INVESTOR HETEROGENEITY AND EARNINGS ANNOUNCEMENTS

by

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Dedicated to the memory
of my brother and father.

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CHAPTER I

INTRODUCTION

Over the past twenty-five years, much of financial accounting research has examined the market reaction to financial reports (e.g., the earnings-return relation), and added to our understanding of the usefulness of accounting information. More recently, a significant line of inquiry has also developed around the information asymmetry prevalent in the market at the time of an earnings news release, and how it influences market reaction to earnings news, as measured by bid-ask spreads, depths and block trades.[1]

In this project, I study the trading reaction following an earnings release, and focus on the reaction of different investor groups. I address two questions relating to investor behavior. The first question is : "How does the trading reaction of different investor groups differ?" Specifically, my purpose is to understand the effect of information asymmetry, and to determine whether (or how) it gives different investor groups differential incentives to trade. This is followed up with a second question investigating the economic effects of such trading behavior: "Who profits from earnings news?"

The first question requires a study of the trading behavior of different investor groups following earnings announcements. Conventional wisdom suggests that earnings announcements resolve uncertainty about firm value by providing value-relevant public information. The alternate view is that there is an increase in information asymmetry in the market following an information release, to the extent that investors are surprised by

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[1]See for example, Daley, Hughes and Rayburn (1992), Lee, Mucklow and Ready (1992), Seppi (1992), and Skinner (1992).

the new information (See Kim and Verrecchia, 1994; and Skinner, 1992). Under this alternate view, some traders, perhaps because they specialize in the stock, are especially adept at processing the firm's earnings information. If there is a big surprise, these traders are able to increase their information advantage by processing the implications of the announcement more quickly and expertly than other market participants. These studies predict that volume is driven up by this dispersion in belief changes following an announcement. Thus, the trading behavior of investor groups following an announcement reflects the information asymmetry effect.

The second question looks at the profitability of the trading strategies adopted by investor groups in the post-announcement period. Specifically, I investigate whether any group of investors reaps the benefits of its information advantage, and whether there is a class of disadvantaged investors that tends to lose in the trading following earnings announcements.

Another related question I investigate deals with trading before an earnings announcement. Is there any information leakage before the earnings announcement that is exploited by any of the trading groups?

The questions addressed in this study are important to accountants because, as providers of general purpose financial reports, they must consider the needs of a wide constituency of users.[2] Yet little is known about how subgroups of users differ in their reaction to accounting information. By addressing these two questions on how different investor groups react to earnings information, I attempt to bridge this gap. The results of this study should provide insights into how effective news announcements are in meeting the needs of different investor groups. The second part of my thesis should show whether

[2]The FASB's Statement of Financial Accounting Concepts (SFAC) lists no less than three different user groups: potential investors, creditors and others making rational investment, credit or other decisions.

any class of investors is economically disadvantaged by the present structure of information flow. This question should be of interest to SEC regulators.[3] The wealth distribution effects of news release should be of concern to exchange officials who specify disclosure requirements for listed companies, and who are interested in encouraging small investors to trade.[4]

To identify the different trader groups and to study their trading patterns, I use a new data base of trades, orders, reports and quotes (the TORQ data set) in this study. This data set is unique in that it identifies incoming orders by the type of trader (individuals, institutions, exchange members, program trades)[5], the type of order (market or limit) and the direction of trade (buy or sell). Moreover, it separately identifies the participants on the buy side and sell side of each trade by these investor categories, and keeps track of whether their orders were partially or fully executed. This data set is limited in its coverage, both intertemporally (only three months) and cross-sectionally (only a size-stratified sample of 144 firms). Moreover, the uncoded trader type orders potentially reflects the trading of two or more classes of traders. Nevertheless, it still offers an unprecedented opportunity to study investor behavior at a micro level, and allows the researcher to investigate empirical questions related to investor heterogeneity that have not been explored before.

Earlier studies that have looked at volume and trading reaction have tended to focus more on the information content of trading volume. These include Beaver (1968),

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[3]E.g., Recently the SEC announced a new study "Market 2000", to evaluate market directions and regulations to consider (among others) the issue of investor protection.

[4]The NYSE fact book for the year 1991 lists a number of initiatives the exchange has taken to increase the participation of individual investors.

[5]The TORQ data set identifies trader type by coding each trade. However, about 16% of all trades in the TORQ data set are not coded.

who observed that as information providers, accountants are interested not only in the aggregate wealth effect of news events as measured by the price reaction, but also in the reaction of individual users, which is better captured by trading volume.[6] Subsequent studies show that the volume reaction to earnings persists for several days (Morse, 1981), and that both the magnitude and duration of the volume reaction increase with unexpected earnings and decrease with firm size (Bamber, 1986, 1987).

More recently, Cready (1988), Cready and Mynatt (1991), and Lee (1992) use intraday transactions data to document differential behavior in the volume reaction of small and large dollar-valued trades. The focus of these intraday studies has been on investor reaction to accounting news, as reflected in the abnormal trading around the news release date. While these studies focus on investor heterogeneity in the market place, they cannot accurately identify the different investor groups. By using the TORQ data set this study is able to specifically categorize trades into five major investor groups. Moreover, I investigate the profitability of the trading strategies adopted by different investor groups—a question that has not been studied before.

The results of this study show that all investor groups identified by the data set increased their *total* (active plus passive) trading volume in the post announcement period.[7] Analysis of *active* trading volume shows that individuals, institutions and members increase their active trading in the post announcement period. Analysis of *net active* volume (active minus passive) reaction shows that specialists tend to be more

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[6]For a summary of different theories of volume see Karpoff (1987). See Jang and Ro (1989), and Holthausen and Verrecchia (1990) for a critique and analysis in an event study context. These studies show that interpreting volume as direct evidence of information may be simplistic. Rather, volume is modeled to be a function of several factors including dispersion of prior beliefs (Varian, 1987) and dispersion or consensus of belief changes.

[7] The terms active, net active, passive and total trading volume are defined in Chapter IV.

passive in this period. These results indicate that sophisticated traders take active positions which are often filled by naive individual investors, and by the specialist.

The *proportional total* trading volume, i.e., the volume of an investor group expressed as a proportion of the total period volume, does not show a sustained pattern of increase or decrease. This implies that all traders increased their *total* volume proportionately. Analysis of the active side of trades shows that institutional traders increase their *proportion of active trading* in this period. In contrast, the *proportion of active trading* by individuals goes down. The active proportional trading results are weakly significant. These results show the heterogeneity of reaction of different investor groups following an earnings announcement.

Analysis of the returns to trading by investor groups in select post-announcement periods shows that institutional investors earn a significant return from their trade over a two day period. Large individual investors (> $10,000) earn significant returns in the first hour after announcement, but the two day return to this group is insignificant. This suggests that individual traders with superior knowledge wait for the announcement to break to trade on their knowledge. The analysis of returns also show that institutional investors and members anticipate stock price movements over the two days following the earnings announcement.

To set up the research methodology followed in this study, I investigate two methodological issues relating to market microstructure. It is fairly common in the literature to use trading sizes as a proxy for different classes of investors. I provide evidence on the trading sizes preferred by different classes of investors. In the process, I discuss the success and pitfalls of the Cready (1988) and Lee (1992) method of separating small investors. This should be of interest to researchers using intraday data that is not as finely partitioned as the TORQ data set. Secondly, while I use the Lee-Ready (1991) algorithm to identify the "active" side of each trade (i.e., the side that initiates a trade), I provide an analysis of the efficiency of the Lee-Ready algorithm.

The rest of this dissertation is organized as follows. The next chapter develops the research questions. Chapter III deals with data description and sample selection. Chapter IV describes the methodology used to test the hypotheses and addresses some methodological questions pertaining to the use of and inferences drawn from intraday data. In Chapter V the results of the analyses are presented and discussed. Chapter VI summarizes the findings, and discusses possible future research. There are four appendices. The first provides a description of the institutional details of a modern day exchange such as the NYSE. The second provides a detailed description of the files in the TORQ data set. The third provides a description of the Lee-Ready algorithm for determining the active side of a trade. The fourth describes the rules used to determine the active side of a trade using the TORQ data base.

CHAPTER II

HYPOTHESES FORMULATION

Theories of Volume

Prior studies have shown that earnings announcements are accompanied by abnormally high trading volume. Beaver (1968) interpreted this by observing that volume "reflects the changes in expectations of individual investors." Thus, volume reactions reflect a lack of consensus among market participants and capture changes in portfolio positions that may not be manifested in price changes.

This view has been subject to debate. Watts and Zimmerman (1986) argue that the problem is "the lack of an economic theory of volume." Holthausen and Verrecchia (1990) provide an economic rationale for studying volume by showing that both unexpected price changes and volume are influenced by informedness, the extent to which market participants become more knowledgeable, and consensus, the extent of agreement among participants. Zeibart (1990) shows that the degree of change in abnormal trading activity is positively associated with both the change in the level of consensus of analysts' revisions, and the absolute value of the percentage revision in their mean forecasts that proxies aggregate belief. Varian (1987) shows that volume is a function of the dispersion of prior beliefs, though he does not define the role of information in his analysis. Jang and Ro (1989) show that trading volume is a function of factors such as dispersion in belief changes among investors, rather than belief changes per s . They argue that since the possibility of no significant price change exists, a simultaneous volume effect study is necessary to assess information content.

Recently, there has been an increased interest in studying volume to determine how different classes of investors may react differently to earnings news. Kim and Verrecchia (1994) show that earnings announcements provide information that allow certain traders to make judgments about a firm's performance that are superior to the judgments of other traders. As a result, there may be more information asymmetry at the time of the announcement than in non-announcement periods. Informed opinions resulting from the public disclosure may lead to an increase in trading volume.

There is some empirical evidence in Cready (1988) and Lee (1992) that shows the differential behavior in the volume reaction of small and large dollar valued trades. Lee (1992) shows that the reaction of the small dollar valued trades is significantly different from the behavior of large dollar valued trades. However, the question remains whether the small dollar valued trades are small traders, and the large dollar valued trades are institutional traders. Cready (1988) shows that the mean trade size following an announcement is larger than the non-announcement period trade size. He presents this as evidence that large (institutional) investors are more active in the post-announcement period. While the focus of these intraday studies have been on the reaction of different investor groups to earnings news, they cannot identify accurately the different investor groups.

Heterogeneity of Investor Group Reaction to Earnings News

Kim and Verrecchia (1994), hereafter referred to as KV, speculate that to the extent that investors are surprised by new information in an earnings release, there may be an increase in the level of information asymmetry. Under this view, some traders who specialize in the stock and have special knowledge about a firm, may be able to increase their information advantage by processing the implications of the announcement more quickly and expertly than other market participants. They trade to take advantage of their superior information and drive the volume up. Under this view, volume is driven up by the dispersion in belief changes following an announcement.

To provide a better understanding of the hypotheses on trading behavior that follow later in this chapter, I have described the institutional details of the market place in Appendix A to illustrate the market microstructure details that are relevant in understanding trading and price reactions in the market.[8] The rules and procedures that govern the market place may have a significant effect on trading behavior and prices in the market.

In my sample, I identify seven different categories of traders: individuals, institutions, exchange members other than specialists, specialists, program trades, intermarket trades and a residual (mostly floor trades) category.[9] I then rely on popular wisdom to classify them by their sophistication level, i.e., their ability to process and react to information in an earnings announcement. I use this classification to predict their trading behavior.

To predict the nature of their trading, I follow Holden and Subrahmanyam (1992) who suggest that in a large market, competing informed traders with short-lived private information should trade aggressively, i.e., be liquidity demanders. In my tests, I study whether the investor groups identified as sophisticated tend to be liquidity demanders, i.e., initiate trades following an earnings release.

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[8]For more information on trading procedures at the NYSE, see Hasbrouck and Sosebee (1992), and Hasbrouck, Sofianos, and Sosebee (1993).

[9]A more detailed description of how these categories are coded is given in Appendix B.

In keeping with the popular wisdom, **individual investors** are classified as unsophisticated.[10] Cready (1988) and Lee (1992) show that the reaction of the smaller valued trades (which proxies for small traders in their study) is more naive. Here I use a direct proxy—orders placed by individuals that are executed (coded in the TORQ data set)—to verify the reaction of individual traders as a separate class of investors.

Institutional investors typically hold larger stakes and have professional managers managing their investments. They are more likely to posses the technology and resources to react quickly to information in earnings news. I expect to see swifter trading reaction to earnings news from institutional investors.

Program trades represent a sophisticated segment of the market, but their sophistication is typically directed toward arbitrage trades. The NYSE defines program trading as "any trading strategy involving the simultaneous or nearly simultaneous purchase or sale of fifteen or more stocks with a total aggregate value of one million dollars or more."[11] For this reason, it is expected that program traders tune their strategies to avail of portfolio arbitrage opportunities in relation to indexes and futures markets, and the volume generated by program trades is not likely to be correlated with an earnings announcement. I expect to find results in confirmation of this argument—that these trades are neither significantly net active or passive in this period.

Trades by **Exchange members** (classified to include brokerage houses other than specialists) is expected to be sophisticated. They tend to have large research departments and analysts regularly following several industries and stocks. It is anticipated that they will analyze information in announcements swiftly.

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[10]For example, this belief is implicit in the SEC study "Market 2000", one of the goals of which is to provide better protection to small investors.

[11]See Hasbrouck, Sofianos and Sosebee (1993).

Specialist trades are governed by stabilization rules, and market making requirements. As market makers they are intensely aware of changes in stock value, but since they are required to provide liquidity during periods of uncertainty, it is likely that often they may be on the passive side of trades in this period. According to the 1991 NYSE fact book, each specialist is expected "to stabilize stock price movements by buying and selling from his own account against the prevailing trend of the market. Specialists' stabilization rate, the percentage of shares purchased at prices below or sold at prices above the last different price, was 80.9% in 1991." Consequently for the purpose of this study, I predict that the trading activity of specialists should be largely passive.

