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Dr. Brian C. Hatch

Dr. Yan Yu

Three Essays on Trading Volume

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by

Guohua Ma

B. A., Shandong Finance Institute, 1995

M.I.B., Norwegian School of Economics and Business Administration, 2000

Abstract

Trading volume, a stochastic process that is closely related to returns, has received far less attention in modern finance. Because of the joint hypothesis problem of asset returns, trading volume can often provide unique evidence on financial studies.

In Essay 1, I examine the cross-sectional and time series behavior of trading volume for an extended period from 1963 to 2004 on all stocks listed on NYSE/AMEX/NASDAQ exchanges. The cross-sectional analysis shows that trading volume is not linearly related to market capitalization and stock beta. Specially, an inverted U-shape relation represents the relation between stock turnover and market capitalization.

Essay 2 provides some empirical evidence on the motivation of investor trades by conducting an event study on analyst recommendation date. I divide data into two event groups: the recommendation reversal group and the recommendation continuation group. I test heterogeneous-belief model by examining the event date share turnover of two event groups. My empirical tests contradict the major implications of Harris and Raviv (1993)'s heterogeneous belief model and are mostly consistent with Wang (1994)'s hypothesis that investors trade for liquidity and informational reasons.

In Essay 3, I test market-wide disposition impact by examining the trading volume on historical high and historical low days during a period of 84, 168, 252, and 504 trading days respectively. I hypothesize that abnormal trading volume is the highest on historical high days, lower for normal trading days and lowest for historical low trading days if there is a market-wide disposition effect. My empirical evidence suggests the following: abnormal trading volume is much higher for historical high days, lower for historical low days and lowest for normal trading days. On average, abnormal trading volume on historical low days is about twice as much as that of normal trading days. The evidence supports the hypothesis that the market has strong propensity to realize gains, but the evidence contradicts the hypothesis that investors are unwilling to cut losses.

Keywords: Trading Volume, Heterogeneous Beliefs, Disposition Effect, Informational Trading, Liquidity Trading

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Essay 1 The Behavior of Trading Volume

1.1 Introduction

Researchers have long been focused on the behavior of stock returns. Numerous theoretical, empirical and experimental studies have examined the return behavior: the daily, weekly and monthly distribution of stock returns, the cross-sectional and time series properties of stock returns, and asset pricing models are all centered on returns. It goes without question that all these areas are of importance in finance, since essentially every aspect of modern finance is related to returns. However, trading volume, another important stochastic process closely related to returns, received far less attention in academic studies.

Volume is important in the following ways:

First, since both returns and trading volume are jointly determined by market dynamics, studying the behavior of volume can help us understand the dynamics of financial market. When information gets revealed and disseminated into financial market, it not only causes prices and returns to change over time, but also generates trading volume since the process of information revelation and dissemination is realized by investor trading. An interesting question has long perplexed researchers and practitioners: why do investors trade? As implied by Milgrom and Stokey (1982), no trade should occur under asymmetric information setting ("no trade equilibrium"). The fact that we observe extensive trading each day[1] makes it very interesting to understand why investors are willing to trade. It is also important to quest the motives behind investors' trading behavior: Are trades motivated by liquidity reasons, informational reasons, speculative reasons or other reasons? Since different

[1] Average annual turnover on the New York Stock Exchange (NYSE) is 113% in 2005 (see NYSE website: http://www.nysedata.com/nysedata/asp/factbook/viewer_edition.asp?mode=tables&key=317&category=3)

trading motives lead to different return behavior, identifying the true motive the trading will help the understanding of the return behavior on financial market.

Second, trading volume and stock returns are two important statistics that market participants can observe in the stock market. As a well-known adage in the Wall Street stated, “it takes volume to move prices”, volume and prices are “twins” – they are closely related to each other. Karpoff (1987) provide a comprehensive survey for the relation between price changes and trading volume. Practitioners often use volume as an indicator of market trend. To them, volume, just as price or returns, should be taken into consideration when making buy or sell decisions. Specifically, technical analysis makes predictions on future stock price movements based on both volume and price data (Pring 1991; Neftci 1991). Blume, Easley and O’hara (1994) show that traders who apply information from volume and price patterns do better than traders who do not. In their model, volume is not a statistic that describes the market, but rather is a statistic that affects the behavior of the market since investors updates their beliefs after they observe volume data.

Third, trading volume conveys information about a security (e.g., Blume, Easley et al. 1994). Easley, O’hara and Srinivas (1998) show that directional option volume precedes stock price changes, indicating that option volume contains information about future stock prices. The informational role of volume has accepted by researchers that more and more empirical studies use volume as a measure of “informational content” of an event in the financial market (Beaver 1968; Bamber 1986; Jain 1988; Morse 1981; Richardson, Sefcik and Thompson 1986; Ziebart 1990; Chan, Hameed and Tong 2000). Moreover, volume information often has important implications that price or return could not reveal or distinguish (Campbell, Grossman and Wang 1993).

Compared to returns, trading volume raised much less notice in finance research. Many interesting questions regarding trading volume remain unanswered. What empirical data suggest trading volume behavior? Does it support any theoretical models on why investors trade? How does trading volume vary with other factors? Fama and French (1992, 1993) provide an extensive exploration of cross-sectional and time-series properties of return behavior. However, the distributional properties of trading volume were seldom examined in the literature [Lo and Wang (2000) provide a cross-sectional and time-series analysis on NYSE/AMEX weekly data]. Firm size and market β are often considered as important factors that describes firm's characteristics. Fama and French (1992) show that portfolio returns decrease with firm size after controlling for β but the standard CAPM relation between portfolio return and β is not salient after controlling for firm size. Investors trading activity is closely related to returns. Firm size is considered as an important risk factor which captures other things that β could not explain and the influence of firm size on security returns has exceeded β. A natural question is raised: when explaining the behavior of share turnover, will similar trend appear? How will risk play a role in investor trading? The joint relation between share turnover and firm size/ β is explored in this study.

In this chapter I will examine the distributional properties of trading volume. It contributes the literature in the following ways:

First, I examine the cross-sectional distributional properties of trading volume proxied by share turnover. Specifically, I examined the variation of share turnover by portfolios based on firm size and beta deciles similar to Fama and French (1992). I find that while share turnover increases with beta but it is not linearly related to market capitalization.

An inverted U-shape relation represents the relation between stock turnover and market capitalization. That is, stocks with medium market capitalization on average have the highest turnover and stocks with lowest and highest market capitalization have lower turnover.

Second, I examine the time-series properties of share turnover proxied by value-weighted and equal-weighted share turnover indexes during 1963-2004. The test statistics and time series plot show that share turnover is non-stationary over the sample period.

Third, I examine the cross-sectional and time-series properties of trading volume for NYSE/AMEX and NASDAQ daily, weekly and monthly data and for longer time frame (July 1963 to December 2004). Lo and Wang (2000) also look at cross-sectional and time series properties of stock trading volume. They found stock turnovers are significantly related to stock's systematic and residual risk (market β and residual standard deviation from the CAPM regression respectively), market capitalization, dividend yield and price. However, their data are limited to NYSE and AMEX weekly data only. My study gives a comprehensive picture of volume on daily, weekly and monthly basis of both NYSE/AMEX and NASDAQ securities for the extended period of time from July 1963 to Dec 2004. Most of the previous studies focus on the time frame before 1990s and none looked at NASDAQ market. Compared to previous works, this study covers a longer sample period and more data sources. Moreover, this study documented a non-linear relation between share turnover and firm size, which was not captured by previous studies.

The essay is organized as the following: section 1.2 reviews theoretical framework on why investor trades. Section 1.3 reviews related empirical literature on cross-sectional and time-series trading volume. Section 1.4 describes the data and methodology. Section 1.5 provides the empirical results. Section 1.6 concludes the essay.

1.2 Why Do Investors Trade?

Why investors trade? What is the motivation for trading? Milgrom and Stokey (1982) showed that with existence of information asymmetry, rational investors will not trade to each other and we could observe "no-trade equilibrium". This occurs because the following: any party who agree to trade at a specific price would expect a gain from the trade based on his private information; given his willingness to trade, the counter party would figure out he himself would bear the loss from the trade. Therefore, no trade would occur. However, we do observe huge trading activities each day in financial market. Investors show extensive interest in trading securities. The financial theories suggest the following as potential reasons for investor trading:

1.2.1 Tax Heterogeneity

Tax heterogeneity creates incentives for investors to trade because their after-tax returns are largely determined by tax code. Tax rate on capital gains and dividends are often different, and corporation investors have much lower tax on dividend income than on capital gains (6.9% vs. 46%, Michaely and Vial 1996). Some institutions are even exempt from paying taxes on dividends. Therefore, they value $1 pre-tax income quite differently. Differential tax rates cause differences in asset valuations and thus motivate trading in securities. Previous research has found evidences of higher trading volume around ex-day when tax heterogeneity among investors is large (Lakonishok and Smidt 1986; Lakonishok and Vermaelen 1986; Michaely and Vila 1996; Michaely and Murgia 1995).

1.2.2 Liquidity Reasons

Liquidity trading comes from investor's liquidity need or portfolio rebalancing need. It is non-informational. This stream of literature generally falls in rational expectations models. Under asymmetric information settings, investors with superior information wanted to trade with uninformed investors. However, without "sand in the gears", given informed willingness to trade, uninformed investors would refuse to trade since he will lose money to the informed. We would observe "no-trade" equilibrium. However, with either noise traders or informed-trader's non-informational need to trade, trade can occur. In this sense, we believe that private information only can not be the ultimate motive for trade to occur. Liquidity is the ultimate reason. Wang (1994)'s model clearly demonstrates this. In his model, informed investors trade to maximize profits from his private information and private investment opportunities. His demand for trade would be pure "non-informational" when returns on his private investment opportunities are higher than returns on securities on financial market. His motivation for trade can be either informational or non-informational. On the other hand, uninformed investors trade for liquidity reasons. Since uninformed investors could not differentiate the true reasons for the informed trading, they are willing to participate trading when they thought the informed are trading for liquidity reasons. In his model, non-informational trading or liquidity trading of the informed investors is the key for trading to occur. Without liquidity trading, we would observe the "no-trade equilibrium".

Liquidity trading plays a critical role in Admati and Pfleiderer (1988). They develop a model that the concentrated intraday trading volume pattern arises because the strategic trading behavior of liquidity traders and informed traders. In their model, liquidity ("noise") traders prefer to trade when market is "thick"—when their trading does not move price much—in order to minimize the adverse selection cost arising from trade with informational traders. This contrasts with other models where liquidity traders have no discretion over the timing of their trades (Kyle 1985). Informational traders who are interested in maximizing their profit also likes to trade when market is "thick". Since liquidity traders often cluster their trades at the beginning and the end of the trading day, a U-shape pattern in trading volume shows.

1.2.3 Heterogeneous Beliefs of Investors

In Harris and Raviv (1993)'s model, investors trade because they have heterogeneous beliefs on stock future returns and they constantly update their beliefs based on the new signals that enter the market. "Heterogeneous beliefs" in their model does not imply that investors disagree on the direction of the signal, instead, "they agree on whether a given piece of information is favorable or unfavorable, but they disagree on the extent to which the information is important". Based on the parameters that investors use to update their information set, there are two types of investors: responsive speculators and non-responsive speculators. The responsive speculators are more optimistic and give a higher value when the signal is favorable and more pessimistic and give a lower value when the signal is unfavorable. Compare to the responsive investors, the unresponsive speculators are less optimistic on favorable signal and less pessimistic on unfavorable signal. Thus when there is a cumulative favorable signal, the responsive group will have all shares on the market. When there is a cumulative unfavorable signal, the less responsive group will have all shares on the market. Therefore, only when cumulative signal switches directions, trade can occur. Otherwise, shares will not change hand.

1.2.4 Risk sharing

Risk-sharing is another important reason for investor trading. Campbell, Grossman and Wang (1993) build a model to explain the phenomenon that first-order daily return auto-correlation declines with volume. In this model, risk-averse market-makers trade stocks from liquidity or non-informational traders. When some traders become more risk averse, risk is allocated from those people who become more risk-averse to the rest of the market. At the same time, the expected return must rise to compensate those investors bearing the risk. As a result, trading volume increases and stock prices fall to reflect the higher expected return. Llorente et al. (2002) model trading activity due to both risk-sharing and speculative (informational) reasons to demonstrate the different time-series return dynamics caused by different trading motives.

1.2.5 Overconfidence

Odean (1998a) develops a model that traders trade because they are overconfident – they believe their information is more precise than it actually is. Overconfidence increases trading volume, increases market depth, and decreases the expected utility of overconfident traders. Some empirical studies, such as Odean (1999) support this hypothesis. Overconfidence essentially is another ramification of heterogeneous beliefs model in Harris and Raviv (1993).

All the above models have one thing in common: investors are different. They are either different in their need (heterogeneous liquidity need), or beliefs (heterogeneous beliefs), or tax bracket (tax heterogeneity), or behavior (over-confidence). These differences are not necessarily mutually exclusive. It is possible that investors might have several of the above differences and thus trade for several reasons at the same time. Trading activity in financial market might reflect several of those heterogeneities. It might also be true that only one type of heterogeneity is dominating the market and return behavior is mostly affected by this type of heterogeneity.

1.3 Related Literature

Researchers have noticed that volume is closely related to price and volatility of returns[2]. Theories related to volume itself start to raise attention only recently. Lo and Wang (2000) proves that under two-fund separation, every stock's turnover should be exactly the same and no cross-sectional variation in stock share turnovers should be observed. That is, when investor holds only riskless asset and portfolio of risky asset, each time they balance the portfolio, the share turnover of every stock in the portfolio normalized by the number of shares outstanding would be identical and we would see no cross sectional variation in stock share turnover. Furthermore, with (K+1)-fund separation, turnover should satisfies an approximately linear K-factor structure. They use weekly data for NYSE and Amex securities to test the linear structure of share turnover. Using principal component analysis, they find that more than 90% of the share turnover variation can be explained by a two-factor linear model. However, it is generally very hard to identify the meaning of the main factors in principal component analysis. Therefore, even Lo and Wang (2000) identified that there are two factors that explains turnover variation well, what exactly are those two factors remain unrevealed and so is the motive of trading. Tkac (1999) develops a theoretical rebalancing benchmark for trading volume and shows that about 20% of the samples firms

[2] For the relation between volume and volatility, see Harris (1987), Jain and Joh (1988), Mulherin and Gerety (19890, Jones, Kaul and Lipson (1991), Anderson (1996), Foster and Viswanathan (1995). For the relation between volume and price, see the survey of Karpoff (1987), Pfleiderer (1984), Gallant, Rossi and Tauchen (1992), Kim and Verrecchia (1991), Barber and Loeffler (1993), Heimstra and Jones (1994), Kandel and Pearson (1995), Chan, Hameed and Tong (2000), Llorente, Michaely, Saar and Wang (2002).

from NYSE/AMEX exhibit consistent trading behavior with what her rebalancing model predicts. Investors trading activity could not be explained by portfolio rebalancing alone. In fact, some studies have shown that risk and firm size can affect trading activity.

1.3.1 Risk and Volume

How does risk related to trading volume? Suppose investors are trading for risk sharing and portfolio rebalance purposes. When risk increases, the cost of deviation from Pareto optimal portfolio given the existence of transaction costs also increases thus investors would like to frequently rebalance their portfolio to their optimal level, as a result, trading volume should be larger for firms with high risk than those with low risk. However, on ex-dividend days, investors trade to deviate from their optimal portfolio and the cost of deviation is much lower hence risk reduces volume. Michaely and Vila (1996) examine this relation between risk and volume around ex-dividend days. They find that market risk has a negative effect on trading volume proxied by share turnover.

Gerety and Mulherin (1992) examine the trading volume at the daily opening and closing of financial market and they find that investors' heterogeneous ability to bear risk causes abnormally large trading volume at the daily opening and the close. As risk increases, risk-averse investors tend to trade more when they face uncertainties on the financial market.

1.3.2 Size and Volume

The relation between size and volume is ambiguous. Large firms tend to have more disclosure and news coverage, larger and diverse investor base, and they typically have more analysts' coverage as well. Compared to smaller firms, their prices should more closely reflect available information on the market than smaller firms. Therefore, there should be less opportunity for investors to acquire private information and profitably trade on. On the other hand, smaller firms tend to have less investors, news and analyst coverage, thus earnings and dividend surprises tend to be larger for smaller firms[3]. This gives opportunity for information-based trading. Basembinder, Chan and Seguin (1996) suggest that market-wide information is only reflected in the volume of the largest 20% of NYSE firms. This suggests that larger firms should have more trading activity since their trading reflects market information much more than smaller firms do. Tkac (1999) finds that size is negatively related to excess trading behavior (measured by excess turnover) for a group of NYSE/AMEX firms. Michaely and Vila (1996) use size as a proxy for transaction costs to test the relation between transaction cost and trading volume around the ex-dividend date. Lo and Wang (2000) examine the relation between share turnover and size. They found that the relation can be positive or negative depending on the sub-period in their sample.

Empirical evidence on the relation between firm size and trading activity seems to be contradictory. There are no models or theory which offers explanation to reconcile those empirical results. Given the importance of firm size in explaining stock returns, the relation between firm size and volume needs to be examined carefully.

1.3.3 Time Series Properties of Trading Volume

Not much literature examines the time series property of trading volume. Instead, some literature examines the relation between realized or expected return and volume, volume and volatility, etc. Lo and Wang (2000) document positive autocorrelation for both value-weighted and equal-weighted turnovers for up to the first 10 orders.

[3] Bamber (1986) suggests that firm size is negatively related to information in earnings announcements.

1.3.4 Measures of Trading Volume

Volume reflects market participants' trading interest and is an important measure of market activities. Previous literature uses different types of measures of trading activity:

1) Share Volume

Trading activity is measured as number of shares traded during a specific period of time. Sometimes it is often referred as "raw volume". Ying (1966); Lamoureux and Poon (1987); Admati and Pfleiderer (1988); Gallant Rossi et al. (1992); Hiemstra and Jones (1994); Berry and Howe (1994); Anderson (1996); Lamoureux and Lastrapes (1990); Lee, Ready et al. (1994); Easley, Kiefer et al. (1996) all used share volume as their definition of trading volume.

2) Dollar Volume

Dollar volume is defined as number of shares traded multiply share price. That is,

$$V_i = P_i * Q_i \qquad 1.1$$

Where P_i denotes share price for stock i, and Q_i denotes number of shares traded during specific time interval.

In their paper, Mitchell and Mulherin (1994), Flemming and Remolona (1999), Tkac (1999), James and Edmister (1983), and Lakonishok and Vermaelen (1986) all used dollar volume as a measure of trading volume.

3) Share Turnover

Share turnover is defined as number of shares traded divided by firm's total number of shares outstanding. That is,

$$\tau_i = Q_i / N_i \qquad 1.2$$

Where N_i denotes number of shares outstanding for stock *i*, and Q_i denotes number of shares traded during specific time interval. This is a common and popular definition used in previous studies (Jain 1988; Jain and Joh 1988; Ziebat 1990; Michaely and Vila 1996; Bamber, Barron et al. 1997; Tkac 1999; Chordia and Swaminathan 2000; Lo and Wang 2000; Lee and Swaminathan 2000).

There are other measures of volume that are rarely used in the literature, such as number of trades or transactions (Conrad, Hameed et al. 1994), or trading days per year (James and Edmister 1983). Among all these measures, turnover is the most reasonable definition. Either share volume or dollar volume are absolute measures of trading activity and thus makes comparison of volume across stocks really hard. Furthermore, comparison of volume for the same firm over time becomes difficult since individual firm's outstanding shares vary with time especially when individual firms often have stock split, new issues or repurchases. On the other hand, share turnover measure is comparable across firms and through time, therefore makes it the most effective and reasonable measure for trading volume. I adopt share turnover measure in my study as the only measure of volume.

To understand the difference of share turnover and share volume, I calculate average share volume for each decile of share turnover using NYSE/AMEX stocks. The results are listed in Table 1.1. From the table, we can see that share volume does not monotonically increase with share turnover. Firms in the highest turnover decile have medium market capitalization, lower share outstanding and the highest β.

1.4 Data and Methodology

1.4.1 Data

My data comes from two sources: 1) the Center for Research in Security Prices (CRSP) daily and monthly data; 2) COMPUSTAT annual industrial data. The time frame for this study is from July 1963 to December 2004 with a total of 2218 weeks. In order to examine weekly data, I use CRSP daily data to construct CRSP weekly data. From CRSP daily and monthly files, I can obtain return and number of shares traded for all NYSE/AMEX/NASDAQ stocks. I can calculate share turnover based on raw share volume and shares outstanding. From CRSP, I take all NYSE, AMEX, and NASDAQ firms qualifying the following:

1) The firm's share code is in either 10 or 11. that is, I include only common shares into my sample;

2) The firm's SIC code is not between 6000 and 7000. That is, I excluded all financial firms from the data. As in Fama and French (1992) state, financial firms normally have very high leverage and their size and risk are not comparable with industrial firms ;

3) The firm has no missing prices for year June each year. The firm's market equity is calculated based on the market price of the equity in June;

4) The firm must have monthly returns for at least 24 of the 60 months preceding July of year t since β will be calculated based on a regression of monthly stock returns on market returns.

My COMPUSTAT data range from 1962-2004. Firms must have COMPUSTAT data on total book asset, book equity and earnings for the previous fiscal year. I add this requirement to make the sample cleaner and comparable to Fama and French (1992). Since Fama and French (1992) examine the distribution of returns and their methodology and results are well-accepted, following their methodology when examining the distribution of trading volume makes empirical results on volume easy to compare with those on returns. I match CRSP return and volume data for July of year t to June of year t+1 to COMPUSTAT fiscal yearends in calendar year t-1.

Because of the advantage of share turnover over other measures of volume explained above, I use share turnover as a measure of trading activity. All return and turnover numbers in this essay are reported in unit of percent for daily, weekly or monthly data.

1.4.2 NYSE/AMEX versus NASDAQ Volume

NASDAQ trading volume is not comparable to NYSE/AMEX trading volume. The difference comes from different market structures. NYSE is an auction market where specialist mostly matches buy and sell orders, while NASDAQ is a dealer market where dealer commonly trades securities as intermediaries between buyers and sellers. On a dealer's market, every trade dealer participate will be reported as trading volume together with trading between public investors. As a result, NYSE recorded share volume give a more precise measure of trades by public investors, while NASDAQ recorded share volume tends to be inflated because the following: 1) dealer participate most trades and dealers normally takes twice as many trades to link a buyer and a seller as specialists; 2) inter-dealer trades. NYSE trading volumes are also slightly inflated because specialists sometimes act like a dealer – buy and sell for their own sake, but since there is only one specialist for a stock there are no inter-dealer trades on NYSE stocks. Atkins and Dyl (1997) find that when firms previously traded on NASDAQ National Market System switched to trade on NYSE during 1988-1990, their average daily trading volume (measured in raw volume) dropped to about 50% of the volume that previously traded on NASDAQ. Beginning in 1997, Security and Exchange Committee (SEC) changed order-handling rules and trade-reporting rules. Under the new rules, public limit orders are able to directly compete with market maker's quotes. Moreover, public investors now have access to electronic communication networks (ECNs). All these make NASDAQ market more similar to NYSE market. In addition, more and more investors trade via ECNs where trading volume is only counted once even dealers trade with both the buyer and the seller individually. This alleviates the double-counting problem on volume. Anderson and Dyl (2005) examine trading volumes of a group of firms that previously traded on NASDAQ but changed to NYSE during 1997 – 2002. They find that mean daily trading volume decreased for about 25% after the switch but the reduction in volume varies for individual stocks. Moreover, the difference between NYSE and NASDAQ market structure has become blurred since NASDAQ has added auction market characteristics (such as allowing public limit orders to compete with dealer's quote directly and the introduce of electronic communication networks (ECNs)) and many NYSE stocks have significant volume traded dealers in the NASDAQ intermarket (Weston 2000). Without a well-accepted way to adjust NASDAQ trading volume, examining the share turnover of NYSE/AMEX and NASDAQ market separately is a reasonable choice.

1.4.3 β Estimation

Since I form portfolios based on size and β deciles, similar to Fama and French (1992). As explained in Fama and MacBeth (1973), β estimations derived from portfolios are much more precise estimates of the true β than from individual stocks. I use NYSE stock Market Equity (ME) in June of each year to determine the 10 size deciles. Using only NYSE stocks to determine deciles can reduce the influence of large amount of small firms on NASDAQ market and thus create relatively stable firm size criteria over time. Number of firms in each of the ten deciles varies even in the same year, but the breakpoints are relatively stable over time. Otherwise, if I use all NYSE/AMEX/NASDAQ firms to create ME deciles, most portfolios would have a large number of small stocks after 1973, after NASDAQ stocks entered the sample. The breakpoints would be much smaller compared to earlier periods.

Pre-ranking β s are estimated in the same way as in Fama and French (1992): using each of the previous 5 years monthly stock returns ending at June of year t to run an OLS regression on value-weighted market returns. Note that only those stocks that have more than 24 monthly returns are included and only NYSE stocks that satisfy the COMPUSTAT-CRSP data requirements are included. Using only NYSE stocks to determine β breakpoints make sure that small firms from NASDAQ do not skew the breakpoints drastically year from year.

Size and pre-ranking β s are highly correlated (see Chan and Chen 1988; Fama and French 1992; Lo and Wang 2000). This high correlation often creates problems for empirical studies. For example, returns are positively related to stock β s and also negatively related to firm sizes. It is hard to identify which one is the true proxy for risk. Fama and French (1992) find a way to get away from this problem. They first form portfolios based on size, then subdivide each size decile into 10 portfolios based on pre-ranking betas of each individual stocks. This design allows β varying within each size decile thus separate the effects of β that is unrelated to size. They find that return does not show much variation with β and size explains most of the variation of returns. Similar situation occurs to turnover. Lo and Wang (2000) conduct a cross-sectional analysis of weekly turnover of NYSE and AMEX stocks during 1962 to 1996. Their explanatory variables include: size, return β, stock price, average dividend yield, indicator variable of S&P 500 Index membership. Their regression results show the following: 1) β is positively related to turnover across all sub-periods; 2) for the sub-periods 1962-1966 and 1967-1971, size is negatively related to turnover. For the sub-periods 1982-1986, 1987-1991 and 1992-1996, size is positively related to turnover. While for sub-periods 1972-1976 and 1977-1981, size is positively or negatively related to turnover—depending whether stock price variable is in the regression or not. This is perplexing. I hypothesize that that the relation between turnover and size is not a linear one and should be examined separately from the effect of β. I follow Fama and French (1992) to form portfolios first based on size deciles, then on β deciles. This allows variation of β that is not related to sizes.

1.4.4 Time Aggregation

While holding period return can not be obtained by adding all sub-period returns together, share turnover has a nice property: time aggregation. That is, turnover can be summed across dates to obtain time-aggregated turnover. The summed turnover is a robust measure of volume since the measure is comparable across stocks and over time, without effects of events that change firm's total number of shares available for trading, such as stock splits or repurchases. Lo and Wang (2000) use time aggregation to obtain weekly stock share turnovers based on daily stock turnovers. I use the same methodology to obtain weekly share turnovers in this study.

1.5 Empirical Results

1.5.1 Cross Sectional Trading Volume

Some studies documented volume is closely related to firm size and market beta. Lo and Wang (2000) find that both firm size and market beta are significantly related to weekly share turnover of NYSE and AMEX stocks. Market beta is positively related to share turnover in all sub-periods of the study; however, market capitalization can be positively, negatively or not related to share turnover depending which sub-periods the data falls in. This phenomenon is hard to explain. In order to reveal the relation between share turnover and market capitalization/market beta, I examine the cross-sectional share turnover distributions by the following:

1) Monthly turnover by market equity deciles and beta deciles;

2) Weekly turnover by market equity deciles and beta deciles;

3) Daily turnover by market equity deciles and beta deciles

Fama and French (1992) examine NYSE/AMEX/NASDAQ stocks based on market equity and market beta. I follow their methodology.

1.5.1.1 Monthly Turnover by Market Equity Deciles and Beta Deciles

Table 1.2 Panel A shows average turnover, average return and average size for all 100 portfolios formed first by market equity deciles and then by beta deciles for NYSE/AMEX monthly data from July 1963 to December 2004. The 100 portfolios are formed first based on ME deciles then based on beta deciles. The average return and average size numbers by portfolios follow similar trends as in Fama and French (1992): return decreases as ME decile increases, while does not show strong relation with β s.

