15-14:30	0.465	0.528	0.469	0.508	0.443	0.483	0.30
14:30-14:45	0.337	0.439	0.376	0.448	0.388	0.398	0.64
14:45-15:00	0.313	0.408	0.367	0.373	0.410	0.374	0.64
15:00-15:15	0.311	0.362	0.441	0.410	0.439	0.392	1.03
15:15-15:30	0.364	0.452	0.389	0.474	0.409	0.418	0.67
15:30-15:45	0.370	0.455	0.444	0.433	0.450	0.430	0.55
15:45-16:00	0.700	0.846	0.862	0.785	0.850	0.809	1.29
All	0.422	0.473	0.485	0.481	0.474	0.467	
F_{int}	17.02 [a]	8.02 [a]	9.94 [a]	11.43 [a]	11.60 [a]		
F_{first}	187.68 [a]	61.77 [a]	85.89 [a]	101.70 [a]	96.01 [a]		
F_{ninth}	22.44 [a]	16.45 [a]	14.74 [a]	19.59 [a]	24.82 [a]		
$F_{sixteenth}$	66.69 [a]	55.88 [a]	61.33 [a]	54.33 [a]	81.64 [a]		

Note: Turnover per stock is calculated by dividing the cumulative volume during an interval by the number of floating shares (number of outstanding shares*float). The reported results are the equal weighted averages of individual stock mean turnovers. F_{int} tests the hypothesis of equality of mean turnover during all intervals in a given weekday. F_{first} ,F_{ninth} , and $F_{sixteenth}$ test the hypotheses that mean turnover in interval 1, 9, and 16 are not different from the mean turnover in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean turnover during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday-Friday, respectively. F_{first} , F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday-Friday, respectively. F_{day} has degrees of freedom of (4,272).

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 47
Average Return Volatility during 15 Minute Intervals by Weekday ($\times 10^{-4}$)

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00-10:15	2.737	1.770	2.925	2.155	3.671	2.647	0.67
10:15-10:30	0.982	0.763	0.768	0.798	1.130	0.888	0.33
10:30-10:45	0.541	0.816	0.443	1.070	1.004	0.773	0.69
10:45-11:00	0.420	0.241	0.360	0.382	0.375	0.355	0.52
11:00-11:15	0.420	0.279	0.541	0.311	0.584	0.426	0.61
11:15-11:30	0.535	0.288	0.306	0.239	0.461	0.366	0.66
11:30-11:45	0.332	0.170	0.282	0.284	0.254	0.264	0.54
11:45-12:00	0.356	0.270	0.261	0.297	0.221	0.281	0.58
14:00-14:15	0.922	1.126	0.978	1.358	1.083	1.092	0.31
14:15-14:30	0.385	0.760	0.470	0.409	0.443	0.495	1.13
14:30-14:45	0.373	0.210	0.310	0.620	0.606	0.421	1.67
14:45-15:00	0.183	0.229	0.534	0.204	0.327	0.295	3.33 [b]
15:00-15:15	0.279	0.410	0.489	0.400	0.441	0.403	0.42
15:15-15:30	0.396	0.417	0.358	0.357	0.737	0.453	0.75
15:30-15:45	0.502	0.278	0.365	0.406	0.730	0.455	1.05
15:45-16:00	0.334	0.623	0.414	0.295	0.526	0.440	1.50
All	0.606	0.541	0.613	0.599	0.787	0.628	
F_{int}	5.58 [a]	5.57 [a]	4.11 [a]	4.86 [a]	4.41 [a]		
F_{frst}	70.09 [a]	63.38 [a]	52.55 [a]	51.77 [a]	53.99 [a]		
F_{ninth}	9.41 [a]	18.20 [a]	19.15 [a]	21.92 [a]	3.48 [c]		
$F_{sixteenth}$	0.51	2.27	0.00	0.88	0.02		

Note: The reported results are the equal weighted averages of individual stock volatilities, proxied by return squared. F_{int} tests the hypothesis of equality of mean volatility during all intervals in a given weekday. F_{frst}, F_{ninth}, and $F_{sixteenth}$ test the hypotheses that mean volatility in interval 1, 9, and 16 are not different than the mean volatility in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean volatility during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday-Friday, respectively. F_{frst}, F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday-Friday, respectively. F_{day} has degrees of freedom of (4,272).

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 48
Average Return during 15 Minute Intervals by Weekday

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00-10:15	-0.245	-0.020	0.017	0.301	0.287	0.065	1.10
10:15-10:30	-0.006	-0.112	0.081	0.139	-0.010	0.017	0.57
10:30-10:45	-0.092	-0.272	0.059	-0.235	-0.137	-0.136	1.25
10:45-11:00	0.027	-0.066	-0.041	-0.108	-0.123	-0.062	0.56
11:00-11:15	0.012	-0.104	-0.170	-0.118	0.002	-0.075	0.82
11:15-11:30	-0.072	-0.010	-0.146	-0.021	-0.119	-0.073	0.54
11:30-11:45	-0.055	-0.025	-0.088	0.055	-0.108	-0.044	0.85
11:45-12:00	0.153	0.066	0.112	-0.052	0.229	0.102	2.23 [c]
14:00-14:15	-0.040	0.021	-0.026	-0.052	0.113	0.003	0.22
14:15-14:30	0.016	-0.021	-0.098	0.055	0.065	0.003	0.48
14:30-14:45	0.039	0.040	0.003	-0.050	0.034	0.014	0.19
14:45-15:00	-0.095	0.005	-0.142	-0.125	0.072	-0.057	1.60
15:00-15:15	-0.244	0.018	-0.062	-0.043	0.063	-0.054	1.94
15:15-15:30	-0.029	0.051	-0.122	-0.049	0.176	0.006	1.58
15:30-15:45	-0.052	-0.037	0.075	-0.001	0.085	0.014	0.48
15:45-16:00	0.139	0.473	0.369	0.301	0.455	0.348	3.32 [b]
All	-0.034	0.001	-0.011	0.000	0.068	0.004	
F_{int}	1.09	2.43 [a]	1.64 [c]	1.92 [b]	1.87 [b]		
F_{frst}	3.98 [b]	0.03	0.29	10.55 [a]	4.74 [b]		
F_{ninth}	0.01	0.39	0.03	0.01	0.78		
$F_{sixteenth}$	3.49 [c]	34.78 [a]	20.93 [a]	13.88 [a]	17.89 [a]		

Note: Return per stock is calculated as the difference of log prices at the end and at the beginning of an interval. The reported results are the equal weighted averages of individual stock mean returns. F_{int} tests the hypothesis of equality of mean return during all intervals in a given weekday. $F_{frst,}$ F_{ninth}, and $F_{sixteenth}$ test the hypotheses that mean return in interval 1, 9, and 16 are not different than the mean return in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean return during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday-Friday, respectively. F_{frst} , F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday-Friday, respectively. F_{day} has degrees of freedom of (4,272).

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 49
Regression Results for the Test of a Contemporaneous Relationship between Volume and Return

	Specification 1		Specification 2		Specification 3	
	Estimate	p Value	Estimate	p Value	Estimate	p Value
Intercept	-0.3302	<.0001	-0.1962	0.0137	-0.0087	0.9291
|R|	0.4910	<.0001	0.5394	<.0001	0.3741	0.0045
|R| D	-0.0622	0.0720	-0.0688	0.0398	-0.2782	0.0510
Dum(Tue)			-0.0048	0.9426	-0.0429	0.5829
Dum(Wed)			-0.0115	0.8691	-0.0668	0.3945
Dum(Thu)			0.0079	0.9102	0.0232	0.7777
Dum(Fri)			0.0216	0.7571	0.0176	0.8267
Dum(10:30)			-0.0088	0.8750	-0.1335	0.1991
Dum(10:45)			0.0151	0.8238	-0.1452	0.1339
Dum(11:00)			-0.0153	0.8329	-0.1867	0.0707
Dum(11:15)			0.0121	0.8728	-0.2309	0.0310
Dum(11:30)			0.0178	0.8238	-0.2044	0.0537
Dum(11:45)			-0.0081	0.9176	-0.3351	0.0013
Dum(12:00)			-0.0194	0.8106	-0.1584	0.1506
Dum(14:15)			-0.0044	0.9567	-0.2171	0.0536
Dum(14:30)			-0.0267	0.7432	-0.1572	0.1546
Dum(14:45)			-0.0106	0.8941	-0.2925	0.0081
Dum(15:00)			-0.0150	0.8544	-0.1063	0.3552
Dum(15:15)			-0.0023	0.9758	-0.3119	0.0025
Dum(15:30)			-0.0086	0.9059	-0.2265	0.0403
Dum(15:45)			-0.0089	0.9002	-0.2143	0.0496
Dum(16:00)			-0.0188	0.7630	0.0681	0.4971
Aftaug			-0.3361	<.0001	-0.3298	<.0001
|R| Dum(Tue)					-0.0770	0.4519
|R| D Dum(Tue)					0.2576	0.0217
|R| Dum(Wed)					0.0608	0.5753
|R| D Dum(Wed)					0.0262	0.7984
|R| Dum(Thu)					-0.0452	0.6374
|R| D Dum(Thu)					0.0504	0.6099
|R| Dum(Fri)					-0.0615	0.5072
|R| D Dum(Fri)					0.1352	0.1843
|R| Dum(10:30)					0.2315	0.2079
|R| D Dum(10:30)					-0.1063	0.5492
|R| Dum(10:45)					0.1035	0.5144
|R| D Dum(10:45)					0.2445	0.1791
|R| Dum(11:00)					0.2182	0.1698
|R| D Dum(11:00)					0.0509	0.7699
|R| Dum(11:15)					0.2658	0.1146