Some trades on the NYSE are the result of **inter-market** transactions. However, it is difficult to gauge the relative sophistication of the participants in such a trade, and therefore, difficult to predict whether inter-market trades (with NYSE as the executing or committing market) are likely to be more sophisticated. Consequently, I do not make any predictions about their trading behavior.

After the TORQ trades have been classified into the six categories above, there remain some uncoded trades that are not classifiable. Discussions with exchange officials suggest that these may consist mainly of floor trades. It is expected that floor traders typically represent sophisticated investors, who find it to their advantage to employ the floor traders though it is costlier to them.[12] Brown, Clinch and Foster (1991) quote anecdotal evidence to suggest that floor traders are among the first to react to earnings information. However, in view of the ambiguity of classification, I make no predictions regarding the trading behavior of the residual (floor) category.

In summary, I expect individual traders to exhibit unsophisticated behavior. I expect institutional and member (other than specialist) trades to exhibit sophisticated

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[12]See Appendix A for an example.

behavior. Program trades represent a different type of sophistication, and may not derive any advantage from information asymmetry during earnings announcements. Hence, their trading may not appear sophisticated. Specialists, because of their unique position, should be net passive in this period. It is difficult to predict the behavior of intermarket trades and uncoded trades.

For the first hypothesis, I assess the systematic difference in trading observed among five trader groups: individuals, institutions, members, program trades and specialists. I analyze the trading behavior of these investor groups by observing their trading reaction in each half-hour until the end of the day following the announcement at select post announcement intervals. The hypothesis stated in null form is :

(H1) **Investor groups do not differ in their volume reaction and speed of response to earnings news.**

In the post announcement period I expect to see trading volume reaction vary with the level of sophistication of the trading group. Hence, I test to see if the institutional reaction is swift and strong, i.e., there is significant abnormal volume in the periods immediately following the news announcement. I test to see if the individual reaction is slower and weaker. To provide an analysis of the Lee criterion for segmenting trades on the basis of value, I further classify the trading of individual traders into trades below $10,000 and trades greater than or equal to $10,000, in my investigation of the trading reaction of individuals. I verify if the program trading response is insignificant, indicating a lack of correlation to the news in the announcement. I also study specialist trades to see if they play a larger role in providing liquidity in the period immediately after the announcement. This ties in with the argument that uncertainty in the market immediately after an announcement may reduce available liquidity and cause the specialist to provide a substantial portion of the liquidity for any trades that take place. Further, I verify the trading volume prior to an announcement to study if there is leakage of information prior to the earnings release.

Profitability of Trading Strategies

Next, I assess the wealth distribution consequence of trading to the investor groups. The SEC regulators and exchange officials are concerned with the question of providing a level playing field. If, as hypothesized, any of the trading groups enjoys an information advantage after the announcement that they can trade on, then it may be expected that their trading strategy should yield positive returns. I compute trading returns earned by each investor group from trades in select intervals that range from half-hour periods to periods that extend to the end of the following day. In computing the returns, I assume that all transactions are unraveled at the end of the day following the announcement. Thus, the typical holding period for computing returns starts from the time of the transaction and ends at the end of the day following the announcement. In other words, I compute the returns as if buyers hold their stocks from the moment of purchase to the end of the day following the announcement. Similarly, I assume that sellers go short on their sales, and cover their short sales at the end of the day following the announcement. Each investor group's rate of return is computed for all the trades in each period investigated. Since I wish to ascertain whether sophisticated investor groups profit from their information, I expect to see such groups earn significant positive returns over the two day period. In particular, I expect to see the trades they enter into in the periods immediately following the announcement would be most profitable, since it would allow them to take advantage of their information before market wide dissemination and change in prices.

However, stated in the null form, the hypothesis tested is:

(H2a) **None of the investor groups earn significant returns from their trading after an earnings announcement.**

In addition to the analysis of returns in the post-announcement period, I study returns from trading in the period prior to announcement. SEC is concerned with the effect of news leakage in the market place. I test whether returns from trading by different investor groups is significantly higher than zero and is indicative of information leakage. The null hypothesis tested is:

(H2b) **None of the investor groups earn significant returns from their trading before an earnings announcement.**

CHAPTER III

DATA DESCRIPTION AND SAMPLE SELECTION

The TORQ Data Set

The TORQ data set used in this study contains information on *trades, quotes, order processing information and audit trail data* for a sample of 144 firms whose primary listing is on the NYSE. These firms were randomly selected from a size-stratified population of NYSE firms in the summer of 1990. Originally fifteen firms were selected from each of ten deciles formed on the basis of equity capitalization. Six of the 150 firms selected were delisted before final data collection began on November 1, 1990, leaving a final sample of 144 firms. Data are available for three months from November 1990 to January 1991.[13]

The data set contains four principal data files: the consolidated trade file (CT), the consolidated quote file (CQ), the system order data base file (SOD), and the audit file (CD). Figure 3-1 provides an illustration of how the four files are interrelated. The CT files provide information on each trade (time, volume, price, exchange on which traded and trading condition codes), and the CQ files provide information on each quote revision (bid and ask prices and depths, time, exchange and condition codes).[14]

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[13]For more information on the TORQ data base, see Hasbrouck (1992).

[14]The information in the CQ and CT files are provided in real-time to market participants through the Consolidated Tape System (CTS), and in archival form to researchers through the Institute for the Study of Security Markets (ISSM) or the Trade and Quote data set (TAQ) provided by NYSE.

The unique feature of the TORQ data base is in the information provided in the audit (CD) and order (SOD) files. The audit file provides information on the number and type of parties to a trade, and volume traded by each. It is linked to the trade file by trade sequence number.[15] For each trade, it provides information on the order type of orders (market, limit) that make up the buy and sell side. However, this wealth of information is available only for NYSE trades. While trades in other exchanges are reported in the CD file, the unique information fields that report this information are blank.

For certain order types, it is possible to trace the order to the SOD file to obtain further details. The SOD file contains order entry and processing information for orders from three sources: the superDOT system (the electronic order processing system at the NYSE), the OARS (the Opening Automated Report System, used at market openings), and ITS (the Intermarket Trading system, used to transfer orders between market centers). Since these three systems report orders placed in the NYSE, the SOD file is limited to NYSE orders. For this time period, the SOD orders combine for 55% of the total orders and 31% of all volume on NYSE. The unique order information available from the SOD file are: time of order placement, order routing, partial executions and "stopped" orders. However, the link between the CD file and SOD file is more difficult to establish due to the absence of unique identifiers between the files.

With the detailed information in the CD file, it is possible to carefully determine the identity of the trader on either side of each trade. In this paper, I primarily use information from the CT, CQ and CD files. Moreover, I restrict my analysis to trades that appear in the CT file, since the CT file contains information made available to all investors through the Consolidated Tape.

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[15]If a reported trade in the CT file consists of batch orders, i.e., more than one participant on either or both sides (buy, sell) of the trade, then there may be more than one corresponding record in the Audit (CD) file pertaining to that trade.

The TORQ data base uses an "account type" classification code to distinguish between trading groups, and the type of orders posted. I use these account codes to classify traders into seven categories: Individuals, Institutions, Exchange Members (other than specialists), Program Trades, Specialists, Intermarket Trades and Residual Trades. Some trades (e.g., specialist trades) are not explicitly coded in the data base, and are coded in this study on the basis of information received from the stock exchange in discussions. Table 3-1 presents the CD file breakdown of trader categories for the active side of NYSE trades for entire three month period for the 144 firms.[16] Appendix B presents in detail the structure of the TORQ data base, and the classification method.

In terms of trading strategy, I expect individual traders to be more naive, and institutional traders to be more sophisticated. Floor traders (residual trades) who represent, by and large, institutional traders, are expected to be sophisticated. However, since their classification presents an ambiguity, I do not explicitly hypothesize or test their trading behavior. Though program traders are sophisticated, it is expected that they tune their strategies to avail of portfolio arbitrage opportunities in relation to indexes and futures markets, and their trades are not likely to be correlated to the information in an earnings announcement. Member traders are likely to be sophisticated. The specialists have an affirmative obligation to maintain a "fair and orderly" market. This ensures that the specialists will be liquidity providers in the post-announcement period.[17]

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[16]The Lee-Ready (1991) algorithm is used to identify the active side of each trade. They define the active side as the side with the greater need for immediate execution, i.e., liquidity demanders in a trade. Some trades (15% of all trades) have more than one participant type on the active side. These trades have been included in the count of each trader group that participated in such a trade.

[17]The market maker is assumed to be uninformed in several market microstructure models (Kyle 1985; Glosten and Milgrom 1985; Easley and O'Hara 1987). The specalist is in a unique position of continuously observing the order flow, getting information from the floor.

Sample Firms

To arrive at the sample of firms used in this study, I searched the Dow Jones News Service (DJNS) for each and every earnings announcement made by any of these firms during the period of November 1990 to January 1991. To ensure availability of post-earnings data until the end of the day following the announcement, I had to restrict myself to stories that appeared between November 1, 1990 and January 30, 1991. I found 84 announcements (by 83 firms) during this period.[18] The DJNS stories report the exact time of announcement (to the minute) that I use as the announcement time for the tests. The list was filtered to remove firms that had trading halts (4 announcements) on announcement day.[19] In addition to trading halts, two announcements pertaining to firms that had changes in shares outstanding of greater than 10% during the three month period were dropped, since tests of statistical significance of volume reaction that are used in this study may be affected by substantial changes in shares outstanding. The final sample is 78 firm announcements. Table 3-2 contains the sample selection information and describes the filters that were used. Of the 78 announcements, 42 were made during NYSE trading hours, and 36 outside trading hours.[20]

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[18]I searched the period October 20 to February 10, and found 113 firms making at least 1 announcement in the period. Of the 31 firms that could not be traced, 16 are funds that do not declare an earnings number. The other 15 firms could not be traced in any source of news. Watts (1992) reports that occasionally editors at Dow-Jones may not publish a report based on the importance of the company. However, not all missing companies were small companies. There were 30 announcements made during late October or early February, including 8 firms that announced on January 31, 1991.

[19]Trading halts have a disproportionate effect on intraday patterns that make the interpretation of results difficult. See King, Pownall and Waymire (1991); and Lee, Ready and Seguin (1992).

[20]The overnight announcement sample includes five firm announcements that were made during trading hours, but after 3:30 p.m.

Descriptive statistics of the sample on the basis of type of announcement (good, bad and unclassifiable) are also provided.[21] The news is considered good (28 announcements) if the actual EPS was equal to or higher than the latest available analyst forecast (the mean analyst forecast reported by IBES or the VALUELINE forecast).[22] Where the actual EPS was less than the forecast by more than 5%, the announcement is classified as bad news (31 announcements). The remaining nineteen firms were unclassifiable.[23] Table 3-3 shows the distribution of announcement times (by time of day) and news classification for the sample firms. Of the good news firms, 17 released the news during the day, and 11 after trading hours. In the case of bad news firms, 18 released the news during the day, and 15 after trading hours. Interestingly in this sample, unlike previous studies, there is no significant deviation in the behavior of good news and bad news firms when it comes to the timing of news release. Figure 3-2 shows the distribution of announcements by calendar date. Forty six percent of the announcements were made during the second half of January 1991. However, since the tests in this study are devised by creating a separate non-announcement distribution for each firm, the effect of clustering should be mitigated in the analysis. Analysis of the primary SIC codes of these firms reveals that the sample represents a wide cross-section of industries covering 40 two-digit SIC codes. The highest frequency is for investment firms (6 firms) followed by electronic computer and device companies (5).

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[21]Of the 19 unclassifiable firms, analyst forecasts were not available for sixteen firms.

[22]Where forecasts for the same firm is available from both IBES and VALUELINE, I took the most recent forecast. If the VALUELINE forecast date is more recent than the beginning of the month in which the IBES forecast is made, the VALUELINE forecast is taken, otherwise the IBES forecast is taken.

[23]I also classified the announcements on the basis of the immediate price reaction to earnings news. By this classification, the number of good news announcements is 31. There are 29 bad news announcements, and 18 neutral announcements. Both classifications produce very similar samples of firms.