Average monthly turnover by portfolios ranges from 3.04 percent to 10.89 percent. Across all ME deciles, share turnover increases with β; however, the relation between ME and share turnover is not a linear one. Instead, they show an inverted "U" shape relation. As shown by **Figure 1.1**, when plotted on ME and β deciles, turnover does not follow a linear relation. Instead, it shows a bell-shaped figure. Regression models that designed to capture a linear relation often fail to capture this non-linear relation and sometimes give misleading parameter estimates. Lo and Wang (2000) finds that ME can be positively or negatively related to turnover, depending on which sub-period the data are. If the relation between ME and turnover is not a linear one, then it is hard to model it using linear regression models. The data shows that share turnovers are higher with medium level MEs than either lower or higher level ME. Among the 100 portfolios, the largest share turnover occurs at the portfolio with 10^{th} β decile and 7^{th} and 8^{th} ME decile.

Table 1.2 Panel B shows average turnover, average return and average size for all 100 portfolios formed first by market equity deciles and then by beta deciles for NASDAQ monthly data from January 1973 to December 2004. We can see similar trends hold for NASDAQ stocks except that turnover increased with β decile except at the 10^{th} β decile. The relation between firm size and turnover is a hump shape but is less regular than that of NYSE/AMEX stocks.

1.5.1.2 Weekly Turnover by Market Equity Deciles and Beta Deciles

I calculated individual holding period return for weekly data from CRSP daily data. This is calculated using the following formula:

$$r_w = \prod_{i=1}^{k}(1+r_i)-1 \qquad 1.3$$

Where r_w denotes weekly return, r_i denotes daily return, k denotes number of days in that week.

I aggregated weekly turnover by summing all daily turnover in each week. Portfolios are still determined the same way as in monthly portfolios. The breakpoints for size and β deciles are determined by monthly data. That is, the breakpoints for size deciles are determined by market capitalization at June of each year on only NYSE stocks on CRSP. Each of the 10 size deciles is subdivided to 10 β portfolios based on pre-ranking β s of individual stocks. Pre-ranking β s are estimated using previous five years of monthly returns ending in June of year *t*. Since firm's β does not change in short period of time, such as a week or a month, I use their monthly data to estimate β and assign one β for each stock for all weeks in that year. Same logic applies to size decile. Even firm's market equity varies week by week; I form portfolios by comparing individual stock's ME in June and the breakpoints obtained from only NYSE stocks in June. Once the 100 portfolios are formed each year, the formation does not change within the same year, but it will change across the years.

Table 1.3 Panel A presents average weekly turnover and average weekly return for all 100 portfolios for NYSE/AMEX stocks (July 1963 – December 2004) and Panel B for NASDAQ stocks (January 1973 – Dec 2004). Average weekly turnover follows a similar trend as monthly turnover: it increases as β increases, while first increases with ME deciles then decreases. A non-linear relation still exists for weekly data. Figure 1.33 and Figure 1.4 gives a visual look of the data and the inverted "U" shape is most salient for high β deciles.

The cross-sectional results on average returns in Fama and French (1992) are robust on weekly data. Again, β does not seem to relate to returns over the whole sample period, and return increase with ME in all β deciles.

1.5.1.3 Daily Turnover by Market Equity Deciles and Beta Deciles

For daily data, all portfolios are formed the breakpoints for size and β deciles are determined by monthly data. That is, I use the same 100 portfolios as in monthly and weekly data. The average daily turnover and average daily returns for all 100 portfolios are illustrated in Table 1.4. Again, turnover show an inverted "U" shape with ME and increases as β increases as shown in Figure 1.5 and Figure 1.6. Fama and French (1992) results on average returns by size and β decile are still solid with daily data.

To summarize, the cross-sectional distribution properties of share turnover show a strong relation between turnover and size/ β. Turnover increases with β for monthly, weekly and daily data, which is consistent with previous work (Lo and Wang 2000). Size is not linearly related to turnover. Instead, an inverted "U" relation exists between turnover and size.

1.5.2 Time Series Trading Volume

In order to have an overview of the behavior of the entire time-series volume, I constructed value-weighted and equal-weighted turnover indexes. The reason for forming indexes instead of examining individual stock behavior is to have an overview of the time series properties of the market from 1963-2004. Value-weighted indexes are constructed by the following: for each month/day/week, I weight each individual security's turnover by their market capitalization relative to the whole market. Equal-weighted indexes are constructed by assigning equal weight to all stocks in the sample during the sample period. Value-weighted and equal-weighted returns can also be constructed as in the same way.

Figure 1.77 plots the value-weighted and equal-weighted turnover for NYSE/AMEX monthly data. Value-weighted turnover has been increasing since 1963 but the early 70s experienced lower turnover. NYSE/AMEX stock turnover reached the highest level in the 2000s. Taking logarithm can smooth turnover distribution. The lower two charts in Figure 1.77 show the logarithm of monthly value-weighted and equal-weighted turnover indexes. Up-going trend persists in both charts. NASDAQ monthly turnover index series are plotted in Figure 1.8. We can see that NASDAQ monthly turnover experience similar trends except in the period around year 2000 when the market for high-tech stocks is crashed.

Table 1.5 (Table 1.6) reports summary statistics for value-weighted/equal-weighted NYSE/AMEX (NASDAQ) monthly turnover indexes over 1963-2004 and those of over 5-year sub-periods. Over the entire sample, the overall value-weighted and equal-weighted turnover index for NYSE/AMEX (NASDAQ) is 4.53% (14.02%) and 5.14% (8.96%).

Average monthly turnover has generally increased over the sample period. Among all sub-periods, 2002-2004 has the highest value-weighted and equal-weighted turnovers.

The first 10 autocorrelations for both value-weighted and equal-weighted turnovers reported in Table 1.5 are positive, ranging between 0.88-0.95 for value-weighted index and 0.78-0.93 for equal-weighted index. Box-Pierce Q-statistics are significant at the 1% level, indicating strong serial autocorrelation and non-stationary data series.

Weekly and daily data are plotted in Figure 1.99 - Figure 1.1112 and their summary statistics are reported in Table 1.7 - Table 1.10. Similar trend persist in weekly and daily data.

1.6 Summary

This study provides a comprehensive overview of the behavior of trading volume. The major results are: 1) cross-sectional trading volume increases with the increase of β; 2) cross-sectional trading volume is not linearly related to size, instead, the relation between turnover and size follows an inverted "U" shape; 3) share turnover is increasing over the past 40 years; 4) share turnover is non-stationary over time and highly positively autocorrelated.

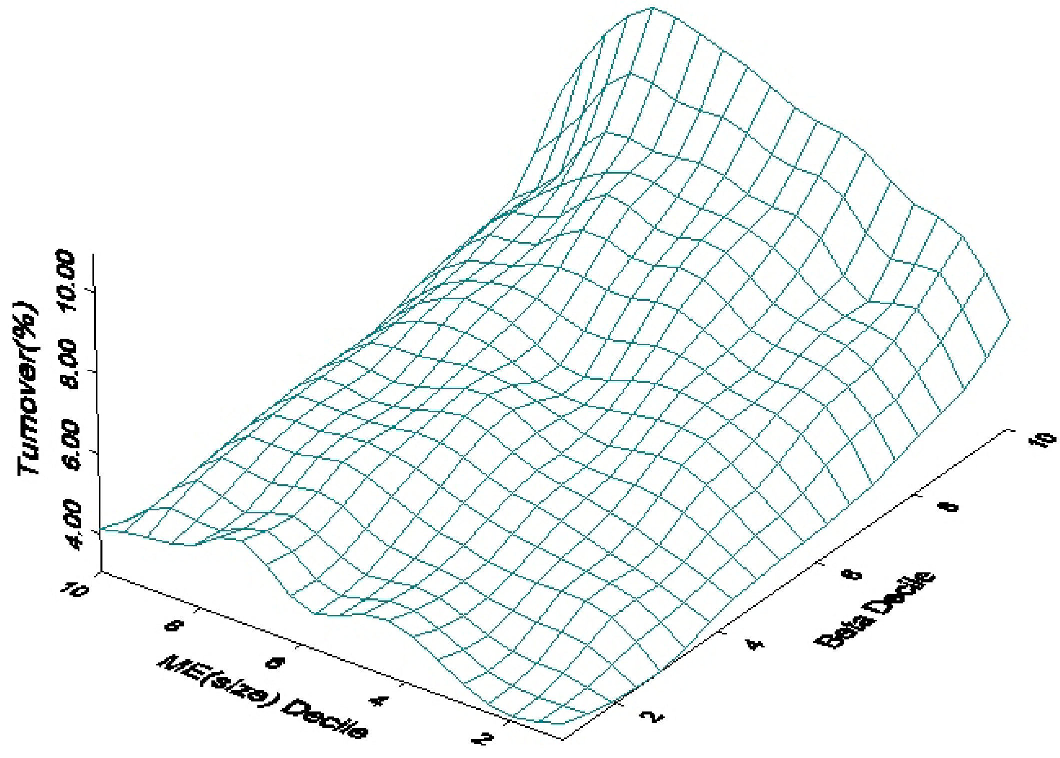

Figure 1.1: Monthly Turnover by ME (Size) and Beta Deciles – NYSE/AMEX Stocks

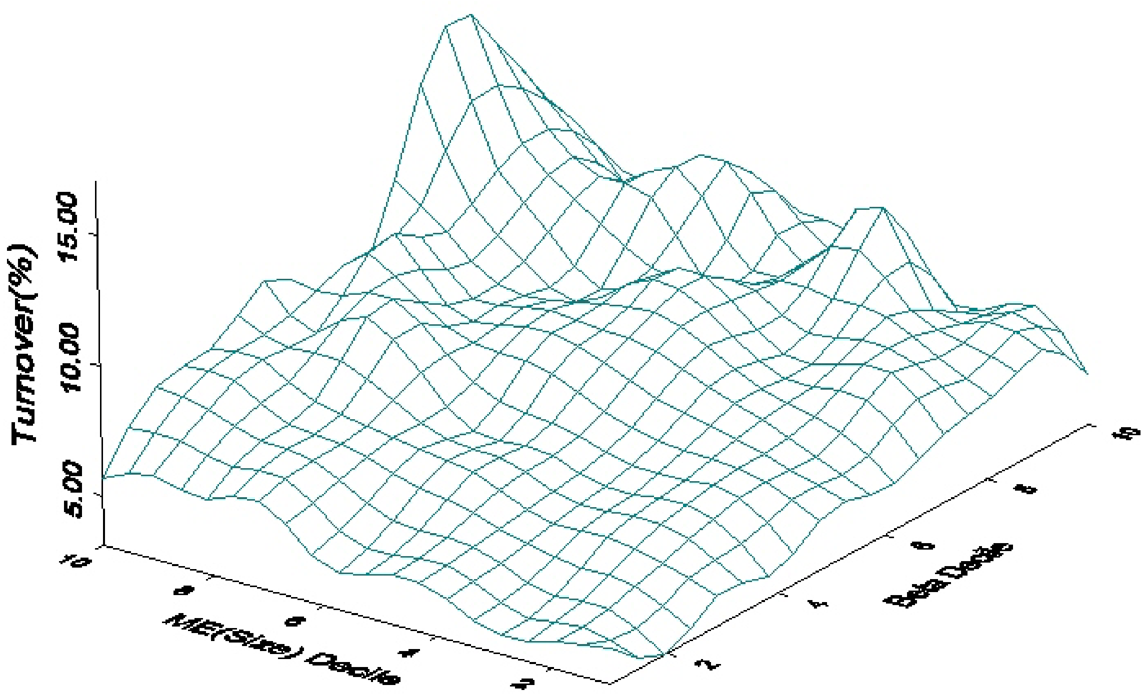

Figure 1.2: Monthly Turnover by ME (Size) and Beta Deciles – NASDAQ Stocks

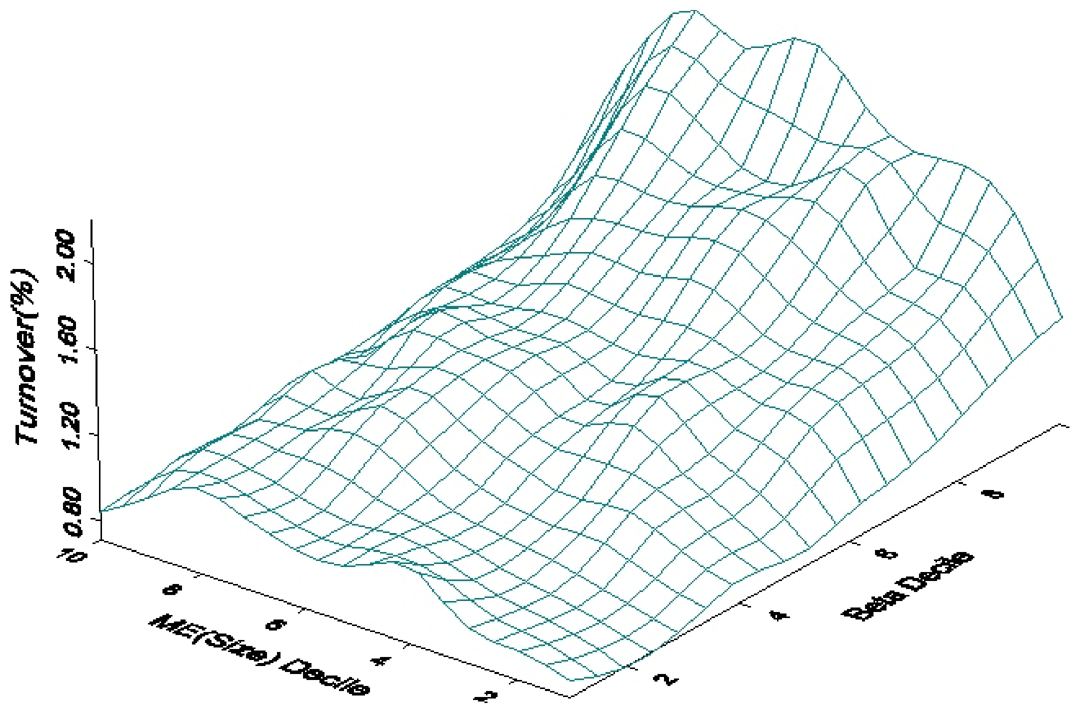

Figure 1.3: Weekly Turnover by ME (Size) and Beta Deciles – NYSE/AMEX Stocks

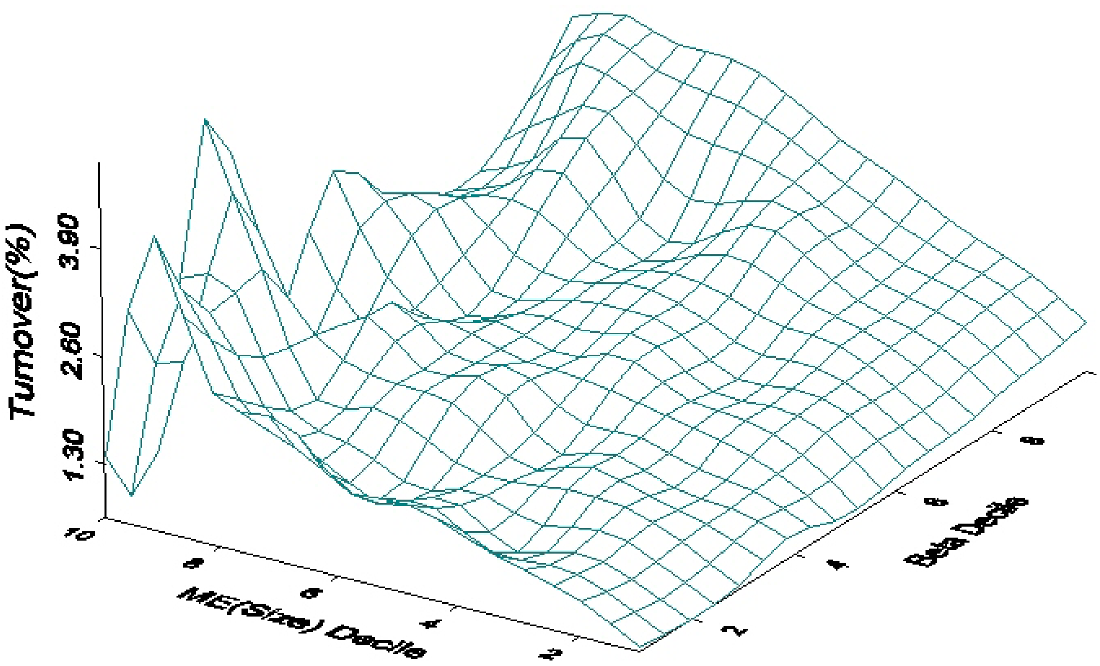

Figure 1.4: Weekly Turnover by ME (Size) and Beta Deciles – NASDAQ Stocks

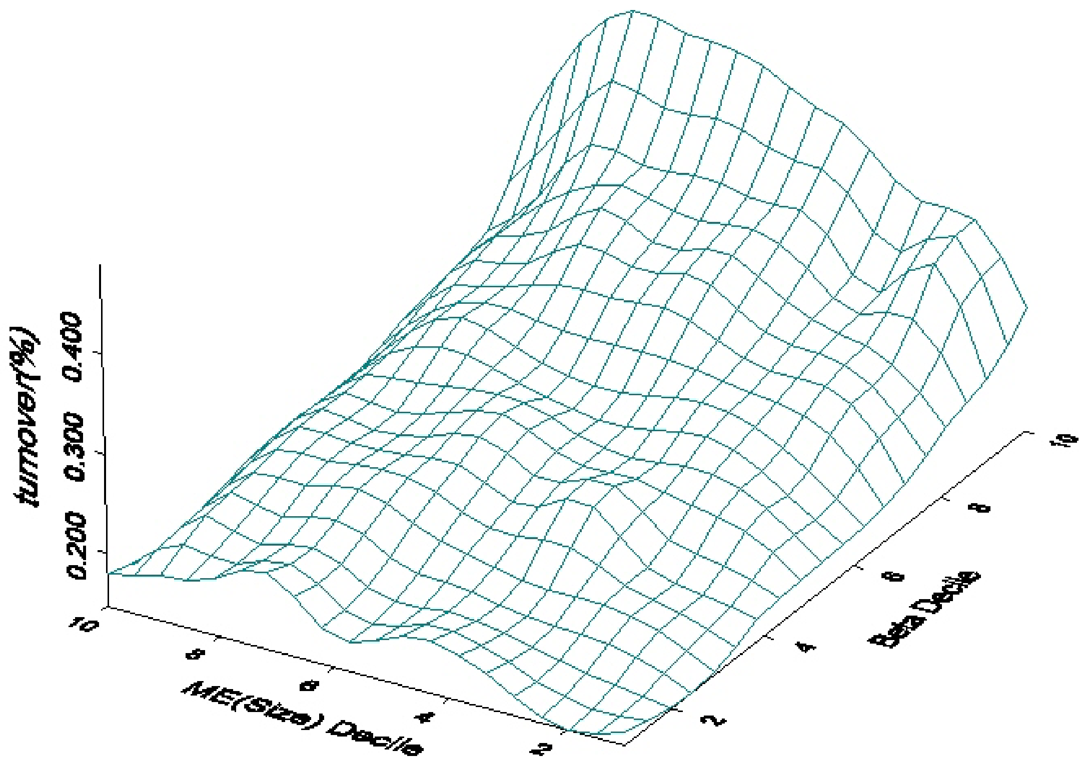

Figure 1.5: Daily Turnover by ME (Size) and Beta Deciles – NYSE/AMEX Stocks

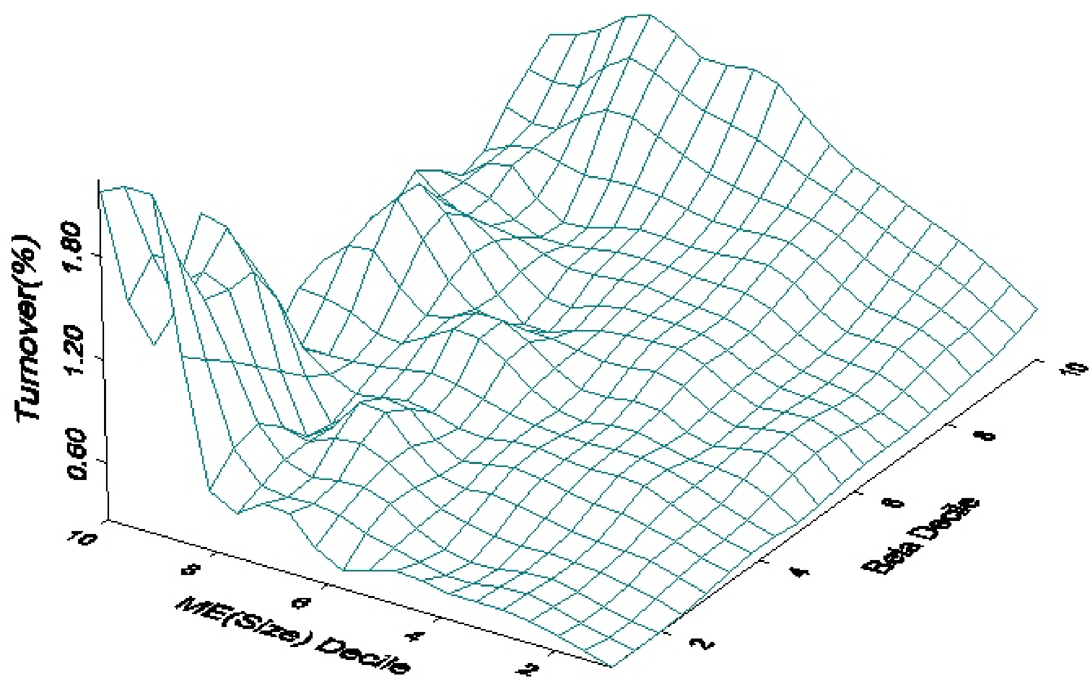

Figure 1.6: Daily Turnover by ME (Size) and Beta Deciles – NASDAQ Stocks

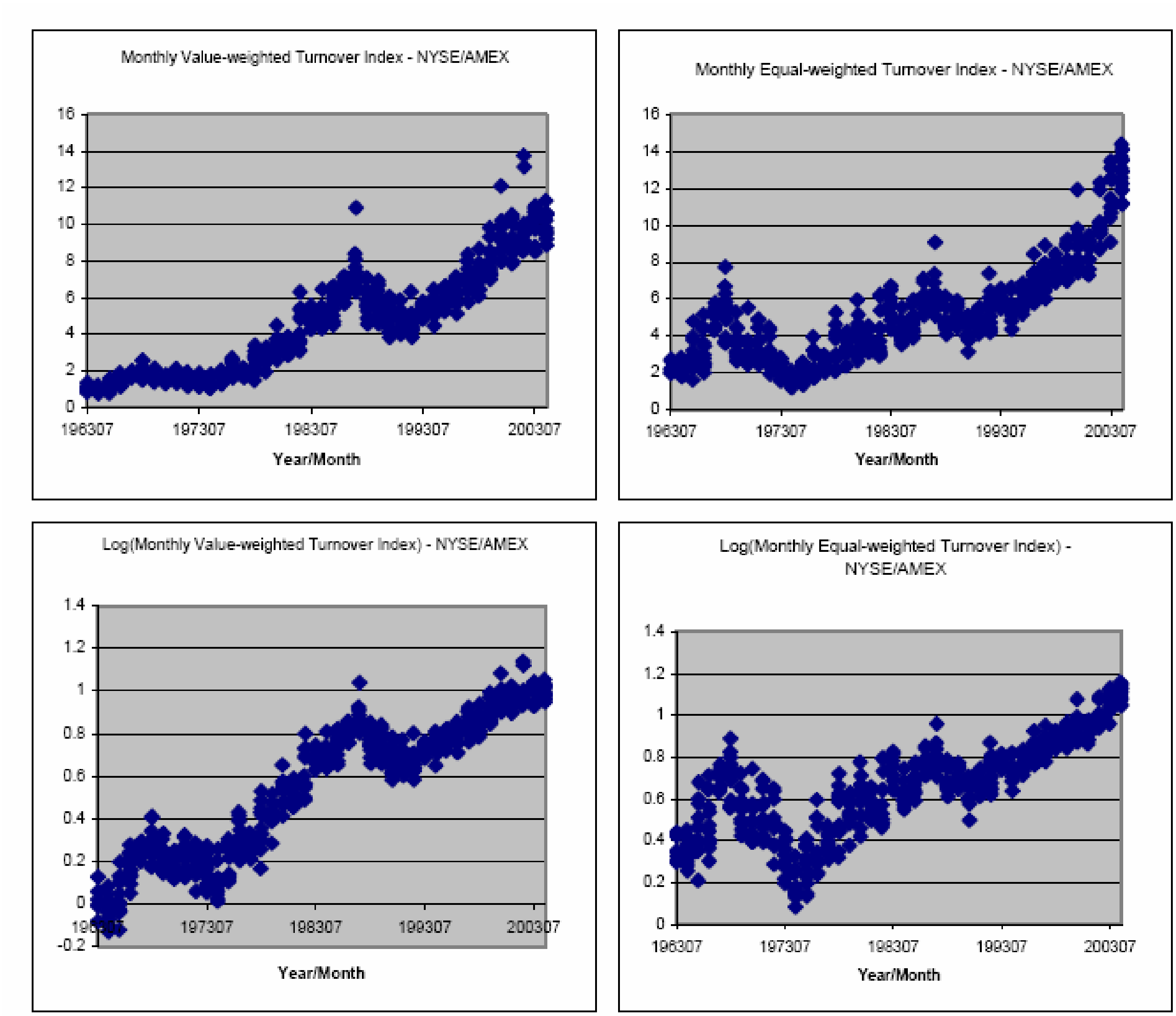

Figure 1.7: NYSE/AMEX Monthly Value-weighted and Equal-weighted Turnover Indexes, 1963-2004

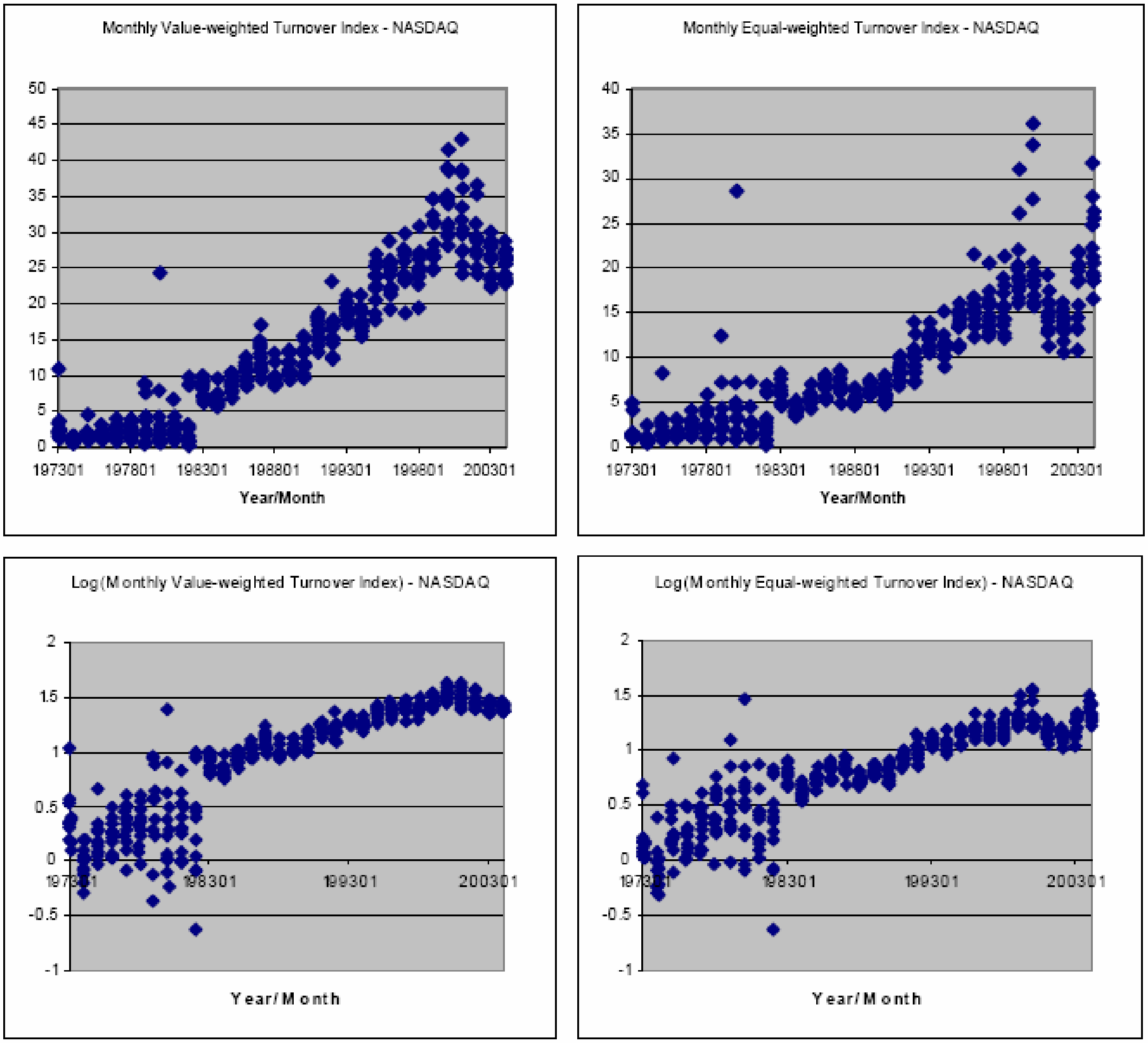

Figure 1.8: NASDAQ Monthly Value-weighted and Equal-weighted Turnover Indexes, 1973-2004