Table 49-continued

	Specification 1		Specification 2		Specification 3	
	Estimate	p Value	Estimate	p Value	Estimate	p Value
|R| D Dum(11:15)					0.1659	0.3409
|R| Dum(11:30)					0.2578	0.1006
|R| D Dum(11:30)					0.1203	0.4788
|R| Dum(11:45)					0.4521	0.0040
|R| D Dum(11:45)					0.0108	0.9525
|R| Dum(12:00)					0.1435	0.3714
|R| D Dum(12:00)					0.1146	0.4989
|R| Dum(14:15)					0.2944	0.0975
|R| D Dum(14:15)					0.0124	0.9510
|R| Dum(14:30)					0.1146	0.4618
|R| D Dum(14:30)					0.1538	0.4035
|R| Dum(14:45)					0.3020	0.0791
|R| D Dum(14:45)					0.1866	0.3280
|R| Dum(15:00)					-0.0635	0.6643
|R| D Dum(15:00)					0.3975	0.0184
|R| Dum(15:15)					0.2993	0.0877
|R| D Dum(15:15)					0.2829	0.1386
|R| Dum(15:30)					0.3000	0.0222
|R| D Dum(15:30)					0.0144	0.9253
|R| Dum(15:45)					0.2162	0.1163
|R| D Dum(15:45)					0.1438	0.4479
|R| Dum(16:00)					-0.1217	0.4355
|R| D Dum(16:00)					0.0368	0.8236

Note: The three specifications are versions of the model in equation (10).

Table 50
Granger Causality: Relationship between Return and Volume

Dependent	$Return_t$		$Volume_t$	
	Coefficient	p Value	Coefficient	p Value
Intercept	0.0000	1.0000	0.0000	1.0000
$Return_{t-1}$	0.0290	0.3194	0.0394	0.0389
$Return_{t-2}$	0.0793	0.0014	0.0694	<.0001
$Return_{t-3}$	0.0562	0.0558	0.0548	0.0018
$Return_{t-4}$	0.0287	0.2745	0.0202	0.3038
$Volume_{t-1}$	-0.0374	0.1519	0.2634	<.0001
$Volume_{t-2}$	-0.0107	0.6931	0.0895	0.0021
$Volume_{t-3}$	0.0364	0.2134	0.1460	<.0001
$Volume_{t-4}$	-0.0092	0.7494	0.1705	<.0001
Wald	3.99	0.4075	30.86	<.0001

Table 51
Granger Causality: Relationship between Return Volatility and Volume

Dependent	$\lvert Return_t \rvert$		$Volume_t$	
	Coefficient	P Value	Coefficient	P Value
Intercept	0.1615	0.0043	0.2350	<.0001
$\lvert Return_{t-1} \rvert$	0.1135	0.0204	0.0376	0.2394
$\lvert Return_{t-2} \rvert$	-0.0434	0.3285	-0.0677	0.0177
$\lvert Return_{t-3} \rvert$	-0.0716	0.1325	-0.0709	0.0086
$\lvert Return_{t-4} \rvert$	0.0198	0.6135	-0.0066	0.8370
$Volume_{t-1}$	-0.0659	0.0124	0.2528	<.0001
$Volume_{t-2}$	0.0066	0.8173	0.1102	0.0005
$Volume_{t-3}$	0.0544	0.0811	0.1596	<.0001
$Volume_{t-4}$	-0.0254	0.3949	0.1609	<.0001
D_{t-1}	-0.1460	0.0004	-0.0641	0.0770
D_{t-2}	-0.1144	0.0041	-0.1193	0.0006
D_{t-3}	-0.0354	0.4169	-0.0654	0.0632
D_{t-4}	-0.0661	0.1243	-0.0808	0.0298
Wald	8.59	0.0723	40.34	<.0001

APPENDIX B

FIGURES

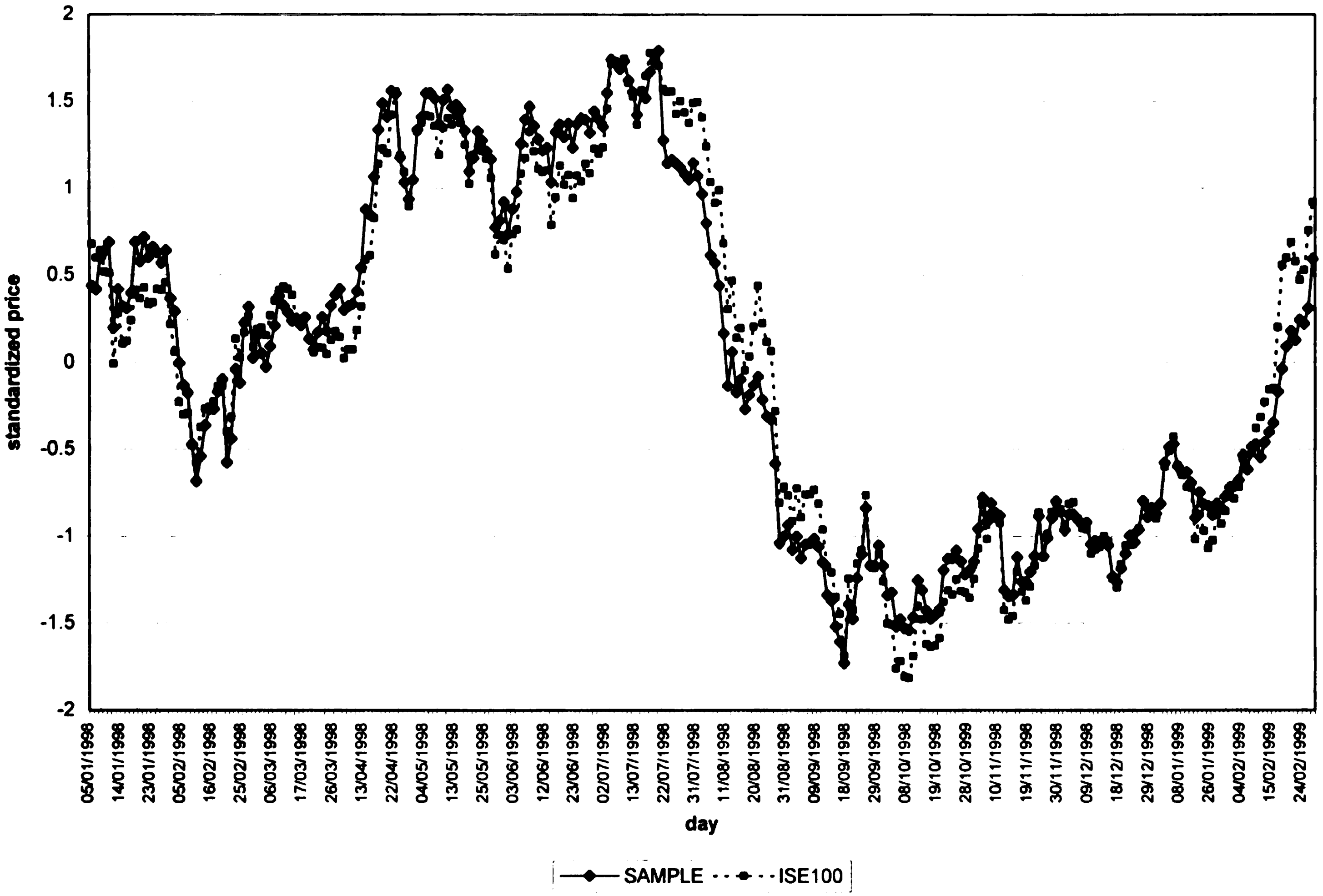

Figure 1
Standardized Price Level of ISE100 Index and Equal Weighted Portfolio of Sample Firms