Figure 3-1

Torq Data Set Overview

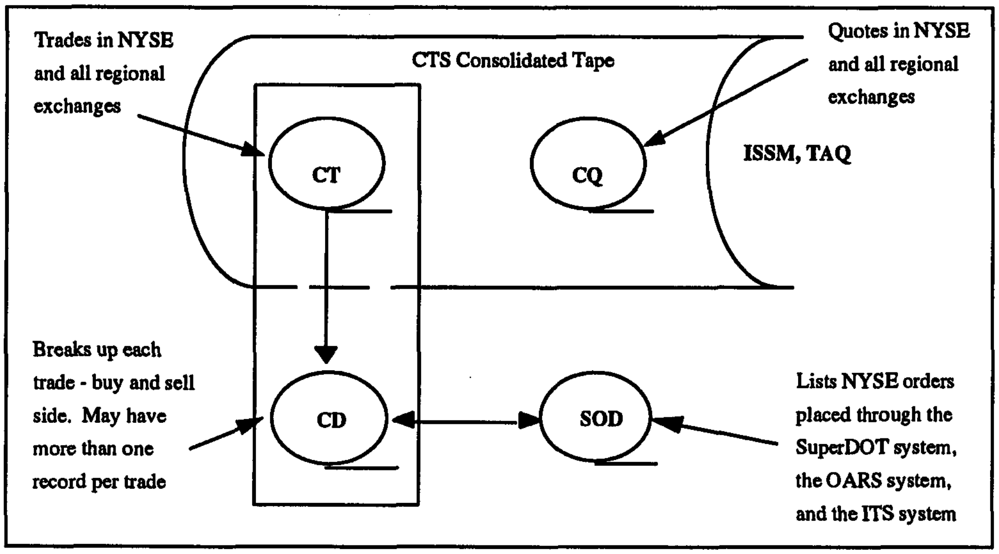

Figure 3-2

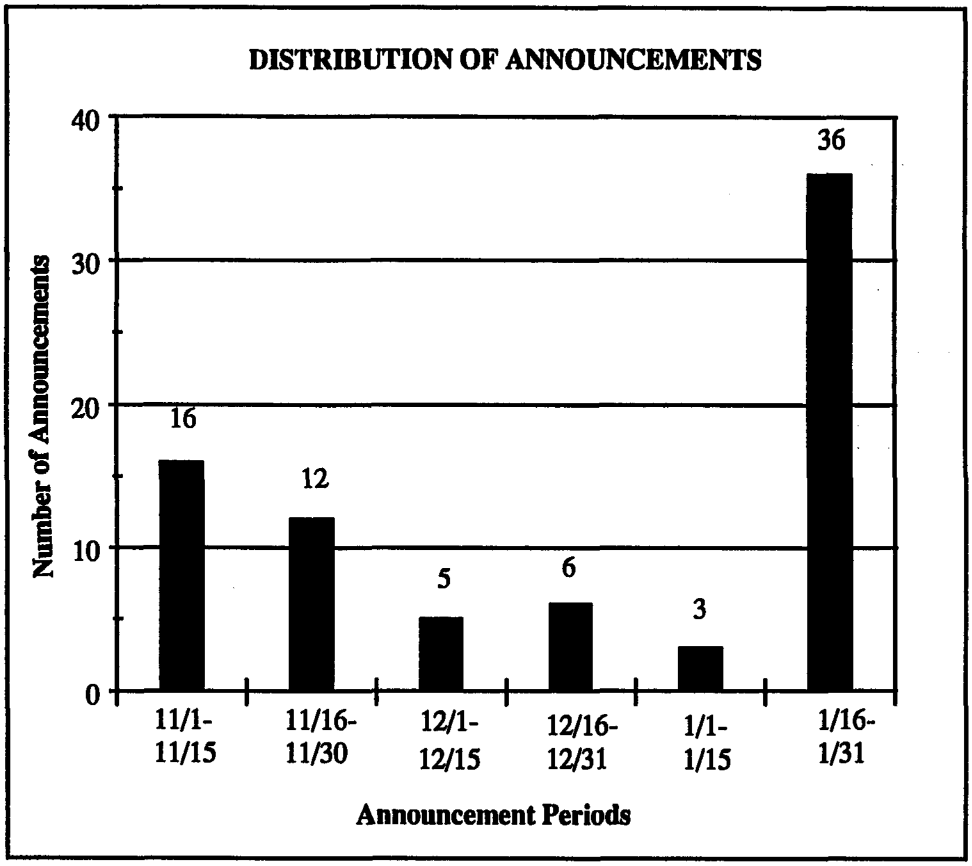
DISTRIBUTION OF ANNOUNCEMENTS
Number of Announcements
0
10
20
30
40
16
12
5
6
3
36
11/1-
11/15
11/16-
11/30
12/1-
12/15
12/16-
12/31
1/1-
1/15
1/16-
1/31
Announcement Periods

TABLE 3-1

Trader Category Breakdown of NYSE Trades (*Active* Side)

Type of Participants[a, b]

Type of Participants	Number of Trades %	Share Volume %
Individuals	30.1%	11.2%
Agency (Institutional)	32.8%	52.5%
Program Trades	11.4%	7.3%
Members	6.4%	8.3%
Specialist Trades	2.0%	3.8%
Intermarket Trades	10.0%	9.3%
Residual	7.3%	7.6%

[a]The table is computed from the trades of all 144 firms in the TORQ data base from the audit trail records in the CD file. These statistics are computed for the period November 1, 1990 to January 31, 1991. The Lee-Ready (1991) algorithm is used to identify the active side of each trade. Some trades (15% of all trades) have more than one participant type on the active side. All such trades have been included in the count of each trader group that participated in such a trade.

[b]Type of participants refers to the trader type initiating the trade. The members category includes all member organizations of the NYSE trading on their own account except specialists. Intermarket trades are those that are initiated on another market and executed on the NYSE or initiated on the NYSE and executed on another market. Trades that are not coded or clearly identifiable from the TORQ data set are put in a residual category. Trades initiated by individuals, institutions and program trades are coded accordingly.

TABLE 3-2

Selection of Sample Firms

NYSE Firms in the TORQ data set		144
Number of firms for which no earnings report were found on the Broadtape during November 1, 1990 to January 30, 1991[a]		61
Firms with at least one announcement		83
Actual Number of announcements		84
• Changes in Shares Outstanding > 10%[b] • Trading Halts[c]	2 4	 6
Total Sample Announcements		78
• During Trading hours • Outside Trading hours[d]		42 36
• Good News Announcements • Bad News Announcements • Unclassifiable[e]		28 31 19

[a] Of these, 22 companies reported earnings in October or early February, and so there were no announcements in the three month period. Another 16 companies were funds that do not declare earnings. And 15 companies could not be traced in any source of news. Watts (1992) reports that occasionally the editors at Dow-Jones may not publish a report based on the importance of the company. However, all missing companies were <u>not</u> small firms; 8 companies reported earnings on January 31, 1991. In order to analyze trading reactions until the end of the second day following an announcement, these firms were left out of the sample.

[b] Substantial changes in total shares outstanding affects volume statistics as well as tests of significance. Stocks where a new issue changed the outstanding shares by more than 10% during this 3 month period were removed.

[c] Trading halts have a disproportionate effect on intraday patterns (See King, Pownall, Waymire, 1991; Lee, Ready and Seguin, 1991). Hence, stocks that had a trading halt on the day of the news release were dropped.

[d] The list of overnight announcements include five announcements that were made after 3:30 p.m. during the trading day.

[e] Firms are classified as good news if the actual EPS reported is equal to or above the latest available analyst forecast (IBES or value line). They are classified as bad news if the actual EPS reported is at least 5% lower than the latest forecast. Forecasts are not available for 16 firms. Three firms that may be classified as neutral, where actual EPS is between 0-5% lower than forecast, are combined with the unclassifiable group.

TABLE 3-3

Distribution of Announcement Times for Sample Firms

Announcement Time	Good[a]	Bad	Neutral	Total
Morning - before opening of trading	5	7	3	15
Evening - after close of trading	6	8	7	21
Overnight:	11	15	10	36
9:30-10:00	0	2	2	4
10:00-11:00	2	3	1	6
11:00-12:00	5	4	2	11
12:00-1:00	7	1	0	8
1:00-2:00	1	3	3	7
2:00-3:00	2	1	1	4
3:00-4:00	0	2	0	2
Daytime:	17	16	9	42
Total	28	31	19	78

[a] Classification of News into "Good" and "Bad" is based on latest available Analyst (IBES, value line) forecast. Announcements are classified as bad news if the actual EPS reported is at least 5% lower than latest forecast. Forecasts are not available for 16 firms. Three firms that may be classified as neutral, where actual EPS is between 0-5% lower than forecast, are combined with the unclassifiable group.

CHAPTER IV
METHODOLOGY

Volume Measures

To measure investor reaction to a news event, I use two volume measures. The volume measures I report in this study always refer to the trading volume of each investor group. For most tests, I analyze the nature of volume reaction, "active or passive," of each trading group. Lee (1992) defines the active side as "the side with the greater need for immediate execution." It is possible to identify an active side to a transaction (the side that initiates the trade) because in a double dutch auction system such as at the NYSE, trading takes place only when a market order arrives.[24] Typically, the market order (the active side) is met either by a standing limit order or the specialist.[25]

The two volume measures used in this study are:

$$(1)\ f_{it}^{z} = \frac{\textit{No. of firm i trades of investor group z during period t}}{\textit{Average daily trades of firm i by investor group z during Nov.'90 - Jan.'91}},$$

and,

$$(2)\ T_{it}^{z} = \frac{\textit{No. of firm i trades of investor group z during period t}}{\textit{Total number of trades of firm i during period t}}$$

The first measure is designed to check whether the volume reaction of any particular investor group is significantly different for the period under investigation in

[24]Trading may also take place with a limit order that is priced to be immediately executable. Occasionally, two market orders may cross, but that situation is rare.

[25]See Appendix A for a description of how trades get executed on the trading floor.

comparison to a non-announcement period. This measure is similar to that used in Lee (1992). If the news release provides new information to any particular investor group, then it is expected that there would be significantly higher trading by the investor group in question. By analyzing volume reaction over several periods in the post-announcement period, it is possible to check whether the different investor groups react simultaneously or if there is a discernible time difference in their trading reaction.

The second measure is a proportional measure used to test if the volume of any investor group shows a proportionally greater increase or decrease during the event period. This metric measures whether any particular investor group commits to a larger proportion of the trading volume in the event period.

These measures are computed for both the announcement and non-announcement periods in order to develop a measure of abnormal trading during the event period (i.e., announcement period reaction minus non-announcement period reaction). The abnormal trading reaction is averaged across all firms in the sample to produce three measures that are presented in the results for each investor group: the mean abnormal total trading reaction, the mean abnormal active trading reaction, and mean abnormal net volume reaction. The **mean abnormal total trading reaction** of each group is defined as the total trading by the group (regardless of whether it is on the active or passive side) in the event period less their trading in a matched non-announcement period. This is analogous to a simple volume measure and shows the abnormal participation by each group during the event period. The **mean abnormal active trading reaction** shows how much excess trading was *initiated* by each group after an earnings announcement. It is measured as the abnormal active side trading of each group. The **mean abnormal net volume reaction** shows the change in the net position (active minus passive trading) of each group. The idea is to determine whether investor groups take an active role in the market to trade aggressively on their information.

The classification of investor type in this study is as per the scheme presented in Chapter II and Appendix B. Identification of the active and passive sides to a trade is done on the basis of the Lee-Ready (1991) algorithm.

Volume Tests

To infer statistical significance of the volume measures used in this study, I use a Monte-Carlo resampling technique that compares the cross sectional mean of a statistic during the announcement period with an empirical distribution of the corresponding statistic generated from a non-announcement period.[26] Significance levels are based on non-parametric statistics and the research design controls for firm sample composition and announcement times.

The tests are based on trades observed during specific time intervals following an announcement. For each of the two volume measures described above in this section, I compute an announcement period average for each investor group for each time period studied.[27] I compare the event period average to an empirical distribution of the same statistic obtained by random sampling, with replacement, from non-announcement periods. This comparison yields a significance level for a test against the null hypothesis that the announcement period observations represent random draws from the non-announcement empirical distribution.

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[26]The procedure used here is similar to an approach described in Chapter 3 of Noreen (1989). This method was used in Lee, Mucklow and Ready (1993).

[27]I investigate the half-hour, one hour and three hour interval immediately following an announcement. In addition, I analyze the period from the announcement time to the end of the day following, and the day before the announcement. Finally, I analyze 27 half-hour periods. Of these, period zero is a half-hour period with the announcement time at its center. Thirteen half-hour periods are analyzed before and after this period for a total of 27 periods.

The procedure for computing the test statistic is as follows. I compute the trading volume for the half-hour (or whatever period being investigated) immediately following the announcement. For example, Exxon announced its fourth quarter earnings for 1990 on January 24, 1991 at 12:59 p.m. The half-hour volume refers to the trading volume from 12:59 p.m. to 1:29 p.m. on January 24th.[28] The equally weighted average of all such volumes is computed for each investor group across all firms in the sample. The result is an event period volume for the half-hour period for each investor group z. For each firm announcement included in the event period, a non-event control observation is randomly drawn with replacement from the non-event distribution for the same firm and the same time of day. In this example, a control observation is drawn randomly from the sample of all investor group z volumes during 12:59 p.m. to 1:29 p.m. for Exxon for non-event days. An equally weighted average across firms of these non-event observations is computed. To create a reference distribution, this process is repeated 300 times, generating 300 non-event period observations for each event period observation. Once the reference distribution is constructed, I test whether the event period volume (X) could have been a random draw from the reference distribution F(x). The null hypothesis that the event period volume is a random draw from the reference distribution is rejected at the α level of significance if $X > x(\alpha)$, where $F(x(\alpha)) = 1-\alpha$, based on the reference distribution F(x).

This process is repeated for all event periods investigated. For each event period studied, an appropriate non-announcement distribution is first created for this procedure to be implemented.

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[28]In this example, I describe the procedure for a volume statistic (f_{it}^{z}) computed for the half-hour interval immediately following the earnings announcement. The procedure used for the other volume statistic and intervals is identical.

Return Measures and Tests

There are two return measures used in this study to ascertain profits earned from trading by each investor group is computed as given below. The first measure is based on the change in mid-spreads over time and reflects the effect of the information event in moving the price to its new equilibrium over the time period investigated. The second measure is a very conservative measure of actual returns earned. It takes actual prices to compute returns and has the effect of charging the trader the prevailing bid-ask spread as trading costs. Since it is possible for traders to negotiate lower transaction costs, this measure of returns is extremely conservative. The return to an investor group for trading in a firm for a given period is computed as follows:

$$R_{it}^{z} = \frac{\sum_{n}(P_{d1} - P_n)(V_n)(x_n)}{\sum_{n} P_n V_n},$$

where:

R_{it}^{z}= Return to investor group *z* in period *t* from firm *i* trades.

P_{d1}= Price at the end of day following the announcement for firm *i* stock. Under option 1, this is the prevailing mid-spread at the end of the day following. Under option 2, where the original trade was a buy (sell), the bid (ask) at the end of the day following is taken.

P_n= Transaction price of nth trade in period. Under option 1, the prevailing mid-spread at transaction time is taken. Under option 2, the actual transaction price is taken.

X_n = +1 (-1) if nth trade is a buy (sell) based on active side classification,

V_n = Number of shares traded in the nth trade, and,

n = number of active trades in firm *i* by investor group *z* in period *t*.

Determining the average return of investor group *z* in period *t* is done in two steps. First, the return to investor group *z* in firm *i* in period *t* is computed as shown above.