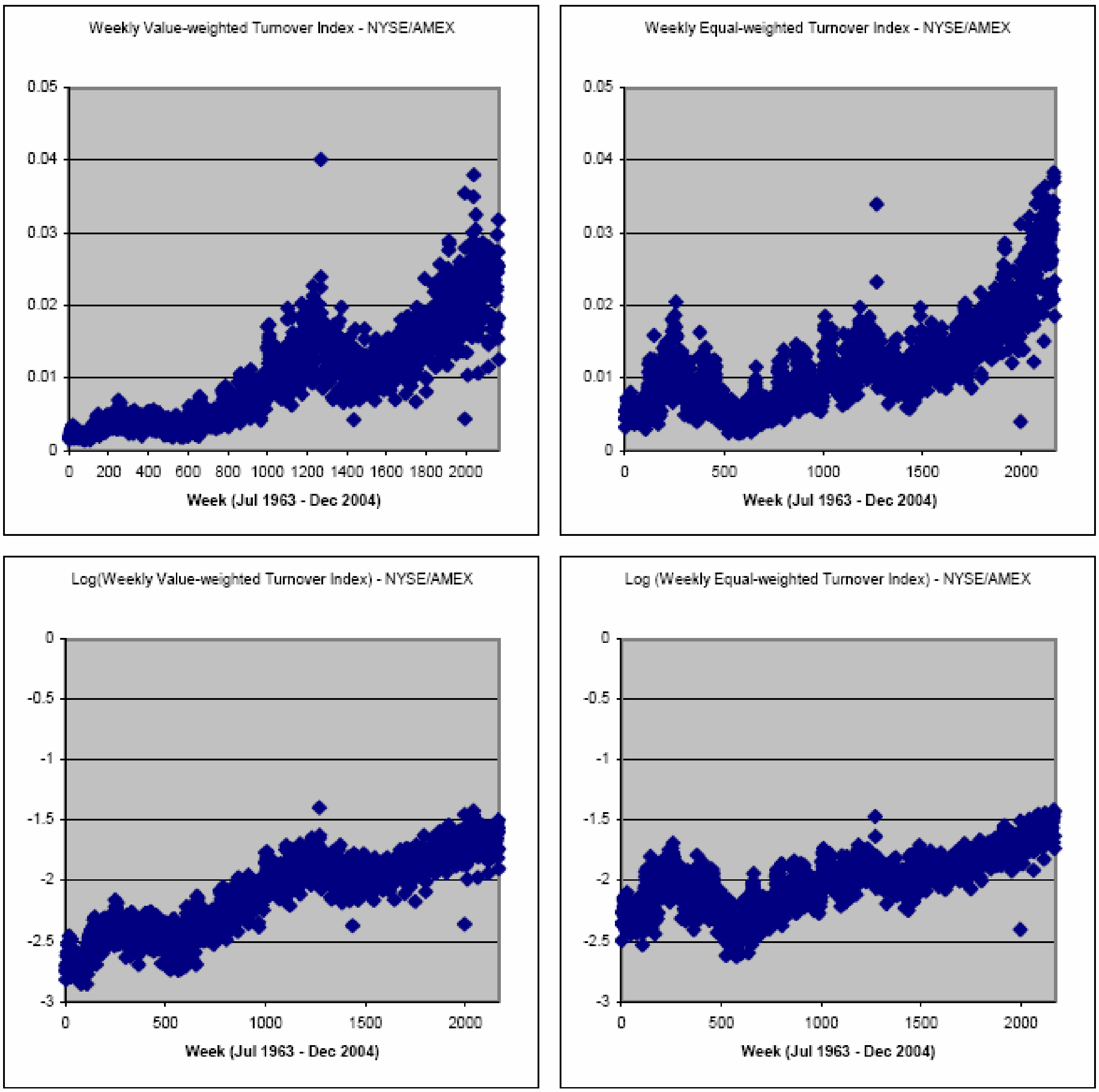

Figure 1.9: NYSE/AMEX Weekly Value-weighted and Equal-weighted Turnover Indexes, 1963-2004

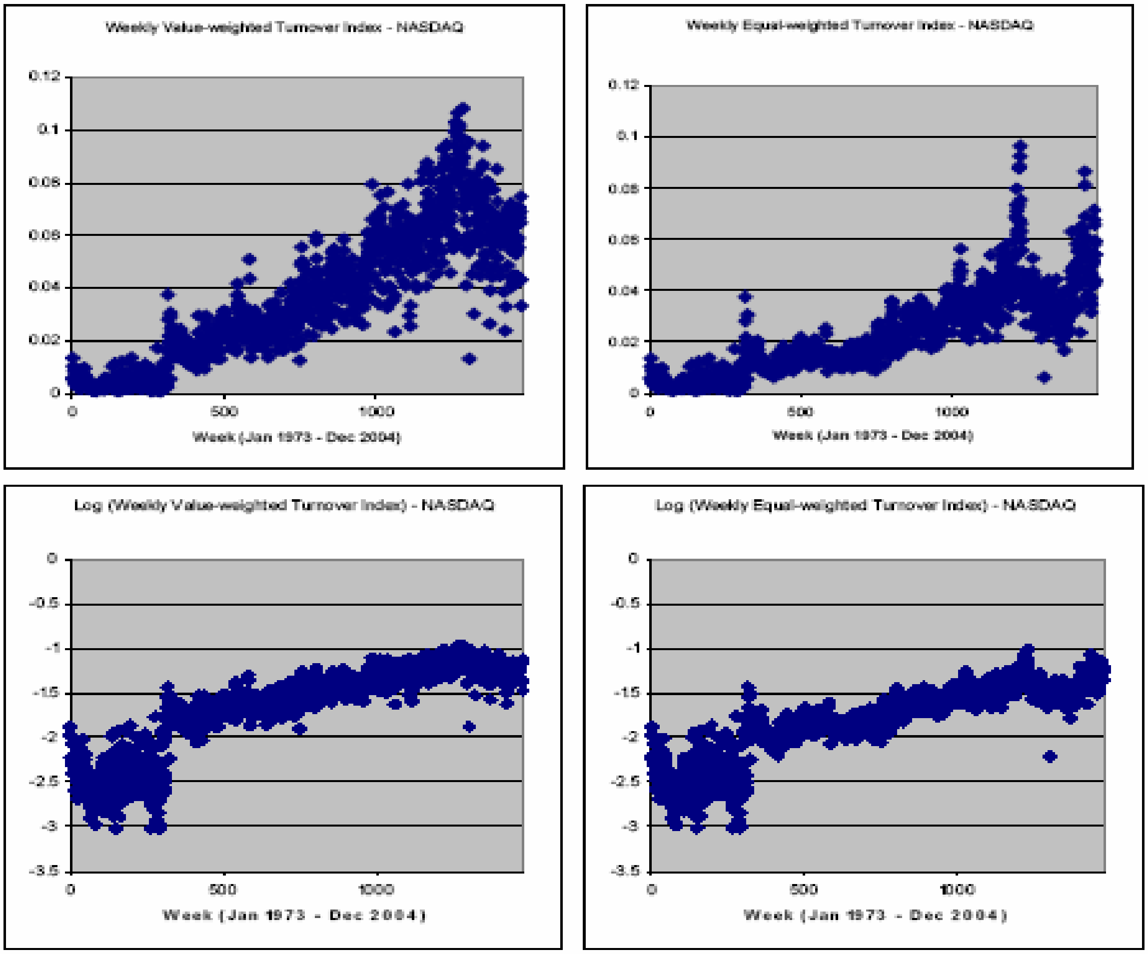

Figure 1.10: NASDAQ Weekly Value-weighted and Equal-weighted Turnover Indexes, 1973-2004

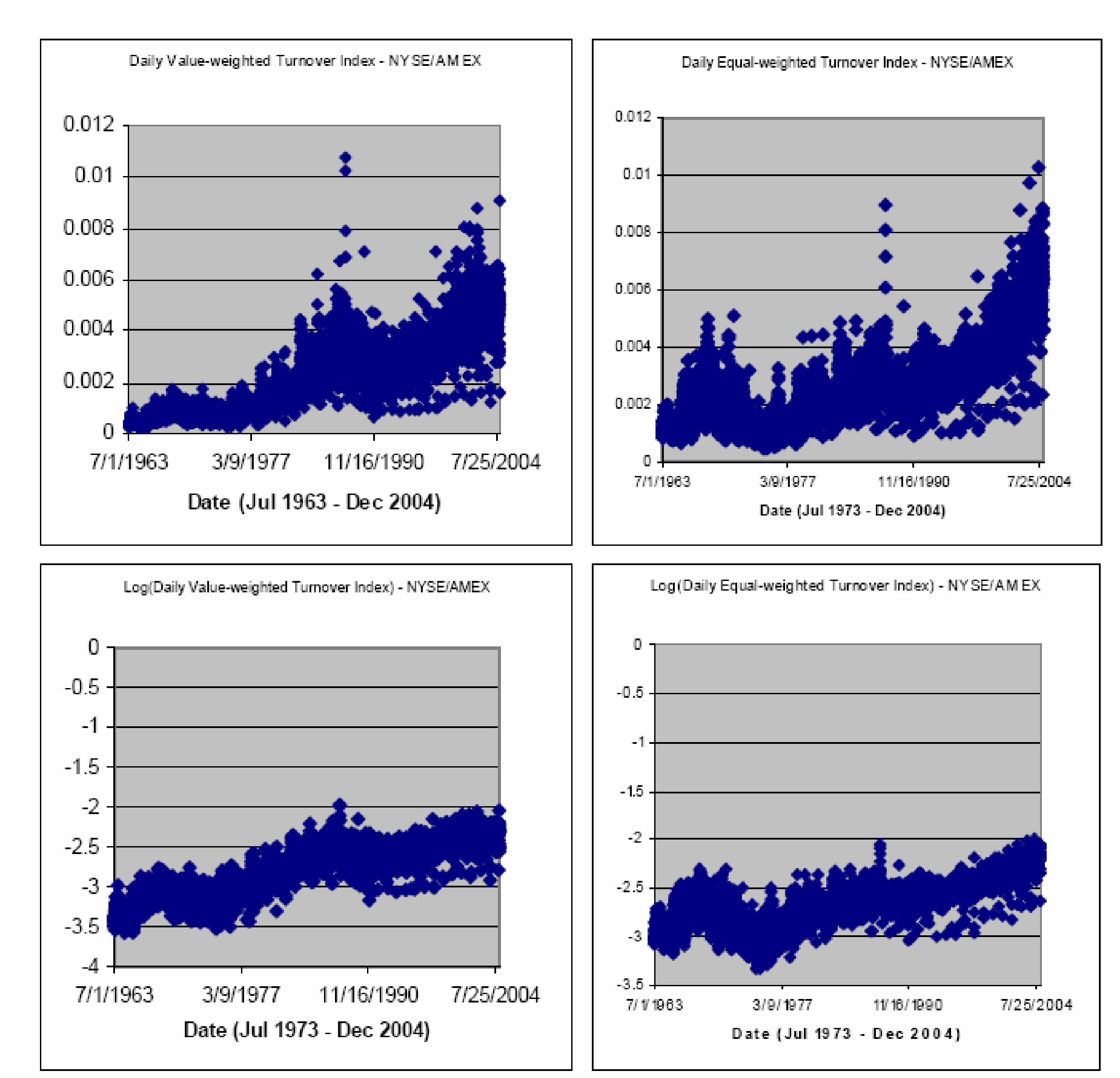

Figure 1.11: NYSE/AMEX Daily Value-weighted and Equal-weighted Turnover Indexes, 1963-2004

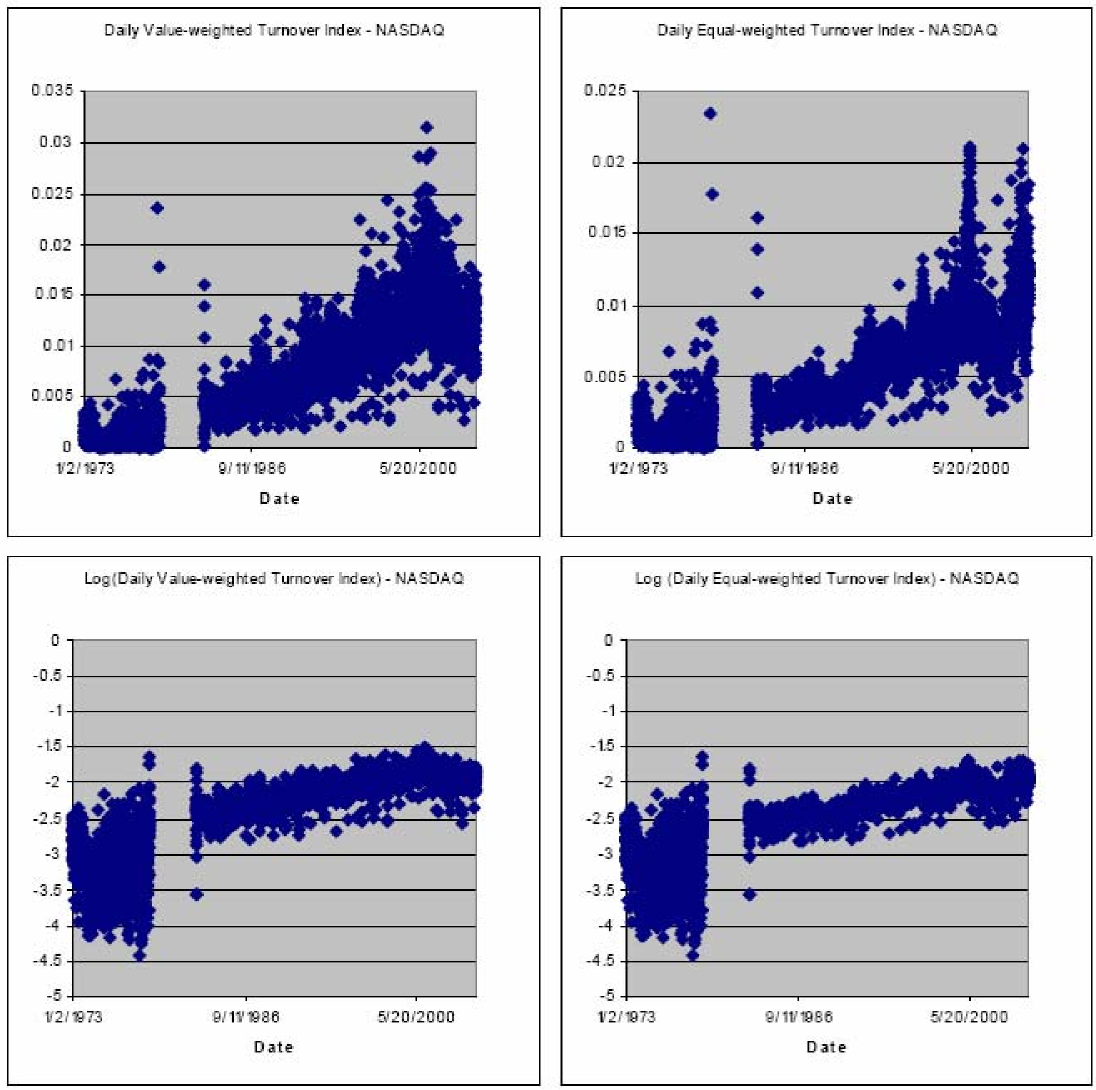

Figure 1.12: NASDAQ Daily Value-weighted and Equal-weighted Turnover Indexes, 1973-2004

Table 1.1: Monthly share turnover and monthly share volume for NYSE/AMEX firms during 1963-2004

Turnover Decile	**Average Share Turnover**	**Average Share volume**	**Average Size** (ME)	**Average Beta**	**Average Share Outstanding** (in thousands)	**Average Share Price**
1	0.89	280763	2.69	0.93	17017	12.36
2	1.86	1612577	3.31	1.01	48534	18.90
3	2.48	2416977	3.36	1.06	58141	21.86
4	3.10	2797847	3.37	1.10	57343	23.58
5	3.74	3389465	3.35	1.13	56772	24.74
6	4.45	3781852	3.33	1.18	54268	25.26
7	5.43	4277838	3.26	1.23	50210	25.33
8	6.71	4554736	3.17	1.28	43402	25.13
9	8.95	4433679	3.03	1.34	32564	24.58
10	18.25	7410267	2.91	1.48	28174	24.78

Turnover deciles are obtained yearly based on NYSE stocks only. All NYSE/AMEX stocks are allocated to the 10 turnover deciles each year. Individual stock's turnover is calculated based on their monthly raw trading volume (turnover is calculated as shares traded divided by the number of shares outstanding. The average size of the stocks in each decile is the average of monthly averages of ln(ME) for stocks in that decile at the end of June of each year, with ME denominated in million dollars. βs are estimated using previous five years of monthly returns ending in June of year t.

All turnover numbers are reported in unit of percent and are not annualized.

Table 1.2: Average Turnover, Average Returns, and Average Size for Portfolios Formed on Size and then β Deciles

Panel A: Monthly NYSE/AMEX Data: July 1963 to June 2004

Sample Period	All	Small-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	β-10
Average Monthly Turnover (in percent)											
All	5.64	4.08	4.07	4.51	4.82	5.11	5.38	5.89	6.53	7.07	8.91
Small-ME	3.95	3.44	3.08	3.04	3.46	3.69	3.81	3.95	4.39	4.78	5.82
ME-2	4.92	3.13	3.41	3.98	3.96	4.51	4.81	5.55	5.77	6.46	7.62
ME-3	5.25	3.58	3.52	4.17	4.34	5.10	5.59	5.69	6.28	6.24	8.03
ME-4	5.76	4.30	4.01	4.22	4.79	5.00	5.76	6.19	6.62	7.62	9.04
ME-5	6.02	4.27	4.20	4.53	5.07	5.25	5.51	6.63	7.57	7.84	9.33
ME-6	6.20	3.95	4.17	4.94	5.60	5.90	5.35	6.44	7.32	8.33	10.01
ME-7	6.62	5.08	4.91	5.47	5.55	5.85	6.03	6.67	7.98	8.21	10.50
ME-8	6.46	4.63	4.58	5.30	5.41	5.55	6.34	6.51	6.99	8.41	10.89
ME-9	6.17	4.35	5.00	5.32	5.58	5.67	5.90	6.18	6.76	6.98	9.93
Large- ME	5.03	4.10	3.81	4.14	4.42	4.61	4.71	5.14	5.59	5.87	7.93
Average Monthly Return (in percent)											
All	1.25	1.31	1.33	1.37	1.32	1.28	1.35	1.24	1.21	1.13	1.00
Small-ME	1.66	1.73	1.82	1.61	1.49	1.56	1.71	1.59	1.74	1.76	1.57
ME-2	1.37	1.12	1.28	1.42	1.56	1.43	1.47	1.54	1.48	1.35	1.06
ME-3	1.28	1.28	1.18	1.60	1.27	1.55	1.46	1.42	1.37	0.95	0.73
ME-4	1.28	1.30	1.44	1.49	1.31	1.29	1.43	1.15	1.32	1.03	1.05
ME-5	1.29	1.46	1.53	1.32	1.43	1.35	1.46	1.30	0.92	1.25	0.90
ME-6	1.24	1.56	1.52	1.53	1.34	1.12	1.07	1.14	1.13	1.00	1.00
ME-7	1.22	1.25	1.21	1.31	1.37	1.17	1.32	1.36	1.27	0.93	1.03
ME-8	1.17	1.30	1.16	1.27	1.31	1.26	0.95	1.18	1.00	1.23	1.01
ME-9	1.08	1.12	1.16	1.19	1.14	1.06	1.38	0.84	0.99	0.96	0.94
Large- ME	0.94	1.03	1.00	0.93	0.98	0.99	1.21	0.89	0.87	0.86	0.69
Average Size (ln(ME))											
All	5.84	5.85	5.87	5.87	5.86	5.86	5.84	5.84	5.81	5.81	5.76
Small-ME	2.77	2.72	2.77	2.78	2.78	2.86	2.80	2.81	2.73	2.79	2.68
ME-2	4.22	4.21	4.22	4.21	4.23	4.23	4.23	4.23	4.20	4.21	4.20
ME-3	4.74	4.75	4.74	4.77	4.75	4.76	4.75	4.74	4.74	4.72	4.67
ME-4	5.18	5.18	5.19	5.19	5.18	5.19	5.19	5.17	5.17	5.16	5.15
ME-5	5.61	5.63	5.64	5.62	5.62	5.63	5.62	5.61	5.58	5.61	5.56
ME-6	6.02	6.04	6.06	6.04	6.04	6.04	6.00	6.02	6.01	6.00	6.01
ME-7	6.45	6.46	6.46	6.46	6.48	6.46	6.46	6.44	6.44	6.44	6.43
ME-8	6.96	7.00	6.97	6.97	6.97	6.96	6.95	6.97	6.94	6.95	6.91
ME-9	7.58	7.59	7.61	7.62	7.60	7.56	7.61	7.56	7.58	7.55	7.53
Large- ME	8.83	8.88	9.00	9.07	8.96	8.86	8.82	8.83	8.67	8.70	8.50

Panel B: Monthly NASDAQ Data: July 1963 to June 2004

Sample Period	All	Small- β	β -2	β -3	β -4	β -5	β -6	β -7	β -8	β -9	β -10
Average Monthly Turnover (in percent)											
All	7.3	5.07	5.55	6.37	6.87	7.65	7.93	8.51	8.93	9.27	7.55
Small-ME	4.95	4.42	3.07	4.28	3.9	5.2	4.78	5.64	6.06	7.08	5.06
ME-2	6.1	4.06	4.3	5.06	5.7	5.97	6.05	7.58	7.25	7.56	7.32
ME-3	6.23	3.79	4.24	5.45	5.83	6.43	6.93	7.17	8.31	7.84	6.49
ME-4	6.96	4.74	5.05	5.44	5.85	6.79	7.88	7.57	8.21	11.38	7.22
ME-5	7.41	4.87	5.37	6.39	6.54	7.58	8.86	9.33	8.71	8.4	8.31
ME-6	7.64	4.6	5.65	6.84	6.53	8.57	8.82	9.75	7.73	9.8	8.77
ME-7	8.45	6.37	6.88	7.24	7.98	8.52	8.97	7.87	10.22	11.78	8.93
ME-8	8.68	5.96	7.12	7.73	10.2	8.92	8.65	9.4	11.13	9.48	9.2
ME-9	9.4	6.33	7.89	8.74	9.03	11.3	10.25	11.38	12.46	10.99	7.95
Large- ME	9.05	5.66	8.26	8.79	10.38	8.33	10.47	17.04	15.84	12.59	7.08
Average Monthly Return (in percent)											
All	1.40	1.50	1.41	1.52	1.46	1.49	1.39	1.56	1.19	1.67	0.91
Small-ME	1.73	2.16	1.59	1.86	1.02	2.03	1.86	2.59	0.51	2.85	0.99
ME-2	1.53	1.18	1.18	1.50	1.68	1.93	1.71	2.05	1.38	2.19	0.68
ME-3	1.53	1.42	1.49	1.72	1.74	1.53	1.70	1.64	1.21	1.91	1.05
ME-4	1.34	1.51	1.52	1.58	1.45	1.58	1.39	1.56	1.24	1.01	0.57
ME-5	1.38	1.74	1.40	1.73	1.70	1.69	1.22	0.64	1.29	1.02	1.32
ME-6	1.32	1.52	1.74	1.45	1.26	1.37	0.96	1.19	1.66	1.31	0.73
ME-7	1.37	1.59	1.69	1.56	1.48	1.60	1.08	1.19	1.28	1.13	1.10
ME-8	1.15	1.34	1.35	1.16	1.54	1.03	1.15	2.43	1.23	3.06	1.20
ME-9	1.44	1.43	1.05	1.45	1.67	0.80	1.02	0.93	1.22	1.22	0.71
Large- ME	0.94	1.14	0.60	0.47	0.66	0.94	2.25	1.48	0.30	0.58	0.82
Average Size (ln(ME))											
All	5.84	6.17	5.98	5.97	5.91	5.99	5.85	5.76	5.75	5.54	5.47
Small-ME	3.37	3.20	3.43	3.45	3.31	3.50	3.45	3.55	3.39	3.37	3.04
ME-2	4.40	4.52	4.48	4.45	4.44	4.45	4.40	4.45	4.39	4.46	4.06
ME-3	4.93	5.00	5.00	5.03	5.01	4.97	5.00	5.00	4.90	4.94	4.53
ME-4	5.36	5.46	5.44	5.44	5.47	5.44	5.44	5.42	5.33	5.29	4.92
ME-5	5.81	5.91	5.89	5.92	5.90	5.89	5.85	5.84	5.83	5.71	5.39
ME-6	6.23	6.34	6.34	6.35	6.29	6.29	6.27	6.30	6.17	6.14	5.71
ME-7	6.71	6.87	6.91	6.79	6.76	6.80	6.66	6.65	6.80	6.67	6.15
ME-8	7.16	7.27	7.26	7.28	7.29	7.22	7.15	7.13	7.16	7.11	6.72
ME-9	7.85	7.93	8.05	8.01	7.91	7.90	7.88	7.80	7.90	7.63	7.30
Large- ME	9.37	9.29	9.91	9.89	9.88	9.88	9.39	9.54	9.54	9.27	8.38

Portfolios are formed yearly from 1963 to 2004 based on size deciles and β deciles. The breakpoints for size are determined by market capitalization at June of each year on only NYSE stocks on CRSP. All NYSE, AMEX, and NASDAQ stocks are first allocated to 10 size deciles based on NYSE size breakpoints, then each of the 10 size deciles is subdivided to 10 β portfolios based on pre-ranking β s of individual stocks. Pre-ranking βs are estimated using previous five years of monthly returns ending in June of year *t*. To ensure enough data points for the estimation, for each stock, a minimum of 24 non-missing monthly returns in the previous five years is required to estimate the βs. Average monthly returns are calculated based on the monthly returns on the resulting 100 portfolios.

Individual stock's turnover is calculated based on their monthly raw trading volume (turnover is calculated as shares traded divided by the number of shares outstanding). Share turnover/average returns/market equity for NASDAQ stocks are reported separately.

The average return of a portfolio is the average of monthly equal-weighted portfolio returns, in percent.

The average size of the portfolio is the average of monthly averages of ln(ME) for stocks in portfolio at the end of June of each year, with ME denominated in million dollars.

The "All" column shows statistics for equal-weighted size-decile (ME) portfolios. The "All" row shows statistics for equal-weighted portfolios of the stocks in each β group.

All return and turnover numbers are reported in unit of percent – they are not annualized.