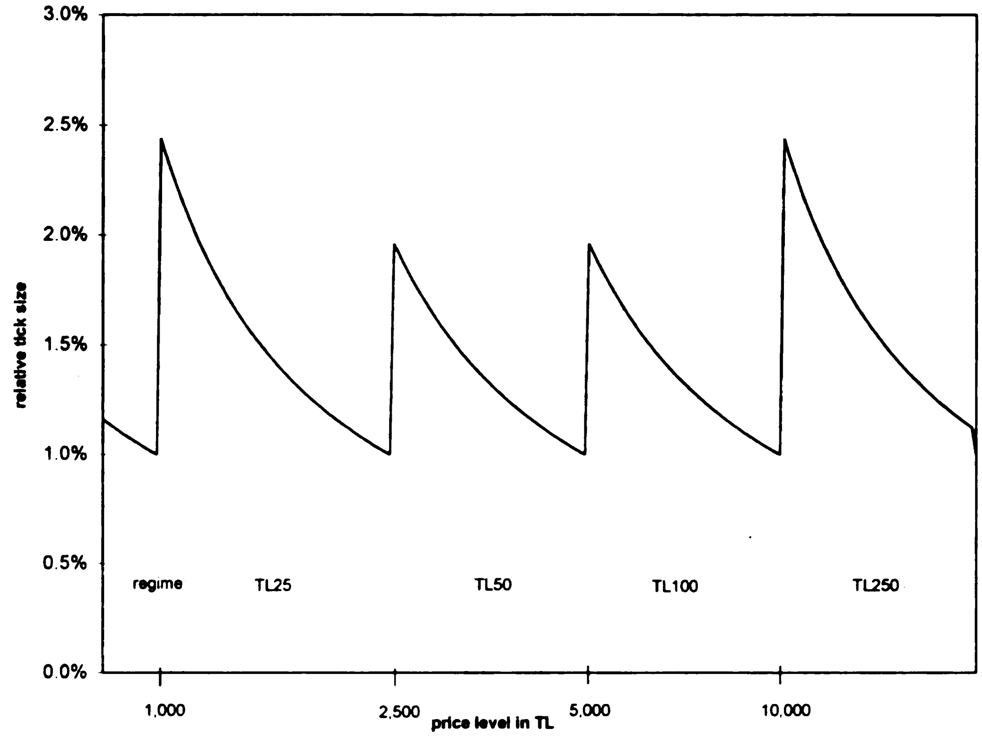

Figure 2
Tick Rule on the ISE

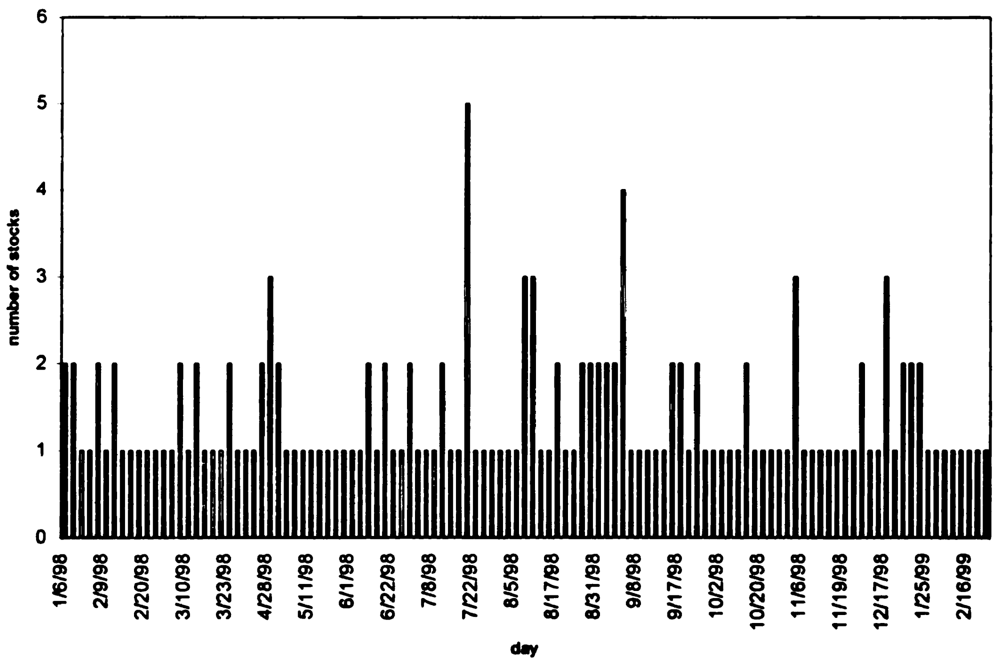

Figure 3
Distribution of Nontrivial Spread over Time

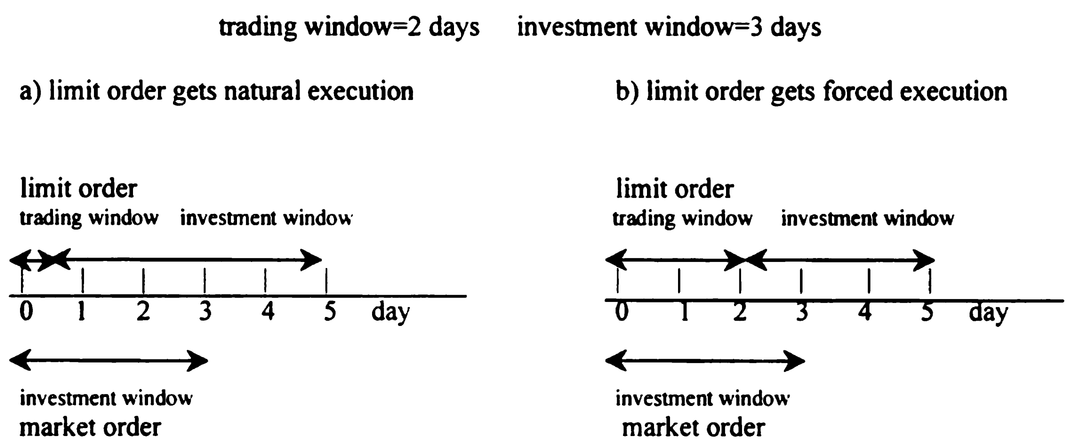

Figure 4
Timing of Events in the Experiment

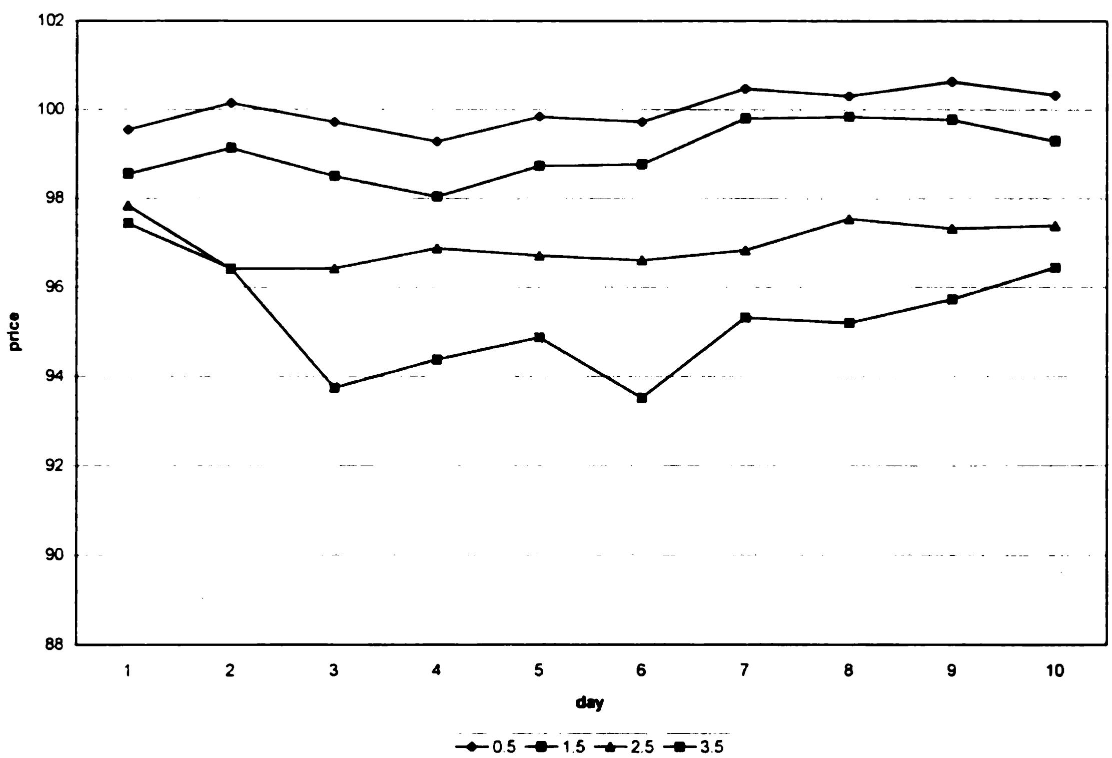

Figure 5
Standardized Market Price during 10 Days Following the Order Submission for Executed Limit Orders