Next, the firm returns are summed and averaged to arrive at investor group return in any period:

$$R_t^g = \sum_i R_{it}^g.$$

It should be noted that this measure assumes that buyers sell their purchases at the end of the day following the announcement, and sellers sell short, and cover their short sales by buying at the end of the day following the announcement. Moreover, since the first measure computes returns based on the mid-spread, this measure ignores transaction costs to trading. The second measure assumes transaction costs since it-uses actual transaction prices of stocks that may typically be bought by the average trader at the ask and sold at the bid. Tests of significance verify whether the mean return earned by the group is significantly different from zero. In addition to providing a crude measure of returns, these metrics provide a measure of how different investor groups anticipate price movements in the market.

In addition, to test whether the returns earned by groups are significantly higher than market returns in the same period, I collect tick-wise market returns data for S&P 500 futures coinciding with the post-announcement period of each firm analyzed, and compute a market adjusted return. I then do a t-test to verify whether the market adjusted investment group return is significantly higher than zero.

Finally, I compute matching non-announcement period returns for each firm for no news days available in the sample. I adjust the announcement period return with the mean non-announcement period return. This measure presents a time series adjusted abnormal return of the sample firms.

Methodological Issues

There are some methodological issues that arise from the use of this data. I address two important issues in this dissertation, and propose others for future research.

Direction of Trade

Lee-Ready (1991) propose a popular algorithm (See Appendix C) to determine trade direction. Under this algorithm, if a trade is at the quote or outside the quote, the trading price is compared to the quote to determine direction. If the trade is at or above the ask, it is a buy; and if at or below the bid, it is a sell.[29] Where the trade is at the mid-point between the bid and the ask, the active side is determined on the basis of a tick test, i.e., a trade is classified as a buy (sell) if it occurs on an up tick or zero up tick (down tick or zero down tick). For a trade between the quotes, but not at mid-point, direction of trade is based on proximity to bid/ask. Trades above the mid-point of the spread are classified as sells, and trades at prices below the mid-point are classified as buys.

This algorithm (or variations of it) has been used in a number of studies to determine market response to information.[30] Similar classifications (that are a subset of this general rule) have been used in the finance literature to study the behavior of prices, the behavior of the market maker, and the block market.[31]

With the TORQ data set, it is possible to determine whether the order placed is a buy or a sell, and by looking at the order flow and method of execution, determine which

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[29]It should be noted that very few trades (less than .5% of the trades in Lee 1992, and less than .1% in this sample) are above the ask or below the bid.

[30] See for example Lee (1992), and Radhakrishna (1994).

[31] See for example, Harris (1989), Lee (1993), Madhavan and Sofianos (1994), and Cheng and Madhavan (1994).

side initiated the trade.[32] The order information contained in the SOD file allows the researcher to determine when exactly an order was placed, with what conditions, and how it was executed. The information in the audit (CD) file allows me to unambiguously identify the active side in some cases, such as when the order on one side is a market order, and the order on the other side is a limit order. In general, the procedure followed in this paper is to first use the audit file information to determine trade direction. Where this information is inadequate such as when there are market orders on both sides, or only limit orders on both sides, I identify the order(s) from the SOD file to determine the initiating party to a trade.

There are some limitations to the tests performed here. The SOD file is limited to orders on NYSE that pass through the SuperDOT, OARS and ITS systems. Thus, in a case where a trade is not unambiguously classifiable with the information in the CD file, it is not possible to classify the trade direction if the order record is not available. This problem is more acute when there are multiple participants on any one side of a trade. One or more of the participants may use a floor broker and consequently their order would not be reported in the SOD file.

Using the information in these two files, it is possible to determine the trade direction for 44% (133,096) of the trades with a single participant on either side of the trade, and 31% (45,530) of the trades with multiple participants on either sides (overall 40%). Analysis is presented separately for single and multiple trader trades.

Table 4-1 provides some descriptive statistics of the analysis conducted. There are 455,161 NYSE trades in the stock of the sample firms (in TORQ data base) during the period covered. Of these 1,667 trades were out of sequence or have special condition codes, and are therefore eliminated from the analysis. The opening trade of the day is a

[32] Refer to Appendix B for a description of the TORQ data base.

batch trade not double auction, and consequently excluded from the analysis of which side initiates the trade. There are 5,713 such trades in this sample. Audit records were not available for 55 trades in the TORQ data set. Of the remaining 447,726 trades, 301,933 trades (67%) are single participant trades, and 145,793 (33%) are multiple participant trades. However, 33% (67%) of the volume was transacted in single (multiple) participant trades during this period.

Determining the active side of a trade requires that the initiator of a trade be determined unambiguously. Where trades have market orders or marketable limit orders on one side and pure limit orders on the other side, it is the market order that initiates the trade. Thus the market side is the active side of that trade, and the limit order the passive side. Intermarket trades are coded to show whether NYSE is the executing market or the committing market. The committing market is taken as the initiator of such trades, and the executing market the facilitator. Thus, the committing market is taken as the active side.

At times market orders are "stopped" by the specialist and subsequently cleared in batches. Thus, a market order may not be immediately executed, but made to wait for future execution with a minimum price guaranteed (usually the standing quote at the time). Some stopped orders are subsequently filled by the specialist, or filled with limit orders or arriving market orders at prices that may be better than the guaranteed price (usually a price between the quotes). Therefore, in all cases where there are market orders on both sides of an order, or both sides have only limit orders, I search the order file. Matching orders to trades is a difficult exercise, but using an array of values to match the orders with the audit file record,[33] I was successful in identifying the order that was executed in a trade 96% of the time (when the audit file code indicated that an order may be available).

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[33] See Hasbrouck (1992) for a description of how to match an audit file record with its order file record.

If a market order was stopped, the subsequent market order that triggered the execution of the stopped order is taken as the active side. Similarly, when both sides of the trade have only limit orders, the side that has a marketable limit and has the order placed closer to execution time is taken as the active side. I check to ensure that in all such cases that the order was placed within a quarter hour of the execution time, and was not a long pending limit order.

In case a market or marketable limit order is met by the specialist, the market side is taken to be active, with the specialist providing the liquidity on the passive side. It may be argued that it is not ambiguous that the market order side of trades met by a specialist should be the active side. The number of such trades is quite small and if these trades were dropped from the analysis, the results do not change.[34]

The results of the analysis of single participant trades is presented in Table 4-2. The first row of the table shows that the TORQ classification is in agreement with the Lee-Ready Classification 90% of the time. Of the single participant trades, 85% are at the tick, and the Lee-Ready Classification is correct in identifying 96% of all such cases. Where the trade is at the middle of the spread, the L-R classification is correct 64% of the time. Analysis of reasons for disagreements show that 24% of the disagreements are triggered when an order is stopped. Roughly, 13% of the cases occur when there is an intermarket trade, and 9% of the disagreement is caused by cases where the market order is met by the specialist. When the trade is inside the spread but not at the middle of the spread, the LR algorithm is accurate 69% of the time. Roughly 27% of the disagreements occur when the trade is between NYSE and another participating market. Another 16% of the cases occur when a market order is stopped and 13% when a market order is stopped.

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[34] Appendix D lists the filters used to determine trade direction with the TORQ data set.

The results of the analysis of multiple participant trades is presented in Table 4-3. With multiple participants, the TORQ classification is in agreement with LR classification 81% of the time. Qualitatively, the results are similar to single participant trades. The LR test accurately determines direction 86% of the time when the trade is at the bid or ask. Trades in the middle of the spread are correctly classified 62% of the time. Trades that were stopped contribute to 25% of the disagreements, and 37% of the disagreements are caused by cases where a market order is met by a specialist. For trades inside the spread but not at mid-quote, the LR algorithm is accurate 61% of the time. Some 22% of the inaccuracies occur when a market order is stopped.

These results suggest that the L-R classification is most accurate when the trades are at the bid or ask. It is accurate more than 93% of the time, and may reliably be used to determine the direction of all such trades. However, its performance in identifying direction of trades within the spread is mixed. For trades inside the spread, it is accurate only 64% of the time, slightly better than a random strategy. Thus, it seems that for studies that require greater accuracy of classification, it might be preferable to leave out such trades from the analysis.

I also examine whether the 5 second delay rule suggested by Lee-Ready (1991) has any impact on the accuracy of determining trade direction. Lee-Ready point out that on occasion a quote that is modified after a trade is reported before the trade since the quote change enters the system faster than the trade report. This is because the quote change is entered from the specialist workstation and enters the computer system more quickly than the trade reporting system that uses a card reader. To remedy the problem, they suggest that when a quote precedes a trade by less than five seconds, it is preferable to take a prior quote as the prevailing quote at the time of that trade. Table 4-4 provides an analysis of the delay rule. I find that the 5 second rule comes into play less than 4% of the time. I compare the 5 second rule with a 3 second rule and a no delay rule, and find that accuracy in determining trade direction drops by 1% and 3% respectively when compared to the 5 second rule. Thus the loss of accuracy in not using the 5 second rule does not seem to be very serious for this sample. However, the 5 second rule still performs the best, and in view of documented delays in reporting trades, using the 5 second rule seems preferable.

Identification of Trader Type

The second methodological issue addressed in this dissertation pertains to trader type identification. The TORQ data set is coded for identification of trader groups. However, other popular data bases covering more companies and longer periods (such as ISSM and TAQ) do not. Trader type classification is therefore required to be inferred on the basis of some arbitrary proxy. The problem of accurate identification of trader type has been resolved in prior studies by using dollar value or trade size as a proxy for trader type. Lee (1992) assumes that small dollar-valued trades (less than/equal to $10,000) are initiated by small traders, and large dollar valued trades are institutional traders. However, the question remains whether the small dollar valued trades are small traders, and the large dollar valued trades are institutional traders. Cready (1988) assumes that institutional traders have larger mean trade sizes. However, that interpretation is open to question.

This problem is solved with the TORQ data set, which is coded for the identification of trader groups.[35] I use the TORQ data to assess whether the classification schemes used in these studies are efficient in identifying individual and institutional traders. The evidence I present should be of use to researchers in classifying individual and institutional trades when working with less finely partitioned data sets.

I analyze the trader classification on the active side of trades, since the active side is the focus of most microstructure studies. The active side is determined for this purpose

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[35]Refer to Appendix-B for an evaluation of these classification schemes using the TORQ data base.

using the Lee-Ready (1991) algorithm. In Tables 4-5 and 4-6, I compare results of the classification scheme used by Lee (1992) and Cready (1988) respectively, with the TORQ classification, for all 144 firms over the full three month period. These results are very similar to an analysis of announcement period trading by different trader groups.[36]

On the active side, 15% of the trades (40% of the share volume) were batched, i.e., trades with multiple participants where several orders were batched into a single trade for execution. Using the TORQ information, where there is more than one trader in a trade, I increase the count of each trader group that participated in the trade at the appropriate dollar value or share volume size of their trade.

In Table 4-5, I provide a comparison with the Lee method. The Lee method classifies trades into one of two categories—individual and institutional—based on dollar value of trade. In Panel A, I report the results of a sensitivity analysis using several dollar value cut-off levels to demarcate individual and institutional trades. Column 1 of the table shows the *percentage of trades below the cut-off level that were actually initiated by individuals* as identified by TORQ. Column 2 shows the *percentage of trades by individuals that is below the cut-off value.* The second row of this table represents the Lee classification, i.e., a $10,000 cut-off. Using this cut-off 46% of the total trades are identified as individual. However, of these only 59% (refer column 1) are actually individuals. Column 1 shows that since individuals typically trade in smaller values, using a higher cut-off value for classification progressively diminishes accuracy. This is borne out by the evidence in Column 1. As the cut-off value is increased, the percentage of trades below cut-off value by individuals decreases. Column 2 shows that there are always some individual traders that trade in high dollar values. For example, at least 3%

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[36] Since the Cready (1988) and Lee (1992) classification identified traders around an earnings announcement, I conduct a similar analysis of trades of firms that made earnings announcements, for a three day period surrounding earnings announcements. These results are very similar to the results reported here for the full sample.

of trades initiated by individuals are above $100,000 in value. But 66% of trades by individuals are below $10,000 in value, and 84% percent of individual trades are below $20,000 in value.

Table 4-6, Panel A, presents a similar sensitivity analysis using different trade sizes to separate individual and institutional trades. This provides a comparison with the Cready method that classifies trades into high, medium and low wealth categories based on trade size. From Column 2, it can be seen that 67% of individual trades are for 400 shares or less, and 83% of trades are for 900 shares or less. The stocks in this sample range from penny stocks to $118 in value. From Column 1, it can be seen that 58% of the 100 share trades are by individuals; and this proportion steadily decreases as the trade size increases. Not surprisingly, these tables show that most individual trades are of smaller value and size, compared to institutional trades.

To provide a measure of the optimal cut-off that may be used to distinguish between individual and institutional trades in Panel B of Tables 4-5 and 4-6, I estimate the error probabilities in using these cut-off vales. Assuming a null hypothesis that the trade is individual initiated, there are two types of sampling errors possible: (1) wrongly classifying a trade as institutional when it is initiated by individuals (Type I error), and (2) wrongly classifying a trade as individual when it is institutional (Type II error). In Table 4-1, Panel B, I estimate the error probabilities in using the Lee classification. The Lee method (row 2) has a 13% chance (column 1) of rejecting any randomly selected trade from the whole sample as institutional, when it is actually individual initiated. And, it has a 19% chance (column 2) of accepting a trade as individual initiated when it is not. A simple rule of the thumb that cumulates the two error probabilities shows that the $10,000 cut-off value has the lowest cumulative error probability.

In Table 4-6, Panel B, I estimate the sampling errors in using the cut-off values (trade sizes) shown in Panel C. It can be seen that as we increase the number of trade sizes to classify as individuals, the probability of rejecting an individual-initiated trade as institutional (column 1) decreases. At the same time, the probability of wrongly classifying institutional trades as individual (column 2) increases. Using the same simple rule of the thumb, a cut-off value of 400 shares presents the optimal cut-off point.

Based on this analysis, it seems that there is some error in using trade size or value as a cut-off for determining individual and institutional trades. However, this error is minimized for the period under study if one were to use 400 shares or $10,000 as the cut-off value.