Table 1.3: Average Turnover, Average Returns, and Average Size for Portfolios Formed on Size and Then β Deciles
Panel A: Weekly NYSE/AMEX Data: July 1963 to June 2004

Sample Period	All	Small-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	β-10
Average Weekly Turnover (in percent)											
All	1.23	0.95	0.92	0.96	1.05	1.12	1.17	1.26	1.41	1.57	1.85
Small-ME	0.90	0.79	0.71	0.74	0.82	0.78	0.85	0.90	1.00	1.14	1.22
ME-2	1.10	0.85	0.79	0.80	0.92	0.94	1.12	1.22	1.27	1.42	1.67
ME-3	1.17	0.89	0.83	0.87	1.03	1.08	1.17	1.24	1.37	1.45	1.81
ME-4	1.28	1.07	0.89	0.91	1.01	1.25	1.28	1.31	1.51	1.80	1.81
ME-5	1.31	0.99	0.97	0.94	1.07	1.12	1.20	1.42	1.66	1.68	2.00
ME-6	1.35	0.96	0.96	1.05	1.16	1.27	1.26	1.38	1.63	1.65	2.20
ME-7	1.39	1.03	1.00	1.19	1.28	1.29	1.28	1.43	1.58	1.80	2.06
ME-8	1.41	1.11	1.05	1.12	1.14	1.37	1.27	1.34	1.61	1.94	2.18
ME-9	1.30	0.99	1.09	1.10	1.20	1.13	1.26	1.28	1.35	1.58	2.01
Large-ME	1.06	0.84	0.87	0.87	0.92	0.99	1.03	1.10	1.14	1.26	1.59
Average Weekly Return (in percent)											
All	0.57	0.52	0.51	0.55	0.55	0.57	0.63	0.60	0.57	0.64	0.57
Small-ME	0.77	0.68	0.72	0.75	0.60	0.72	0.89	0.80	0.71	0.86	1.01
ME-2	0.65	0.50	0.55	0.52	0.66	0.63	0.80	0.78	0.67	0.79	0.64
ME-3	0.64	0.59	0.49	0.54	0.60	0.63	0.71	0.60	0.72	0.75	0.77
ME-4	0.58	0.55	0.66	0.58	0.47	0.49	0.58	0.55	0.62	0.65	0.65
ME-5	0.59	0.54	0.57	0.51	0.70	0.69	0.63	0.61	0.51	0.70	0.43
ME-6	0.56	0.46	0.54	0.69	0.60	0.59	0.61	0.56	0.54	0.55	0.48
ME-7	0.56	0.50	0.48	0.51	0.45	0.53	0.58	0.68	0.62	0.62	0.59
ME-8	0.53	0.50	0.43	0.43	0.52	0.56	0.53	0.61	0.58	0.58	0.59
ME-9	0.45	0.43	0.43	0.56	0.43	0.45	0.50	0.45	0.39	0.54	0.36
Large-ME	0.36	0.41	0.28	0.38	0.43	0.40	0.40	0.36	0.38	0.38	0.22
Average Size (ln(ME))											
All	5.73	5.74	5.77	5.76	5.76	5.75	5.74	5.72	5.71	5.70	5.65
Small-ME	2.71	2.64	2.70	2.74	2.75	2.78	2.76	2.74	2.72	2.65	2.60
ME-2	4.11	4.11	4.11	4.13	4.15	4.12	4.12	4.12	4.10	4.11	4.08
ME-3	4.64	4.65	4.63	4.66	4.65	4.66	4.63	4.64	4.64	4.64	4.56
ME-4	5.07	5.07	5.09	5.07	5.10	5.07	5.07	5.08	5.08	5.07	5.03
ME-5	5.49	5.51	5.52	5.52	5.51	5.51	5.50	5.48	5.46	5.49	5.45
ME-6	5.90	5.93	5.93	5.92	5.90	5.91	5.92	5.87	5.90	5.88	5.86
ME-7	6.34	6.37	6.35	6.37	6.35	6.35	6.36	6.34	6.33	6.32	6.28
ME-8	6.86	6.91	6.87	6.88	6.84	6.84	6.87	6.84	6.85	6.87	6.82
ME-9	7.46	7.40	7.49	7.49	7.48	7.47	7.47	7.47	7.46	7.42	7.43
Large-ME	8.71	8.77	9.01	8.82	8.90	8.77	8.69	8.64	8.59	8.59	8.33

Panel B: Weekly NASDAQ Data: July 1963 to June 2004

Sample Period	All	Small-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	β-10
Average Weekly Turnover (in percent)											
All	1.80	1.55	1.18	1.38	1.41	1.56	1.61	1.76	1.99	2.37	2.73
Small-ME	0.87	0.71	0.64	0.72	0.90	0.71	0.82	0.88	1.01	1.12	1.26
ME-2	1.30	1.09	0.99	1.08	1.11	1.19	1.34	1.35	1.48	1.63	1.71
ME-3	1.52	1.29	1.12	1.32	1.18	1.46	1.46	1.67	1.73	1.85	2.03
ME-4	1.67	1.54	0.97	1.37	1.41	1.58	1.48	1.71	2.06	2.12	2.42
ME-5	1.93	1.73	1.39	1.26	1.32	1.82	1.94	1.95	2.46	2.55	2.77
ME-6	2.06	1.75	1.10	1.49	1.98	1.72	1.92	2.11	2.11	2.80	3.20
ME-7	2.24	2.42	1.42	1.83	1.80	1.96	1.91	1.99	2.04	2.89	3.57
ME-8	2.47	2.31	1.81	1.68	2.46	1.91	1.70	2.32	3.02	3.27	3.60
ME-9	2.97	4.21	2.93	2.99	1.67	1.92	2.63	2.59	2.62	3.53	3.84
Large-ME	2.96	1.38	1.22	4.92	2.06	3.17	2.91	2.39	2.34	2.88	3.68
Average Weekly Return (in percent)											
All	0.56	0.45	0.55	0.46	0.55	0.61	0.59	0.62	0.61	0.57	0.57
Small-ME	0.70	0.62	0.59	0.59	0.72	0.67	0.71	0.71	0.85	0.80	0.76
ME-2	0.60	0.46	0.43	0.56	0.72	0.54	0.85	0.73	0.55	0.55	0.65
ME-3	0.55	0.49	0.47	0.34	0.42	0.76	0.59	0.60	0.59	0.72	0.53
ME-4	0.59	0.51	0.78	0.53	0.63	1.06	0.62	0.53	0.54	0.38	0.33
ME-5	0.60	0.67	0.47	0.80	0.65	0.28	0.74	0.69	0.84	0.34	0.58
ME-6	0.57	0.59	0.68	0.29	0.44	0.29	0.58	0.50	0.51	1.00	0.79
ME-7	0.51	0.75	0.37	0.04	0.54	0.73	0.13	1.00	0.45	0.46	0.64
ME-8	0.45	-0.03	0.69	0.50	0.19	0.54	0.77	-0.10	0.77	0.70	0.23
ME-9	0.37	-1.13	0.48	0.16	-0.06	0.83	-0.32	0.66	0.88	0.73	0.57
Large-ME	0.31	0.00	0.13	0.23	1.37	-0.25	1.35	0.65	0.08	-0.46	0.72
Average Size (ln(ME))											
All	5.47	5.23	5.24	5.32	5.28	5.45	5.46	5.49	5.65	5.68	5.80
Small-ME	2.56	2.29	2.47	2.55	2.55	2.57	2.62	2.59	2.66	2.67	2.64
ME-2	4.29	4.27	4.27	4.31	4.31	4.32	4.32	4.29	4.30	4.29	4.27
ME-3	4.85	4.82	4.89	4.89	4.88	4.85	4.89	4.81	4.87	4.85	4.80
ME-4	5.33	5.29	5.38	5.37	5.35	5.37	5.34	5.36	5.30	5.29	5.26
ME-5	5.76	5.74	5.76	5.77	5.79	5.79	5.83	5.80	5.74	5.70	5.70
ME-6	6.20	6.11	6.18	6.14	6.30	6.21	6.35	6.22	6.17	6.20	6.14
ME-7	6.61	6.49	6.49	6.39	6.82	6.56	6.52	6.66	6.60	6.77	6.79
ME-8	7.05	6.94	6.75	7.12	6.65	7.04	7.18	6.93	7.22	7.25	7.12
ME-9	7.82	7.10	7.21	7.34	7.79	8.00	7.54	8.19	8.50	8.33	7.65
Large-ME	9.26	8.73	8.97	9.38	9.08	8.62	9.83	9.62	9.12	9.46	9.24

Portfolios are formed yearly from 1963 to 2004 based on size deciles and β deciles. The breakpoints for size are determined by market capitalization at June of each year on only NYSE stocks on CRSP. All NYSE, AMEX, and NASDAQ stocks are first allocated to 10 size deciles based on NYSE size breakpoints, then each of the 10 size deciles is subdivided to 10 β portfolios based on pre-ranking β s of individual stocks. Pre-ranking βs are estimated using previous five years of monthly returns ending in June of year t. To ensure enough data points for the estimation, for each stock, a minimum of 24 non-missing monthly returns in the previous five years is required to estimate the βs. Average weekly returns are calculated based on the weekly returns on the resulting 100 portfolios.

Individual stock's turnover is calculated based on their weekly raw trading volume (turnover is calculated as shares traded divided by the number of shares outstanding). Share turnover/average returns/market equity for NASDAQ stocks are reported separately.

The average return of a portfolio is the average of weekly equal-weighted portfolio returns, in percent.

The average size of the portfolio is the average of weekly averages of ln(ME) for stocks in portfolio at the end of June of each year, with ME denominated in million dollars.

The "All" column shows statistics for equal-weighted size-decile (ME) portfolios. The "All" row shows statistics for equal-weighted portfolios of the stocks in each β group.

All return and turnover numbers are reported in unit of percent – they are not annualized.

Table 1.4: Average Turnover, Average Returns, and Average Size for Portfolios Formed on Size and Then β Deciles
Panel A: Daily NYSE/AMEX Data: July 1963 to June 2004

Sample Period	All	Small-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	β-10
Average Daily Turnover (in percent)											
All	0.256	0.184	0.184	0.203	0.221	0.231	0.242	0.268	0.296	0.324	0.406
Small-ME	0.190	0.161	0.149	0.152	0.172	0.175	0.180	0.187	0.214	0.232	0.276
ME-2	0.232	0.147	0.160	0.179	0.183	0.218	0.217	0.259	0.264	0.337	0.355
ME-3	0.242	0.170	0.169	0.191	0.200	0.231	0.253	0.268	0.287	0.292	0.361
ME-4	0.266	0.196	0.182	0.195	0.249	0.232	0.259	0.277	0.307	0.350	0.409
ME-5	0.273	0.193	0.187	0.203	0.225	0.238	0.247	0.299	0.341	0.357	0.437
ME-6	0.280	0.175	0.185	0.219	0.249	0.264	0.248	0.300	0.326	0.369	0.467
ME-7	0.295	0.223	0.216	0.243	0.245	0.261	0.267	0.298	0.355	0.363	0.474
ME-8	0.289	0.206	0.204	0.234	0.240	0.244	0.287	0.290	0.317	0.376	0.488
ME-9	0.273	0.192	0.221	0.233	0.246	0.248	0.262	0.276	0.301	0.310	0.446
Large-ME	0.221	0.179	0.168	0.180	0.197	0.204	0.206	0.225	0.244	0.258	0.349
Average Daily Return (in percent)											
All	0.067	0.067	0.066	0.068	0.068	0.068	0.070	0.066	0.066	0.066	0.061
Small-ME	0.122	0.118	0.119	0.106	0.110	0.113	0.123	0.122	0.129	0.142	0.143
ME-2	0.071	0.055	0.058	0.075	0.075	0.074	0.073	0.078	0.077	0.084	0.058
ME-3	0.066	0.065	0.058	0.073	0.059	0.081	0.075	0.082	0.068	0.059	0.044
ME-4	0.066	0.066	0.075	0.070	0.075	0.067	0.068	0.050	0.067	0.062	0.059
ME-5	0.064	0.068	0.068	0.062	0.068	0.069	0.067	0.066	0.052	0.060	0.055
ME-6	0.061	0.072	0.070	0.071	0.066	0.062	0.060	0.050	0.060	0.046	0.051
ME-7	0.061	0.054	0.056	0.060	0.068	0.059	0.067	0.067	0.063	0.052	0.059
ME-8	0.057	0.064	0.054	0.062	0.057	0.058	0.048	0.056	0.054	0.065	0.054
ME-9	0.052	0.054	0.056	0.054	0.056	0.051	0.060	0.043	0.049	0.049	0.049
Large-ME	0.047	0.050	0.047	0.049	0.047	0.048	0.059	0.042	0.045	0.045	0.037
Average Size (ln(ME))											
All	5.75	5.75	5.77	5.79	5.77	5.77	5.76	5.74	5.72	5.73	5.68
Small-ME	2.74	2.71	2.73	2.75	2.74	2.82	2.78	2.76	2.73	2.75	2.65
ME-2	4.13	4.12	4.12	4.13	4.15	4.14	4.13	4.14	4.12	4.14	4.12
ME-3	4.65	4.66	4.65	4.67	4.65	4.67	4.67	4.66	4.65	4.63	4.59
ME-4	5.09	5.08	5.10	5.09	5.10	5.10	5.09	5.06	5.09	5.08	5.07
ME-5	5.51	5.52	5.53	5.52	5.52	5.53	5.51	5.51	5.48	5.50	5.48
ME-6	5.92	5.94	5.94	5.93	5.92	5.96	5.91	5.90	5.91	5.91	5.91
ME-7	6.36	6.36	6.35	6.37	6.39	6.37	6.37	6.35	6.34	6.36	6.35
ME-8	6.87	6.91	6.88	6.87	6.87	6.86	6.87	6.87	6.85	6.87	6.85
ME-9	7.48	7.48	7.50	7.51	7.50	7.48	7.51	7.46	7.49	7.47	7.44
Large-ME	8.73	8.80	8.94	9.04	8.85	8.78	8.74	8.69	8.53	8.58	8.39

Panel B: Daily NASDAQ Data: July 1963 to June 2004

Sample Period	All	Small-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	β-10
Average Daily Turnover (in percent)											
All	0.72	0.43	0.45	0.52	0.55	0.63	0.67	0.70	0.76	0.94	1.25
Small-ME	0.36	0.26	0.26	0.30	0.34	0.32	0.37	0.38	0.41	0.46	0.56
ME-2	0.52	0.36	0.33	0.40	0.43	0.52	0.58	0.52	0.60	0.67	0.78
ME-3	0.58	0.41	0.40	0.43	0.57	0.50	0.54	0.58	0.62	0.77	0.94
ME-4	0.68	0.42	0.36	0.49	0.57	0.61	0.73	0.73	0.85	0.96	1.09
ME-5	0.74	0.45	0.42	0.53	0.60	0.57	0.74	0.78	0.88	1.02	1.29
ME-6	0.82	0.38	0.61	0.57	0.58	0.76	0.72	0.82	0.88	1.07	1.57
ME-7	0.91	0.68	0.60	0.89	0.65	0.96	0.66	0.78	0.88	1.21	1.54
ME-8	0.95	0.49	0.74	0.49	0.64	0.75	0.91	0.94	0.78	1.32	1.74
ME-9	1.21	2.24	1.42	1.37	0.71	0.94	1.38	0.98	1.07	1.13	1.58
Large-ME	1.18	----	1.10	1.70	0.73	0.98	0.80	1.15	0.95	1.18	1.47
Average Daily Return (in percent)											
All	0.08	0.09	0.08	0.08	0.09	0.09	0.08	0.07	0.08	0.09	0.07
Small-ME	0.16	0.17	0.16	0.16	0.16	0.15	0.14	0.14	0.16	0.16	0.17
ME-2	0.08	0.09	0.09	0.07	0.09	0.08	0.08	0.07	0.08	0.07	0.08
ME-3	0.07	0.06	0.06	0.09	0.06	0.10	0.07	0.08	0.07	0.07	0.05
ME-4	0.07	0.07	0.06	0.07	0.10	0.06	0.08	0.06	0.05	0.07	0.06
ME-5	0.08	0.10	0.07	0.08	0.10	0.08	0.07	0.06	0.07	0.07	0.07
ME-6	0.07	0.06	0.09	0.07	0.09	0.05	0.05	0.05	0.09	0.10	0.06
ME-7	0.06	0.10	0.06	0.08	0.05	0.09	0.07	0.05	0.06	0.07	0.03
ME-8	0.06	0.04	0.06	0.06	0.06	0.04	0.00	0.14	0.05	0.06	0.07
ME-9	0.07	-0.12	0.04	0.02	0.06	0.14	0.12	0.06	0.04	0.10	0.06
Large-ME	0.06	---	0.16	-0.04	0.06	0.21	0.04	0.00	0.05	0.06	0.08
Average Size (ln(ME))											
All	5.52	5.13	5.25	5.35	5.51	5.52	5.47	5.53	5.64	5.72	5.92
Small-ME	2.60	2.30	2.50	2.57	2.61	2.63	2.60	2.66	2.70	2.73	2.70
ME-2	4.40	4.39	4.41	4.40	4.42	4.41	4.40	4.38	4.39	4.41	4.37
ME-3	4.96	4.94	4.95	4.98	4.94	5.00	4.95	5.01	4.96	4.94	4.92
ME-4	5.45	5.44	5.53	5.48	5.49	5.43	5.44	5.43	5.41	5.42	5.39
ME-5	5.88	5.84	5.91	5.87	5.98	5.91	5.85	5.86	5.83	5.88	5.88
ME-6	6.30	6.20	6.30	6.28	6.50	6.27	6.23	6.35	6.27	6.39	6.24
ME-7	6.77	6.67	6.81	6.76	6.78	6.69	6.83	6.74	6.91	6.93	6.62
ME-8	7.17	7.02	6.89	7.04	7.13	7.14	6.81	7.50	7.26	7.42	7.30
ME-9	7.96	7.30	7.36	7.79	7.67	7.95	8.07	8.10	8.37	8.37	7.85
Large-ME	9.45	----	9.48	9.56	8.75	10.13	9.01	9.36	9.64	9.79	9.37

Portfolios are formed yearly from 1963 to 2004 based on size deciles and β deciles. The breakpoints for size are determined by market capitalization at June of each year on only NYSE stocks on CRSP. All NYSE, AMEX, and NASDAQ stocks are first allocated to 10 size deciles based on NYSE size breakpoints, then each of the 10 size deciles is subdivided to 10 β portfolios based on pre-ranking βs of individual stocks. Pre-ranking β s are estimated using previous five years of monthly returns ending in June of year *t*. To ensure enough data points for the estimation, for each stock, a minimum of 24 non-missing monthly returns in the previous five years is required to estimate the βs. Average daily returns are calculated based on the daily returns on the resulting 100 portfolios.

Individual stock's turnover is calculated based on their daily raw trading volume (turnover is calculated as shares traded divided by the number of shares outstanding). Share turnover/average returns/market equity for NASDAQ stocks are reported separately.

The average return of a portfolio is the average of daily equal-weighted portfolio returns, in percent, not annualized.

The average size of the portfolio is the average of daily averages of ln(ME) for stocks in portfolio at the end of June of each year, with ME denominated in million dollars.

The "All" column shows statistics for equal-weighted size-decile (ME) portfolios. The "All" row shows statistics for equal-weighted portfolios of the stocks in each β group.

All return and turnover numbers are reported in unit of percent – they are not annualized.

Table 1.5: Summary Statistics for Monthly Value-weighted and Equal-weighted Turnover and Return Indexes of NYSE/AMEX Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (498) Months and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	4.53	5.14	1.46	1.29
Std. dev.	2.86	2.64	4.24	5.63
Skewness	0.56	1.09	-0.25	-0.15
Kurtosis	-0.59	1.16	2.14	3.73
Percentiles:				
Min	0.74	1.21	-21.03	-28.31
5%	1.11	1.93	-5.42	-7.58
10%	1.34	2.22	-3.59	-5.05
25%	1.81	3.07	-1.06	-1.96
50%	4.51	4.66	1.48	1.27
75%	6.50	6.43	4.19	4.55
90%	8.69	8.83	6.35	8.03
95%	9.86	10.68	7.69	9.76
Max	13.76	14.37	17.79	31.54
Autocorrelations				
ρ_1	0.95	0.93	0.03	0.19
ρ_2	0.94	0.90	-0.05	-0.04
ρ_3	0.94	0.88	0.00	-0.04
ρ_4	0.92	0.85	-0.03	-0.05
ρ_5	0.92	0.85	0.08	0.00
ρ_6	0.91	0.83	-0.03	-0.02
ρ_7	0.90	0.82	-0.01	-0.04
ρ_8	0.89	0.81	-0.07	-0.12
ρ_9	0.90	0.81	-0.02	-0.03
ρ_{10}	0.88	0.78	0.03	0.03
Box-Pierce Q12	4179.59	3578.94	8.18	29.76
	(0.000)	(0.000)	(0.010)	(0.010)
		1963-1966(42 month)		
Mean	1.16	2.77	0.98	1.14
Std. dev.	0.30	0.88	2.56	3.77
Skewness	0.71	1.22	-1.12	-1.21
Kurtosis	-0.40	0.66	2.03	2.04
		1967-1971 (60 month)		
Mean	1.73	4.14	1.21	1.34
Std. dev.	0.28	1.23	4.48	6.82
Skewness	0.79	0.52	-0.18	-0.01
Kurtosis	0.91	-0.28	-0.59	-0.09
		1972-1976 (60 month)		
Mean	1.62	2.30	1.02	0.79
Std. dev.	0.36	0.79	5.22	7.97
Skewness	0.71	1.10	0.70	1.23

Kurtosis	0.67	0.86	2.05	3.31
		1977-1981 (60 month)		
Mean	2.73	3.45	1.37	1.85
Std. dev.	0.69	0.88	4.50	5.84
Skewness	0.16	0.46	-0.30	-1.31
Kurtosis	-0.70	-0.19	0.36	2.98
		1982-1986 (60 month)		
Mean	5.25	4.85	2.07	1.57
Std. dev.	1.02	1.06	4.17	4.68
Skewness	-0.12	0.09	0.45	0.44
Kurtosis	-0.44	-0.74	0.20	-0.15
		1987-1991 (60 month)		
Mean	5.75	5.12	1.76	1.00
Std. dev.	1.28	0.96	5.22	6.09
Skewness	1.27	1.37	-1.28	-1.86
Kurtosis	3.25	3.93	5.35	8.28
		1992-1996 (60 month)		
Mean	5.60	5.96	1.51	1.41
Std. dev.	0.78	0.84	2.39	3.22
Skewness	0.05	0.12	-0.44	-0.18
Kurtosis	-0.55	0.35	0.02	1.18
		1997-2001 (60 month)		
Mean	8.10	7.98	1.90	0.94
Std. dev.	1.24	1.03	4.31	5.23
Skewness	0.65	0.96	-0.51	-0.53
Kurtosis	0.63	2.24	0.16	2.10
		2002-2004 (36 month)		
Mean	10.05	11.50	1.03	1.73
Std. dev.	1.13	1.60	3.93	5.09
Skewness	1.40	-0.05	-0.50	-0.43
Kurtosis	3.26	-1.12	0.14	0.67

Table 1.6: Summary Statistics for Monthly Value-weighted and Equal-weighted Turnover and Return Indexes of NASDAQ Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (498) Months and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	14.02	8.96	2.80	2.06
Std. dev.	10.63	6.80	8.40	8.84
Skewness	0.42	0.95	0.19	0.43
Kurtosis	-0.94	0.74	1.33	2.27
Percentiles:				
Min	0.24	0.23	-28.06	-29.89
5%	1.02	1.03	-9.92	-11.07
10%	1.26	1.40	-7.23	-7.13
25%	3.14	3.28	-2.15	-3.18
50%	11.69	6.96	2.65	1.71
75%	23.73	13.81	7.03	6.16
90%	28.35	18.43	13.69	13.61
95%	31.17	20.59	17.26	16.89
Max	42.93	36.11	34.31	39.33
Autocorrelations				
ρ_1	0.94	0.89	0.12	0.19
ρ_2	0.93	0.85	0.03	-0.03
ρ_3	0.93	0.83	0.00	0.00
ρ_4	0.92	0.81	0.03	0.01
ρ_5	0.91	0.79	0.01	0.02
ρ_6	0.91	0.80	0.03	-0.02
ρ_7	0.90	0.79	-0.01	0.00
ρ_8	0.90	0.78	-0.08	-0.01
ρ_9	0.90	0.76	-0.02	0.04
ρ_{10}	0.89	0.75	0.03	0.00
Box-Pierce Q12	3211.74	2500.04	9.58	15.20
	(0.000)	(0.000)	(0.010)	(0.010)
		1972-1976 (49 month)		
Mean	1.87	1.68	0.30	1.87
Std. dev.	1.54	1.32	9.55	11.61
Skewness	4.51	3.16	1.18	1.01
Kurtosis	25.40	13.00	2.66	1.29
		1977-1981 (60 month)		
Mean	3.02	3.42	4.98	5.73
Std. dev.	3.42	3.88	10.27	11.91
Skewness	4.54	5.10	-0.08	-0.24
Kurtosis	26.21	31.40	0.37	0.72
		1982-1986 (60 month)		

Mean	7.49	5.03	2.04	0.96
Std. dev.	3.02	1.84	5.89	5.99
Skewness	-0.93	-0.64	0.36	0.60
Kurtosis	0.27	0.20	-0.05	0.85
1987-1991 (60 month)				
Mean	12.58	6.74	2.86	1.01
Std. dev.	2.72	1.36	7.26	6.18
Skewness	0.55	0.62	-1.22	-1.94
Kurtosis	-0.60	-0.14	4.57	9.23
1992-1996 (60 month)				
Mean	19.99	12.50	2.79	1.34
Std. dev.	3.74	2.62	4.50	4.77
Skewness	0.26	0.51	-0.18	0.32
Kurtosis	-0.58	1.16	-0.38	1.73
1997-2001 (60 month)				
Mean	29.01	17.50	4.05	1.41
Std. dev.	5.33	4.92	11.50	10.47
Skewness	0.65	2.00	-0.04	0.29
Kurtosis	-0.01	4.77	-0.37	0.96
2002-2004 (36 month)				
Mean	26.94	18.06	1.70	2.14
Std. dev.	3.20	5.07	6.89	7.80
Skewness	1.05	0.74	0.14	0.06
Kurtosis	1.85	0.14	-0.20	-0.25

All return and turnover numbers are reported in unit of percent – they are not annualized.

P-values for Box-Pierce statistics are reported in parentheses.

Table 1.7: Summary Statistics for Weekly Value-weighted and Equal-weighted Turnover and Return Indexes of NYSE/AMEX Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (2166) Weeks and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	1.04	1.18	0.30	0.27
Std. dev.	0.68	0.63	2.00	2.15
Skewness	0.69	1.17	-0.22	-0.63
Kurtosis	-0.20	1.50	3.44	5.41
Percentiles:				
Min	0.14	0.24	-12.33	-18.74
5%	0.24	0.42	-2.91	-3.14
10%	0.29	0.50	-2.02	-2.23
25%	0.41	0.70	-0.86	-0.86
50%	0.99	1.08	0.44	0.44
75%	1.50	1.49	1.46	1.50
90%	2.03	2.00	2.56	2.48
95%	2.34	2.45	3.31	3.40
Max	4.01	3.83	14.19	11.22
Autocorrelations				
ρ_1	0.93	0.92	0.01	0.27
ρ_2	0.90	0.89	0.02	0.12
ρ_3	0.89	0.87	0.04	0.10
ρ_4	0.89	0.87	-0.03	0.05
ρ_5	0.89	0.86	-0.03	0.03
ρ_6	0.88	0.85	0.07	0.06
ρ_7	0.88	0.85	-0.03	-0.03
ρ_8	0.88	0.84	-0.05	-0.03
ρ_9	0.87	0.83	0.00	0.01
ρ_{10}	0.87	0.82	-0.01	-0.01
Box-Pierce Q12	17167.88	16033.84	26.85	235.26
	(0.000)	(0.000)	(0.010)	(0.000)
		1963-1966 (183 Weeks)		
Mean	0.26	0.64	0.21	0.21
Std. dev.	0.08	0.22	1.38	1.60
Skewness	0.83	1.47	-0.29	-1.33
Kurtosis	0.10	2.14	3.34	4.34
		1967-1971 (261 weeks)		
Mean	0.40	0.95	0.24	0.30
Std. dev.	0.08	0.32	1.82	2.44
Skewness	0.38	0.60	-0.12	-0.29
Kurtosis	0.20	-0.14	1.03	0.69
		1972-1976 (261 weeks)		

Mean	0.37	0.53	0.20	0.09
Std. dev.	0.10	0.20	2.52	2.80
Skewness	0.80	1.29	0.36	0.54
Kurtosis	1.13	1.85	3.71	1.87
1977-1981 (261 weeks)				
Mean	0.62	0.79	0.27	0.37
Std. dev.	0.18	0.23	1.97	2.16
Skewness	0.36	0.64	-0.34	-1.26
Kurtosis	-0.60	-0.14	1.24	4.42
1982-1986 (261 weeks)				
Mean	1.21	1.12	0.45	0.37
Std. dev.	0.30	0.29	2.01	1.92
Skewness	0.28	0.44	0.37	0.28
Kurtosis	-0.30	-0.44	1.95	1.18
1987-1991 (261 weeks)				
Mean	1.32	1.18	0.36	0.19
Std. dev.	0.36	0.27	2.23	2.29
Skewness	1.87	2.35	-1.15	-2.42
Kurtosis	11.85	16.41	4.79	18.83
1992-1996 (261 weeks)				
Mean	1.29	1.37	0.32	0.30
Std. dev.	0.24	0.24	1.22	1.23
Skewness	-0.08	0.11	-0.19	-0.67
Kurtosis	-0.33	-0.32	0.31	1.83
1997-2001 (260 weeks)				
Mean	1.86	1.85	0.37	0.21
Std. dev.	0.38	0.32	2.34	2.29
Skewness	0.19	0.13	-0.40	-0.93
Kurtosis	1.53	2.46	1.77	4.51
2002-2004 (157 weeks)				
Mean	2.31	2.65	0.19	0.39
Std. dev.	0.41	0.50	2.02	2.11
Skewness	-0.10	-0.09	-0.38	-0.37
Kurtosis	1.47	-0.36	2.79	0.20

Table 1.8: Summary Statistics for Weekly Value-weighted and Equal-weighted Turnover and Return Indexes of NASDAQ Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (2166) Weeks and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	3.54	2.25	0.43	0.15
Std. dev.	2.47	1.58	3.66	3.19
Skewness	0.39	0.86	0.03	0.19
Kurtosis	-0.78	0.83	6.01	7.81
Percentiles:				
Min	0.06	0.06	-25.20	-20.82
5%	0.25	0.25	-5.18	-4.57
10%	0.35	0.35	-3.65	-3.07
25%	1.54	1.05	-1.30	-1.18
50%	3.12	1.86	0.44	0.10
75%	5.62	3.37	2.25	1.38
90%	6.88	4.30	4.41	3.57
95%	7.83	4.90	5.57	5.04
Max	10.84	9.67	22.83	22.83
Autocorrelations				
ρ_1	0.93	0.94	0.01	0.14
ρ_2	0.91	0.92	-0.01	0.06
ρ_3	0.90	0.91	0.05	0.10
ρ_4	0.91	0.90	-0.01	0.03
ρ_5	0.91	0.89	0.05	0.05
ρ_6	0.89	0.88	0.05	0.04
ρ_7	0.89	0.87	-0.07	-0.07
ρ_8	0.89	0.87	0.02	0.02
ρ_9	0.89	0.86	-0.01	0.00
ρ_{10}	0.89	0.85	0.03	0.02
Box-Pierce Q12	12055.16	11709.16	21.33	65.02
	(0.000)	(0.000)	(0.010)	(0.000)
		1972-1976 (212 weeks)		
Mean	0.41	0.41	0.06	0.06
Std. dev.	0.24	0.24	5.37	5.37
Skewness	1.60	1.60	0.48	0.48
Kurtosis	2.99	2.99	1.51	1.51
		1977-1981 (111 weeks)		
Mean	0.57	0.57	0.34	0.34
Std. dev.	0.53	0.53	2.97	2.97
Skewness	3.29	3.29	3.96	3.96
Kurtosis	14.35	14.35	29.49	29.49
		1982-1986 (212 weeks)		
Mean	1.96	1.32	0.48	0.31
Std. dev.	0.50	0.35	2.37	1.94
Skewness	0.22	0.77	0.50	1.13
Kurtosis	-0.52	1.68	3.55	5.76

	1987-1991 (261 weeks)			
Mean	2.91	1.62	0.50	0.07
Std. dev.	0.75	0.37	2.81	2.18
Skewness	0.69	0.72	-1.68	-2.62
Kurtosis	0.60	0.41	12.73	22.37
	1992-1996 (261 weeks)			
Mean	4.60	2.94	0.51	-0.12
Std. dev.	1.05	0.68	2.10	1.63
Skewness	0.31	0.45	-0.19	-0.29
Kurtosis	-0.17	0.57	-0.01	1.58
	1997-2001 (260 weeks)			
Mean	6.67	4.06	0.70	0.19
Std. dev.	1.54	1.21	5.04	3.88
Skewness	0.20	1.73	-0.45	-0.78
Kurtosis	0.34	4.90	3.23	4.01
	2002-2004 (157 weeks)			
Mean	6.19	4.15	0.26	0.43
Std. dev.	1.16	1.25	3.33	2.94
Skewness	-0.45	0.81	0.10	-0.05
Kurtosis	0.89	0.71	-0.27	-0.61

All return and turnover numbers are reported in unit of percent – they are not annualized.