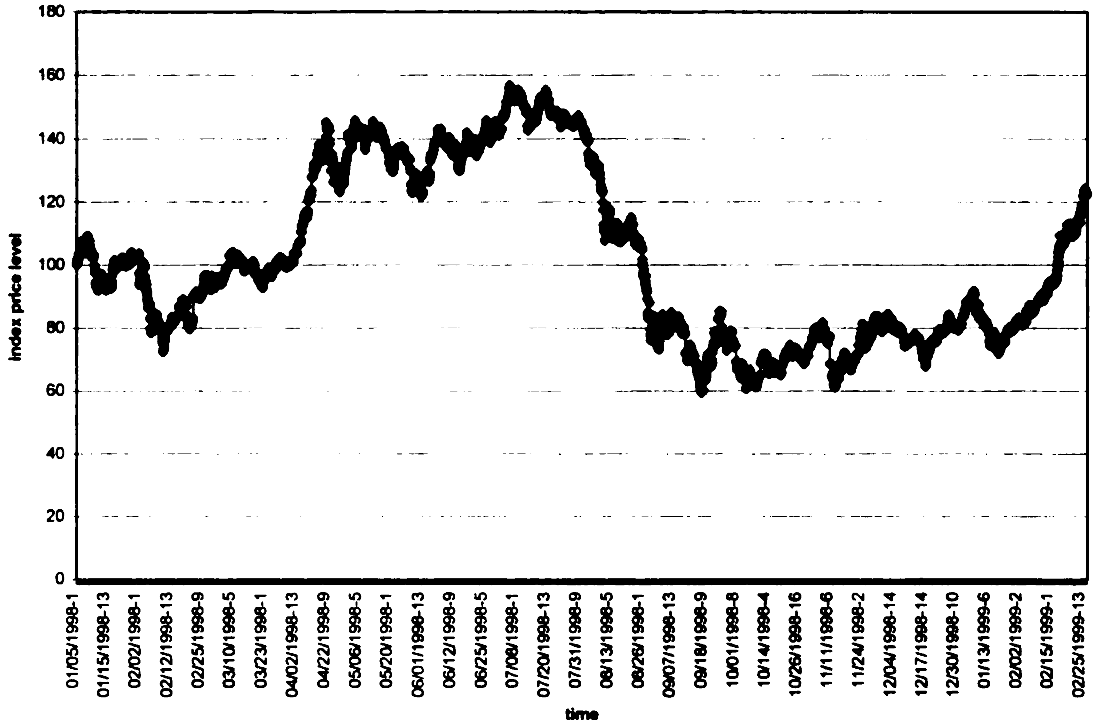

Figure 6
Index Price Level over Time

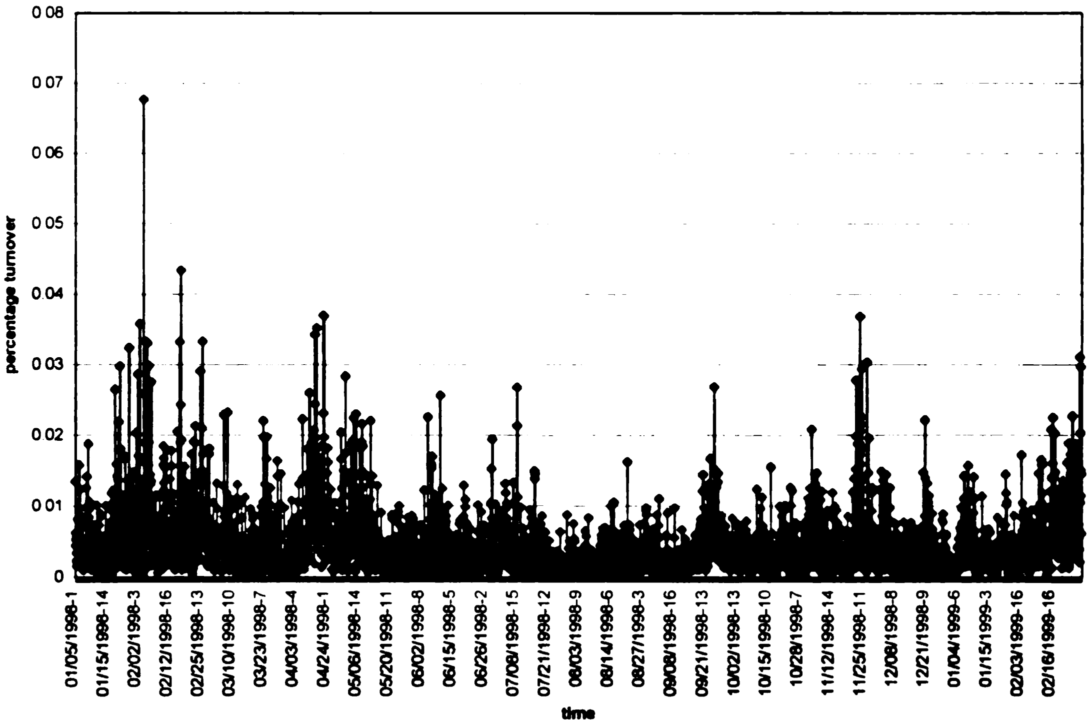

Figure 7
Percentage Turnover over Time

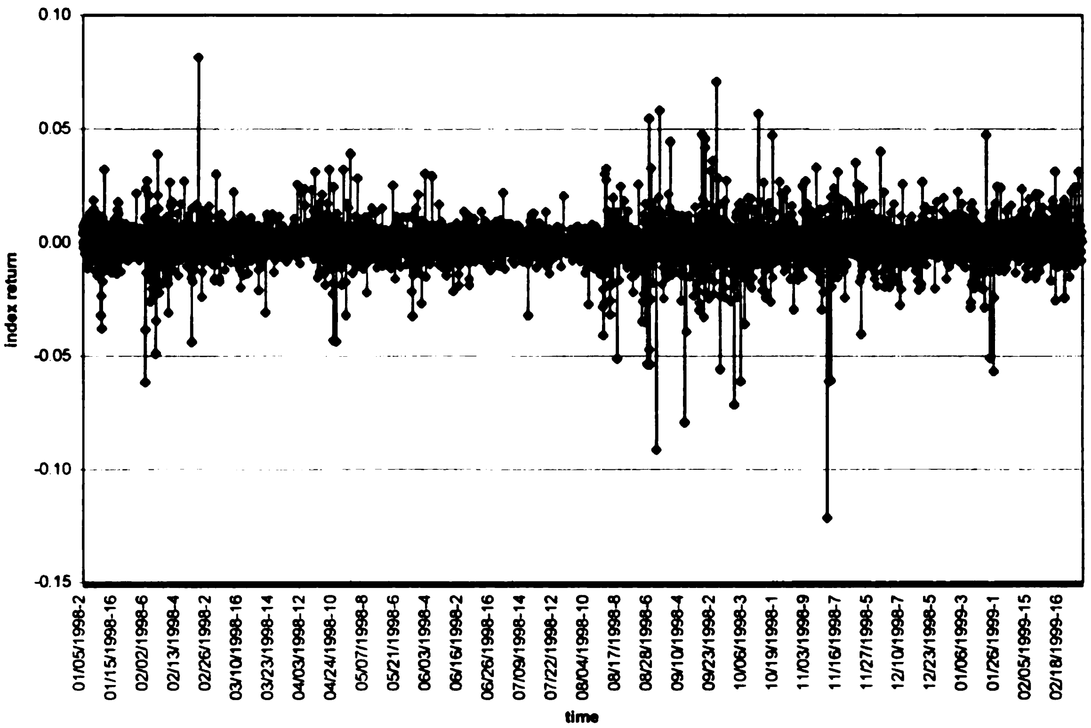

Figure 8
Index Return over Time

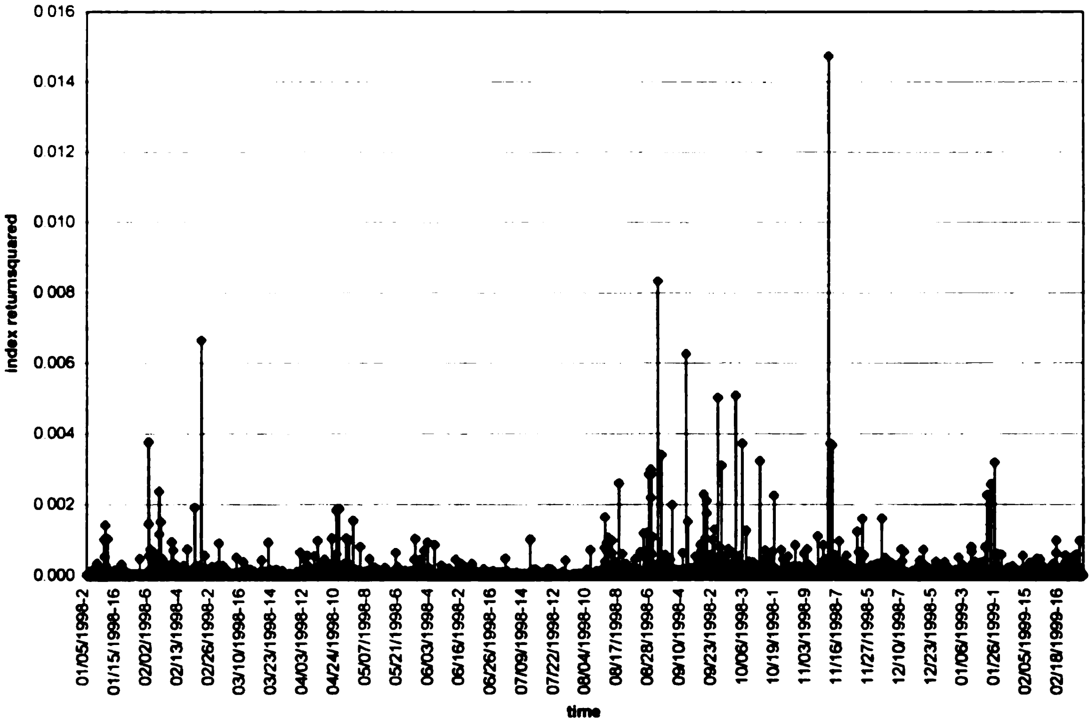

Figure 9
Index Return squared over Time

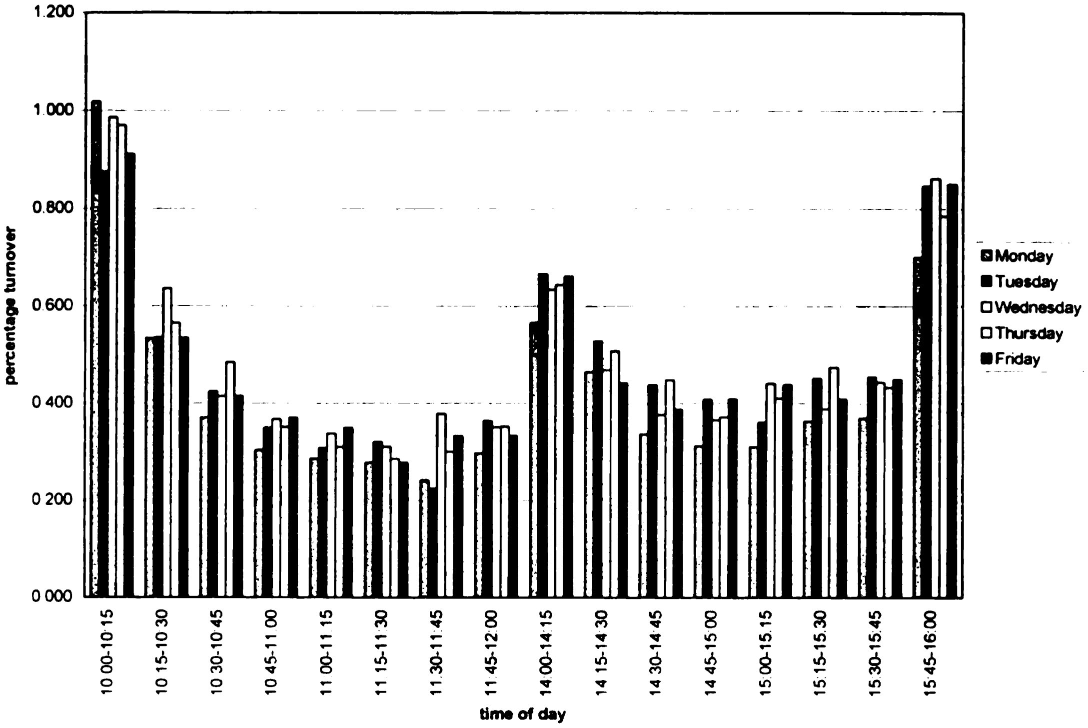

Figure 10
Average Intraday Turnover

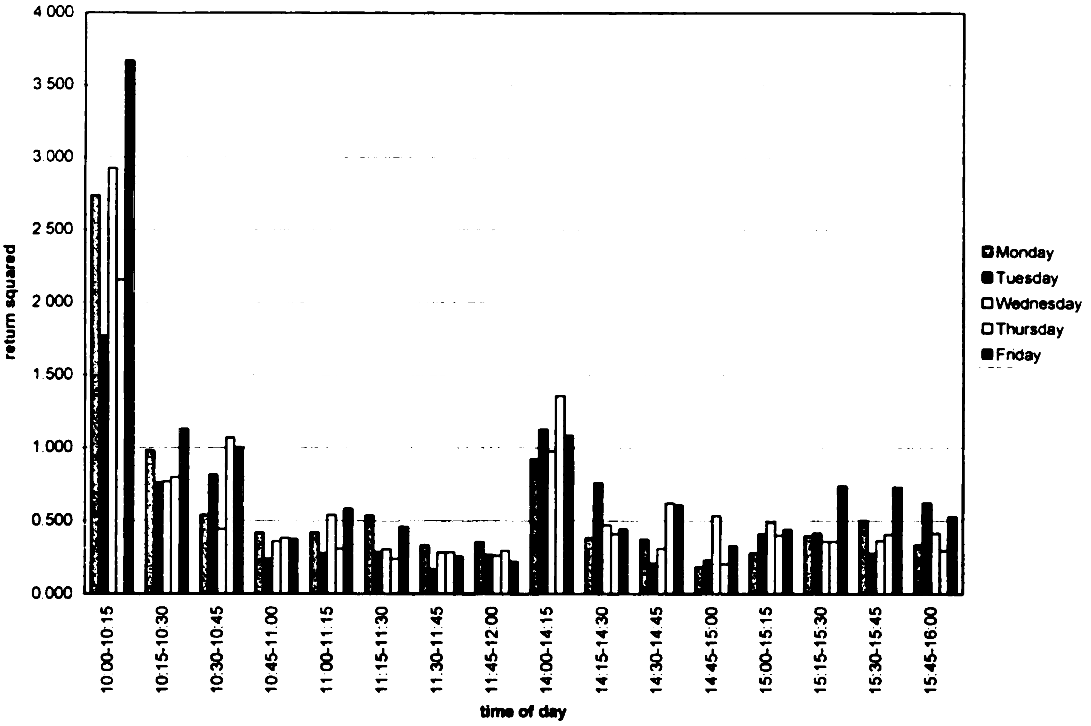

Figure 11
Average Intraday Volatility

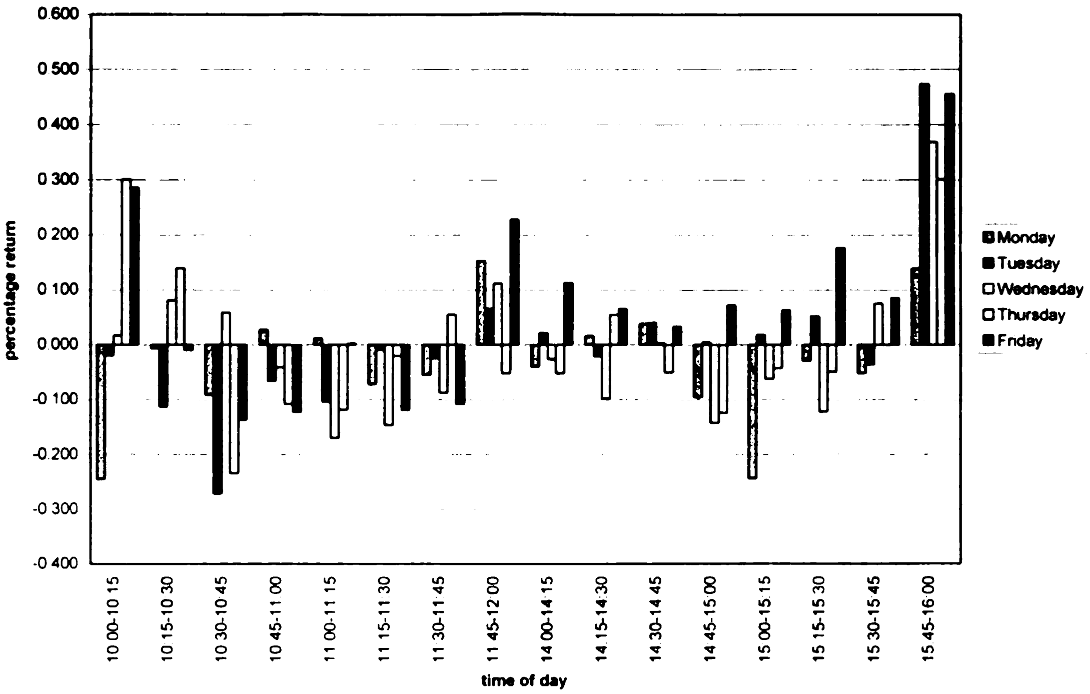

Figure 12
Average Intraday Return

APPENDIX C

DETAIL TABLES

Table 52
Unconditional and Conditional Returns for Market and Limit Orders, Investment Window of 5 Days

	Test			
	0.5	1.5	2.5	3.5
Discount	0.788	2.335	3.845	5.378
Fraction Executed	85.92	67.49	53.95	52.67
Limit Orders				
All	-2.827 [a]	-2.898 [a]	-2.955 [a]	-3.230 [a]
Executed	-3.111 [a]	-3.153 [a]	-4.351 [a]	-4.314 [a]
Unexecuted	0.285	-2.223 [a]	-0.841	-3.106 [a]
Market Orders				
All	-1.911 [a]	-2.193 [a]	-2.545 [a]	-4.117 [a]

Note: The first row reports average percentage discount from the equilibrium price at the close of the day preceding the order submission day used to determine limit buy order prices. The second row reports the fraction of limit buy orders that are naturally executed during the trading window. Rows 3-5 report unconditional, conditional on natural execution, and conditional on forced execution overall returns for limit buy orders. Row 6 reports the unconditional overall returns for market orders.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 53