TABLE 4-1

TORQ Data Set: Descriptive Statistics

NYSE Trades in TORQ: Total		455,161
Trades not analyzed:		
Out of sequence trades:	1,667	
Opening trades:	5,713	7,380
Trades analyzed:		447,781
Trades with no audit file records		55
Trades with single participants per side	301,933	
Trades with multiple participants	145,793	
Trades tested for trade direction		447,726

TABLE 4-2

Performance of the Lee-Ready (1991) Algorithm

in Identifying the Active Side of Trades

Single Participant on Each Side of the Trade

L-R vs. TORQ	Trade Price[a]			
	At Tick (or outside)	Middle of Spread	Inside spread, but not middle	Overall
Agree[b]	96%	64%	69%	91%
Disagree	4%	36%	31%	9%
Number of trades	112,198 (85%)	17,886 (13%)	3,012 (2%)	133,096 (100%)

The analysis in this table is based on NYSE trades in the TORQ data set. Analysis is restricted to 133,096 trades that have one participant each on the buy and sell side, and are unambiguously classifiable with both Lee-Ready (1991) and the TORQ information. This represents 44% of all NYSE single participant trades reported in the TORQ data set.

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[a] This refers to the transaction price at which the trade was executed with reference to the prevailing quote.

[b] This refers to the percentage of trades that fulfill the condition specified in the column heading where the determination of the active side with the TORQ information agrees with the Lee-Ready classification.

TABLE 4-3

Performance of the Lee-Ready (1991) Algorithm

in Identifying the Active Side of Trades

Multiple Participants on Either Side of the Trade

L-R vs. TORQ	Trade Price[a]			
	. At Tick (or outside)	Middle of Spread	Inside spread, but not middle	Overall
Agree[b]	86%	62%	61%	82%
Disagree	14%	38%	39%	18%
Number of trades	36,946 (85%)	7,441 (13%)	1,143 (2%)	45,530 (100%)

The analysis in this table is based on NYSE trades in the TORQ data set. Analysis is restricted to 45,530 trades that have more than one participant each on the buy and sell side, and are unambiguously classifiable with both Lee-Ready (1991) and the TORQ information. This represents 31% of all NYSE multiple participant trades reported in the TORQ data set.

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[a] This refers to the transaction price at which the trade was executed with reference to the prevailing quote.

[b] This refers to the percentage of trades that fulfill the condition specified in the column heading where the determination of the active side with the TORQ information agrees with the Lee-Ready classification.

TABLE 4-4

Test of Five Second Delay Rule

in Identifying the Prevailing Quote

	No. of Trades	%
Cases where 5 second rule is implemented	7036	4% [of all trades analyzed]
Increase (Decrease) in accuracy determining trade direction compared to the five second rule:		[As % of trades where 5 second rule implemented]
3-second rule	(63)	(1%)
No delay rule	(258)	(4%)

The analysis in this table is based on NYSE trades in the TORQ data set. Analysis is restricted to 178,626 trades that are unambiguously classifiable with both Lee-Ready (1991) and the TORQ information. This represents 40% of all NYSE trades reported in the TORQ data set.

TABLE 4-5

Classifying Trades into Individual and Institutional

on the Basis of Trade Value

PANEL A: CLASSIFICATION ACCURACY		
Trade Value[a]	% of trade below cut-off value initiated by individuals[b]	% of trades by individuals below cut-off value[c]
≤ $5,000	60%	39%
≤ $10,000	59%	66%
≤ $20,000	55%	84%
≤ $50,000	49%	94%
≤ $100,000	46%	97%
PANEL B: ESTIMATED ERROR PROBABILITIES		
Trade Value[a]	Pr. (Rejecting Individual trades as institutional)[d]	Pr. (Accepting institutional trades as individual)[e]
≤ $5,000	.24	.11
≤ $10,000	.13	.19
≤ $20,000	.06	.27
≤ $50,000	.02	.39
≤ $100,000	.01	.46

[a] Values in this column represent the dollar values used to classify individual and institutional traders, e.g., row two represents a scheme similar to Lee (1992). In row two, if the value of shares traded in a transaction calculated at year-end (12/31/90) prices is less than or equal to $10,000, the trade is classified as initiated by individuals. Where the trade value is greater than $10,000, it is classified as institutional. The classification presented in this table is done with the active side of all NYSE trades in the TORQ data set, but does not include batched and intermarket trades.

[b] The 60% in the first row of this column signifies that of all the trades below $5,000 in value, 60% were actually initiated by individuals.

[c] The 39% in the first row of this column means that 39% of all individual initiated trades (based on TORQ classification) were below $5,000 in value.

[d] This is an estimate of Type I error (rejecting the null when true) in using this cut-off value for classifying individual investors with the whole sample.

[e] This is an estimate of Type II error (accepting the null when the alternate is true) in using this cut-off value for classifying individual investors with the whole sample.

TABLE 4-6

Classifying Trades into Individual and Institutional

on the Basis of Trade Size

PANEL A: CLASSIFICATION ACCURACY		
Trade Size[a]	% of trade below cut-off value initiated by individuals[b]	% of trades by individuals below cut-off value[c]
100 shares	58%	31%
≤ 200 shares	57%	51%
≤ 400 shares	55%	67%
≤ 900 shares	51%	83%
≤ 1,900 shares	47%	94%

PANEL B: ESTIMATED ERROR PROBABILITIES		
Trade Size[a]	Pr. (Rejecting Individual trades as institutional)[d]	Pr. (Accepting institutional trades as individual)[e]
100 shares	.28	.09
≤ 200 shares	.20	.16
≤ 400 shares	.13	.22
≤ 900 shares	.06	.32
≤ 1,900 shares	.02	.43

[a] Values in this column represent the share trade sizes used to classify individual and institutional traders. E.g., row two represents a scheme analogous to Cready (1988). In row two, where the number of shares traded in a transaction is less than or equal to 200 shares, the trade is classified as initiated by individuals. Where the trade size is larger than 200 shares, it is classified as institutional. The classification presented in this table is done with the active side of all NYSE trades in the TORQ data set, but does not include batched and intermarket trades.

[b] The 58% in the first row of this column signifies that of all the trades in which 100 shares were transacted, 58% were actually initiated by individuals.

[c] The 31% in the first row of this column means that 31% of all individual initiated trades (based on TORQ classification) were of 100 shares trade size.

[d] This is an estimate of Type I error (Rejecting the null when true) in using this cut-off value for classifying individual investors with the whole sample.

[e] This is an estimate of Type II error (Accepting the null when the alternate is true) in using this cut-off value for classifying individual investors with the whole sample.

CHAPTER V

TESTS OF HYPOTHESES

AND DISCUSSION OF RESULTS

Trading Reaction

Several studies[37] have documented an increase in trading volume in the post-announcement period. In this study, I investigate if the trading volume reaction is uniform across all trading segments of the market. Further, I ascertain the nature of the trading behavior exhibited, which group is active and when.

In Table 5-1, I present the **mean abnormal total trading reaction** of each investor group after an announcement. To be included in the analysis, a firm should have at least 20 non-announcement days with at least five trades per day in the time interval analyzed. This may vary the number of firms included in the analysis in different periods since many of the small firms do not have five trades for long stretches. Analysis of the volume is presented for several select periods: a half-hour, one hour, three hours after announcement. Also for comparison, the volume to the end of the day after announcement, and the day before announcement is presented. The mean abnormal total trading reaction is computed using the volume measure f_{it}^{z}, where a group's total trade in a particular period (both active and passive) is scaled by its average daily *total* trading volume. It can be seen in Table 5-1 that there is an increase in volume across the board

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[37]See for example, Morse (1981), and Bamber (1986, 87).

for all investor groups after an announcement. All groups have significant abnormal volume over all periods examined on the day of the announcement. This is consistent with earlier studies that have documented an increase in overall volume following a news announcement.

This effect seems to continue on the following day. Analyzing trading until the end of the day following the announcement, I find significantly higher volume in all trading groups. It can be seen that the trading pattern of individuals and institutions seem to follow a similar pattern showing an increasing trend over the two days. Analysis of trading on the day before an announcement shows only individuals and market makers trading above their average. Other groups have kept a lower profile. This makes clear the general increase in activity after the announcement that contrasts with the period before the announcement.

Table 5-1 presents the results after winsorization, i.e., firms that show abnormally high (low) volume have their high (low) abnormal volume set at 99% (1%) of the volume distribution of the firm. Winsorization does not affect the results of any trader group besides program trades.[38] From Table 5-1, it can be seen that abnormal program trading is insignificant in most periods, and weakly significant in two periods.

Hypothesis 1 of this study requires me to test whether the speed and type of trading differ by investor groups. To more specifically test and document the level of informed trading that takes place in the post-announcement period, I study the active and net trading (i.e., the active minus the passive trading position) of each investor group. The

[38] Without the winsorization, program trading seems to increase significantly in the post-announcement period. Results for other trade groups do not change. On investigation, it is observed that the large increase in program trading is caused by a small stock in which there is no program trading over the entire three month sample period except for two trades during the post-announcement period. On conducting the analysis without the stock in question, the increase in program trading becomes statistically insignificant, but the results for all other trade groups remain virtually the same.

active side of each trade is the side that "demands execution." The passive side provides liquidity. I study active and net trading because a trader with short-lived information in a competitive market should trade actively to take advantage of his/her information. This is in keeping with Holden and Subrahmanyam (1992), who suggest that in a competitive market, competing informed traders should trade aggressively. An analysis of the net active position of each investor group should provide a measure of informed trading in the post-announcement period.

In Table 5-2, the **mean abnormal active trading reaction** is presented for the same time periods using the same volume measure f_{it}^{z}. The mean abnormal active trading reaction is computed by subtracting non-event period active volume from the event period active volume and scaling by average daily *active* trading volume. Analysis of active volume reveals that individuals, institutions and members are active traders in the post-announcement period. Individuals who trade in lots valued higher than $10,000 show trading reactions very similar to all individuals in the group.[39] Program traders are not significantly active nor are specialists. This is in keeping with our hypothesis that specialists are likely to be liquidity providers in this period of information asymmetry. It is interesting to note that both individuals and institutions are active traders in the day before the announcement. However, the magnitude of institutional reaction after the announcement is somewhat larger than the individual reaction. The specialists do not trade very actively in the first hour after an announcement, but their active trading picks up after that. It can be seen in Table 5-3, where the **mean abnormal net volume reaction** of trader groups are presented, that specialist are involved in many more trades as liquidity providers in this period. Trading by individuals is not significantly net active indicating that while there is significant active trading, there is also a large level of passive

[39] Trading by individuals in lot sizes exceeding 400 shares were also analyzed. The results obtained (not presented here) were similar.

trade participation by individuals. Active trading by individuals seem to pick up on the day following the announcement. Again, the trading of individuals who make larger trades seem to follow the pattern of all individual traders in the market. This seems to indicate that while a $10,000 cut-off does a decent job of separating individual and institutional trades, the behavior of individuals trading larger values is different from that of institutions. Researchers using such cut-offs in the future should contend with the noise this engenders in their analysis and interpretation of data. Institutions, as may be expected, are focused active traders, and their net reaction is also significantly positive. The spurt in member trading seems to be limited to the day of announcement.

Table 5-4 shows the change in proportional abnormal volume (T^{z}_{it}) over a three hour period and a period ending at the close of the day following the announcement. To ensure that there are enough trades in each period to compute meaningful proportions, I restricted the analysis to include firms that had at least five trades in the period analyzed. This reduced the number of firms if the analysis period was of short duration, since some firms in the sample go for long periods without any trades and average less than five trades a day. I, therefore, present the analysis for two periods only: three hours after announcement, and the period to the end of the day following the announcement. With this restriction, there were 46 firms in the sample for the three hour analysis of active trading, and 53 firms for total trading. Over longer periods, the number of firms in the analysis increases. In Table 5-4, the proportional volume on the day prior to announcement is also presented. From this analysis it can be seen that the proportion of active trading by individuals is lower. The proportion of institutional volume shows a significant increase over the initial period, and a marginal increase over the longer two day window. It is also interesting to note that institutional trading in the pre-announcement period is below its non-announcement average though not significant. Over the longer window, it looks like institutions and members increase their proportion of active trading while individuals, and program trades provide the liquidity. The proportion of other groups do not seem to be significantly different from their non-announcement period proportions.

The overall picture that emerges from Tables 5-1 to 5-4 is that all the investor groups increase their volume in the post-announcement period. The trading of members seems to peak and taper off sooner than the trading of individual traders in the two day period analyzed. That is suggestive of their ability to trade swiftly after an announcement. Institutional traders continue to trade strongly over the two day period. Institutional volume goes up in proportional analysis. Specialists and individuals seem to be providing liquidity in the post-announcement period which may be expected since the former group provides market marking services in times of uncertainty, and latter group may comprise of a larger number of naive traders.

This analysis provides several answers to questions raised in Hypothesis 1. There is evidence that both individuals and institutions react, but the reaction of individuals is different from institutional traders in many ways. Institutions maintain a lower profile before the announcement, but they remain net active in this period. While the individuals trade actively in the post-announcement period, there is a large chunk of passive trading by individuals with the result that their active and passive trading positions seem to cancel out in this period. Member institutions are extremely active immediately after the announcement, but their trading is very quick and short-lived. The swift trading reaction of institutions and members observable on the day of the announcement seems to provide evidence of their better ability to process and react to information.

The specialist volume increases in this period, and as a group they are significant liquidity providers. This ties in with the notion that the uncertainty in the market in the post-announcement period places a greater demand on the specialist's market making services.

Trading Return

The second hypothesis studied in this dissertation requires an investigation of the returns from trading earned by different investor groups in the post- and pre-announcement periods. The focus of these tests is in finding out if the returns earned by the investor groups reveals the possibility of their possessing special knowledge or information about the firm. I use a short horizon return measure to study if any of the investor groups may turn a quick profit following the announcement. It should be noted that this measure is merely illustrative since the trading horizon of different investor groups is not known.