P-values for Box-Pierce statistics are reported in parentheses.

Table 1.9: Summary Statistics for Daily Value-weighted and Equal-weighted Turnover and Return Indexes of NYSE/AMEX Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (10446) Days and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	0.22	0.26	0.07	0.07
Std. dev.	0.14	0.13	0.87	0.83
Skewness	0.75	1.16	-0.83	-0.83
Kurtosis	0.06	1.54	22.23	17.97
Percentiles:				
Min	0.03	0.05	-17.95	-14.78
5%	0.05	0.09	-1.31	-1.28
10%	0.06	0.11	-0.91	-0.84
25%	0.09	0.15	-0.36	-0.31
50%	0.20	0.23	0.08	0.11
75%	0.31	0.32	0.51	0.49
90%	0.42	0.43	1.01	0.90
95%	0.48	0.53	1.42	1.23
Max	1.08	1.03	9.21	9.86
Autocorrelations				
ρ_1	0.94	0.95	0.13	0.30
ρ_2	0.92	0.92	-0.02	0.08
ρ_3	0.91	0.91	-0.01	0.08
ρ_4	0.91	0.91	-0.01	0.09
ρ_5	0.91	0.91	0.00	0.08
ρ_6	0.90	0.90	-0.01	0.04
ρ_7	0.89	0.89	-0.02	0.04
ρ_8	0.89	0.89	0.00	0.04
ρ_9	0.89	0.89	-0.01	0.02
ρ_{10}	0.90	0.89	-0.01	0.02
Box-Pierce Q12	85967.82	85948.59	178.81	1325.30
	(0.000)	(0.000)	(0.000)	(0.000)
		1963-1966 (883days)		
Mean	0.06	0.14	0.05	0.05
Std. dev.	0.02	0.05	0.55	0.60
Skewness	1.03	1.40	0.01	-1.08
Kurtosis	1.04	1.83	7.16	6.34
		1967-1971 (1234 days)		
Mean	0.08	0.21	0.06	0.07
Std. dev.	0.02	0.07	0.71	0.91
Skewness	0.69	0.69	0.43	0.21
Kurtosis	1.16	0.14	4.28	5.33
		1972-1976 (1262 days)		
Mean	0.08	0.12	0.05	0.03
Std. dev.	0.02	0.04	0.95	0.96
Skewness	1.03	1.41	0.27	0.22

Kurtosis	1.86	2.65	1.59	2.51
1977-1981 (1263 days)				
Mean	0.13	0.17	0.07	0.09
Std. dev.	0.04	0.05	0.81	0.82
Skewness	0.75	1.05	-0.04	-0.92
Kurtosis	0.81	1.91	1.82	6.94
1982-1986 (1265 days)				
Mean	0.25	0.24	0.10	0.08
Std. dev.	0.07	0.06	0.83	0.70
Skewness	0.80	0.71	0.22	0.04
Kurtosis	1.37	0.41	2.60	2.33
1987-1991 (1264 days)				
Mean	0.27	0.26	0.09	0.06
Std. dev.	0.08	0.06	1.14	0.98
Skewness	2.31	2.62	-3.30	-3.02
Kurtosis	15.18	20.53	56.25	59.19
1992-1996 (1265 days)				
Mean	0.27	0.30	0.08	0.08
Std. dev.	0.06	0.05	0.56	0.51
Skewness	0.31	0.08	-0.36	-0.88
Kurtosis	0.84	0.79	1.96	3.17
1997-2001 (1254 days)				
Mean	0.39	0.39	0.10	0.06
Std. dev.	0.08	0.07	1.05	0.86
Skewness	0.81	0.74	-0.34	-0.77
Kurtosis	2.72	2.83	3.35	4.79
2001-2004 (756 days)				
Mean	0.48	0.57	0.05	0.09
Std. dev.	0.08	0.10	1.07	0.98
Skewness	0.27	0.15	0.26	-0.11
Kurtosis	3.54	1.55	2.40	1.17

Table 1.10: Summary Statistics for Daily Value-weighted and Equal-weighted Turnover and Return Indexes of NASDAQ Ordinary Common Shares (CRSP Share Codes 10 and 11, SIC Codes not between 6000 and 7000) for July 1963 to December 2004 (10446) Days and Sub-periods

Statistic	τ^{VW}	τ^{EW}	R^{VW}	R^{EW}
Mean	0.74	0.50	0.13	0.06
Std. dev.	0.52	0.34	1.63	1.27
Skewness	0.43	0.74	0.43	0.33
Kurtosis	-0.47	0.83	9.51	16.48
Percentiles:				
Min	0.00	0.00	-12.31	-10.67
5%	0.04	0.04	-2.49	-1.89
10%	0.06	0.06	-1.58	-1.17
25%	0.33	0.26	-0.53	-0.42
50%	0.67	0.45	0.09	0.05
75%	1.15	0.74	0.83	0.55
90%	1.43	0.92	1.69	1.18
95%	1.62	1.08	2.52	1.77
Max	3.15	2.35	16.45	16.45
Autocorrelations				
ρ_1	0.94	0.95	0.10	0.22
ρ_2	0.91	0.92	-0.04	0.03
ρ_3	0.90	0.91	0.01	0.07
ρ_4	0.91	0.92	0.02	0.06
ρ_5	0.91	0.92	-0.02	0.02
ρ_6	0.90	0.91	0.00	0.03
ρ_7	0.89	0.90	0.00	0.02
ρ_8	0.89	0.90	-0.04	-0.01
ρ_9	0.90	0.90	-0.02	0.00
ρ_{10}	0.90	0.90	-0.01	0.01
Box-Pierce Q12	58682.55	59659.65	98.32	435.11
	(0.000)	(0.000)	(0.000)	(0.000)
		1972-1976 (1018 days)		
Mean	0.08	0.08	0.01	0.01
Std. dev.	0.07	0.07	2.25	2.25
Skewness	2.51	2.51	0.41	0.41
Kurtosis	10.39	10.39	4.58	4.58
		1977-1981 (1263 days)		
Mean	0.12	0.12	0.07	0.07
Std. dev.	0.17	0.17	1.15	1.15
Skewness	6.56	6.56	5.45	5.45
Kurtosis	66.67	66.67	77.82	77.82
		1982-1986 (1265 days)		

Mean	0.42	0.31	0.13	0.07
Std. dev.	0.12	0.10	0.86	0.70
Skewness	1.72	4.23	1.08	2.33
Kurtosis	11.93	48.73	15.56	34.80
1987-1991 (1264 days)				
Mean	0.62	0.40	0.15	0.05
Std. dev.	0.17	0.09	1.19	0.92
Skewness	1.03	0.95	-1.43	-2.81
Kurtosis	1.89	1.21	21.87	35.79
1992-1996 (1265 days)				
Mean	0.96	0.67	0.16	0.05
Std. dev.	0.24	0.14	0.98	0.67
Skewness	0.52	0.34	-0.35	-0.83
Kurtosis	1.13	0.81	1.72	3.68
1997-2001 (1254 days)				
Mean	1.39	0.88	0.22	0.09
Std. dev.	0.34	0.26	2.37	1.41
Skewness	0.84	1.77	0.32	-0.42
Kurtosis	1.70	4.21	3.42	5.36
2001-2004 (756 days)				
Mean	1.29	0.89	0.09	0.12
Std. dev.	0.24	0.27	1.75	1.17
Skewness	-0.05	1.03	0.38	-0.18
Kurtosis	1.75	1.70	1.33	0.07

All return and turnover numbers are reported in unit of percent – they are not annualized.

P-values for Box-Pierce statistics are reported in parentheses.

Essay 2 Does Investor Trade on Beliefs? – Evidence from Trading Volume on Analyst Recommendation Dates

2.1 Introduction

To identify the motive of investor trading can enhance the understanding of the behavior of asset prices. Investors trade because they are different. However, investors are different in many ways: their tax brackets, demand for liquidity, beliefs, information set, etc. All these differences can motivate investor's trade, and each has different implications on trading volume and asset pricing behavior.

Unlike models for asset pricing, not many theoretical models on trading volume were developed in previous academic research. There are five possible reasons that motivate investor trading in the finance literature : 1) Tax heterogeneity; 2) Risk sharing (Campbell, Grossman et al. 1993); 3) Heterogeneous beliefs on public information (Harris and Raviv 1993) ; 4) Liquidity-motivated (Wang 1994); 5) Overconfidence (Odean 1998b). I will focus on the speculative trading models of trading behavior in this paper: heterogeneous-belief model of Harris and Raviv (1993) and liquidity-motivated trading model of Wang (1994). Harris and Raviv (1993) model investors trade on different beliefs of public information. In their model, risk neutral investors have same information set but when they see a public signal they update their beliefs based on different likelihood function. In another words, investors differ only on the way they update their beliefs. Investors are classified into two groups based on their likelihood function: the responsive group and the non-responsive group. Investors in the responsive group are more optimistic on positive signal but more pessimistic on negative signal than those in the non-responsive group. Trade occurs because they form different beliefs even their prior information set is the same. On the other hand, Wang (1994) suggests that under asymmetric information setting the key element for investor trades is motivated mainly by investor's demand for liquidity.

Both models can potentially explain abnormal trading volume on normal trading days, especially active trading behavior following a public signal. Trading behaviors in both speculative models arise from disagreement among investors over public signals and final asset prices. However, the sources of disagreement are different: Wang's liquidity-motivated trading volume model assumes investors have different private information, while Harris and Raviv's heterogeneous-belief model assumes that investors receive the same information but their interpretations are different ("differences of opinion").

But do investors trade on different beliefs? Is volume data consistent with Harris and Raviv (1993)'s hypothesis? To answer this question, I analyze market trading behavior on the date of analyst recommendation announcement. One of the key predictions of Harris and Raviv (1993) is that trading volume occurs only when investors see a reversal on public signals. That implies that trading volume should be higher when public signal changes directions. This naturally leads to the following hypothesis: stocks experienced two opposite public signals (reversal signals) have higher trading volume than stocks with two consecutive positive or negative signals (continuation signals). I conduct an event study based on trading volume on the analyst recommendation announcement date. I divide stocks into two groups: the reversal group and the continuation group. The reversal group includes stocks that have either a first positive then negative recommendation or a first negative then positive recommendation for any consecutive two analyst recommendations. The continuation group contains stocks that have two consecutive positive or negative analyst recommendations. I find that contradict to Harris and Raviv (1993), the continuation group has a significantly higher turnover than the reversal group (52.8% for NYSE/AMEX firms and 42.8% for NASDAQ firms). These results are confirmed with our robustness checks. The empirical results are robust even after we control for analysts' upward bias in their recommendations and other factors that might affect trading volume (such as S&P 500 membership and option availability). This suggests that the heterogeneous-belief model does not explain most of the variation in trading volume during normal trading days where public information enters the market consecutively. Instead, my empirical tests show evidence that is consistent with the rational trading volume models: investors trade for liquidity and informational reasons.

Both models predict that trading volume is positively correlated with absolute price change[4] and absolute mean recommendation change. However, Harris and Raviv (1993) suggest that the above two correlations should be stronger for the reversal group than the continuation group. In addition, size should not affect trading volume according to Harris and Raviv (1993). Three additional hypotheses were developed and tested. Correspondingly, three major empirical results are the following: 1) absolute price change is positively related to share turnover and has a larger impact on turnover for the continuation group than for the reversal group on event date for NASDAQ stocks but not for NYSE/AMEX stocks; 2) the absolute change in mean recommendation grade has significant positive impacts on turnover on the event date, but the positive impacts is similar between the reversal and continuation group; 3) firm size has an significant impact on trading volume and the relation between firm size and trading volume is an inverted U-shape. These results do not support with the hypothesis that investors trade on heterogeneous beliefs. Moreover, the

[4] See Karpoff (1987) for related literature.

empirical results are consistent with Wang (1994)'s trading volume model and other rational expectations pricing models based on disagreement on private information.

Any signal in the market can trigger investor trading behavior. These signals include dividend announcement, earnings announcement, merger and acquisitions and other corporate and economic news. Event studies on dividend and earnings announcement are often observed in the finance literature. Clearly dividend earnings announcement would not be a good choice since besides other reasons for trade tax heterogeneity triggers most trades among investors on dividend payout date. I choose to use analyst recommendation data to test investor trading behavior for the following reasons: 1) unlike earning announcement and other event, analyst recommendations give a strong and clear signal to the market even ordinary investor can easily understand the meaning of the signal without further examining and interpreting the data; 2) compare to earnings announcement and other corporate event, analyst recommendation itself does not trigger much information asymmetry between informed investor and uninformed investor. This can be regarded as a clean public signal that can serve the purposes of testing the Harris and Raviv (1993) model.

The essay is organized as the following: Section 2.2 reviews the related theoretical model and empirical work of trading volume. Section 3 presents model's implication and develop testable hypothesis. Section 4 describes the data and methodology. The empirical results are detailed in section 5. Section 6 presents robustness check. Section 7 concludes the essay.

2.2 Related Work

There are not many theoretical models developed for trading volume. The possible reasons for trading are: tax-heterogeneity, heterogeneous belief (or differences in opinion), risk-sharing, liquidity and over-confidence. This study focuses on speculative reasons that motivate trading behavior. Both heterogeneous-belief and liquidity motivated trading volume models belong to this group. Among them, there are no theoretical models developed for tax-heterogeneity. Since tax-motivated trading does not explain the massive trading activity during ordinary trading days, and this reason has been extensively-examined and well-documented (see Lakonishok and Vermaelen 1986; Mitchell and Mulherin 1994; Michaely and Vila 1996), I will not focus on this reason. In fact, in my study, I try to minimize the effect of tax-motivated trading by eliminating trading days around dividend payout date since my intention is to identify trading reasons other than tax-heterogeneity.

People tend to think that private information motivates investors to trade. However, in a world where investors are either informed or uninformed, no trade should occur. Milgrom and Stokey (1982) demonstrate this "no-trade" equilibrium: given the existence of informed and uninformed investors, the uninformed know that they are trading with the informed. The willingness to trade of the informed investors signals that the uninformed will take the loss. Therefore, the uninformed should never trade with the informed. Grossman and Stiglitz (1980) also showed that when acquiring information is costly, investors would not trade if price is perfectly informative on the relevant information. Just like adding sand into gears, adding noise traders into the market can break "no-trade-equilibrium" (Kyle 1985; Black 1986). Campbell, Grossman et al. (1993) present a theoretical model to explain the phenomenon that stock prices tend to decline on a high volume day. In their model, risk-averse market makers trade with risk-neutral liquidity and non-informational traders. As market makers take more position, they become more risk-averse, and price should rise or fall to compensate this type of risk. Risk sharing is the main reason for trading in their model. Their empirical study supported their hypothesis. Wang (1994) develops a model where informed and uninformed investors trade with a key motivation of trading under information asymmetry – liquidity needs ("noise") from the informed investors. Without the liquidity need from the informed investors, Wang (1994)'s model would also reach the same equilibrium as Milgrom and Stokey (1982) – the "no trade equilibrium". However, because the informed investors experience random liquidity shock as a result of high return from their private investment opportunities, they sometimes trade their stocks at a discount to take advantage of better private investment opportunities. As a result, they trade for both liquidity and informational reasons. Since uninformed investors are unable to distinguish whether the trade is informational or liquidity-motivated, they are willing to take the other side of the trade hoping they are trading with the informed liquidity need. In these models, demand for liquidity is the key for the trade to occur. In Admati and Pfleiderer (1988), liquidity trading plays an important role. In their model, liquidity ("noise") traders prefer to trade when market is "thick"—when their trading does not move price much—in order to minimize the adverse selection cost arising from trade with informational traders. As a result, trading volume clusters because the strategic trading behavior of liquidity traders and informed traders.

Harris and Raviv (1993) present a multi-period model where investors trade based on their beliefs. While each investor is risk-neutral, has no private information, has the same prior before the public signal comes to the market, and even has same density function to update their beliefs, the parameters they used to update their density function is different. Based on the parameters that investors use to update their information set, there are two types of investors: responsive speculators and non-responsive speculators. The responsive is more optimistic when the public signal is positive and more pessimistic when the public signal is negative. On the other hand, the non-responsive group is more pessimistic on positive public signals and more optimistic on negative public signals. When two consecutive positive signals comes to the market, there would not be any trade on the second signal since the optimistic one has bought all shares when the first positive signal comes and they certainly will not sell any shares when the second signal is also positive – they remain optimistic during the whole period and no trade should occur. In fact, trade only occurs when the public signal changes direction, i.e., from positive to negative or from negative to positive.

Odean (1998a)'s model can be regarded as another version of trading based on differences in beliefs and information. In his model, overconfidence investors over-estimate the precision of his private signal and under-estimate the precision of other investor's information, since each acts over-confidently, they would ignore the information inferred from the price and participate trade. That is, each one thinks himself is right while all others are wrong – even he can perfectly infer the expectation of others from the price. When the signal is public signal and all traders have the same level of over-confidence, no trade would occur. This is because with same public signal traders overvalue that signal equally, no trade can possibly occur. This contradicts some empirical studies that trading volume tends to increase when public information arrives at the market (Berry and Howe 1994; Flemming and Remolona 1999; Lee, Ready et al. 1994). When we extend the model to multiperiods and only allow public signals enter the market, the only way that overconfidence investors can trade is to have variable degree of over-confidence. Some empirical studies support this hypothesis. Barber and Odean (2001) find that due to overconfidence, men trade 45% more than woman and on average they earn a much lower return than women. Odean (1999) examines individual trading activities at a nationwide brokerage account and he finds that because of their overconfidence investors trade too much. Stocks they buy significantly underperform the ones they sell.

Several empirical studies relate to my essay. Using intraday data from NYSE/AMEX, Foster and Viswanathan (1990) find that trading volume and adverse selection costs are both higher at the open but trading volume is lower on Monday when adverse selection costs are high. Just like Admati and Pfleiderer (1988), this provides empirical evidence of informational trading on financial market. Some studies show that trading volume is positively related to public events. Lo and Wang (2000) conduct cross-sectional analysis on trading volume on NYSE stocks and find that trading volume is positively related S&P 500 membership. Berry and Howe (1994) examined intraday data on NYSE stocks and document positive relation between public news and trading volume. Lee, Ready et al. (1994) examine 852 trading halts from NYSE and find that trading halts increase trading volume. Lamoureux and Poon (1987) find that both raw volume and number of transactions increase (decrease) after forward (reverse) split ex-day, however, their results are hard to interpret since a relative measure of volume such as turnover should be used in a study when number of shares outstanding changes on the event date. Bamber (1987) finds that the magnitude and the duration of abnormal trading volume are positively related to unexpected quarterly earnings.

Bamber, Barron et al. (1997) and Ziebat (1990) find that share turnover is positively related to the prior dispersion of beliefs. However, this prior dispersion of beliefs is measured by dispersion of analyst forecast – which is often considered as a proxy for information asymmetry level. Therefore, their evidence actually supports rational trading volume models.

My study focuses on the hypothesis testing based on the models of Harris and Raviv (1993) and Wang (1994). I develop hypotheses directly test the implication of those two models on volume when multiple public signals of the same nature arrive market.

2.3 Hypotheses Development

My empirical hypotheses are developed based on the multi-period trading volume model of Harris and Raviv (1993). For the purpose of this study, I do not consider abnormal trading that arises from tax-heterogeneity since that type of trading does not provide more insight to the question I raise here. I examine the effect of consecutive public signals on trading volume by classifying the types of signals into two groups: the continuation group and the reversal group. When two consecutive signals that arrive in the market are of the same sign (that is, ++ or --), I group the event to the continuation group; when two signals are of different signs (that is, +- or -+), I group the event to the reversal group. All the following hypotheses are based on the prediction of Harris and Raviv (1993).

Hypothesis 1: *Trading volume of the reversal group is higher than that of the continuation group.*

Based on the difference of opinion model of Harris and Raviv (1993), trades can only occur when public signal changes direction. Both the responsive and non-responsive investors agree on the content and direction of the public signal (i.e., they have same priors). However, they form probability density functions to update their posterior beliefs (same functional form but different parameters). Their valuation on the asset after each public signal should be different, but this does not imply trading opportunities each time with the arrival of a public signal. Consider that two consecutive positive public signals arrive at the market. The responsive investors have higher valuation on the asset on the first positive public signal, and they should have all assets on the market immediately after the first public signal (either acquiring by trade or with originally endowment). When the second positive signal comes, they still have higher valuation on the asset than other investors on the market and they refuse to sell even at the highest offer price of the non-responsive investors. As a result, no trade occurs on the second positive signal. For the same logic, the same situation holds for two consecutive negative signals. In fact, only when the public signal changes directions, trades occur among those two groups of investors. Therefore, according to Harris and Raviv (1993), trading volume should be higher when public signals change directions.

Hypothesis 2: *Absolute price changes are positively correlated with trading volume. Moreover, the correlation between absolute price changes and trading volume should be stronger for the reversal group than for the continuation group.*

One of the major implications of Harris and Raviv (1993) is that the correlation of price and absolute change in price is positively correlated. This is also implied in Wang (1994)(Wang 1994). Therefore the positive correlation between absolute price change and volume *per se* can not differentiate the two models. However, in Harris and Raviv (1993), the correlation of trading volume and absolute price change is higher when volume is positive. This leads to my second hypothesis that the correlation between trading volume and absolute price change is higher for reversal group than for continuation group. Wang (1994) considers the level of information asymmetry as a key factor that determines the correlation between absolute price change and volume. The logic is the following: since the informed investor trades either because of informational advantage or portfolio rebalancing (better private investment opportunity), the uninformed must be compensated more to be attracted into a trade when the level of information asymmetry is high on the market. The expected return must be higher. Thus the higher absolute price change can generate more volume, or more volume follows higher absolute price change. The higher the information asymmetry level, the higher the correlation between absolute price change and volume would be. It is hard to conjecture whether the continuation group or the reversal group has higher level of information asymmetry. Therefore, according to Wang (1994), the reversal group can have higher, lower or equal amount of correlation between absolute price change and volume than the continuation group.

Hypothesis 3*: The absolute change in the analyst recommendation and trading volume is positively correlated. Moreover, the positive correlation between volume and absolute change in analyst recommendation is stronger for the reversal group than for the continuation group.*

This is formally stated in Theorem 2 in Harris and Raviv (1993). The intuition is analogous to Hypothesis 2: analyst recommendation change can affect the speculator's beliefs about the probability of high outcome and for any given recommendation change that results no trading volume, there will be a corresponding higher value of recommendation change that results higher trading volume. Similar to hypothesis 2 on the correlation between absolute change in price and volume, the positive correlation between volume and absolute change in analyst recommendation is stronger for the reversal group than for the continuation group.

Hypothesis 4: *Firm size does not have any effect on trading volume.*

Since all investors in Harris and Raviv (1993) trade on their differences of beliefs, but not information or liquidity reasons, firm size should not affect their trading activity. Instead, in Wang(1994)'s model, investors trade for both liquidity and informational reasons (market microstructure literature documents the existence of informational trading, see Easley, O'hara et al. (1998), Easley, Kiefer et al. (1996). A natural extension of Wang's model would be an inverted U-shape relation between firm size and share turnover.

Assume investors trade for both informational and liquidity reasons as described in Wang (1994). For firms with different firm size, the level of information asymmetry among investors is different. Large firms tend to attract more financial analysts and make more disclosures than small firms; therefore they have less information asymmetry between firms and investors and between investor themselves. Small firms, on the other hand, tend to have higher information asymmetry level between informed and uninformed investors. Large firms' securities are more liquid; and with less adverse selection cost they tend to attract more uninformed traders. With higher level of adverse selection costs, small firms tend to drive away uninformed investors. Remember in Wang (1994)'s model, informed investors trade for both liquidity and informational reasons, and the uninformed trade only for liquidity reasons. However, the informational trades only occur when the uninformed believes they are not subject to adverse selection costs. At the extreme, if information asymmetry level is huge, then the uninformed will not trade at all and trading volume would be zero. On the other hand, if there is no informational asymmetry at all, then only liquidity trades on the market. In this case, trading volume is determined purely by the informed investors' liquidity shock or portfolio rebalancing needs, and thus should be smaller than the trading volume of similar stocks that attract both informational and liquidity trading. Some previous empirical studies have documented trading behaviors motivated by informational and liquidity reasons respectively. Llorente, Michaely, Saar and Wang (2002) show that for stocks with low information asymmetry (large firms), returns following high-volume days exhibit strong reversals, indicating trading behavior is mostly motivated by liquidity or risk-sharing reasons. They also find that for stocks with higher information asymmetry, returns following high-volume days exhibit weak reversals or even continuations, indicating trading is mostly information-based. Similarly, Conrad, Hameed and Niden (1994) find that high-volume securities experience price reversals and low-volume securities experience price continuations. This indicates that trades on low-volume securities are more likely to be informational and trades on high-volume securities are more likely to be motivated by liquidity reasons.

The hypothesized relation between share turnover and information asymmetry/liquidity are presented in Figure 2.1. As shown in Figure 2.1, cross-sectionally, neither the largest firms nor the smallest firms have the highest trading volume. The medium sized firms should have the highest trading volume.