Differential Returns, Investment Window of 5 Days

Part A: Unconditional

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.925 [c]	2.124 [a]	-0.422	-0.954
2	-0.401	-2.381 [a]	3.459 [a]	5.479 [a]
3	0.327	-2.092 [b]	3.131 [a]	1.336
4	-0.160	0.198	1.041 [a]	4.912 [a]
5	0.205	0.688 [b]	-2.525 [a]	2.024 [a]
6	-3.740 [a]	-2.764 [a]	3.089 [a]	3.686 [a]
7	-6.451 [a]	-4.741 [a]	-6.177 [a]	-8.131 [a]
8	1.171	1.737 [b]	-7.215 [a]	-11.710 [a]
9	-0.516 [b]	1.088 [a]	-1.796 [a]	3.936 [a]
10	-0.463	-0.792 [c]	2.731 [a]	7.842 [a]
Overall	-0.916 [a]	-0.706 [a]	-0.411	0.887 [c]
Wilcoxon p	<.0001	0.000	0.459	0.001

Part B: Conditional on Execution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	0.654	1.875 [b]	2.527	-9.021 [a]
2	-0.629	-3.831 [a]	3.297 [a]	7.285 [a]
3	0.239	0.038	2.321 [b]	1.336
4	-2.223 [b]	-0.974	1.500 [a]	4.300 [a]
5	0.258	1.279 [b]	-0.047	2.874
6	-3.650 [a]	-2.407 [a]	2.661 [a]	3.512 [a]
7	-6.451 [a]	-4.014 [a]	-10.767 [a]	-2.822 [b]
8	2.335 [a]	3.335 [a]	-11.989 [a]	7.045 [b]
9	-0.516 [b]	1.088 [a]	-3.025 [a]	7.922 [a]
10	-1.588 [a]	-3.927 [a]	-1.418	-0.717
Overall	-1.181 [a]	-0.793 [b]	-1.494 [a]	1.689 [a]
Wilcoxon p	<.0001	0.018	0.061	<.0001