For each period analyzed, I compute a profit (or loss) from each trade in the period. For this purpose, I assume that all trades in the post-announcement period are short horizon trades that will be liquidated at the end of the day following the announcement. The idea behind this analysis is to provide a measure of the information in the news announcement, and is not an attempt to estimate true returns that may be earned by different investor groups. In addition, it should be noted that the analysis provides a measure of how well different investor groups anticipate price movements.

Since every trade has both buyer(s) and seller(s), I use the Lee-Ready algorithm to determine if the trade is a buy or a sell. To compute returns, I assume that all stock purchases during a period of analysis (e.g., the half-hour after announcement) will be held until the end of the day following and then liquidated at the prevailing price at the end of the following day. Similarly, stocks sold in this period are assumed to be short sales that will be closed at the end of the following day. Thus, the profit earned is the difference between transaction price and the price at the end of the next day. I use two different measures of the next day price: mid-spread at the end of the day and the transaction price at close on the following day.

In addition to the raw returns computed as above, for each period I compute a market adjusted return. For this purpose, I use tick data of S&P 500 futures that matches with the holding period and adjust the raw return earned for each period by subtracting from it the S&P 500 futures return.

Two facts should be noted in interpreting the analysis that follows. First, the returns are computed only for the active side of trading. Thus, returns to individuals refers to all active trading done by individuals in a period. Secondly, it should be noted that the return from a value weighted portfolio of the stocks in my sample purchased at announcement time and sold at the end of the following day would provide a return, before transaction costs, of less than a quarter ($ .24) for each unit of the portfolio held. This works out to a 1.3% return before transaction costs. An equally weighted portfolio yields 1.4%. After adjusting for transaction costs, it is likely to be less than one-half percent. Therefore, investors picking these stocks randomly will not make a significant return. Only an investor who picks judiciously may earn a return even before adjusting for transaction costs.

The returns (raw) earned by different investor groups in the post-announcement period is presented in Table 5-5, Panels A and B. The first column takes all trades in the half-hour interval after announcement, and computes a return for holding and liquidating at the end of the day following the announcement. An equally weighted mean return for all stocks in the portfolio is computed and presented. Tests of significance verify whether the mean portfolio return earned by an investor group is significantly different from zero. Similarly, returns from trades in the first hour, three hours, and in a period ending at the end of the next day are computed and presented in the following columns. The returns presented in Panel A are computed on the basis of mid-quote changes, and Panel B on the basis of price to price changes. Thus, the returns in panel B have a measure of adjustment for transaction costs.

It may be seen that individual traders who are active in the first one hour and trade in larger values (> $10,000) earn a significant raw return prior to transaction costs (see Panel A). The return from their trading in the first hour is significant at the 10% level even after adjusting for transaction costs (see Panel B). In contrast, the smaller individual traders do not make significant returns from their post-announcement trading. In the first half-hour they seem to be generating negative returns. Over the three hour and two day periods, both small and large individual traders perform poorly. Institutional traders and members earn a significant return on a mid-spread to mid-spread basis only from their trading on the day following the announcement. Thus, the trading of institutional traders entering the market a few hours after the announcement seems to anticipate price movements.

In Panels C and D, I present market adjusted returns, where the raw return is adjusted for the S&P futures index return for a similar period. The market was in a rising trend during November 1990 to January 1991 and rose nearly 10% in this period. The S&P futures tick-wise return reflects this raising trend. From Panel C, it may be seen that market adjusted returns earned by large individual traders (> $10,000) is higher than zero at the 10% significance level. The smaller individual traders seem to lose significantly in the first half-hour. After taking into transaction costs, market adjusted returns are insignificant for both small and large individual traders except for the two day return which is significantly negative for both the groups. Over the two day period, the return earned by members prior to transaction costs is significantly positive at the 10% level. After taking transaction costs into consideration, their return is not significant. However, it should be noted that members are likely to be in a position to negotiate down their transaction costs. Program traders tend to lose money from their two day trading after adjusting for transaction costs.

The picture that emerges from the analysis of Panels A to D, seems to indicate that some large individual traders, possibly with inside information, jump in immediately after an announcement and trade profitably. With the exception of these trades seen in the first hour, it seems that the trading of individual traders is not very distinguished, and they do a poor job of anticipating price movements. In contrast, institutional and member trades executed in the market a few hours after the announcement seem to anticipate price movements well.

In Panels E and F, I present a time series analysis of return. To arrive at this measure, I compute a non-announcement period return through random sampling with replacement. This return is computed for the same stocks at different periods that match the announcement period in duration and time of the day. The raw event period return is adjusted for the mean non-announcement period return to provide a measure of abnormal return. The test of significance is done by computing a non-event period sigma (standard error) from the reference distribution created with the random sampling. It can be seen that the time series abnormal return from trading over the full period ending the day following is significantly higher than non-announcement period return for members. Individuals trading in values above $10,000 do significantly better than in the non-announcement period in the one to three hours immediately following the announcement. Individuals trading in smaller values do not perform well. Thus, these results are quite similar to those obtained from the cross-sectional analyses presented in Panels A through D.

To give a better idea of the performance in different stocks, I also present returns from trading in S&P 500 stocks in the sample. Panel G and Panel H show returns for sample firms that are also S&P 500 firms, on the basis of mid-quotes and transaction prices respectively. Since the sample size is small there is not adequate power in doing significance tests, however significance statistics are provided after conditioning the cut-off t-value for the sample size. Hence these results should be interpreted with some caution. It may be seen that the pattern of returns earned by different groups is very similar to the results presented in Panels A through F. Large individual traders (>

$10,000) profit from their trading in first one after the announcement. Institutions and members do not seem to have significant profits from their trading on the day of the announcement. But, they do earn significant raw returns over the their trading in the two day period.

Panels I and J gives results from trading in the largest third of firms in the sample. Analysis of medium firms is given in Panels K and L. The results are similar to the results for S&P 500 stocks. Analysis of small firms, given in Panels M and N, is presented for completeness. However, the sample size is often so small since there is not a lot of trade in these firms, that the results do not have the necessary power. It is interesting to note that the specialists do not take an active position in such firms on the day of announcement. Indeed, it is expected that they will be on the passive side of such firms after announcement.

In addition to the post-announcement analysis of returns, I examine whether there is information leakage prior to earnings announcement that presents profitable opportunities for investors. For this purpose, I analyze returns from trading prior to the announcement. The raw returns from trading in the half-hour, full hour, three hours, and two days prior to the announcement is presented in Table 5-6. It can be seen that none of the trader groups make a significant return in this period, save for small individual traders (< $10,000). It is interesting to note that small individual traders anticipate price movements in the half-hour prior to the announcement. In fact, their trading in the day before also yields positive returns. But, in the post-announcement period their performance is unspectacular. It is possible that after the announcement they are either taken by surprise, or are not able to get favorable executions with the increase in overall trading frequency in the market.

Analysis of trading returns of all other investor groups seem to indicate that there is no information leakage in the period prior to the announcement. Thus, by and large, market participants react to the information in earnings in the post-announcement period.

TABLE 5-1

Mean Abnormal Total Trading Reaction in Select Periods

Investor Group	First half-hour after announcement	First full hour	First 3 hours	To end of the next day	Previous day
Individual	.075**(62)	.142**(68)	.410**(64)	.928**(78)	.123*(75)
Indiv. >$10k	.031**(62)	.053**(68)	.136**(64)	.311**(78)	-.015 (75)
Institutional	.114**(62)	.162**(68)	.451**(64)	1.09**(78)	.099 (75)
Members	.281**(62)	.291**(68)	.347*(64)	.755** (78)	.127 (75)
Program	.453*(61)	.358(64)	.393(60)	1.61#(73)	-.113 (71)
Specialist	.203**(62)	.239**(68)	.616**(64)	1.28**(78)	.461*(75)

Mean Abnormal Total trading reaction is computed as follows: event period total (active plus passive) volume minus a mean non-announcement period volume, of that group in that period. The volume measure used for this table is f^z_{it}. To compute this measure, each investment group's trading volume for a period is scaled by the group's average total daily volume. The number of firms is given in the parentheses.

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* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-2

Mean Abnormal Active Trading Reaction in Select Periods

Investor Group	First half-hour after announcement	First full hour	First 3 hours	To end of next day	Previous day
Individual	.065**(62)	.117**(68)	.334**(64)	.835*(78)	.116#(75)
Indiv > $10k	.026#(62)	.042**(68)	.117**(64)	.291**(78)	-.021 (75)
Institutional	.145**(62)	.209**(68)	.582**(64)	1.240**(78)	.165* (75)
Members	.431**(62)	.403*(68)	.526*(64)	1.097* (78)	.280 (75)
Program	-.016 (60)	-.040 (63)	-.066 (59)	.787*(72)	-.361 (70)
Specialist	.109 (62)	.077 (68)	.449*(62)	.901* (75)	.694*(72)

Mean Abnormal Active trading reaction is computed as follows: event period active volume minus a mean non-announcement period active volume, of that group in that period. The volume measure used for this table is f_{it}^{z}. To compute this measure, each investment group's trading volume for a period is scaled by the group's average active daily volume. The number of firms is given in the parentheses.

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* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-3

Mean Abnormal Net Volume Reaction in Select Periods

Investor Group	First half-hour after announcement	First full hour	First 3 hours	To end of next day	Previous day
Individual	.011 (62)	.008 (68)	.026 (64)	.204* (78)	.062 (75)
Indiv > $10k	.003 (62)	.002 (68)	.023 (64)	.101*(78)	-.013 (75)
Institutional	.077*(62)	.115**(68)	.351**(64)	.501**(78)	.199*(75)
Members	.212*(62)	.093(68)	.280(64)	.191 (78)	-.087 (75)
Program	-1.3(60)	-1.2(63)	-.99(59)	-.594(72)	-1.78 (70)
Specialist	-1.23(62)	-1.6(68)	-3.5*(62)	-6.30**(75)	-1.38 (72)

Mean Abnormal Net Volume reaction is computed as follows: event period net (active-passive) volume minus a mean non-announcement period volume, of that group in that period. The volume measure used for this table is f_{it}^{z}. To compute this measure, each investment group's trading volume for a period is scaled by the group's average total daily active volume. The number of firms is given in the parentheses.

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* Significance at 5% level

** Significance at 1% level

TABLE 5-4

Trading Reaction of Investor Groups - Proportional Volume@

PANEL A: Total Trading Reaction

Investor Group	First 3 hours	To end of next day	Previous Day
Individual	-.015 (53)	.001 (77)	.011 (71)
Institutional	.018# (53)	.015 (77)	-.001 (71)
Members	-.001 (53)	-.002 (77)	.001 (71)
Program	-.005 (53)	-.008# (77)	.008 (71)
Specialist	.006 (53)	.003 (77)	-.002 (71)

PANEL B: Active Trading Reaction

Investor Group	First 3 hours	Until the end of the day after announcement	Previous Day
Individual	-.067* (46)	-.034# (72)	.024 (64)
Institutional	.036* (46)	.030# (72)	-.004 (64)
Members	.004 (46)	.007 # (72)	.001 (64)
Program	-.009 (46)	-.015# (72)	.002 (64)
Specialist	-.000 (46)	-.000 (72)	.001 (64)

@ The volume measure used for this table is T_{it}^{z}. To compute this volume measure, each investor group's trading volume for a period is scaled by the period's total volume. The number of firms is given in parentheses.

A firm to be included in the analysis for computation of proportional abnormal volume should have at least 5 trades in each period analyzed.

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* Significance at 5% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

Returns are calculated for the active position of each trade in the time period analyzed.

PANEL A: Raw Returns computed from mid-spread to mid-spread (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.012 (39)	.010 (49)	.011 (54)	.001 (76)
Ind. >$10k	.025 (23)#	.022 (30)*	.006 (36)	.000 (54)
Institutional	.010 (46)	-.003 (54)	.011 (58)#	.007 (73)*
Members	.002 (29)	.001 (30)	.004 (32)	.009 (55)*
Program	.006 (18)	-.000 (23)	-.003 (24)	.003 (41)
Specialist	.006 (16)	.007 (17)	-.005 (24)	.005 (40)

PANEL B: Raw Returns computed from transaction price to end price (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.017 (39)#	.004 (49)	.003 (54)	-.009 (76)#
Ind. > $10k	.022 (23)	.019 (30)#	.003 (36)	-.002 (54)
Institutional	.004 (46)	-.011 (54)	.001 (58)	-.002 (73)
Members	-.002 (29)	-.002 (30)	.001 (32)	.004 (55)
Program	.003 (18)	-.003 (23)	-.008 (24)	-.003 (41)
Specialist	.003 (16)	.005 (17)	-.008 (24)	-.005 (40)

* Significance at 5% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL C: Market Adj. Returns computed from mid-spread to mid-spread (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.018 (39)#	.005 (49)	.007 (54)	-.001 (76)
Ind. > $10k	.017 (23)	.016 (30)#	.001 (36)	-.002 (54)
Institutional	.006 (46)	-.008 (54)	.008 (58)	.005 (73)
Members	-.002 (29)	-.003 (30)	.002 (32)	.008 (55)#
Program	-.002 (18)	-.005 (23)	-.008 (24)	.001 (41)
Specialist	-.002 (16)	-.000 (17)	-.011 (24)	.003 (40)

PANEL D: Market Adj. Returns computed from transaction price to end price (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.024 (39)*	-.001 (49)	-.000 (54)	-.012 (76)*
Ind. > $10k	.014 (23)	.013 (30)	-.002 (36)	-.005 (54)**
Institutional	-.000 (46)	-.015 (54)	-.003 (58)	-.005 (73)
Members	-.006 (29)	-.007 (30)	-.002 (32)	.003 (55)
Program	-.004 (18)	-.008 (23)	-.012 (24)#	-.005 (41)*
Specialist	-.005 (16)	-.003 (17)	-.014 (24)#	-.007 (40)

* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL E: Time Series Returns computed from mid-spread to mid-spread (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.016 (36)**	.008 (47)	.009 (54)	-.001 (76)
Ind. > $10k	.022 (16)**	.021 (25)**	.007 (35)#	-.001 (54)
Institutional	.012 (40)#	-.005 (51)	.006 (58)	.002 (73)
Members	-.011 (13)	-.002 (21)	-.004 (29)	.008 (53)**
Program	.003 (17)	-.004 (21)	-.008 (21)	-.002 (38)
Specialist	-.012 (5)	-.005 (9)	-.002 (19)	.007 (36)

PANEL F: Time Series Returns computed from transaction price to end price (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To the end of next day
Ind. < $10k	-.015 (36)*	.009 (47)	.009 (54)	-.003 (76)
Ind. > $10k	.022 (16)**	.021 (25)**	.008 (35)#	.000 (54)
Institutional	.012 (40)*	-.003 (51)	.004 (58)	.001 (73)
Members	-.012 (13)	-.003 (21)	-.005 (29)	.008 (53)**
Program	.004 (17)	.-004 (21)	-.009 (21)	-.002 (38)
Specialist	-.013 (5)	-.006 (9)	.-002 (19)	-.000 (36)

* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL G: Raw Returns (S&P 500) computed from mid-spread to mid-spread (# of firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	.001 (17)	.004 (20)	.007 (22)	.006 (27)#
Ind. > $10k	.023 (15)#	.021 (18)*	.005 (17)	.001 (25)
Institutional	-.002 (22)	.003 (24)	.008 (22)#	.005 (27)**
Members	.004 (18)	.002 (19)	-.004 (18)	.007 (27)**
Program	.006 (17)	-.002 (21)	.-005 (21)	.004 (27)
Specialist	.007 (12)	.009 (13)	.001 (16)	.005 (24)

PANEL H: Raw Returns (S&P 500) computed from transaction price to end price (firms)

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.002 (17)	.002 (20)	.001 (22)	.001 (27)
Ind. > $10k	.020 (15)	.018 (18)#	.001 (17)	-.002 (25)
Institutional	-.004 (22)	.002 (24)	.004 (22)	.001 (27)
Members	.001 (18)	-.001 (19)	-.007 (18)	.005 (27)*
Program	.004 (17)	.-004 (21)	-.009 (21)	-.001 (27)
Specialist	.005 (12)	.007 (13)	-.001 (16)	.003 (24)

* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL I: Raw Returns (Large Firms) computed from mid-spread to mid-spread

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	.006 (19)	.009 (22)#	.004 (20)	.003 (26)
Ind. > $10k	.014 (13)	.012 (17)*	.004 (18)	.000 (26)
Institutional	.002 (21)	.004 (25)	.004 (20)	.003 (26)#
Members	.014 (17)	.013 (18)	.008 (18)	.006 (26)*
Program	.004 (15)	-.003 (19)	-.002 (17)	.001 (23)
Specialist	.005 (10)	.007 (11)	-.008 (14)	-.001 (22)

PANEL J: Raw Returns (Large Firms) computed from transaction price to end price

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	.004 (19)	.007 (22)	.002 (20)	.001 (26)
Ind. > $10k	.011 (13)	.009 (17)	.001 (18)	-.003 (26)
Institutional	.000 (21)	.003(25)	.001 (20)	.000 (26)
Members	.012 (17)	.010 (18)	.005 (18)	.005 (26)#
Program	.002 (15)	-.005 (19)	-.005 (17)	-.000 (23)
Specialist	.004 (10)	.006 (11)	-.010 (14)	-.003 (22)

* Significance at 5% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL K: Raw Returns (Medium Firms) computed from mid-spread to mid-spread

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.019 (11)	-.001 (15)	-.003 (22)	.002 (26)
Ind. > $10k	.068 (8)*	.055 (11)*	.017 (16)	.002 (23)
Institutional	.019 (18)	.014 (20)	.009 (25)#	.005 (26)**
Members	-.022 (9)	-.024 (9)	-.016 (13)	.001 (20)
Program	.016 (3)	.015 (4)	-.005 (7)	-.002 (15)
Specialist	.009 (6)	.008 (6)	.019 (8)#	.014 (14)*

PANEL L: Raw Returns (Medium Firms) computed from transaction price to end price

Investor Group	First half-hour	First full hour	First 3 hours	Until end of next day
Ind. < $10k	-.027 (11)	-.006 (15)	-.008 (22)	-.003 (26)*
Ind. > $10k	.065 (8)#	.053 (11)*	.014 (16)	-.002 (23)
Institutional	.015 (18)	.010 (20)	.003 (25)	.001 (26)
Members	-.026 (9)	-.028 (9)	-.021 (13)	-.004 (20)
Program	.008 (3)	.008 (4)	-.015 (7)	-.009 (15)#
Specialist	.002 (6)	.002 (6)	.014 (8)	.012 (14)#

* Significance at 5% level

** Significance at 1% level

\# Significance at 10% level

TABLE 5-5

Raw Return from Trading after Announcement

PANEL M: Raw Returns (Small Firms) computed from mid-spread to mid-spread

Investor Group	First half-hour	First full hour	First 3 hours	To end of next day
Ind. < $10k	-.042 (9)	.026 (12)	.049 (12)	-.002 (24)
Ind. > $10k	-.074 (2)	-.074 (2)	-.068 (2)	-.004 (5)
Institutional	.014 (7)	-.063 (9)	.030 (13)	.015 (21)
Members	.009 (3)	.009 (3)	.216 (1)	.038 (9)
Program	. (0)	. (0)	. (0)	.041 (3)#
Specialist	. (0)	. (0)	. (0)	.006 (4)

PANEL N: Raw Returns (Small Firms) computed from transaction price to end price

Investor Group	First half-hour	First full hour	First 3 hours	Until end of next day
Ind. < $10k	-.051 (9)#	.013 (12)	.025 (12)	-.029 (24)
Ind. > $10k	-.082 (2)	-.082 (2)	-.066 (2)	-.006 (5)
Institutional	-.011 (7)	-.097 (9)	-.002 (13)	-.011 (21)
Members	-.003 (3)	-.004 (3)	.211 (1)	.022 (9)
Program	. (0)	. (0)	. (0)	.006 (3)
Specialist	. (0)	. (0)	. (0)	-.075 (4)**

** Significance at 1% level

Significance at 10% level

TABLE 5-6

Raw Return from Trading before Announcement

Returns are calculated for the active position of each trade in the time period analyzed.

PANEL A: Raw Returns computed from mid-spread to mid-spread (# of firms)

Investor Group	Half-hour before	One hour before	Three hours before	From previous day
Ind. < $10k	.026 (34)*	.017 (46)	.020 (44)	.014 (71)*
Ind. > $10k	.009 (19)	-.003 (25)	-.012 (28)	-.000 (47)
Institutional	-.005 (34)	-.000 (40)	-.008 (43)	-.002 (73)
Members	-.006 (15)	-.006 (18)	-.014 (19)	.002 (46)
Program	.009 (19)	.008 (18)	.005 (18)	.014 (33)
Specialist	-.027 (9)	-.019 (11)	-.024 (13)	.004 (30)

PANEL B: Raw Returns computed from transaction price to end price (# of firms)

Investor Group	Half-hour before	One hour before	Three hours before	From previous day
Ind. < $10k	.021 (34)	.012 (46)	.015 (44)	.005 (71)
Ind. > $10k	.007 (19)	-.006 (25)	-.014 (28)	-.003 (47)
Institutional	-.011 (34)	-.004 (40)	-.017 (43)	-.011 (73)
Members	-.014 (14)	-.015 (18)	-.022 (19)#	-.004 (46)
Program	.005 (18)	.005 (18)	-.003 (18)	.011 (33)
Specialist	-.034 (9)	-.025 (11)	-.031 (13)	-.001 (30)

\# Significance at 10% level

CHAPTER VI
CONCLUDING COMMENTS

Summary of Findings

In this study, I study the effect of earnings announcements on different investor groups in the market place. To the extent that investors are surprised by the information in the news, there may be an increase in the level of information asymmetry due to differential abilities of market participants to process the information. Traders who secure such an information advantage have incentives to trade on their short-lived superior information at the expense of other trading groups who do not possess the same level of sophistication in processing the earnings news.

Analysis of the trading behavior of different investor groups in the post-announcement period provides some evidence of difference in behavior. While all investor groups increase their trading in the post-announcement period, only the sophisticated groups (institutions and exchange members) are net active traders. Members show great quickness of response. They are net initiators of trade at this juncture, as would be expected of informed traders. Individuals exhibit more naive and mixed behavior in the period immediately following the announcement. Specialists tend to be passive traders providing liquidity to the market, which is in keeping with their hypothesized behavior in a period of information asymmetry. Thus, the trading behavior of the investor groups points to an increase in asymmetry, and provides evidence on the differential sophistication of investor groups in responding to the news.

Investigation of raw returns earned from trading shows that large individual traders (> $10,000), computed from mid-spread to mid-spread is significant in the first half-hour after announcement. In contrast, the trading of institutions and members seem to earn positive returns only on the day after announcement. However, these results are weaker (10% significance level) after adjusting for transaction costs and market returns. The market showed an upward trend during this period with the buildup for gulf war, and while there is increased trading and profits in the post-announcement period, it is not significantly higher than market returns except as noted above.

However, these results should be interpreted subject to the caveat that a number of restricting assumptions have been made in computing these returns. The window of opportunity to trade on information is quite short, and the assumptions made on holding periods and liquidating stocks by the end of the next day, especially the assumption of short selling may not be actually implementable.

Analysis of trading prior to the announcement indicates that there is no information leakage prior to the announcement. However, it is interesting to note that small individual traders (< $10,000 trades) who successfully trade in the half-hour prior to the announcement become inefectual in the post-announcement period. There are three explanations for this. It is possible that they are trading on inside information and are anxious to cash in before the news hits the market. A second possibility is that they are naive traders, and the new information from the announcement does not reach them in time, and they are surprised by the changes in prices after an announcement. A third explanation is that in the increased market activity after an announcement, they are unable to get favorable executions.

Future Research Opportunities

This study shows the vast scope for further work in understanding investor behavior and understanding the market mechanism. A few promising avenues for future research are discussed below.

This study focuses on the effect of possible asymmetry arising after an announcement due to differential processing abilities. However, there are a number of models that motivate trading behavior both before and after the announcement due to information asymmetry arising from insider information. Some of these models have been developed as two period models, with the public information (such as an earnings announcement) being revealed between the two periods.[40] Studying trading and price behavior both before and after the announcement would be a natural extension to this study.

In addition, since most models apply equally to any news event, it would be interesting to study if similar behavior is observed with other news events such as analysts' recommendations.

There have been a number of studies in the microstructure literature on the determinants of price movements in the market. It is argued that the information in trading volume is incorporated into price because it proxies for trader identity. Trader identity is important to the market as a measure of specialized or insider information that is revealed by the trade in a stock.[41] Using the trader type classification in the TORQ data set, it would be interesting to test if the trader group identity has a distinct effect on price over and above the normal volume effect observed.

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[40]See for example, Demski and Feltham (1994) and Bushman, Datta, Hughes and Indjejikian (1992).

[41]See for example, Easley and O'Hara (1987, 1992).

There is also scope for further methodological work such as understanding the reasons and effect of batching of trades and stopping of orders by the specialist. Studying the flow of orders to investigate what triggers the execution of specific limit orders would also be interesting.

This study will hopefully encourage discussion, debate, further investigations and improved understanding of investor behavior and market mechanism.

APPENDICES

APPENDIX A

INSTITUTIONAL DETAILS

Trading in equity securities on the New York Stock Exchange (NYSE) generally involves a continuous two-sided auction.[42] All trading in a given stock is done at the stock's assigned "post" on the exchange floor presided over by a specialist.

Customer Order

A typical customer's order with a broker will contain the following information: type of order (market or limit), direction of trade (buy or sell), the quantity to be traded, and if a limit order, the price desired. A market order is a direction (to the broker) to trade in that stock immediately at the best available price. In contrast, a limit order enjoins the broker to buy (sell) at a price equal to or better than the desired price.

Order Processing by the Broker

On receiving the order, the broker may submit it for execution in a number of different ways. He may send the order directly to the specialist over the superDOT system. This requires him to enter the order electronically and transmit it over data communication lines to the specialist's post. Alternately, he may forward it to the brokerage firm's booth on the exchange floor by telephone. Once the order is received at the booth, the clerk at the booth may either transmit the order electronically to the specialist's post or page the floor broker representing the brokerage and give her the order for further processing and execution. If the order is forwarded to the floor broker, he

[42]The exceptions are the opening trade of each day (which is a single call auction), and certain block trades (which are negotiated away from the exchange floor).

typically takes the order with him to the specialist's post and waits until an order that matches the one he has on hand arrives at the specialist's post. In some cases, he may leave the order with the specialist for execution. Executing through the floor broker is labor intensive and expensive, and employed only if it advantageous to the client to do so.[43]

Order Processing at the Specialist Post

All the orders that reach the specialist's post go into the "display book." The display book (DB) is a computer terminal that keeps track of all limit orders and incoming market orders. At any point in time, the DB will show the near-the-market portion of limit orders with the specialist. Information in the DB is available to the specialist and all floor brokers who request for it, but is <u>not</u> widely communicated to other exchanges through the intermarket terminal system (ITS). When a market order is received at the specialist's post, it is executed immediately. The exchange regulations enjoin the specialist to ensure immediate execution of any market order that is received, unless the specialist guarantees a price at least as good as the prevailing price. (The order is then called a "stopped order" and executed later.) A limit order is executed in the price/time priority in which it is received at the specialist's post.

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[43]The advantage to a client from using a floor broker arises from the fact that the floor broker is able to observe the order flow in the market, and has a better sense of when to release the order for execution. This allows the floor broker to obtain a better execution price.