2.4 Data and Methodology

2.4.1 Data

My data comes from three sources: 1) I/B/E/S analyst recommendation detail data; 2) the Center for Research in Security Prices (CRSP) daily data; 3) COMPUSTAT annual industrial data. The time frame for this study is from January 1995 to March 2004. I start with I/B/E/S analyst recommendation details data and obtained 9,500 firms that have analyst recommendation data during 1995-2004. I then merge this data set with CRSP daily dataset to obtain firms daily turnover, daily return, and dividend payout information. I need dividend payout information because of the following: this study aims to identify investors trading motivations other than well-documented tax-motivated trading. Many studies have shown that around dividend payout date, investors trade because of differential tax on dividends and capital gains. To avoid the contamination of abnormal trading motivated by tax-heterogeneity around dividend payout date, I exclude those observations that analyst recommendation occurred 10 days before or 10 days after a dividend payout date. The sample of dividend payout stocks is obtained from CRSP daily data. I include only those stocks that pay out cash dividends and those with dividends taxable at the same rate as ordinary dividend. Those stocks that pay out stock dividends and other types of dividends that are not taxable as ordinary dividends are not considered since the differential tax effect is small. Excluding those dividend events that have differential tax effect will allow us to focus on other reasons for trading than tax motivated trading.

From CRSP, I take all NYSE, AMEX, and NASDAQ firms qualifying the following:

1) The firm’s share code is in either 10 or 11. that is, I include only common shares into my sample;

2) The firm’s SIC codes are not between 6000 and 7000. That is, I excluded all financial firms from the data.

3) The firm has no missing daily returns, daily share volume and total number of shares outstanding;

I merge CRSP dataset with my selected I/B/E/S sample. I then delete those recommendations that occurred during the dividend announcement date. This approach might cause some inaccuracy on measuring the direction of the signal, but the tradeoff is worthwhile since I avoided the contamination of dividend motivated trading.

To examine the direction of public signal for two consecutive recommendation dates, I need at least three recommendations for each stock during the sample period. I compare the current recommendation to the most recently one to define the direction of the signal (upgrade or downgrade). I/B/E/S analyst recommendations have five grades: "1" for strong buy, "2" for "buy", "3" for hold, "4" for underperform and "5" for sell. An upgrade means that analyst recommendation moves from higher grade to lower grade (5 to 1). A downgrade means that analyst recommendation movers from lower grade to higher grade (1 to 5). The stock should have at least 3 recommendations occurred during the whole sample period. I add a restriction that the time interval between two consecutive recommendation dates from the same analyst on the same stock should no more than 91 days (a quarter). If the time interval between two public signals is too long, then other signals that can affect investors' beliefs will be more likely come in and contaminate my results. It is possible that more than one analyst follows the same stock and makes their recommendations on the same date. For those date, I average their recommendations based on the number of analysts who made the recommendation on that specific date. I then put the sample into two groups: the reversal group contains those stocks that have two consecutive signals with opposite directions (either first an upgrade then a downgrade or first a downgrade then an upgrade); the continuation group contains those stocks that have two consecutive signals with same directions (i.e., both signals are upgrades or downgrades).

I use COMPUSTAT data to test hypothesis 4 – the effect of market size on trading volume. I calculated market size just as in Fama and French (1992). For analysis purposes, I also subdivide the sample into ten deciles based on their market capitalization.

My final event sample consists of 5,143 stocks and 13,972 events with 11,282 events in the reversal group and 2,690 events in the continuation group. Panel A of Table 2.1 presents the summary statistics for event date return, share turnover, absolute price change and absolute recommendation change for both the whole sample and three sub-sample periods (1995-1997, 1998-2000, 2001-2004). We can see that average event date turnover is not significantly different from zero, and the distribution is skewed. Average number of brokers that follow a stock is 3.13 for NYSE/AMEX firms and 2.29 for NASDAQ firms. The average number of brokers in the sub-periods shows that number of analyst following has been increasing for both NYSE/AMEX and NASDAQ firms during 1995-2004. On average, NYSE/AMEX firms have slightly more analyst following than NASDAQ firms. Event date share turnover for NASDAQ firms on average is higher than NYSE/AMEX firms (2.72% vs. 1.00%). While average event date share turnover for NYSE/AMEX firms has increased during 1995-2004, average event date share turnover for NASDAQ firms first increased greatly in the second sub-period and then dropped in the third sub-period. The trend in NASDAQ share turnover is consistent with the ups and downs of internet boom. The absolute change in mean recommendations does not have much variation since analyst recommendation has only 5 discrete grades. Panel B in Table 2.1 shows the number of analyst recommendations by year and by group. The number of events in the reversal group is much higher than that of the continuation group (the percentage of events in the reversal group in the whole sample is about 81%). Notice that the number of recommendations is smaller in year 2004 because I/B/E/S only has data for part of the year for year 2004.

2.4.2 Share Turnover

Share turnover is defined as number of shares traded during a specific period of time divided by total number of shares outstanding. Since share turnover is normalized trading volume and immune to corporate events that change firm's share outstanding such as stock dividend and share repurchase, it is comparable among stocks and over time. Other measures of trading activity such as raw trading volume and dollar volume do not have this feature. Because of the advantage of share turnover over other measures of volume, I use share turnover as a measure of trading activity. All return and turnover numbers in this essay are reported in unit of percent – they are not annualized.

As explained in chapter 1.4.2, NASDAQ trading volume is not comparable to NYSE/AMEX trading volume and should be examined separately. I conduct all hypothesis tests separately and report empirical results separately for NYSE/AMEX and NASDAQ stocks.

2.4.3 Should share turnover be adjusted by market share turnover?

Some previous studies adjust individual stock's trading volume by market trading volume in the way similar to standard CAPM models (Abnormal Volume or Abnormal Turnover, see Bamber 1987; Ziebat 1990; Stickel 1991; Tkac 1999), while some other studies used individual stock's share turnover without adjusting by aggregate market turnover (Bamber, Barron and Stober 1997; Flemming and Remolona 1999; Chordia and

Swaminathan 2000; Lee and Swaminathan 2000). Specifically, Lo and Wang (2000) prove that if CAPM holds, every individual stock should have exactly the same share turnover and two-fund separation holds. Therefore, it is necessary to adjust individual stocks by market share turnover. In this study, individual stock's share turnover is adjusted by aggregate market share turnover. I adjust share turnover by the following:

$$ATOV_{i,t} = TOV_{i,t} - TOV_{m,t}$$

where $ATOV_{i,t}$ denotes abnormal share turnover for individual stock *i* on date *t*, while $TOV_{i,t}$ denotes unadjusted share turnover for individual stock *i* on date *t*. $TOV_{i,t}$ denotes share turnover for the whole market on date *t* (value traded on the whole equity market divided by market capitalization of the whole market), which is calculated as the following:

$$TOV_{m,t} = \frac{\sum_{i=1}^{n} p_{i,t} * Shrtrd_{i,t}}{\sum_{i=1}^{n} p_{i,t} * Shrout_{i,t}}$$

Where $p_{i,t}$ denotes the closing share price for stock *i* on date *t*, while $Shrtrd_{i,t}$ denotes number of shares traded for stock *i* on date *t*, and $Shrout_{i,t}$ denotes total number of shares outstanding stock *i* on date *t*.

2.5 Empirical Results

2.5.1 Event Date Share Turnover

I divide the whole sample into two groups: those events that the stocks have two consecutive signals of opposite directions (an upgrade and a downgrade) are grouped into the reversal group; those events that the stocks have two consecutive signals of same directions (both are upgrades or downgrades) are grouped into the continuation group. According to Harris and Raviv (1993), when investors are homogeneous in all respects except the density function they used to update their beliefs, trade can occur only when the public signals change directions. That is, we expect to see a much larger trading volume for the reversal group, but not the continuation group. I formally test this hypothesis by grouping all stocks based on analyst recommendation data during 1995–2004 into the reversal group and continuation group and conduct an event study on turnover for both groups on the event date. I apply a two-sample t-test to test different in mean turnover for the above two groups for both NYSE/AMEX and NASDAQ firms and for all sub-periods.

A two-sample t-test is equivalent to a one-factor ANOVA model. One can also use one factor ANOVA model to test the difference for group means and both techniques should generate the same test results and equivalent test statistics. One advantage of ANOVA analysis is that unlike t-test, it can easily test the difference in means for multiple groups. In this study when there are more than two groups, I use one-factor ANOVA model to test the difference in means. I also use ANOVA analysis to test multiple factor models.

Table 2.2 exhibits the t-test results for the test of mean share turnover/return for the reversal group and the continuation group on the recommendation date. Panel A presents the t-test results for share turnover by event group. Across all sub-periods and exchanges, the continuation group has a significantly higher turnover than the reversal group on the event date (52.8% for NYSE/AMEX firms and 42.8% for NASDAQ firms for the whole sample period). This result contradicts Harris and Raviv (1993)'s prediction. The evidence of trading based on heterogeneous beliefs on public signal is not obvious. Then this raises a question: Does this provide evidence that investors trade on liquidity and informational reasons just as Wang (1994) describes in his model? To answer this question, we need to know whether the reversal group and the continuation group have differential information contents and whether this creates different informational asymmetry effect on the informed and the uninformed investors.

T-test statistics for share turnover show significant higher turnovers for the continuation group over all three sub-periods and across all exchanges, but with a decline in turnover differences between the continuation group and the reversal group over the sub-periods (from 66.6% to 33.8% for NYSE/AMEX and from 67.9% to 19.4% for NASDAQ). This might reflect the facts that analyst recommendation has become less biased over the past ten years. This will be examined in detail in Section 6.

Panel B in Table 2.2 shows the t-test of mean return for the reversal group and the continuation group. The mean return of the reversal group on event date is significantly higher than that of the continuation group except for NYSE/AMEX stocks during sub-period 1995-1997. The difference is -0.95% for NYSE/AMEX stocks and -2.75% for NASDAQ firms for the whole sample period. This is consistent with Campbell, Grossman et al. (1993) where risk-averse investors trade for risk-sharing reasons and stock returns tend to decline more on a high volume day. Lee and Swaminathan (2000) also find that high turnover stocks earn lower returns when they examine the daily NYSE/AMEX stock return and turnover behavior.

2.5.2 Share Turnover and Absolute Price Change

Both Harris and Raviv (1993) and Wang (1994) predict that trading volume and absolute price change are positively correlated. However, Harris and Raviv (1993) imply that the correlation should be higher for the reversal group than for the continuation group. In Wang (1994)'s model, the correlation increases with the information asymmetry level between the informed and the uninformed. I test hypothesis 2 by regressing turnover on absolute price change, group dummy variable and the interaction term between the previous two variables. The regression model is the following:

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot \left|\triangle P_t\right| + \beta_3 \cdot Group \cdot \left|\triangle P_t\right| \qquad 2.2$$

Where *ATOV* denotes the event date abnormal share turnover, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $\left|\triangle P_t\right|$ denotes absolute change in prices, and $Group * \left|\triangle P_t\right|$ denotes the interaction term.

Panel A in Table 2.3 presents the regression results for all sub-period and by exchanges. The absolute price change on event date has a significant positive effect on share turnover, which is consistent with Harris and Raviv (1993) and Wang (1994). However, Harris and Raviv (1993) suggest that the positive correlation between absolute price change and turnover is higher for reversal group than for the continuation group. The coefficient in the interaction term (group * absolute price change) is significantly positive for overall NASDAQ stocks, all three NASDAQ sub-periods, and two NYSE/AMEX subperiods (1995-1997, 2001-2004). This suggests the opposite – the positive correlation is higher for the continuation group than for the reversal group.

Panel B in Table 2.3 shows that event date returns are negatively correlated with absolute price change. The correlation between absolute price and return is higher for the reversal group than for the continuation group in some periods (NYSE/AMEX 2001-2004, NASDAQ 1995-2004).

2.5.3 Share Turnover and Absolute Change in Mean Recommendations

One of the major implications of Harris and Raviv (1993) model is that the absolute change in analyst recommendations is positively correlated with volume. I test this hypothesis by using the following regression model:

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot \left|\triangle M_t\right| + \beta_3 \cdot Group \cdot \left|\triangle M_t\right| \qquad 2.3$$

Where *ATOV* denotes the event date abnormal share turnover, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $\left|\triangle M_t\right|$ denotes absolute change in mean recommendations, and $Group * \left|\triangle M_t\right|$ denotes the interaction term.

Panel A in Table 2.4 presents the test statistics for the above regression model. The coefficient on absolute change in mean recommendations in most sub-periods is insignificant (except NYSE/AMEX 2001-2004 and overall NYSE/AMEX), indicating that there is not a significant relation between share turnover and absolute change in mean recommendations.

Panel A in Table 2.4 also shows the test statistics for the interaction term (group * absolute change in mean recommendation). The results are mixed. For NYSE/AMEX, only one sub-period (1995-1997) shows that the correlation between turnover and absolute change in mean recommendation is higher for the reversal group which is consistent with Harris and Raviv (1993). For NASDAQ, the correlation between turnover and absolute change in mean recommendation is higher for the continuation group for sub-period 1998-2000 and 2001-2004 and the whole sample period.

Overall, regression results in this section do not generate strong evidence that support Harris and Raviv (1993)'s heterogeneous belief model.

2.5.4 Share Turnover and Firm Size

I test the relation between share turnover and firm size. I define firm size deciles just as described in Fama and French (1992). I use the following ANOVA model to test the effect of firm size on share turnover:

$$ATOV_{ijk} = \mu + G_i + \tau_j + \left(G\tau\right)_{ij} + \varepsilon_{ijk} \qquad 2.4$$

Where $ATOV_{ijk}$ denotes abnormal share turnover for stock *k* in the *i*th size decile and *j*th event group, μ denotes overall mean effect for both event groups (i.e., the reversal group versus the continuation group). G_i denotes the effect of event groups, τ_j denotes the effect of size deciles, $\left(G\tau\right)_{ij}$ denotes the interaction term, and ε_{ijk} denotes error term.

Table 2.5 Panel A shows the test statistics for the ANOVA model. The model is significant at 1% level for all sub-periods and across the exchanges. Firm size and event group are both significant factors that affect share turnover. I plot share turnover by firm size by two event groups in Figure 2.2.2 and Figure 2.3 for NYSE/AMEX stocks and NASDAQ stocks respectively. For both exchanges and across all size deciles, share turnover of continuation group exceeds that of reversal group. The relation between firm size and share turnover is not a linear one; instead, it is an inverted U-shape. Medium-sized firm has the highest share turnover compared to the largest and smallest firms. This supports (Wang 1994)'s model, suggesting that investors trade for both liquidity and informational reasons. For the smallest firms where information asymmetry is the highest among investors, uninformed investors are reluctant to trade on those stocks since they know that they are facing higher adverse selection costs. In this case, both liquidity motivated and informational trading will be adversely affected. However, for largest firms, there are less information asymmetry and better liquidity, more uninformed traders prefer to trade since the adverse selection cost is smaller. On the other hand, less information asymmetry means less information to trade on. At the extreme, where there is no information asymmetry and no one trade on private information, all the trades are originated from the liquidity shocks from investors. The trading volume for these pure liquidity trading stocks should be smaller for similar ones that attract both informational trades and liquidity trades.

Panel B in Table 2.5 shows the test statistics of ANOVA model on event day returns. The model is significant at 1% level. Firm size is a significant factor that affects event date returns. The event date return of continuation group is higher than that of the reversal group. Figure 2.4 and Figure 2.5 plot the event date return by firm size deciles for NYSE/AMEX stocks and NASDAQ stocks respectively. The plots show that the reversal group on average has a higher return than the continuation group on event date for both exchanges and across all size deciles except the 4th decile of NYSE/AMEX stocks.

In summary, my analysis of trading volume on analyst recommendation date does not support the hypothesis that investors trade on heterogeneous beliefs or overconfidence; instead, most of the evidence support the hypothesis that investors trade on liquidity and informational reasons.

2.6 Robustness Check

2.6.1 Effect of Option Availability and Index-related Trading

Previous studies indicated that index-related trading activities are non-trivial. On the one hand, the passive indexers hold index stocks and do not trade as actively as active informational traders. On the other hand, inclusion and exclusion of index membership might have informational content and market might respond with this news by actively trading on the stock. Previous research show that firms added to S&P 500 index experience significant increase in trading volume (Harris and Gurel 1986; Shleifer 1986; Beneish and Whaley 1996; Lynch and Mendenhall 1997).

Option availability can also affect the underlying stock's trading activity. First, option can be used to hedge portfolio positions, and investors are more willing to trade stocks when they can hedge their positions. Second, stocks with options listing have lower bid-ask spread and higher liquidity (Kumar, Sarin, and Shastri 1998). Tkac (1999) finds that excess share turnover of individual stocks is positively related to option availability of the stock.

To control the effect of index listing and option availability on this empirical study, I did the following:

a) I exclude those events that are around the S&P 500 inclusion and exclusion dates[5] from the original sample (3 days before and 3 days after the events);

b) I add a dummy variable for option availability denoted as *Opta*—"1" means that the stock has a listed option and "0" denotes no options are available for the underlying stocks in the event sample.

[5] S&P 500 membership changes are obtained from Standard and Poor's website: http://www2.standardandpoors.com

Since option availability[6] data is only available for years 2001-2004, I conduct robustness check using 2001-2004 data. The sample contains 5,177 events. Among them, 1,774 events (34%) occurred when underlying stocks have option listing. I then run the following regression model:

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot \left|\triangle P_t\right| + \beta_3 \cdot Opta + \beta_4 \cdot Size + \beta_5 \cdot Group \cdot Opta$$

Empirical results for this model are listed in Table 2.6. We can see that our major hypotheses still hold: share turnover for the continuation group is significantly higher than that of the reversal group after controlling for factors such as absolute change in price, firm size deciles and option availability. The coefficient for variable *Opta* is positive and significant for NASDAQ events, but not significant for NYSE/AMEX events. This indicates that NASDAQ firms with listed options tend to have more trading activity than firms without listed options on event date, but NYSE/AMEX firms show no difference in trading activities between firms with option-listing and firms without option-listing on event date.

2.6.2 Effect of Global Analyst Research Settlement (GARS)

The impartiality of analyst recommendation has long been an issue and interest for general public and popular press. In order to attract investment bank business which used to be closely connected with their compensation and maintain good relations with firms, analysts tend to bias their recommendations towards more favorable than actual ratings. Many studies have examined this phenomenon (Dugar and Nathan 1995; Michaely and Womack 1999; Lin and McNichols 1998; Cowen et. al 2003; Agrawal and Chen 2004, Kolasinski and Kothari 2004; Barber, Lehavy and Trueman 2004). If analysts are optimistically biased and market is aware of this phenomenon, investors should react more

[6] Option availability data are obtained from the options clearing corporation at the following website: http://www.optionsclearing.com/market/new_listings/archives

drastically to downgrades than upgrades. Specifically, the market reaction on two downgrades in a row (-, -) should be higher than any other combinations ((+, +), (-, +), or (+,-)). This challenges the empirical study in this paper. However, this problem is partially mitigated since the difference in share turnover between the two event groups is harder to find with the existence of analyst optimisms: some of the events in (+, -) and (-, +) should really belong to the (-, -) group since some upgrades (+) should really be downgrades (-).

Both the SRO new rules and GARS serve the same purpose -- to server the ties between investment banking and research activities and mitigate analyst recommendation bias. Announced on April 28, 2003, the Global Analyst Research Settlement (GARS) mandate ten of the largest investment banks to the separate their investment banking activities and research activities by establishing separate departments physically and impose stringent disclosure requirement on analysts' research. In addition, investment banks must provide independent research to their clients. This event has influential impact on the quality of analyst recommendations. Actually, before the GARS event, NASD and NYSE had enacted a series of SRO rules starting as early as July 9, 2002. The latest rule was approved by SEC on July 29, 2003 which separate research analyst compensation from investment banking influence and imposes anti-retaliation and stringent disclosure measures.

The introduction of Self-regulatory Organization (SRO) rules and GARS greatly mitigated the conflict of interest (Kadan et al. 2006). This provides me an opportunity to test the hypothesis by using only *post-reg* data. If we assume GARS and SRO rules are effective in mitigating analyst bias, then the main results for this study should hold in the post-reg period. I choose June 1, 2003 as a cut-off point to define the pre-reg and post-reg dates. Pre-reg dates refer to the date before June 1, 2003 and post-reg refer to the date after June 1, 2003.

Kadan et al. (2006) use September 1, 2002 as a cut-off date. I use a later date in this study because of the following: 1) GARS attracted more pubic attention than the SRO rules: 2) Measures in GARS to mitigate the conflict of interests are more complete and outright; 3) SRO rules completed its final phase of initial amendment on November 6, 2002 even it started on July 9, 2002, and it hard to capture the effect when the rules were coming to the market separately in several months.[7]

The test results are presented in Table 2.7 and Table 2.8. Table 2.7 shows the difference of share turnover for the continuation group and the reversal group, while Table 2.8 breaks out the two groups further into four groups and shows the mean share turnover for each group. As shown in Table 2.8, for NYSE/AMEX stocks, share turnover in the continuation group is significantly higher (45% more) than the reversal group; however, for NASDAQ stocks, share turnover in the continuation group is lower than the reversal group but it is not significant. Table 2.8 shows that for NYSE/AMEX firms, the group (-, -) has the highest share turnover, followed by (+, +) and (-, +) group, and group (+, -) has the least share turnover in four groups. This confirms the main empirical results in the paper and rejects the heterogeneous model of trading volume.

Figure 2.6 and Figure 2.7 plot the share turnover by Pre-GARS and Post-GARS Period on analyst recommendation date for NYSE/AMEX and NASDAQ Stocks respectively. While there hardly any trend on the plot for NASDAQ stocks, the plot for NYSE/AMEX stocks share turnover in the pre-reg vs. the post-reg period is consistent with the conflict of interest story. First of all, the share turnover for all four event groups has increased in the post-reg period, indicating that analyst recommendation is more informative in the post-reg

[7] Similar statistical results hold when November 6, 2002 is used as a cut-off date for post-reg period.

period since the conflict of interest problem was mitigated and thus less analyst bias as a result. Second, the reaction for both the (+, -) group has increased in the post-reg period, but to a less extent than other three groups, indicating that investors react less negatively to downgrade in the post-reg period.

In summary, my empirical tests on earnings announcement data confirm the results conducted on analyst recommendation data. There is no evidence supporting heterogeneous-belief model of trading volume. In stead, the findings provide some evidence on liquidity-based trading and informational trading, which is consistent with Wang (1994)'s model.

2.7 Conclusions

My intension in this study is to test whether investors' trades are driven by heterogeneous beliefs, as described in models such as Harris and Raviv (1993). Heterogeneous-belief trading volume model predicts that trading volume increases when two consecutive public signals change directions, assuming investors have same information set but different probability functions to update their posterior beliefs. I test this model by grouping stocks into recommendation reversal group and recommendation continuation group, and test the difference in share turnover for those two groups on the event date. I find that the continuation group has a significant higher share turnover than the reversal group on the event date, which contradicts the predictions of heterogeneous-belief models.

Other major empirical findings of the study include: 1) absolute price change is positively related to share turnover and has a larger impact on turnover for the continuation group than for the reversal group on event date for NASDAQ stocks but not for NYSE/AMEX stocks; 2) the absolute change in mean recommendation grade has significant positive impacts on turnover on the event date, but the positive impacts is similar between the reversal and continuation group; 3) firm size has an significant impact on trading volume and the relation between firm size and trading volume is an inverted U-shape. These results do not support with the hypothesis that investors trade on heterogeneous beliefs. Moreover, the empirical results are consistent with Wang (1994)'s trading volume model and other rational expectations pricing models based on disagreement on private information.

Table 2.1: Summary Statistics of Analyst Recommendation Data for NYSE/AMEX/NASDAQ stocks during Jan 1995 – Mar 2004
Panel A: Summary Statistics for Daily Return, Share Turnover, Absolute Price Change, and Absolute Change in Recommendations

Statistics	Number of brokers per stock		Number of days between two consecutive recommendations *		Return*		Turnover*		Absolute change in price $\lvert \triangle P_t \rvert$		Absolute change in recommendation $\lvert \triangle M_t \rvert$	
	NYSE/ AMEX	Nasdaq	NYSE/ AMEX	Nasdaq	NYSE/A MEX	Nasdaq	NYSE/ AMEX	Nasdaq	NYSE/ AMEX	Nasdaq	NYSE/ AMEX	Nasdaq
<u>All</u>												
Mean	3.13	2.29	46.87	47.72	0.05%	-0.07%	1.00%	2.72%	4.35	5.32	1.29	1.27
Std. dev.	2.73	2.16	25.89	25.25	0.03	0.05	0.01	0.04	6.22	9.13	0.53	0.51
Skewness	1.92	3.16	0.07	0.02	-0.42	-0.36	5.58	9.06	5.90	7.29	1.67	1.69
Kurtosis	4.40	14.20	-1.17	-1.13	10.99	8.57	57.40	217.68	66.98	88.30	3.65	3.32
Percentiles												
Min	1	1	1	1	-1.06	-1.47	-0.01	-0.01	0.00	0.00	0.20	0.25
5%	1	1	7	8	-0.25	-0.41	-0.01	0.00	0.19	0.18	1.00	1.00
10%	1	1	12	13	-0.18	-0.30	0.00	0.00	0.38	0.38	1.00	1.00
25%	1	1	25	27	-0.09	-0.15	0.00	0.00	1.06	1.08	1.00	1.00
50%	2	1	46	48	-0.01	-0.03	0.00	0.01	2.65	2.77	1.00	1.00
75%	4	3	69	69	0.07	0.10	0.00	0.03	5.38	6.16	2.00	1.50
90%	7	5	84	83	0.16	0.26	0.01	0.05	9.52	11.77	2.00	2.00
95%	9	6	88	88	0.24	0.38	0.02	0.08	13.47	18.13	2.00	2.00
Max	20	20	91	91	1.34	3.36	0.27	1.41	142.83	182.65	4.00	4.00
<u>1995-1997</u>												
Mean	1.82	1.51	43.48	45.73	-1.82%	-3.29%	0.21%	1.77%	3.73	4.66	1.40	1.36
Std. dev.	1.23	1.00	25.59	25.02	0.11	0.20	0.01	0.03	5.49	6.22	0.59	0.57
Skewness	2.11	3.09	0.23	0.12	-0.39	0.21	4.45	4.04	5.55	3.71	1.46	1.53
Kurtosis	5.96	14.21	-1.10	-1.11	2.03	1.50	27.24	23.79	48.28	22.31	2.73	2.59
<u>1998-2000</u>												
Mean	1.94	1.63	48.28	48.87	0.19%	-1.38%	0.30%	2.33%	5.44	7.60	1.25	1.23
Std. dev.	1.43	1.07	25.69	25.02	0.19	0.28	0.01	0.05	7.43	13.56	0.51	0.49
Skewness	2.23	2.34	0.02	-0.01	1.13	1.22	4.81	11.04	4.13	5.85	2.16	2.06
Kurtosis	6.59	7.03	-1.17	-1.11	6.03	12.38	37.84	240.88	25.68	48.97	5.90	4.64
<u>2001-2004</u>												
Mean	2.30	2.06	48.40	48.24	-0.86%	-1.58%	0.62%	2.20%	3.81	3.88	1.25	1.23
Std. dev.	1.61	1.57	26.09	25.54	0.16	0.26	0.02	0.04	5.31	4.95	0.48	0.47
Skewness	1.49	2.18	-0.02	-0.02	-0.28	0.55	5.60	4.00	9.98	3.55	1.28	1.41
Kurtosis	2.12	6.04	-1.17	-1.14	5.64	4.46	54.52	30.53	208.54	20.38	1.76	2.22

* Number of days between two consecutive recommendations is calculated based on the recommendations given by the same broker for the same stock. If ignore the identity of brokers, the time interval for two consecutive recommendations of the same stock is on average 22 days.