Table 53-continued

Part C: Conditional on Nonexecution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	1.035	1.115	-4.749 [b]	5.007 [a]
2	-0.396	-2.000 [a]	4.006 [a]	0.619
3	-1.511	-3.577 [a]	4.127 [b]	
4	4.400 [a]	2.546 [b]	0.052	4.702 [a]
5	0.517	0.575	-3.722 [a]	2.247 [b]
6	-5.173 [a]	-4.118 [a]	10.184 [c]	11.835
7		-26.375 [c]	2.780 [c]	-18.414 [a]
8	-3.210 [b]	-2.041	-5.433 [a]	-13.603 [a]
9			0.126	2.357 [c]
10	4.107 [b]	1.510	6.838 [a]	15.043 [a]
Overall	0.355	-1.119 [b]	0.564	-0.739
Wilcoxon p	0.516	0.037	0.496	0.766

Note: For each firm the difference between subperiod average firm limit buy order return and unconditional market order return forms the basic observation.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 54
Unconditional and Conditional Returns for Market and Limit Orders, Investment Window of 7 Days

	Test			
	0.5	1.5	2.5	3.5
Discount	0.773	2.302	3.859	5.347
Fraction Executed	87.92	63.37	47.61	53.77
Limit Orders				
All	-0.710	-0.555	-0.930	-1.667 [a]
Executed	-0.402	0.699	-2.749 [a]	-3.749 [a]
Unexecuted	-1.109	-4.736 [a]	0.968	3.056 [a]
Market Orders				
All	-1.300 [c]	-1.300 [c]	-1.436 [b]	-4.007 [a]

Note: The first row reports average percentage discount from the equilibrium price at the close of the day preceding the order submission day used to determine limit buy order prices. The second row reports the fraction of limit buy orders that are naturally executed during the trading window. Rows 3-5 report unconditional, conditional on natural execution, and conditional on forced execution overall returns for limit buy orders. Row 6 reports the unconditional overall returns for market orders. The investment window is equal to 7 days in this table.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 55
Differential Returns, Investment Window of 7 Days

Part A: Unconditional

Subperiod	Test 0.5	1.5	2.5	3.5
1	0.130	0.655	0.621	-3.597 [a]
2	1.957 [a]	2.262 [a]	-2.113 [a]	0.912
3	2.528 [a]	2.178 [c]	0.478	9.683 [a]
4	2.442 [a]	2.450 [a]	-0.076	-2.452 [b]
5	2.911 [a]	2.256 [a]	3.706 [a]	2.332 [a]
6	0.340	1.188 [a]	2.290 [a]	1.742 [c]
7	-4.936 [a]	-3.810 [a]	-0.357	-3.812 [b]
8	-4.184 [a]	-5.111 [a]	3.772 [a]	5.904 [a]
9	1.844 [a]	3.154 [a]	-0.038	7.782 [a]
10	2.879 [b]	2.174 [c]	-3.309 [a]	4.843 [a]
Overall	0.590 [b]	0.745 [a]	0.506 [c]	2.340 [a]
Wilcoxon p	0.001	<.0001	0.389	0.005

Part B: Conditional on Execution

Subperiod	Test 0.5	1.5	2.5	3.5
1	0.214	5.549 [a]	-1.925	-2.240
2	0.918	1.067	-4.528 [a]	8.598 [a]
3	2.705 [a]	5.363 [a]	9.898 [a]	7.191 [b]
4	2.401 [a]	4.050 [a]	-2.500	-5.586 [c]
5	4.300 [a]	7.179 [a]	0.867	0.647
6	0.340	4.033 [a]	1.546	1.711 [c]
7	-4.049 [a]	-2.620 [a]	5.938 [a]	-0.728
8	1.295	5.763 [a]	11.912 [a]	-0.085
9	1.844 [a]	3.251 [a]	-2.606 [b]	11.372 [a]
10	3.626 [a]	5.062 [a]	-8.511 [a]	0.926
Overall	1.358 [a]	3.604 [a]	0.951 [c]	2.415 [a]
Wilcoxon p	<.0001	<.0001	0.021	<.0001

Table 55-continued

Part C: Conditional on Nonexecution

	Test			
Subperiod	0.5	1.5	2.5	3.5
1	-3.639	-10.551 [a]	2.024 [c]	-4.474 [a]
2	6.521 [a]	5.519 [a]	-1.412	-4.672 [a]
3	1.598	-0.324	-3.987 [b]	12.175 [a]
4	0.416	0.538	3.508	2.546
5	-3.427 [b]	-1.568	6.229 [a]	4.204 [a]
6		-8.368 [a]	10.361	0.300
7	-21.023 [b]	-17.904 [b]	-19.922 [a]	-16.764 [a]
8	-8.343 [a]	-8.792 [a]	0.381	11.290 [a]
9		0.220	1.613 [c]	-5.271 [a]
10	-16.518	-0.936	-1.297	9.338 [a]
Overall	-3.638 [a]	-3.490 [a]	-0.088	3.583 [a]
Wilcoxon p	0.000	0.000	0.001	<.0001

Note: For each firm the difference between subperiod average firm limit buy order return and unconditional market order return forms the basic observation.

[a] Significant at the 1 percent level.
[b] Significant at the 5 percent level.
[c] Significant at the 10 percent level.

Table 56
Market-Adjusted Differential Limit Buy Order Returns, Investment Window of 5 and 7 Days

Part A:

	Test							
	0.5		1.5		2.5		3.5	
Subperiod	η_1	η_2	η_1	η_2	η_1	η_2	η_1	η_2
1	3.430	-3.418	-0.867	1.233	-2.519 [b]	4.384 [a]	-1.359	1.649
2	-2.803 [b]	3.616 [b]	-0.955	2.531 [b]	-0.283	0.806	-2.441 [b]	4.217 [a]
3	-5.411 [b]	6.501 [a]	-2.843 [b]	6.701 [a]	-2.841 [b]	4.572 [a]		
4	-0.574	1.241	-0.610	1.910 [c]	0.050	-0.006	-0.538	0.617
5	-0.879	1.337	-0.556	1.323	-0.920 [c]	2.910 [a]	-0.079	-1.421
6	-3.505	4.003	-1.682	2.166	1.762	-1.081	16.392 [b]	-16.678 [b]
7			-11.543 [b]	11.07 [b]	-0.762	0.363	-2.620	3.535 [c]
8	-3.217 [b]	3.734 [b]	-1.444	1.668	-1.438 [c]	3.012 [b]	-0.877	7.299 [a]
9					-0.887	1.783	-2.169 [b]	6.835 [a]
10	-1.506	1.865	-1.195	2.355	-0.040	0.754	0.107	2.189
Overall	-2.050 [a]	2.385 [a]	-1.276 [a]	1.887 [a]	-0.998 [a]	1.848 [a]	-1.010 [b]	1.929 [a]

Part B:

	Test							
	0.5		1.5		2.5		3.5	
Subperiod	η_1	η_2	η_1	η_2	η_1	η_2	η_1	η_2
1	-3.001	2.272	-2.698	2.860	-1.176	0.393	-2.733 [b]	2.583
2	-0.318	0.662	-0.272	0.579	-1.165	1.848	-3.658 [a]	7.292 [a]
3	-0.149	0.665	-2.585 [c]	6.905 [a]	-1.316	2.903	1.389	-3.417
4	1.716	-1.195	2.156	-2.591	-1.279	2.371	-1.720	3.751
5	-1.636	2.154	-1.456 [c]	3.904 [a]	0.363	0.202	-0.814	1.436
6			1.670	-1.862	3.877	-3.845	2.090	-2.148
7	-14.812 [a]	15.439 [a]	-10.127 [a]	11.075 [a]	-4.581 [c]	7.326 [b]	-13.456 [a]	15.643 [a]
8	-1.897	2.455	0.038	-2.864	0.350	1.584	-0.146	4.247
9			-6.095 [c]	6.573 [b]	-0.555	1.315	-5.419 [a]	7.115 [a]
10	-18.464 [a]	19.681 [a]	-2.858 [c]	6.422 [a]	-0.161	0.588	1.800	-1.255
Overall	-1.725 [b]	1.964 [b]	-0.812	1.287 [b]	-0.639	1.359 [b]	-1.300 [b]	2.442 [a]

Note: For each firm the difference between window limit order return and average market order return during the corresponding subperiod was regressed on a constant and the difference between portfolio window limit order return and portfolio average market order return during the corresponding subperiod. The residuals from these 30 regressions were stacked to form a vector and were then regressed on a constant and a dummy that takes on the value 1 for natural execution, 0 otherwise. η_1 is the intercept, and η_2 is the coefficient of execution dummy. Subperiod and overall results are reported for each limit order test.

[a] Significant at the 1 percent level.

[b] Significant at the 5 percent level.

[c] Significant at the 10 percent level.