Order Execution

To execute an order the specialist must find a matching order on the opposite side[44]. Primarily, she has three choices in finding a match. She may match the order with an incoming market order. She may match it with a limit order on her books that has price/time priority. Alternately, she may be a counter-party herself. If the first two choices are not available at any point in time, she is required by exchange rules to exercise the third option.[45] However, there are some exchange stipulated restrictions on what trading she can do on her own account. These restrictions (known as stabilization trade requirements) specify the minimum proportion of passive, liquidity trades that she must undertake to stabilize prices, and places restrictions on the proportion of trades she can actively[46] initiate. In 1991, according to the NYSE fact book, specialists participated in 19.7% of the share volume of NYSE.

Market Prices - Bid, Ask and Execution Price

The market price set by the specialist consists of a "bid" price, and an "offer" price. The offer price (also known as the ask price) is always higher than the bid price, and this difference is usually a multiple of one-eighths[47]. The bid is the price at which the specialist guarantees to buy, up to a limit (known as the quoted depth), any incoming market sell

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[44]Other member traders perform the same function to negotiate block trades in the "upstairs market".

[45]Her responsibility to provide liquidity is limited to the level of depth she quotes.

[46]The "active" side of a transaction *demands* liquidity. A market order to trade or an aggressive limit order priced for immediate execution are examples of the "active" side of a transaction. The "passive" side of the transaction *provides* liquidity. Limit orders on the book, and a specialist trade in response to a market order are examples of the passive side. (See Harris (1990), Lee (1992)).

[47]Low priced stocks may trade at one-sixteenths or one-thirty-seconds.

order. The offer is the price at which she offers to sell the stock. The prices quoted are for one share each, though trading typically takes place in lots of hundreds (called "round lots"). The bid and ask are set by the specialist after reviewing the display book, and occasionally ascertaining the orders on hand with the floor brokers. The prices set by her should therefore reflect the order flow at that point in time. The trading (or execution price) is the price at which a trade actually takes place. Lee and Ready (1991) report that roughly 63% of the trades in their sample are at the bid or ask. Approximately 35% of the trades take place at a price between the bid and the ask, and less than 1% outside the bid or ask.

Effect of Information Asymmetry

The difference in the bid and ask may be thought of as the cost of demanding immediate execution, and is often attributed to the specialist's order processing costs, her inventory carrying costs and the information asymmetry that she faces in trading with informed traders.[48] The exchange stipulates that the specialist *must* provide liquidity (up to her quoted depth) if no other buyer or seller is present in the market. This market clearing role may confer a disadvantage on the specialist who is required, on occasion, to trade with investors who may be better informed than she is. If there is increased uncertainty in the market place, trading by specialists is likely to increase, since other liquidity suppliers may stay away from the market until the uncertainty is resolved.

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[48]There is substantive literature in finance on the reasons for the existence of the bid-ask spread, and the components of the bid-ask spread. Many papers have attempted to model the cost components of the spread: order processing costs (Tinic, 1972); inventory holding costs (Amihud and Mendelson,1980; Ho and Stoll,1981); and adverse information costs (Copeland and Galai, 1983; Glosten and Milgrom, 1985). There are several empirical studies that estimate the components of the bid-ask spread (George, Kaul and Nimalendran, 1991; Stoll, 1989; Glosten and Harris, 1988; Madhavan and Smidt,1991, 1992; Hasbrouck, 1991a, 1991b; Petersen and Umlauf, 1990; Huang and Stoll, 1992).

Advantages of Using a Floor Broker

One of the advantages to the specialist and floor brokers arises from the fact that they can observe order flow information and discern available liquidity on both sides. This information is not available to a person outside (such as individual and institutional traders) who only observes the trades. In the event of a public announcement, the location of the specialist and floor brokers gives them an advantage in speed of execution, but this advantage seems somewhat limited since a person outside may transmit orders electronically over high speed lines. In particular, the superDOT system of order transmission favors small investors who might otherwise be at a disadvantage.

Advantage of Using a Floor Broker: An Example

To the investor, there are two advantages to utilizing the services of a floor broker. If price is affected by order flow, an investor with a large sell order may instruct his floor broker to execute his order in pieces over time to avoid having a precipitous effect on price by revealing the full order.[49] Since, the floor broker can see the DB, he has a better sense of when and how much of the client's order to release for execution. Secondly, the floor trader may get opportunities to trade with incoming market orders and obtain a better execution price for his customer. In this sense, the floor trader offers liquidity to the incoming order and is rewarded with the spread. An example will clarify this point. Suppose the broker holds an order to sell 100 shares of company X. The bid and ask prices are 20 and 20½ for the stock. A market sell would fetch a price of $20 per share. Suppose, he waits until a market buy order comes along, and offers to trade at 20⅜, thereby getting a priority over existing ask price. By waiting, he now gets a price of 20⅜ per share.

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[49]Note that this view assumes an order flow effect on prices.

APPENDIX B

DESCRIPTION OF THE TORQ DATA BASE AND TRADER CATEGORY CLASSIFICATION

TORQ: Data Base Description

There are four data files in the TORQ data base. Two files, the trade (CT) file and quote (CQ) file, contain information that is provided in real-time to market participants through the Consolidated Tape System (CTS), and may be found in archival form in the ISSM or TAQ files. However, the information in the order (SOD) file and audit (CD) file is unique to the TORQ data base. The four files contain information on *trades, quotes, order processing information and audit trail data* for a size-stratified sample of 144 firms whose primary listing is on the NYSE, for the period November 1990 to January 1991.[50]

The *trade file* lists all trades that originate from NYSE or one of the regional exchanges on which the stock is traded. The price and volume of each trade are provided as well as a condition code to identify special conditions, if any. A trade sequence code is included in the file to give each trade a unique number. The *quote file* contains each and every quote issued for the stock on the NYSE or regional exchanges. The bid price, ask price, the depth on each side, a condition code and a quote sequence number is included in the quote file. The *order file* contains all orders placed at the NYSE that were received through the superDOT system. For each order, the time the order is received, the direction (buy, sell), an order condition (market, limit), a code for the type of trader (individual, member etc.) and the order quantity is included. Limit orders include the limit price. If an order is executed, the order file contains information on the time of execution, the quantity traded and the execution price. When there are several partial trades of a single order, the file provides information on execution of each trade. The *audit file* gives

[50]For more information on the TORQ data base, see Hasbrouck (1992).

information on buyer type (individual, institutional, etc.) and seller type for each trade. If several orders are simultaneously executed in a reported trade, the report file contains information on each buyer and seller type, and the quantity traded by each. Figure 3-1 provides an illustration of how the four files are interrelated.

The unique feature of the TORQ data base is in the information provided in the audit (CD) and order (SOD) files. The audit file provides information on the number and type of parties to a trade, and volume traded by each. It is linked to the trade file by trade sequence number.[51] For each trade, it provides information on the order type of orders (buy, sell and market, limit) that make up the buy and sell side. However, this wealth of information is available only for NYSE trades. While trades in other exchanges are reported in the CD file, the unique information fields are blank.

For certain order types, it is possible to trace the order to the SOD file to obtain further details. The SOD file contains order entry and processing information for orders from three sources: the superDOT system (the electronic order processing system at the NYSE), the OARS (the Opening Automated Report System, used at market openings), and ITS (the Intermarket Trading system, used to transfer orders between market

[51]If a reported trade in the CT file consists of batch orders, i.e., more than one participant on either or both sides (buy, sell) of the trade, then there may be more than one corresponding record in the Audit (CD) file pertaining to that trade. However, the total shares traded for all CD records with the same trade sequence number should equal the total shares reported in the CT file. Occasionally, there are some differences between the two files. For the entire TORQ data base, the CD file volume is higher than the CT file volume in 7 cases (.000% of total). For trades amounting to approximately 16% of total volume, the CD file volume is less than the CT file volume. On inquiry, the information I received from the NYSE was that these were intermarket orders that were omitted to be reported from the CD file. In addition, some trades appeared in the CD file (approximately 5% of all audit file records) that were not reported in the CT file. These are trades that are not reported on the Consolidated Tape, but are subsequently thrown up by the audit algorithm. Quite often they reflect corrections to trades reported earlier. I restricted my analysis to trades that appear in the CT file, since the CT file contains information made available to all investors through the Consolidated Tape.

centers). Since these three systems report orders placed in the NYSE, the SOD file is limited to NYSE orders. For this time period, the SOD orders combine for 55% of the total orders and 31% of all volume on NYSE. The unique order information available from the SOD file are: time of order placement, order routing, partial executions and "stopped" orders. However, the link between the CD file and SOD file is more difficult to establish in the absence of unique identifiers between the files.

Trader Categories

The TORQ data base uses an account type code to classify trader groups. I use these account types to classify traders into the following categories:

1) Program Traders

The NYSE defines program trading as any trading strategy involving the simultaneous or nearly simultaneous purchase or sale of fifteen or more stocks with a total aggregate value of one million dollars or more. In addition, NYSE members must report index arbitrage trades of all sizes. In this study, I do not distinguish between program trades initiated by NYSE members and institutional traders.[52] Accordingly, all trades coded with account type codes of C, D, J, K, U, or Y are classified as program trades.

2) Members

This category includes trades by member organizations of the NYSE, trading on their own account. During this period, the NYSE had more than 500 member organizations including brokerage firms, floor traders with permission to execute trades on their own account. Specialist trades are excluded from this category. I include all orders

[52]Individual investors may also participate in program trading. For the entire three months, there were 23 program trades (.000% of total trades, and .003% of all program trades) initiated by individuals.

(except program trades) by member organizations (other than specialists) in this category. This category corresponds to the account type code P.

3) Individual Investors

The TORQ data set specifically identifies trades coming from individuals. These reflect orders that the brokerage firms have indicated as being initiated by individual investors. Brokers are encouraged to provide this information where appropriate, so that their clients might receive preferential routing through the Individual Investor Express Delivery Service (IIEDS).[53] All trades coded with an "I" are taken as initiated by individuals.

4) Institutional Investors

All trades coded "A" are taken as institutional trades. The TORQ coding is such that some fraction of these trades may arise from NYSE members who are represented by another member. However, a discussion with NYSE officials suggests that the vast majority of orders with this account code are from institutional investors.

5) Intermarket Trades

This category includes trades that were initiated in another market and executed on NYSE, or initiated from NYSE and executed on another market. The unique trader information in the TORQ data base is available only for the NYSE portion of the trades. For the sake of completeness, I code the side of trade fulfilled by other markets as Intermarket trades.

Intermarket trades are identified two ways. The audit file has an "order type" code (the variables "b type" and "s type") that is coded "I1" or "I2" for intermarket trades.

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[53]This reporting is not independently monitored, but there is little reason to suspect broker misrepresentation. In fact, the total volume of "individual" trades in the TORQ data base is very similar to the total volume of individual trades estimated by Securities Industry Association (SIA) for this time period. The SIA estimation procedure is based on an independent data source (regulatory filings by institutional investors).

These audit records contain information on one side of the trade (the NYSE side), and the record for the other side is missing. In all such cases, I code the other side as ITS. However, these orders account for only 3.5% of the NYSE volume during this period. Discussions with NYSE officials suggest that all intermarket trades may not have been coded I1 and I2, and cases where the volume in the CD file does not add up to the trade volume in the CT file might reflect intermarket trading volume. Coding such cases as ITS brings the ITS volume to approximately 15%, which is closer to the intermarket transaction estimate of NYSE.

6) Specialist Trades

Some trades (19.7% on the buy side, and 21% on the sell side) in the TORQ data base have no account type codes. Discussions with NYSE officials suggest that these include trades by specialists. However, according to the NYSE fact book for 1991, specialist participated in 9.8% of the buy volume, and 9.9% of the sell volume. Therefore, approximately 50% of the volume of these trades were from specialist trades. Further inquiries with the NYSE suggested that trades by specialists were stripped of both account and order type codes. I coded all such trades as specialist trades. Since these trades account for approximately 7% of the volume (buy and sell side) during this period, most but not all specialist trades have been coded in this analysis.

7) Residual Category

All other trades that do not have an account type code have been grouped together in a residual category. I suspect that the bulk of these are agency orders initiated by floor brokers, and primarily reflect institutional investor activities. However, since there is no information on these orders, I classify them as the residual category.

APPENDIX C

INFERRING TRADE DIRECTION: LEE-READY (1991) ALGORITHM

The direction of individual trades is inferred by the following algorithm from Lee and Ready (1991). Only NYSE-issued quotes which are BBO-eligible were used (a quote is BBO-eligible if it qualifies for the National Association of Security Dealers' Best-Bid-Or-Offer calculation):

(1) *Current Quote Match* - If the trade price is at the bid or ask and the current quote was not revised within the last five seconds, then the direction of the trade is determined by the current quote (i.e., a buy if it's at the ask and a sell if it's at the bid).

(2) *Delayed Quote Match* - If the current quote is less than five seconds old, it is ignored and the trade price is compared to the bid and ask prices of the previous quote.

(3) *Outside the Spread* - If the trade price, when compared to the quote in either step 1 or 2 is greater than the ask (less than the bid), then the transaction is deemed a buy (sell).

(4) *Tick Test* - If the trade is at the mid-point of the spread or if a BBO-eligible quote is not available, the tick test is used to determine trade direction. In other words, if the last price change was positive (negative), then the trade is deemed a buy (sell). All out-of-sequence trades are ignored in updating price changes.

(5) *Proximity to Bid/Ask* - If the trade is between the spread but not at the mid-point, then the trade is classified according to its proximity to the bid and ask price. Trades at prices above the mid-point are classified as buys and trades at prices below the mid-point are classified as sells.

(6) *Indeterminable* - This classification is assigned to a trade when none of the above conditions apply. Specifically, it applies to the first trade of the period for each firm and any trade which is reported out of sequence.

APPENDIX D

RULES FOR DETERMINING TRADE DIRECTION WITH THE TORQ DATA BASE

The following rules were applied to determine trade direction:

1. When one side has market (or marketable limit) orders and the other side has none, the side with the market order is taken to be the active side.
2. If there is an intermarket trade, the executing market is the passive side, and the committing market the active side.
3. When both sides have market orders and the orders on one side were stopped, then that side is taken to be the passive side.
4. When one side has market orders and the other side has specialist trades (disguised trades), the market order side is taken to be the active side.

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