Panel B: Number of Analyst Recommendations by Year for Sample NYSE/AMEX/Nasdaq Stocks from Jan 1995-Mar 2004

Year	Total Number of recommendations			Number of events in the Reversal Group			Number of events in the Continuation Group			% of reversal		
	NYSE/AMEX	Nasdaq	All	NYSE/AMEX	Nasdaq	All	NYSE/AMEX	Nasdaq	All	NYSE/AMEX	Nasdaq	All
1995	405	260	665	366	222	588	39	38	77	90.4%	85.4%	88.0%
1996	960	943	1903	830	811	1641	130	132	262	86.5%	86.0%	86.6%
1997	709	842	1551	615	699	1314	94	143	237	86.7%	83.0%	84.4%
1998	941	931	1872	775	810	1585	166	121	287	82.4%	87.0%	84.7%
1999	838	716	1554	693	566	1259	145	150	295	82.7%	79.1%	81.4%
2000	575	676	1251	474	524	998	101	152	253	82.4%	77.5%	79.8%
2001	702	916	1618	580	705	1285	122	211	333	82.6%	77.0%	79.2%
2002	1069	1159	2228	763	789	1552	306	370	676	71.4%	68.1%	70.6%
2003	548	546	1094	434	430	864	114	116	230	79.2%	78.8%	79.2%
2004	120	116	236	100	96	196	20	20	40	83.3%	82.8%	81.8%
Total	6867	7105	13972	5630	5652	11282	1237	1453	2690	82.0%	79.5%	81.0%

Table 2.2: T-test of Share Turnover/Return by Event Group on Analyst Recommendation Date January 1995 – March 2004

Panel A: T-test of Abnormal Share Turnover by Event Group

Sample Period	**Sample Size**		**Average Daily Share Turnover**				
	Reversal Group	**Continuation Group**	**Reversal Group (1)**	**Continuation Group (2)**	**Difference (2)-(1)**	**Difference %**	**T-value**
NYSE/AMEX							
1995-1997	1626	244	0.72	1.19	0.48	66.6%	4.08***
1998-2000	1826	414	1.04	1.56	0.52	50.0%	4.02***
2001-2004	1714	476	1.42	1.91	0.48	33.8%	3.33***
All	5166	1134	1.06	1.63	0.56	52.8%	6.94***
NASDAQ							
1995-1997	1705	300	2.4	4.03	1.63	67.9%	4.13***
1998-2000	1778	386	3.25	4.93	1.68	51.7%	3.02**
2001-2004	1724	565	3.25	3.88	0.63	19.4%	2.44**
All	5207	1251	2.97	4.24	1.27	42.8%	5.57***

*Turnover numbers are reported in percentage terms.

Panel B: T-test of Group Mean Abnormal Return by Event Group

Sample Period	**Sample Size**		**Average Daily Return**				
	Reversal Group	**Continuation Group**	**Reversal Group (1)**	**Continuation Group (2)**	**Difference (2)-(1)**	**Difference %**	**T-value**
NYSE/AMEX							
1995-1997	1626	244	0.1	0.15	0.05	-	0.14
1998-2000	1826	414	0.13	-1.2	-1.33	-	3.19***
2001-2004	1714	476	0.21	1	0.79	-	-3.11***
All	5166	1134	0.15	-0.8	-0.95	-	-4.21***
NASDAQ							
1995-1997	1705	300	0.3	-2.5	-2.80	-	-5.13***
1998-2000	1778	386	0.42	-2.4	-2.82	-	-3.58***
2001-2004	1724	565	0.32	-2.3	-2.62	-	-5.04***
All	5207	1251	0.35	-2.4	-2.75	-	-7.58***

*Returns numbers are reported in percentage terms.

Table 2.3: ANOVA Analysis on Abnormal Share Turnover/Returns and Absolute Price Change on Analyst Recommendation Date

Panel A: Abnormal Share Turnover and Absolute Price Change on Analyst Recommendation Date

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot \left|\triangle P_t\right| + \beta_3 \cdot Group \cdot \left|\triangle P_t\right|$$

Where *ATOV* denotes the event date abnormal share turnover, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $\left|\triangle P_t\right|$ denotes absolute change in prices, and $Group * \left|\triangle P_t\right|$ denotes the interaction term.

Sample Period	**Sample Size**	**Intercept**	**Group**	**Absolute Price change**	**Group*Absolute Price Change**	**Model F-value**
NYSE/AMEX						
1995-1997	1818	0.0061***	0.0028**	0.0003***	0.0004***	24.98***
1998-2000	2192	0.0085***	0.0061***	0.0003***	-0.0002*	23.88***
2001-2004	2154	0.0120***	0.0009	0.0005***	0.0010***	39.17***
All	6164	0.0089***	0.0056***	0.0004***	0.0000	74.46***
NASDAQ						
1995-1997	1990	0.0159***	0.0098***	0.0017***	0.0010*	61.34***
1998-2000	2159	0.0252***	0.0122***	0.0009***	0.0010**	37.16***
2001-2004	2270	0.0246***	-0.0014	0.0020***	0.0017***	61.02***
All	6419	0.0235***	0.0056***	0.0011***	0.0015***	132.91***

Panel B: Abnormal Return and Absolute Price Change on Analyst Recommendation Date

$$ARET = \alpha + \beta_1 \cdot Group + \beta_2 \cdot \left|\triangle P_t\right| + \beta_3 \cdot Group \cdot \left|\triangle P_t\right|$$

Where *ARET* denotes the event date abnormal returns, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $\left|\triangle P_t\right|$ denotes absolute change in prices, and $Group * \left|\triangle P_t\right|$ denotes the interaction term.

Sample Period	**Sample Size**	**Intercept**	**Group**	**Absolute Price change**	**Group*Absolute Price Change**	**Model F-value**
NYSE/AMEX						
1995-1997	1818	0.0014	-0.0015	-0.0002	0.0005	0.50
1998-2000	2192	0.0025	-0.0147***	-0.0002	0.0002	5.37***
2001-2004	2154	0.0050***	0.0000	-0.0007***	-0.0032***	18.25***
All	6164	0.0029***	-0.0091***	-0.0003**	-0.0001	12.55***
NASDAQ						
1995-1997	1990	0.0037*	-0.0268***	-0.0001	-0.0002	14.00***
1998-2000	2159	0.0047	-0.0249***	-0.0001	-0.0006	7.64***
2001-2004	2270	0.0074**	-0.0226***	-0.0011**	-0.0013	17.17***
All	6419	0.0043***	-0.0239***	-0.0001	-0.0009**	33.36***

Table 2.4: ANOVA Analysis on Share Turnover/Returns and Absolute Change in Mean Recommendations on Analyst Recommendation Date

Panel A: abnormal Share Turnover and Absolute Change in Mean Recommendations on Analyst Recommendation Date

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot |\triangle M_t| + \beta_3 \cdot Group \cdot |\triangle M_t|$$

Where *ATOV* denotes the event date abnormal share turnover, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $|\triangle M_t|$ denotes absolute change in mean recommendations, and $Group * |\triangle M_t|$ denotes the interaction term.

Sample Period	Sample Size	Intercept	Group	Absolute Change in Mean Recommendations	Group* Absolute Change in Mean Recommendations	Model F-value
NYSE/AMEX						
1995-1997	1818	0.0068***	0.0099***	0.0003	-0.0041**	10.66***
1998-2000	2192	0.0108***	0.0015	-0.0003	0.0035	9.96***
2001-2004	2154	0.0086***	0.0069*	0.0043***	-0.0009	12.54***
All	6164	0.0096***	0.0067***	0.0008*	-0.0007	30.67***
NASDAQ						
1995-1997	1990	0.0222***	0.0105	0.0013	0.0054	11.31***
1998-2000	2159	0.0286***	-0.0222	0.0031	0.0370***	10.46***
2001-2004	2270	0.0346***	-0.0147**	-0.0016	0.0189***	6.06***
All	6419	0.0295***	-0.0074	0.0002	0.0183***	23.45***

Panel B: Event Date Abnormal Return and Absolute Change in Mean Recommendations on Analyst Recommendation Date

$$ARET = \alpha + \beta_1 \cdot Group + \beta_2 \cdot |\triangle M_t| + \beta_3 \cdot Group \cdot |\triangle M_t|$$

Where *ARET* denotes the event date abnormal return, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $|\triangle M_t|$ denotes absolute change in mean recommendations, and $Group * |\triangle M_t|$ denotes the interaction term.

Sample Period	Sample Size	Intercept	Group	Absolute Change in Mean Recommendations	Group* Absolute Change in Mean Recommendations	Model F-value
NYSE/AMEX						
1995-1997	1818	-0.0003	0.0049	0.0008	-0.0033	0.16
1998-2000	2192	0.0028	0.0044	-0.0011	-0.0169	6.17***
2001-2004	2154	0.0084*	0.0279**	-0.0046	-0.0386***	12.44***
All	6164	0.0033	0.0105*	-0.0014	-0.0189***	14.49***
NASDAQ						
1995-1997	1990	0.0023	-0.0191	0.0006	-0.0077	14.02***
1998-2000	2159	0.0149**	0.0128	-0.0085*	-0.0403**	10.44***
2001-2004	2270	0.0027	-0.0316**	0.0003	0.0032	12.23***
All	6419	0.0066*	-0.0199**	-0.0024	-0.0082	31.64***

Table 2.5: ANOVA Analysis on Share Turnover/Returns, Event Groups and Size Deciles on Analyst Recommendation Date

Panel A: Event Groups, Size Deciles and Abnormal Share Turnover on Analyst Recommendation Date

$$ATOV_{ijk} = \mu + G_i + \tau_j + (G\tau)_{ij} + \varepsilon_{ijk}$$

Where $ATOV_{ijk}$ denotes abnormal share turnover for stock k in the ith size decile and jth event group, μ denotes the overall mean effect for both event groups (i.e., the reversal group versus the continuation group). G_i denotes the effect of event groups, τ_j denotes the effect of size deciles, $(G\tau)_{ij}$ denotes the interaction term, and ε_{ijk} denotes error term.

Source of Variation	**Sample Size**	**F-Value**
NYSE/AMEX	5089	
Group		36.89***
Size decile		15.36***
Group*Size decile		2.40***
NASDAQ	5405	
Group		26.65***
Size decile		12.20***
Group*Size decile		1.80***

Panel B: Event Groups, Size Deciles and Event Date Abnormal Return on Analyst Recommendation Date

$$ARET_{ijk} = \mu + G_i + \tau_j + (G\tau)_{ij} + \varepsilon_{ijk}$$

Where $ARET_{ijk}$ denotes abnormal return for stock k in the ith size decile and jth event group,
μ denotes the overall mean effect for both event groups (i.e., the reversal group versus the continuation group). G_i denotes the effect of event groups, τ_j denotes the effect of size deciles, $(G\tau)_{ij}$ denotes the interaction term, and ε_{ijk} denotes error term.

Source of Variation	**Sample Size**	**F-Value**
NYSE/AMEX	5089	
Group		155.26***
Size decile		1.22
Group*Size decile		3.97***
NASDAQ	5405	
Group		207.18***
Size decile		1.46
Group*Size decile		1.16

Table 2.6: ANOVA Analysis on Abnormal Share Turnover and Option Availability on Analyst Recommendation Date during 2001-2004

$$ATOV = \alpha + \beta_1 \cdot Group + \beta_2 \cdot |\triangle P_t| + \beta_3 \cdot Opta + \beta_4 \cdot Size + \beta_5 \cdot Group \cdot Opta$$

Where *ATOV* denotes the event date abnormal share turnover, *Group* is the dummy variable for event groups (0 means the reversal group and 1 means the continuation group), $|\triangle P_t|$ denotes absolute change in prices, *Opta* is a dummy variable for option availability of stocks, and *Size* denotes firm size decile.

Sample Period	**F-value**	
	NYSE/AMEX	**NASDAQ**
Group	24.18***	11.30***
$\lvert\triangle P_t\rvert$	82.11***	204.49***
Opta	0.43	22.20***
Size	31.34***	6.04**
$Group \cdot Opta$	0.80	0.53
Model F-value	27.77***	45.91***

Table 2.7: T-test of Abnormal Share Turnover by Event Group on Analyst Recommendation Date in the post-GARS period

Exchange	**Sample Size**		**Average Daily Share Turnover**				
	Reversal Group	**Continuation Group**	**Reversal Group (1)**	**Continuation Group (2)**	**Difference (2)-(1)**	**Difference %**	**T-value**
NYSE/AMEX	500	116	1.72	2.46	0.74	43%	2.03**
NASDAQ	441	108	3.92	3.47	-0.45	-11.4%	0.05

*Turnover numbers are reported in percentage terms.

Table 2.8: Event date abnormal share turnover by 4 subgroups in the post-GARS period on analyst recommendation date

Group	**Average Share Turnover**	
	NYSE/AMEX	NASDAQ
(downgrade, upgrade)	1.77%	3.90%
(upgrade, downgrade)	1.65%	3.92%
(downgrade, downgrade)	2.68%	3.72%
(upgrade, upgrade)	2.16%	3.14%

*Turnover numbers are reported in percentage terms.

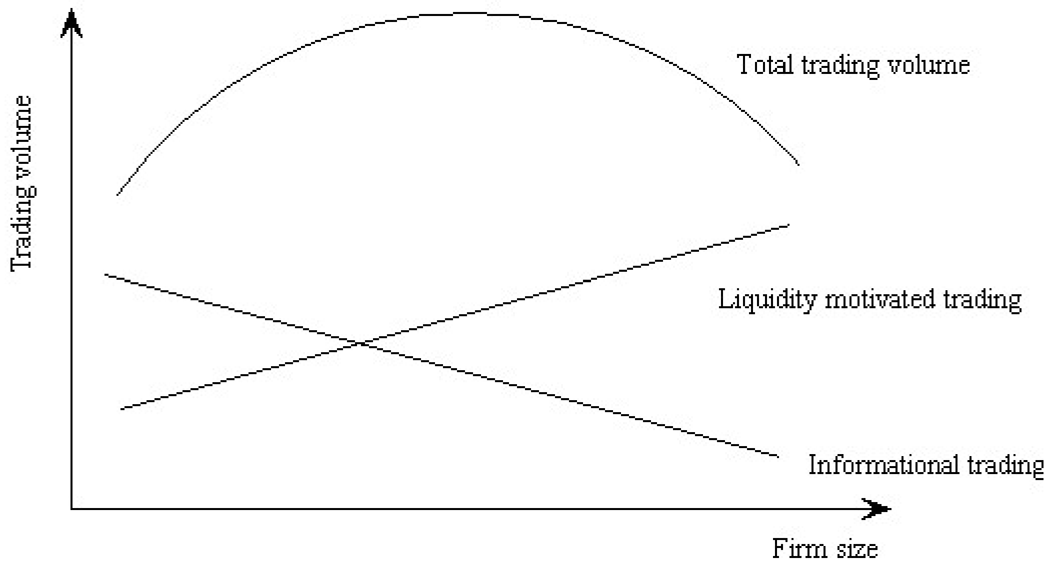

Figure 2.1: Information Asymmetry, Liquidity and Trading Volume

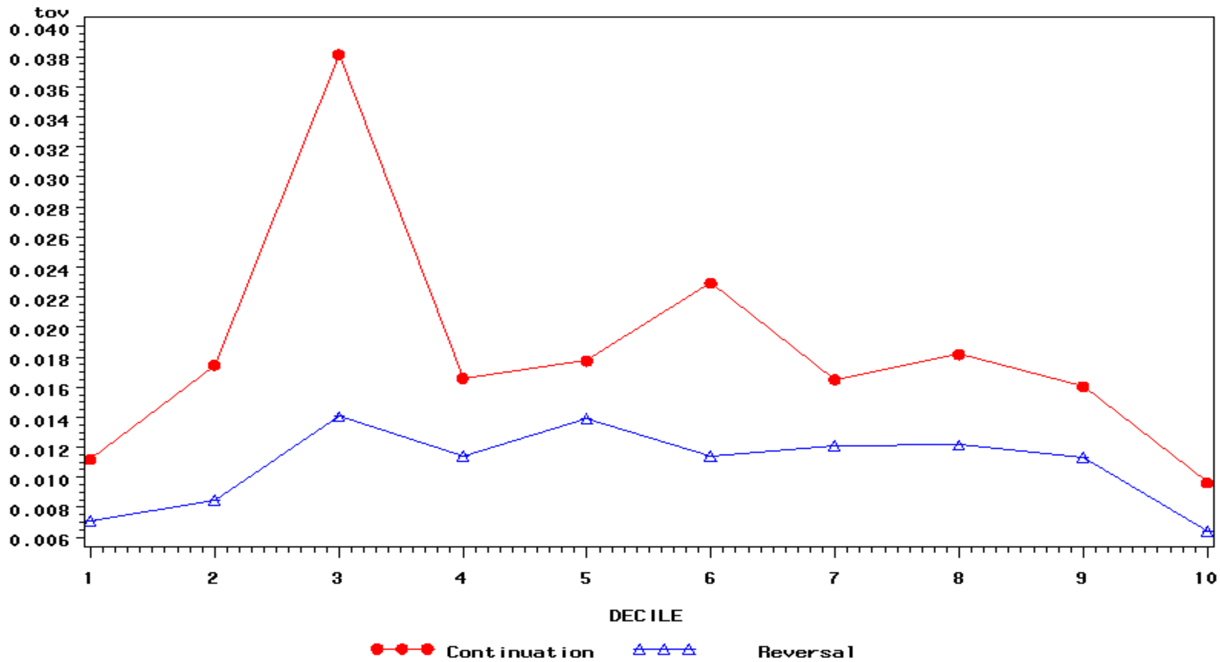

Figure 2.2: Recommendation Date Share Turnover by Size Decile and Event Group – NYSE/AMEX Stocks

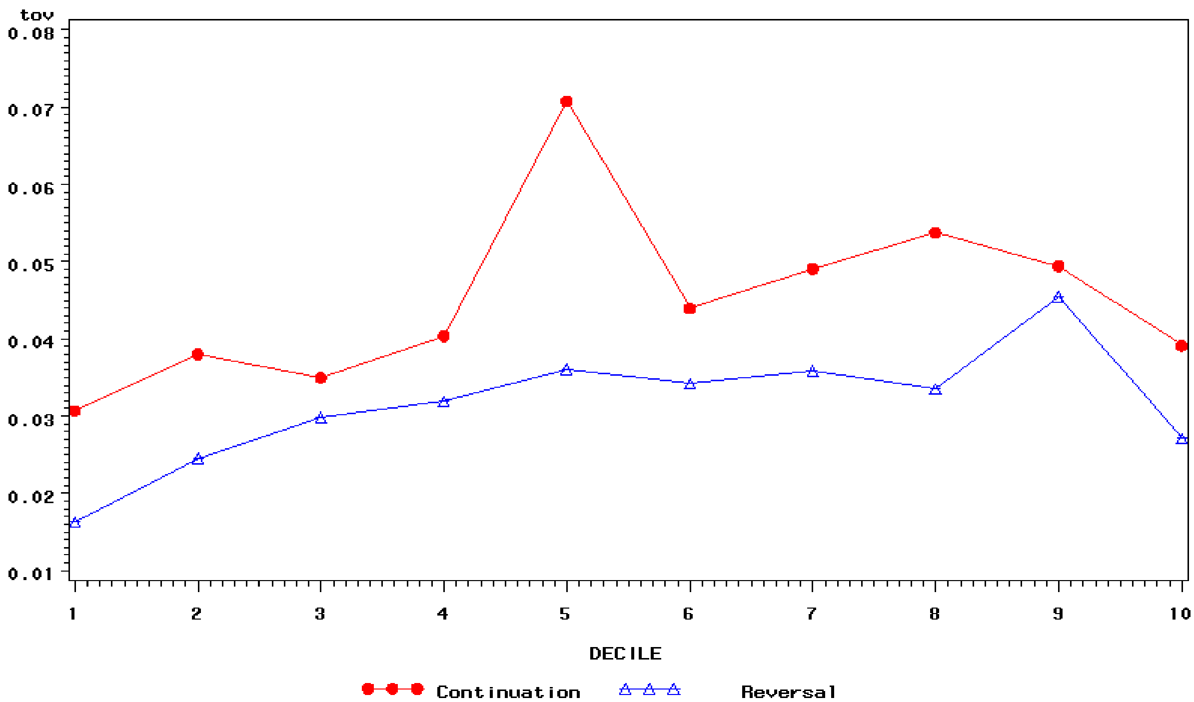

Figure 2.3: Recommendation Date Share Turnover by Size Decile and Event Group – NASDAQ Stocks

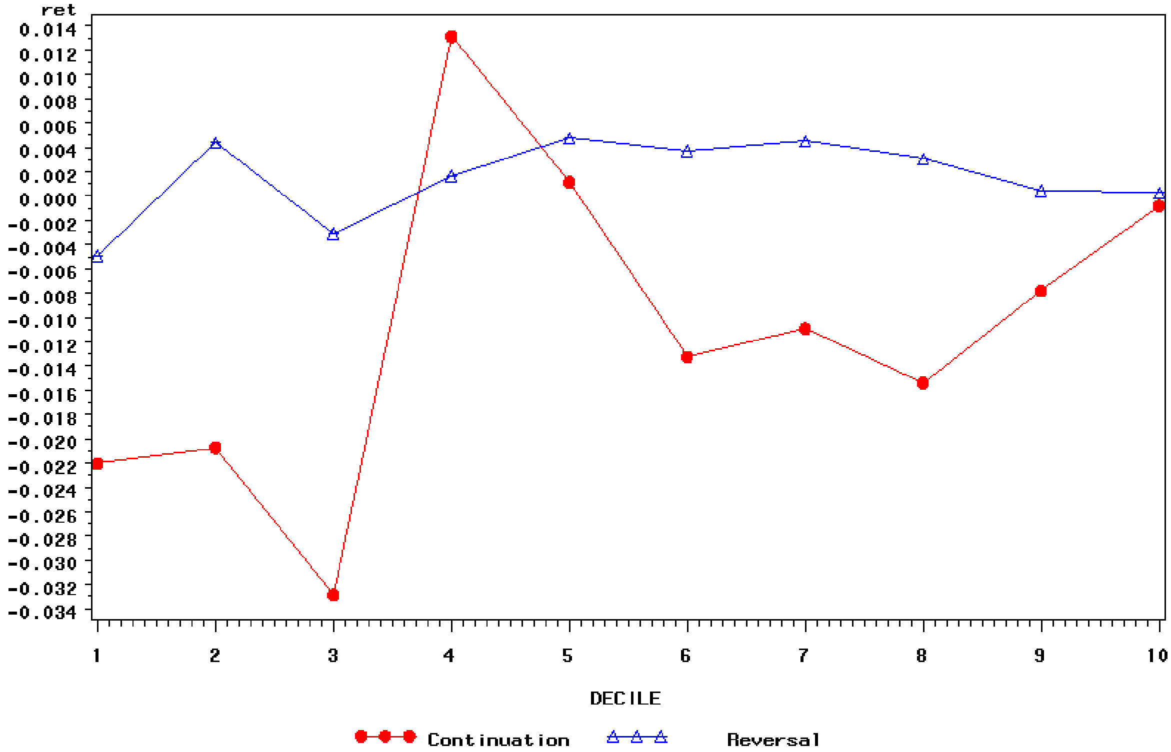

Figure 2.4: Recommendation Date Stock Return by Size Decile and Event Group – NYSE/AMEX Stocks

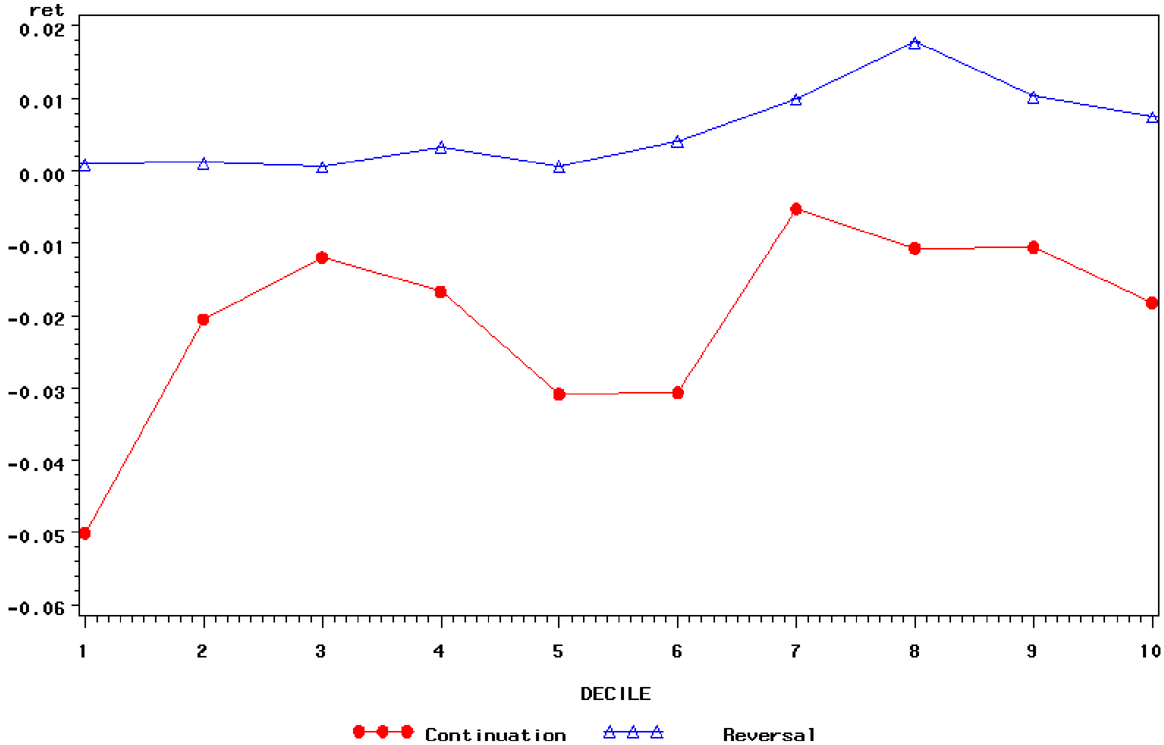

Figure 2.5: Recommendation Date Stock Return by Size Decile and Event Group Group – NASDAQ Stocks

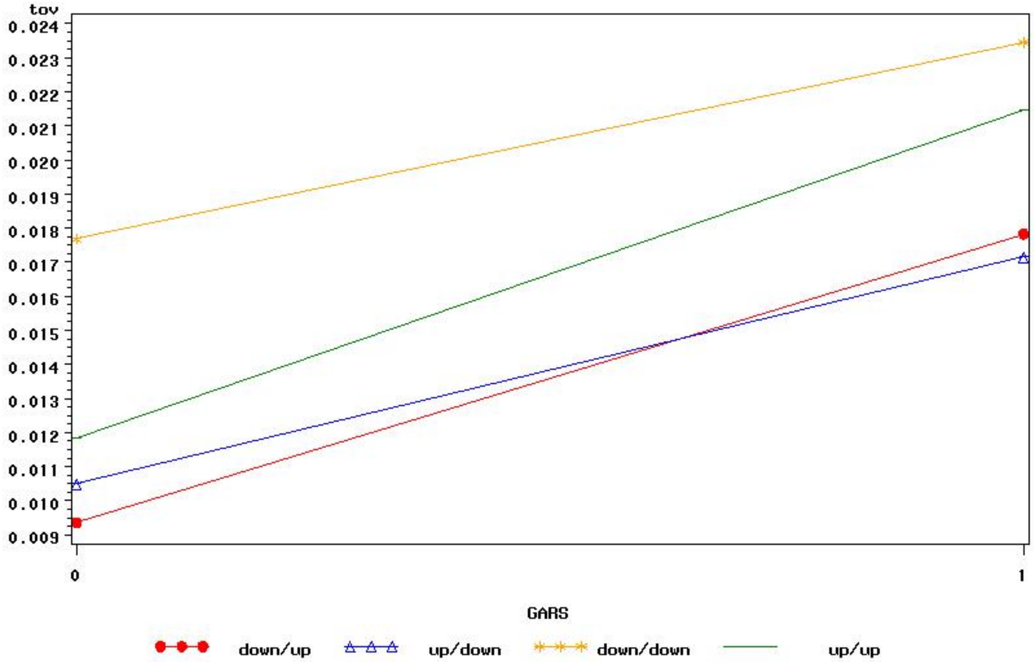

Figure 2.6: Recommendation Date Share Turnover by Pre- and Post-GARS Period – NYSE/AMEX Stocks

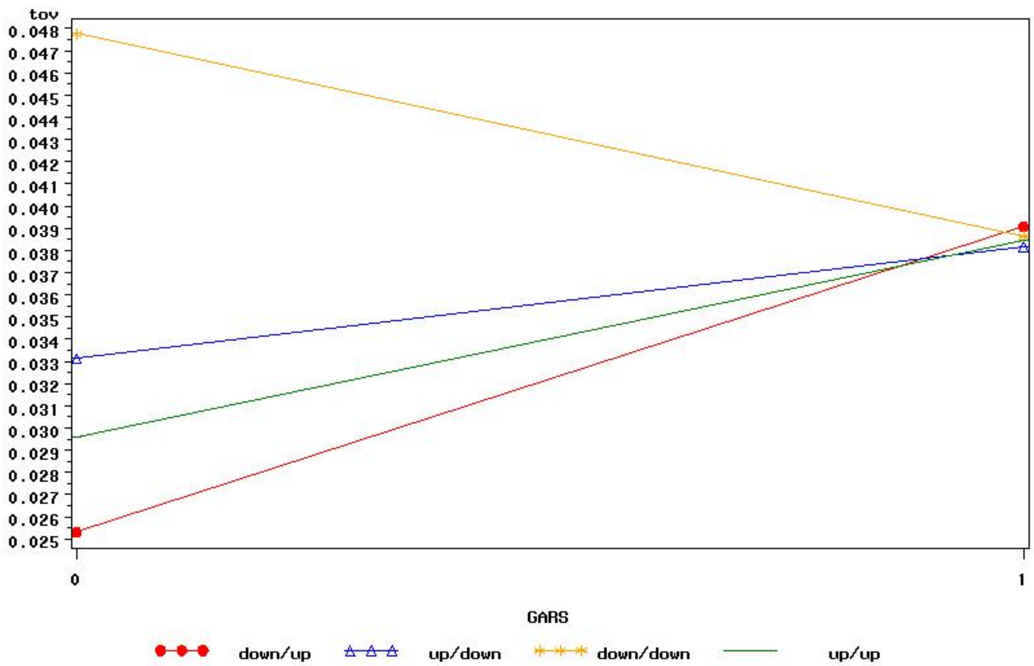

Figure 2.7: Recommendation Date Share Turnover by Pre- and Post-GARS Period – NASDAQ Stocks

Essay 3 Are There Market-wide Disposition Effects? – Evidence of Trading Volume on Historical High and Historical Low Days

3.1 Introduction

Recently, many empirical and experimental studies have shown that individual investors tend to sell assets that have gained value (winners) too soon and delay the selling of assets that have lost value (losers) in their portfolio – a behavior known as the disposition effect. Disposition effect is based on prospect theory (Kahneman and Tversky 1979). Compared to expected utility theory, prospect theory has the following properties: 1) individuals form expectations based on gains and losses, instead of final wealth; 2) individuals are risk-averse in the domain of gains, but risk-seeking in the domain of losses. That is, their value function is S-shaped as depicted in Figure 3.1.