Table 57
Details for the Experiment of Simultaneously Submitting Limit Buy and Sell Orders at ± k Ticks from the Equilibrium Price

		2				3			
		Transaction		Inventory		Transaction		Inventory	
Stock	Subperiod	Sell	Buy	Min	Max	Sell	Buy	Min	Max
Akbnk	1	198	201	-10	6	63	65	-6	4
	2	315	345	-10	31	86	107	-6	21
	3	328	276	-55	1	113	80	-35	1
Akcns	1	234	222	-18	12	77	68	-12	7
	2	285	316	-7	32	103	126	-5	24
	3	289	247	-43	1	96	68	-28	-1
Akgrt	1	147	145	-15	9	45	43	-10	6
	2	166	188	-8	27	65	81	-5	18
	3	206	161	-45	0	91	62	-29	0
Alark	1	185	173	-16	12	75	64	-14	7
	2	187	207	-5	24	73	90	-3	17
	3	237	201	-38	1	95	72	-24	-1
Alctl	1	218	217	-9	11	66	64	-7	7
	2	188	218	-6	32	61	82	-4	22
	3	154	132	-24	3	55	41	-15	2
Arclk	1	216	210	-21	15	63	60	-13	10
	2	243	261	-6	24	83	95	-4	17
	3	238	215	-24	-1	84	68	-17	-1
Bagfs	1	270	250	-26	9	107	91	-19	6
	2	257	281	-16	25	97	113	-11	17
	3	185	178	-8	3	63	57	-6	2
Cukel	1	190	186	-10	14	67	64	-7	8
	2	175	201	-7	27	70	86	-5	17
	3	133	116	-18	-1	50	40	-11	-1
Dohol	1	318	305	-17	21	79	70	-11	14
	2	325	336	-6	23	92	101	-4	15
	3	353	331	-24	1	97	82	-16	1
Efes	2	280	318	-3	42	94	120	-2	29
	3	301	262	-40	1	88	65	-24	-1
Enka	1	155	151	-15	9	47	43	-11	5
	2	177	186	-5	31	78	86	-3	22
	3	225	190	-36	7	95	70	-25	4
Eregl	1	249	244	-17	13	78	74	-11	9
	2	250	279	-10	29	79	97	-6	18
	3	195	187	-10	8	67	61	-8	5
Garan	1	248	248	-7	18	68	67	-6	12
	2	259	287	-6	30	78	96	-4	20
	3	355	291	-65	0	125	81	-44	-1

Table 57-continued

		2				3			
		Transaction		Inventory		Transaction		Inventory	
Stock	Subperiod	Sell	Buy	Min	Max	Sell	Buy	Min	Max
Hurgz	1	278	256	-27	7	112	93	-22	5
	2	288	305	-14	18	99	112	-10	13
	3	305	274	-32	0	97	75	-22	0
Ihlas	1	249	249	-12	20	89	89	-8	14
	2	246	273	-7	29	78	93	-4	18
	3	208	202	-8	4	55	50	-6	2
Isctr	1	232	242	-2	12	70	78	-1	8
	2	297	314	-5	19	93	105	-3	13
	3	310	279	-35	1	96	76	-22	1
Kchol	1	217	216	-8	18	68	68	-4	12
	2	233	253	-8	28	77	91	-4	19
	3	306	274	-28	6	81	61	-20	-1
Migrs	1	143	132	-17	9	46	38	-11	6
	2	187	196	-8	18	72	77	-7	11
	3	208	165	-44	1	83	54	-30	0
Nthol	1	211	207	-10	15	71	69	-5	9
	2	233	264	-1	36	67	88	0	24
	3	162	143	-20	0	60	49	-12	0
Otosn	1	118	126	-2	18	40	44	-2	11
	2	144	173	-3	32	51	70	-2	21
	3	184	153	-32	2	70	50	-20	1
Petkm	1	252	242	-17	3	89	83	-11	2
	2	188	214	-1	27	66	83	0	17
	3	239	191	-48	0	100	69	-31	0
Ptofs	1	295	286	-18	11	95	89	-11	7
	2	244	249	-5	15	89	94	-3	10
	3	298	267	-32	10	123	98	-25	6
Sahol	1	186	178	-16	8	47	42	-10	5
	2	305	325	-8	21	82	96	-5	15
	3	350	296	-56	1	113	80	-34	-1
Thyao	1	345	326	-24	5	109	97	-16	3
	2	241	257	-7	19	86	96	-5	11
	3	167	153	-15	6	52	45	-8	4
Toaso	1	239	239	-9	18	79	79	-5	12
	2	262	286	-3	27	102	120	-2	20
	3	224	208	-21	1	85	75	-13	1
Tuprs	1	386	370	-22	14	120	108	-15	8
	2	327	336	-11	19	98	104	-7	12
	3	201	173	-29	0	59	41	-18	0

Table 57-continued

		2				3			
		Transaction		Inventory		Transaction		Inventory	
Stock	Subperiod	Sell	Buy	Min	Max	Sell	Buy	Min	Max
Uzel	1	214	203	-12	11	64	58	-7	8
	2	269	284	-18	24	97	110	-11	18
	3	229	212	-17	4	84	71	-13	2
Vestl	1	232	206	-34	10	81	63	-22	7
	2	269	270	-14	13	105	108	-9	10
	3	243	208	-35	0	100	80	-20	0
Ykbnk	1	206	201	-14	10	69	66	-9	6
	2	424	446	-24	22	151	167	-17	16
	3	409	355	-57	0	134	99	-37	0

REFERENCES

References

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 3, 593-624.

Ahn, Hee-Joon, Charles Q. Cao, and Hyuk Choe, 1996, Tick size, spread, and volume, *Journal of Financial Intermediation* 5, 2-22.

Aitken, Michael, Philip Brown, Christine Buckland, H.Y. Izan, and Terry Walter, 1996, Price clustering on the Australian Stock Exchange, *Pacific-Basin Finance Journal* 4, 297-314.

Angel, James J., 1997, Tick size, share prices, and stock splits, *Journal of Finance* 52, 655-81.

Anshuman, Ravi, and Avner Kalay, 1998, Market making with discrete prices, *Review of Financial Studies* 11, 81-109.

Arnold, Tom M., and Mark Lipson, 1998, Tick size and limit order execution: An examination of stock splits, working paper, University of Georgia.

Bacidore, Jeffrey M., 1997, The impact of decimalization on market quality:an empirical examination of the Toronto Stock Exchange, *Journal of Financial Intermediation* 6, 92-120.

Bagehot, W.,1971, The only game in town, *Financial Analyst Journal* 27, 12-14.

Ball, Clifford, Walter Torous, and Adrian Tschoegl, 1985, The degree of price resolution: The case of the gold market, *Journal of Futures Markets* 5, 29-43.

Bessembinder, Hendrik, 1997, The degree of price resolution and equity trading costs, *Journal of Financial Economics* 45, 9-34.

Bhattacharya, Utpal, and Matthew Spiegel, 1990, Anatomy of a market failure: NYSE trading suspensions (1974-1988), working paper, University of Iowa.

Biais, Bruno, Pierre Hillion, and Chester Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance* 50, 1655-89.

Blume, Lawrence, David Easley, and Maureen O'Hara, 1994, Market statistics and technical analysis: the role of volume, *Journal of Finance* 49, 153-81.

Booth, G. Geoffrey, Juha-Pekka Kallunki, Ji-Chai Lin, and Teppo Martikainen, 2000, Internalization and stock price clustering: Finnish evidence, *Journal of International Money and Finance*, Forthcoming.

Brown, Sharon, Paul Laux, and Barry Schachter, 1991, On the existence of an optimal tick size, *Review of Futures Markets* 10, 50-72.

Chan, K. C., and Chuan-Yang Hwang, 1998, The impact of tick size on market quality: an empirical investigation of the stock exchange of Hong Kong, working paper, Hong Kong University of Science and Technology.

Cheung, Yan-Leung, Richard Yan-Ki Ho, Peter Pope, and Paul Draper, 1994, Intraday stock return volatility: The Hong Kong evidence, *Pasific-Basin Finance Journal* 2, 261-76.

Chordia, Tarun, and Avanidhar Subrahmanyam, 1995, Market making, the tick size, and payment-for-order flow: theory and evidence, *Journal of Business* 68, 543-75.

Christiano, Lawrence J., and Lars Ljungqwist, 1988, Money does Granger-cause output in the bivariate money-output relation, *Journal of Monetary Economics* 22, 217-35.

Christie, William G., and Paul H. Schultz, 1994, Why do NASDAQ market makers avoid odd-eighth qoutes? *Journal of Finance* 49, 1813-40.

Christie, William G., Jeffrey H. Harris, and Paul H. Schultz, 1994, Why did NASDAQ market makers stop avoiding odd-eighth qoutes? *Journal of Finance* 49, 1841-60.

Clark Peter K., 1973, A subordinated stochastic process model with finite variance for speculative prices, *Econometrica* 41, 135-55.

Cohen, Kalman, Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1981, Transaction costs, order placement strategy, and existence of the bid-ask spread, *Journal of Political Economy* 89, 287-305.

Copeland, Thomas E., 1976, A model of asset trading under the assumption of sequential information arrival, *Journal of Finance* 31, 1149-68.

Domowitz, Ian, 1993a, A taxonomy of automated trade execution systems, *Journal of International Money and Finance* 12, 607-31.

______________, 1993b, Automating the price discovery process:some international comparisons and regulatory implications, *Journal of Financial Services Research* 6, 305-26.

______________, 1995, Financial market automation and the investment services directive, in R. A. Schwartz, ed.: *Global Equity Markets: Technological, Competitive and Regulatory Challenges*, (Irwin Professional Publishing, Burr Ridge, Ill.).

Dutta, Prajit K., and Ananth Madhavan, 1995, Price continuity rules and insider trading, *Journal of Financial and Quantitative Analysis* 30, 199-221.

Easley, D., M. O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Epps, Thomas W., 1975, Security price changes and transaction volumes: theory and evidence, *American Economic Review* 65, 586-97.

Epps, Thomas W., and Mary L. Epps, 1976, The stochastic dependence of security price changes and transaction volumes: implications for the mixtures of distributions hypothesis, *Econometrica* 44, 305-21.

Feige, Edgar L., and Douglas K. Pearce, 1979, The causal relationship between money and income: some caveats for time series analysis, *Review of Economics and Statistics* 61, 521-33.

Foster, Douglas F., and S. Viswanathan, 1990, A theory of the interday variations in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, 593-624.

______________, 1993a, The effect of public information and competition on trading volume and price volatility, *Review of Financial Studies* 6, 23-56.

______________, 1993b, Variations in trading volume, return volatility, and trading costs: evidence on recent price formation models, *Journal of Finance* 48, 187-211.

Foster, Andrew J., 1995, Volume-volatility relationships for crude oil futures markets, *Journal of Futures Markets* 15, 929-51.

Gallant, A. Ronald, Peter E. Rossi, and George Tauchen, 1992, Stock prices and volume, *Review of Financial Studies* 5, 199-242.

Geweke, John, Richard Meese, and Warren Dent, 1983, Comparing alternative tests of causality in temporal systems: analytic results and experimental evidence, *Journal of Econometrics* 21, 161-94.

Glosten, L., and P. Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogenously informed traders, *Journal of Financial Economics* 13, 71-100.

Glosten, Lawrence R.,1995, Is the electronic open limit order book inevitable? *Journal of Finance* 49, 1127-61.

Godek, Paul E., 1996, Why NASDAQ market makers avoid odd-eighth quotes, *Journal of Financial Economics* 41, 465-74.

Goodhardt, C., and R. Curcio, 1991, The clustering of bid/ask prices and the spread in the foreign exchange market, discussion paper 110, London School of Economics.

Granger, C. W. J. and O. Morgenstern, 1963, Spectral analysis of New York Stock Market prices, *Kyklos* 16, 1-27.

Granger, C. W. J., 1969, Investigating causal relations by econometric models and cross-spectral methods, *Econometrica* 37, 424-38.

Grossman, Sanford, Merton Miller, Kenneth Cone, and Daniel Fischel, 1997, Clustering and competition in asset markets, *Journal of Law and Economics* 40, 23-60.

Gwilym, Owain, Andrew Clare, and Stephen Thomas, 1998a, Extreme price clustering in the London equity index futures and options markets, *Journal of Banking and Finance* 22, 1193-1206.

______________,1998b, Price clustering and bid ask spreads in international bund futures, *International Financial Markets, Institutions & Money* 8, 377-91.

Gwilym, Owain, David McMillan, and Alan Speight, 1999, The intraday relationship between volume and volatility in LIFFE futures markets, *Applied Financial Economics* 9, 593-604.

Hamao, Y., and J. Hasbrouck, 1995, Securities trading in the absence of dealers: trades and quotes on the Tokyo Stock Exchange, *Review of Financial Studies* 8, 849-78.

Hamon, Jacques, Puneet Handa, Bertrand Jacquillat, and Robert A. Schwartz, 1995, Market structure and the supply of liquidity, in R. A. Schwartz, ed.: *Global*

Equity Markets: Technological, Competitive and Regulatory Challenges, (Irwin Professional Publishing, Burr Ridge, Ill.).

Hamon, Jacques, Bertrand Jacquillat, and Robert A. Schwartz, 1995, A program to increase the liquidity of shares in the French equity market, in R. A. Schwartz, ed.: *Global Equity Markets: Technological, Competitive and Regulatory Challenges*, (Irwin Professional Publishing, Burr Ridge, Ill.).

Hameed, Allaudeen, and Eric Terry, 1998, The effect of tick size on price clustering and trading volume, *Journal of Business Finance and Accounting* 25, 849-67.

Hamon, Jacques, Puneet Handa, Bertrand Jacquillat, and Robert A. Schwartz, 1993, The profitability of limit order trading on Paris Stock Exchange, working paper, New York University.

Handa, Puneet, and Robert A. Schwartz,1994, Limit order trading, *Journal of Finance* 51, 1835-61.

______________, 1996, How best to supply liquidity in an electronic environment: is disintermediation a desirable route? *Journal of Portfolio Management* 22, 44-51.

Handa, Puneet, Robert A. Schwartz, and Ashish Tiwari, 1994, Quote setting and price formation in an order driven market, working paper, University of Iowa and City University of New York.

______________, 1998, The ecology of an order-driven market, *Journal of Portfolio Management* 24, 47-55.

Hanna, Mark, 1978, Security price changes and transaction volumes: additional evidence, *American Economic Review* 68, 692-95.

Harris, Lawrence, 1986, A transaction data study of weekly and intradaily patterns in stock returns, *Journal of Financial Economics* 16, 99-117.

______________, 1991, Stock Price clustering and discreteness, *Review of Financial Studies* 4, 389-415.

______________, 1994, Minimum price variations, discrete bid ask spreads, and quotation sizes, *Review of Financial Studies* 7, 149-78.

______________, 1997, Decimalization: a review of the arguments and evidence, working paper, University of Southern California.

Harris, Lawrence, and Joel Hasbrouck, 1996, Market vs. limit orders: the superdot evidence on order submission strategy, *Journal of Financial and Quantitative Analysis* 31, 213-31.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.

Haugh, Larry D., 1976, Checking the independence of two covariance stationary time series: a univariate residual cross-correlation approach, *Journal of the American Statistical Association* 71, 378-85.

Hedvall, Kaj, Jonas Niemeyer, and Gunnar Rosenqvist, 1997, Do buyers and sellers behave similarly in a limit order book? A high-frequency data examination of the Finnish stock exchange, *Journal of Empirical Finance* 4, 279-93.

Ho, Richard Yan-ki, Yan-Leung Cheung, and Daniel W.W. Cheung, 1993, Intraday prices and trading volume relationship in an emerging Asian market–Hong Kong, *Pasific-Basin Finance Journal* 1, 203-14.

Hollifield, Burton, Robert A. Miller, and Patrik Sandas, 1999, An empirical analysis of a limit order market, working paper, Carnegie Mellon University and University of Pennsylvania.

Hopewell, Michael H., and Arthur L. Schwartz, 1978, Temporary trading suspensions in individual NYSE securities, *Journal of Finance* 33, 1355-73.

Huang, Roger D., and Hans R. Stoll, 1991, Major world equity markets: current structure and prospects for change (New York University Salamon Center, New York, NY).

International Finance Corporation, Emerging stock markets factbook 1999, (International Finance Corporation, Washington, DC).

Jain, Prem C., and Gun Ho Joh, 1988, The dependence between hourly prices and trading volume, *Journal of Financial and Quantitative Analysis* 23, 269-83.

Jennings, Robert H., Laura T. Starks, and John C. Fellingham, 1981, An equilibrium model of asset trading with sequential information arrival, *Journal of Finance* 36, 143-61.

Karpoff, Jonathan M.,1986, A theory of trading volume, *Journal of Finance* 41, 1069-87.

______________, 1987, The relation between price changes and trading volume: a survey, *Journal of Financial and Quantitative Analysis* 22, 109-26.

Lamoureux, Christopher G., and William D. Lastrapes, 1990, Heteroskedasticity in stock return data: volume versus GARCH effects, *Journal of Finance* 45, 221-29.

Lau, Sie Ting, and Thomas H. McInish, 1995, Reducing tick size on the stock exchange of Singapore, *Pacific-Basin Finance Journal* 3, 485-96.

Lee, Charles M., Mark J. Ready, and Paul J. Seguin,1994, Volume, volatility, and New York Stock Exchange trading halts, *Journal of Finance* 49, 183-214.

McInish, Thomas H., and Robert A. Wood, 1995, Hidden limit orders on the NYSE, *Journal of Portfolio Management 21*, 19-26.

Najand, Mohammad, and Kenneth Yung, 1991, A GARCH examination of the relationship between volume and price variability in futures markets, *Journal of Futures Markets* 11, 613-21.

Niederhoffer, Victor, 1965, Clustering in stock prices, *Operations Research* 13, 258-65.

______________, 1966, A new look at clustering in stock prices, *Journal of Business* 39, 309-13.

O'Hara, Maureen, 1994, Market Microstructure Theory (Blackwell Publishers, Malden, MA).

Osborne, M. F. M., 1962, Periodic structure in the brownian motion of stock prices, *Operations Research* 10, 345-79.

Parlour, Christine A.,1998, Price dynamics in limit order markets, *Review of Financial Studies* 11, 789-816.

Pierce, David A., and Larry D. Haugh, 1977, Causality in temporal systems: characterizations and a survey, *Journal of Econometrics* 5, 265-93.

Porter, David, and Daniel Weaver, 1997, Tick size and market quality, *Financial Management* 26, 5-26.

Sandas, Patrik, 1999, Adverse selection and competitive market making: empirical evidence from a pure limit order market, working paper, University of Pennsylvania.

Sims, Christopher A., 1972, Money income and causality, *American Economic Review* 62, 540-52.

Smirlock, Michael, and Laura Starks, 1985, A further examination of stock price changes and transaction volume, *Journal of Financial Research* 8, 217-25.

Stickel, Scott E., and Robert E. Verrecchia, 1994, Evidence that trading volume sustains stock price changes, *Financial Analysts Journal* 50, 57-67.

Stock, James H., and Mark W. Watson, 1989, Interpreting the evidence on money-income causality, *Journal of Econometrics* 40, 161-81.

Tauchen, George E., and Mark Pitts, 1983, The price variability-volume relationship on speculative markets, *Econometrica* 51, 485-505.

Wang, Jiang, 1994, A model of competitive stock trading volume, *Journal of Political Economy* 102, 127-68.

Wood, Robert A., Thomas H. McInish, and J. Keith Ord, 1985, An investigation of transactions data for NYSE stocks, *Journal of Finance* 40, 723-41.

MICHIGAN STATE UNIVERSITY LIBRARIES
3 1293 02112 5814