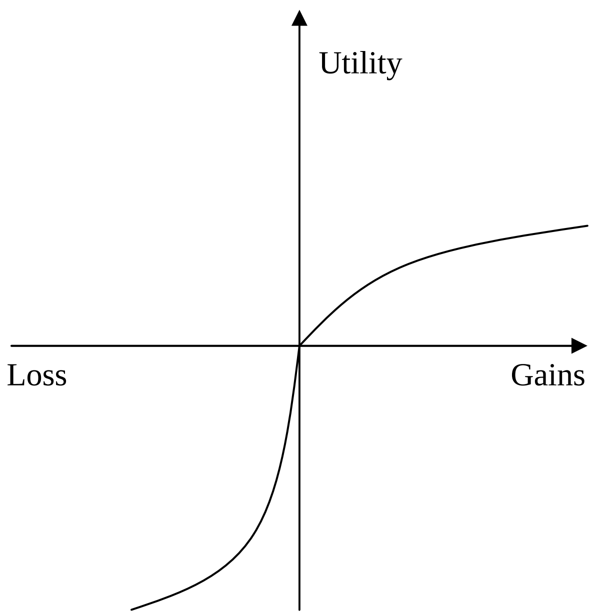

Figure 3.1 Disposition Effect

Disposition effect contradicts the principal of expected utility theory since individuals do not make preferences through maximizing the expected wealth as stated in standard expected utility theory. It has important implications on the standard capital asset pricing model. It implies that investors will demand a risk premium only when they are at gain and will ask no compensation for risk when they are at loss. Moreover, they would like to pay to take the risk when they are at loss. This certainly is a biased irrational behavior since the decision of buying or selling securities should be based on whether it is worth to buy or sell – the difference between the current stock price and its expected value. If stock price exceeds its expected value, then investors should sell the stock; if stock price is below its expected value, then investors should buy the stock. The decision to buy or sell should have nothing to do with any previous price or reference price.

Some empirical studies show that individual investors are subject to disposition effect. While most of the studies are based on individual trading data at the stock market (Shefrin and Statman 1985; Grinblatt and Keloharju 2000; Odean 1998a; Shapira and Venezia 2001; Brown, Chappel et al. 2003; Chen, Kim et al. 2004; Dhar and Zhu 2005; Ivkovic, Poterba et al. 2004; Kaustia 2004a; Kaustia 2004b; Feng and Seasholes 2005), some studies find evidence of disposition effect on traders on futures market as well (Heisler 1994; Coval and Shumway 2004). Individual investor's disposition effect is also well-documented in experimental studies (Weber and Camerer 1998; Haigh and List 2005; Oehler, Heilmann et al. 2002). One exception is Boebel and Taylor (2000). They find that New Zealand individual investors do not exhibit the disposition effect in their trading. Some other studies find that even professional and institutional investors show disposition effect in their daily trading activities (Shapira and Venezia 2001; Grinblatt and Keloharju 2000; Brown, Chappel et al. 2003; Locke and Mann 2005; Jin and Scherbina 2004). In their experimental study, Haigh and List (2005) find that professional subjects exhibit more myopic loss aversion than student subjects.

Since most of the above evidence shows that both individuals and professionals are subject to disposition effect, it is natural that one might consider: does financial market exhibit tendencies of disposition effect? Are there any investors that are immune to disposition effect? Will they be powerful enough to drive away those behavioral biases caused by those who have disposition effect? Professional investors trading behavior becomes very important since those investors are more sophisticated, informed and usually deemed more rational (have less behavioral biases). Moreover, security prices are determined mainly by decisions made by professionals. Grinblatt, Titman et al. (1995) finds that 77% of the mutual fund managers follow a momentum strategy: buy winners and sell losers, which imply that they are not disposition-prone and taking advantage of other investors' irrational behavior. Wermers (2003) find that winning mutual fund managers tend to buy new winners to a greater degree than losing managers who are unwilling to sell their losing stocks. Dhar and Zhu (2005) find that wealthier individuals and professional investors are less subject to disposition effect and trading frequency can reduce the disposition effect. Experimental study in List (2004) shows that while inexperienced investors are subject to prospect theory experienced investors "behave largely in accordance with neoclassical predictions". When examining Finnish stock market trading behavior, Grinblatt and Keloharju (2000) find that some institutional traders (such as non-financial corporations and finance and insurance institutions) exhibit less disposition effect, while disposition effect is the strongest for household, government and non-profit institutional investors.

Moreover, over time investors learn to overcome some behavioral biases. They pay for the lessons they learn in financial market. Using account-level data from a national brokerage firm in the People's Republic of China, Feng and Seasholes (2005) find that investor sophistication (i.e., an indicator of portfolio diversification at the start of an investor's trading life) and trading experience together eliminate the reluctance to realize loss and reduce investor's propensity to realize gains by 37%. Combined with those evidences where both individual and professional investors show disposition effect, these studies make people wonder whether disposition effect will survive in the whole market or how prevalent and powerful disposition effect is on financial market.

It is hard to answer questions of market-wide disposition effect by examining only return data because of the joint hypothesis problem with asset pricing models. Instead, examining trading volume can probably answer some of the above questions because investors' eagerness to realize gains and their reluctance to cut loss can be reflected in trading volume: volume should be higher when most people are realizing their gains and lower when they are cutting losses. I study daily trading volume on days when a stock reaches its maximum and minimum prices for 84-, 168-, 252- (1 year) and 504-day period. I hypothesize that due to disposition effect trading volume should be highest for maximum-price days, lower for normal trading days and lowest for minimum price days. Since on normal trading days trading can be caused by either realizing gains (for those who bought stocks at a lower price) or cut loss (for those who bought at a higher price), its trading volume should be lower than maximum price days and higher than minimum price days if the whole market are dominated by disposition traders. My study show that trading volume is the highest on maximum price days, followed by minimum price days, and is the lowest on minimum price days. This suggests that market react quickly to gains and losses although the effect on realizing gains is larger. This demonstrates market as a whole does not delay the realization of losses. Moreover, the average return is positive on historical high days and negative on historical low days – this contradicts the market-wide profit-taking at gains and reluctance to cut losses.

My work is not the first to test disposition effect by examining trading volume. Lakonishok and Smidt (1986) find that in general abnormal turnover is higher for winner stocks (prices have increased over the past 5, 11, 23 and 35 month) than for loser stocks (prices have decreased over the past 5, 11, 23 and 35 month) based on monthly data. Kaustia (2004a) examines the market-wide disposition effect by investigating IPO trading volume and finds evidence for disposition effect market-wide: namely, "turnover is significantly lower for negative initial return IPOs (initial public offerings) when stock trades below the offer price, and increases significantly on the day the price surpasses the offer price for the first time". At the same time, turnover increases when stock reaches its maximum and minimum prices over the previous month (21 trading days). My study is similar in a way that I also examine market-wide evidence on disposition effect, but my focus is on the maximum and minimum price days for the whole market and I find evidences that contradict with disposition effect.

The essay is organized as the following: section 3.2 reviews previous research on disposition effect. Section 3.3 raises testable hypothesis. Section 3.4 describes the data and methodology. The empirical results are presented in section 3.5. Section 3.6 conducts robustness check. Section 3.7 concludes the essay.

3.2 Previous Research

3.2.1 Evidence on Individual Investors

Abundant studies have shown that individual investors or groups of individual investors are subject to disposition effect – they normally sell too early when securities appreciate and reluctant to cut loss when securities are at loss. Shefrin and Statman (1985) find that investors have a higher propensity to realize gains than losses. Odean (1998b) examines 10,000 accounts at a national discount brokerage house and finds that individual investors have more propensities to realize gains than to cut loss. He rules out motivations such as portfolio rebalancing and transaction costs as possible explanations. Moreover, winner stocks that were sold by investors earn positive abnormal returns for as long as a year, while loser stocks that investors hold earn negative abnormal returns for as long as a year. Ivkovic, Poterba et al. (2004) confirms the disposition effects in Odean (1998b). Chen, Kim et al. (2004) finds disposition effect among Chinese investors. Grinblatt and Keloharju (2000) and Brown, Chappel et al. (2003) also find evidence of disposition effect of individual investors.

Some empirical studies find evidence that support disposition effect on futures market. Heisler (1994) finds that on T-Bond futures market traders tends to hold losers longer than winners. Coval and Shumway (2004) also show that traders on T-Bond futures market show disposition effect since they tend to hold losing positions into the afternoon trading and it takes longer for them to unwind it than those with a winning position.

Individual investors are certainly not homogeneous in their characteristics such as sophistication, trading experience, wealth level, level of risk-aversion, etc. Investor heterogeneity might lead to differences in their behavioral biases. Wermers (2003) find that winning mutual fund managers tend to buy new winners to a greater degree than losing managers who are unwilling to sell their losing stocks. Dhar and Zhu (2005) find that wealthier individuals and professional investors are less subject to disposition effect and trading frequency (an indicator of experience and sophistication) can reduce the disposition effect. Experimental study in List (2004) shows that while inexperienced investors are subject to prospect theory experienced investors “behave largely in accordance with neoclassical predictions”. Feng and Seasholes (2005) examines investor account level data from a Chinese national brokerage and find that investor sophistication and trading experience together eliminate the reluctance to realize loss and reduce investor's propensity to realize gains by 37%.

Not all studies find the disposition effect in investor trading behavior. Using 125 trading account from a retail brokerage in New Zealand, Boebel and Taylor (2000) find that New Zealand individual investors do not exhibit the disposition effect in their trading. They contribute their finding to the fact that retail broker provides "expert" service and investors are well-informed and less subject to the disposition effect.

3.2.2 Evidence on Professional and Institutional Investors

Some empirical and experimental studies show professional or institutional investors are also subject to disposition effect, although might at a lower level or less pervasive than individual investors. Grinblatt and Keloharju (2001) apply logit regressions to Finnish stock market to identify determinants of buying and selling activities, and estimate the probability of buying and selling. They document strong evidence of investor's reluctance to sell at loss, especially for household, government and non-profit institution investors. Haigh and List (2005) find that professional subjects exhibit more myopic loss aversion than student subjects in their experimental study. Shapira and Venezia (2001) examine trading behavior of both individual and professional investors on a major Israeli brokerage and they find that while both are subject to disposition effect but the effect on professionals is smaller. Brown, Chappel et al. (2003) finds that both individual and institutional investors show strong disposition effect on Australian stock market. Locke and Mann (2005) find that CME futures professional traders hold losers significantly longer than winners. Jin and Scherbina (2004) focus their study on mutual funds that have experienced recent managerial change. They find that continuing mutual fund managers tend to "tilt the portfolio composition towards momentum losers by disproportionately selling momentum winners" – a behavior consistent with disposition effect.

3.2.3 Market-wide Evidence

Kaustia (2004a) examines the market-wide disposition effect by investigating IPO trading volume. With 3,444 winners and 775 losers based on their first day returns, he finds that "turnover is significantly lower for negative initial return IPOs when stock trades below the offer price and increases significantly on the day the price surpasses the offer price for the first time".

3.2.4 Related Theoretical Work

Grinblatt and Han (2005) develop a model that relates disposition effect and stock price momentum effect first documented by Jegadish and Titman (1993). In their model, disposition effect creates "a spread between stock's fundamental value and its equilibrium price" and leads to underreaction to information. As investors update their reference points, spread converge and price movements are consistent with momentum effect. They also show that large capital gains imply more profitability of momentum strategies. Strobl (2003) considers disposition effect in an information asymmetric setting. In their model, it is rational for less informed investors to pursue a contrarian strategy: sell at gain and hold on losses. This naturally leads to uninformed under-react to new information and price moment follow a momentum effect.

3.3 Hypotheses Development

Disposition effect predicts that investors tend to realize gains fast and delay to cut loss. To determine gains or losses, I need to know the purchase price of the securities. Many empirical studies use investor's account-level information from brokerages where they can find out the purchase price and date for each stock for a group of individual investor. However, to detect market-wide disposition effect, there is no way to get all purchase and selling prices and further determine their reference point for all investors at individual account level on the market. Using historical highest and lowest prices can help us get away from the reference point problem. The reason is the following: when stocks reach its historical highest prices most investors are in the gain region; if all of them or most of them are subject to disposition effect, then they would be eager to realize their gains. As a result, trading volume should be higher. However, on normal trading days, some investors are in the gain region while some others are at loss, therefore, some investors realize their gains while others are refrain from cutting losses. As a result, we would expect a lower trading volume on those normal trading days. Finally, when stock price reaches its historical low prices, investors are unwilling to cut off losses if they are subject to disposition effect. As a result, we should observe the lowest trading volume on those trading days. This leads to my first hypothesis:

Hypothesis 1: If there is a market-wide disposition effect, abnormal trading volume should be highest when stock price reaches its historical high level, lower for normal trading days and lowest when stock price reaches its historical low level.

It might be the case where investors that are immune to disposition effect dominate the market. As in Grinblatt, Titman et al. (1995), mutual fund managers follow a contrarian trading strategy to take advantage of the irrational behavior of those disposition-prone investors. Other institutional investors might also follow this strategy. When rational investors dominate the market, there will be no market-wide disposition effect and trading volume for all three groups will be similar.

If all investors in the market are subject to disposition effect, i.e., they would sell stocks when they are at gain and hold stocks when they are at loss, we would expect stock price to fall once it reaches its historical high level because of the profit-taking behavior of all investors in the market and to increase when it reaches its historical low level since there will be no sell pressure on the market. This leads to my second hypothesis:

Hypothesis 2*:* If there is market-wide disposition effect, abnormal stock return will be negative when stock price hits its historical high level because of the profit-taking behavior of disposition-prone investors; on the other hand, abnormal stock return will be positive when stock price hits its historical high level.

3.4 Data and Methodology

3.4.1 Data

My data mainly comes from the Center for Research in Security Prices (CRSP) daily data from November 1993 to March 2004. From CRSP, I take all NYSE, AMEX, and NASDAQ firms qualifying the following:

1) The firm's share code is in either 10 or 11. That is, I include only common shares into my sample;

2) The firm's SIC codes are not between 6000 and 7000. That is, I excluded all financial firms from the data;

3) The firm has no missing daily returns, daily share volume and total number of shares outstanding;

Due to stock split, spin-off and other event, stock price, trading volume and share outstanding are not comparable at different times in CRSP original data. I make corresponding adjustments so that I can create a comparable time series data for price, volume and share outstanding. I then take the qualified data and obtain firms that have either a highest or lowest price over the past 84, 168, 252 or 504 days respectively. I then merge this data set with CRSP daily dataset to obtain firms daily turnover, daily return, and dividend payout information. I need dividend payout information because of the following: many studies have shown that around dividend payout date, abnormal trading volume arises because differential tax on dividends and capital gains attract investors to trade. To avoid the contamination of abnormal trading motivated by tax-heterogeneity around dividend payout date, I exclude those observations with historical high or historical low days occurred 10 days before or 10 days after a dividend payout date. The sample of dividend payout stocks is obtained from CRSP daily data. I include only those stocks that pay out cash dividends and those with dividends taxable at the same rate as ordinary dividend. Those stocks that pay out stock dividends and other types of dividends that are not taxable as ordinary dividends are not considered since the differential tax effect is small. Excluding those dividend events that have differential tax effect and thus large abnormal trading volume will help us to better capture the difference in trading volume on event days.

Table 3.1 shows the number of firms and the number of events of high, low and ordinary group for 84, 168, 252 and 504 trading days respectively. For 84 trading days, 3,384 NYSE/AMEX firms and 6,979 NASDAQ firms reached their historical high prices while 3,415 NYSE/AMEX firms and 6,795 NASDAQ firms reached their historical low prices. The number of firms decreases as the time interval increases. The ordinary group contains those firms that have reached either historical high or low prices. I obtain their daily data on normal trading days (not historical high or low days) and make comparisons with those high and low group later. Across all four groups, more firms but fewer events are in the high group.

Table 3.2 shows the number of firms and events by month. From Table 3.2, we observe the following: 1) there are more firms that have experienced historical low prices in December than in January, probably due to the tax-motivated selling in December; 2) there are more firms that have experienced historical high prices in January than in December, which is consistent with the January effect when small firms experience significant price increase in January.

3.4.2 Abnormal Trading Volume

Previous literature has applied different measures as proxies of trading volume: raw volume, dollar volume, number of trades, share turnover, abnormal trading volume, abnormal share turnover, etc. Share turnover is normalized by stock's share outstanding and comparable between different stocks. As proved in Lo and Wang (2000), there should be no cross-sectional variation in share turnover in a CAPM world. In this sense, share turnover is a perfect measure for trading activity. Because of the advantage of share turnover over other measures of volume, I use share turnover as a measure of trading activity. All return and turnover numbers in this essay are reported in unit of percent – they are not annualized.

In a perfect CAPM world, there would be not cross-sectional variation in share turnover since everybody will hold market portfolio and only trade when they need to rebalance (Lo and Wang 2000). However, we do observe cross-sectional variation in share turnover among stocks, which might be affected by market-wide forces. To control for market-wide influences, I apply a CAPM-version of trading volume by regressing daily firm share turnover on the average turnover of a market portfolio (Morse 1982; Lakonishok and Smidt 1986). I also use average daily turnover on different exchanges as market portfolio for those stocks listed on the specific exchange, and I get essentially the same results. I only report the results from the former procedure.

I conduct the following procedure to obtain the abnormal turnovers: I calculate market portfolio turnovers for each date in the sample. The market portfolio turnover is computed as a simple average of the turnovers of all firms in the CRSP database. I then regress individual stock turnovers on market turnover for the previous 365 days starting from Jan 1993 by the following regression:

$$TOV_{it} = a_i + b_i MTOV_t + e_{it} \qquad (1)$$

Where TOV_{it} denotes share turnover for stock *i* on date *t*, $MTOV_t$ denotes the overall market turnover on date *t*, and e_{it} denotes the error term.

I then obtain the daily abnormal turnovers on the event date by the following equation:

$$ATOV_{it} = TOV_{it} - (a_i + b_i MTOV_t) \qquad (2)$$

I use similar method to estimate stock market beta and abnormal returns.

3.4.3 NYSE/AMEX versus NASDAQ Share Turnover

As explained in chapter 1.4.2, NASDAQ trading volume is not comparable to NYSE/AMEX trading volume and should be examined separately. I conduct all hypothesis tests separately and report empirical results separately for NYSE/AMEX and NASDAQ stocks.

3.4.4 Reference Prices

The analysis of disposition effect has been entangled with the definition of reference prices. Do investors set their reference price at the purchase price, or 10%, 20% above purchase price? It is hard to determine because it might be based on psychological factors and might change over time. Moreover, investor heterogeneity leads to different reference price levels. For tests based on account-level information on individual investors, the reference price can be defined as the average purchase price, the highest purchase price, the first purchase price or the most recent purchase price (Odean 1998b). Investors might add commissions on top of the original purchase price to get their reference price if they are considering recoup the costs. However, when it comes to market-wide data, it is even more complicated to determine the reference price since every market participant's purchase price is different and it is not very meaningful to aggregate the reference price of all market participants. When examine market-wide impact of the disposition effect in IPOs, Kaustia (2004a) uses the offer price of IPOs as the reference point. In my study, the above problem gets partially resolved since I examine historical high (low) prices where most of the investors will be in the gain (loss) region no matter their purchase prices. If there is market-wide disposition effect, I would expect much higher trading volume on historical high days and much lower trading volume on historical low days – comparing with trading volume on normal trading days of the same group of stocks.

3.5 Empirical Results

3.5.1 Event Date Share Turnover

Hypothesis 1 states that if there is a market-wide disposition effect, trading volume should be highest when stock price reaches its historical high level, lower for normal trading days and lowest when stock price reaches its historical low level.

I test this hypothesis by grouping all events when stock reaches its historical high or low levels during 1993–2004 into the high group and low group. I then obtain share turnovers for those stocks on their normal trading days and group them in1to the third group: the ordinary group. I apply Analysis of Variance (ANOVA) models to test different in mean turnover for the above three groups. I formally test this hypothesis by the following ANOVA model:

$$ATOV_{ij} = \mu + G_i + \varepsilon_{ij} \qquad (3)$$

Where $ATOV_{ij}$ denotes abnormal share turnover for stock j the ith group. μ denotes the overall mean effect for all three groups (i.e., the high group, the low group or the ordinary group). G_i denotes the effect of different groups, and ε_{ij} denotes the error term.

Table 3.3 shows the ANOVA table. The model is significant with p-value less than 0.001, indicating a strong difference in mean abnormal turnover for the high, low, and ordinary group. Table 3.4 shows average abnormal share turnovers for three groups respectively. We can see that abnormal share turnover is the highest for the high group, lower for the low group and lowest for the ordinary group. On average, abnormal trading volume on historical low days is about twice of that of normal trading days. This implies that investors are prone to realize gains but they are not reluctant to realize losses as disposition effect predicted since share turnover on historical low days are still higher than normal trading days. Combined with previous evidences that individual investors are reluctant to cut loss, this evidence can lead to the hypothesis that rational investors that are immune to disposition effect persist in the market. These investors might be professional or institutional investors, or simply individual investors that are more sophisticated and have more trading experience. Feng and Seasholes (2005) find that sophistication and experience can eliminate the reluctance of cut loss.

3.5.2 Event Date Returns

Hypothesis 2 states that if there is market-wide disposition effect, stock return will be negative when stock price hits its historical high level because of the profit-taking behavior of disposition-prone investors; on the other hand, stock return will be positive when stock price hits its historical high level.

To test this hypothesis, again I group all events into two groups: the high group and the low group. The high group contains stocks that have reached historical high prices and the low group contains stocks that have reached historical low prices. I then add a third group: the ordinary group, i.e., stock returns on normal trading days for those firms that are either in the high or the low group. I test this hypothesis by the following ANOVA model:

$$AR_{ij} = \mu + G_i + \varepsilon_{ij} \qquad (4)$$

Where AR_{ij} denotes abnormal return for stock j the ith group. μ denotes the overall mean effect for all three groups (i.e., the high group, the low group or the ordinary group). G_i denotes the effect of different groups, and ε_{ij} denotes the error term.

Table 3.5 shows the ANOVA table. Again, abnormal returns are significantly different among three groups. The *p*-values for G_i is less than 0.001. Table 3.6 shows the average daily abnormal returns for three different groups. Contrary to my null hypothesis, I find a positive daily return on the high group and a negative daily return on the low group. This clearly contradicts the hypothesis that there is a market-wide profit-taking when stocks appreciate and a market-wide reluctance to cut-loss when stocks are at loss. However, my findings seem to be consistent with the momentum effect.[8]

3.6 Robustness Check

3.6.1 Balanced Design

My sample is not balanced, i.e., some firms might reach historical high prices but does not get to its historical low prices, or vice versa. I examine the disposition effect by using a balanced design in this section. I take those firms that have reached both historical high and low prices for a certain time frame. I then conduct similar analysis as in section 3.4. I find similar results. Table 3.7 shows the test statistics of the ANOVA analysis for abnormal turnover for the sample of firms that have reached its historical high and low prices in 84 trading days. Again, test statistics are similar for the sample of 168, 252 and 504 trading days. Table 3..8 shows the difference in mean abnormal share turnover and mean abnormal returns for the high/low/ordinary group. There is a slight change in the numbers, but the general trend and implications are the same as what I find in section 3.4.

[8] When tracking average returns for up to one-year after historical high and low days, I find positive returns for the high group and negative returns for the low group. This shows a momentum effect on stocks and is consistent with Jegadeesh and Titman (1993).

3.7 Conclusions

Although disposition effect is pervasive among groups of individual investors, there is much less evidence of market-wide disposition effect. I test market-wide disposition impact by examining the trading volume on historical high and historical low days during a period of 84, 168, 252 and 504 trading days respectively. I hypothesize that trading volume is the highest on historical high days, lower for normal trading days and lowest for historical low trading days. My empirical evidence is the following: trading volume is much higher for historical high days, lower for historical low days and lowest for normal trading days. On average, trading volume on historical low days is about twice of that of normal trading days. The evidence supports the hypothesis that the market has strong propensity to realize gains but contradicts the hypothesis that investors are unwilling to cut losses. Furthermore, the return data on historical high and historical low days contradicts a market-wide disposition effect: returns for historical high days are positive and returns for historical low days are negative. This might be consistent with the momentum effect.

Although disposition effect is well-documented and pervasive among individual investors even some professional investors, I find limited evidence that support the market-wide disposition effect.

Table 3.1: Sample Size by Trading Period and High/Low/Ordinary Group

Trading Period	Group	Number of firms		Number of events	
		NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
84 trading days	High	3,384	6,979	188,930	372,676
	Low	3,415	6,795	249,892	354,886
	Ordinary	3,555	7,206	5,710,133	9,970,499
168 trading days	High	3,144	6,553	117,774	246,077
	Low	3,235	6,044	181,883	241,604
	Ordinary	3,479	7,010	5,687,216	9,914,464
252 trading days	High	2,920	6,131	90,239	189,632
	Low	3,054	5,494	150,708	192,282
	Ordinary	3,395	6,791	5,647,967	9,846,075
504 trading days	High	2,356	4,846	51,845	104,442
	Low	2,627	4,306	105,187	121,122
	Ordinary	3,153	5,973	5,513,786	9,428,855

High/Low group contains those events that stocks have reached historical high/low prices with a certain number of trading days (i.e., 84, 168, 252, 504 trading days). Ordinary group contains normal trading days for firms in the High/Low group.

Table 3.2: Number of Firms by Month and High/Low/Ordinary Group

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
NYSE/AMEX Firms												
84 days												
High	6,981	6,677	6,750	6,395	6,915	6,931	6,790	6,421	6,798	6,734	6,714	6,796
Low	5,849	6,219	7,163	7,434	6,887	7,274	7,797	7,828	7,568	7,816	7,157	7,527
Ordinary	9,705	9,723	9,742	9,748	9,774	9,794	9,792	9,778	9,758	9,758	9,745	9,734
168 days												
High	5,807	5,579	5,685	5,340	5,600	5,633	5,553	5,022	5,787	5,626	5,351	5,561
Low	4,539	4,811	5,824	5,979	4,927	5,557	6,371	6,523	6,609	7,063	5,815	6,340
Ordinary	9,509	9,522	9,528	9,528	9,540	9,550	9,560	9,564	9,563	9,567	9,556	9,547
252 days												
High	5,214	4,977	5,102	4,695	4,781	4,867	4,918	4,415	4,988	4,739	4,519	4,849
Low	3,737	4,144	5,080	5,118	4,080	4,701	5,486	5,726	5,712	6,303	4,853	5,479
Ordinary	9,224	9,234	9,241	9,245	9,254	9,261	9,267	9,271	9,272	9,277	9,277	9,276
504 days												
High	3,747	3,637	3,784	3,570	3,466	3,512	3,532	3,052	3,615	3,491	3,452	3,751
Low	2,355	2,669	3,172	3,142	2,417	2,825	3,475	3,789	4,015	4,628	2,988	3,603
Ordinary	8,207	8,215	8,220	8,220	8,228	8,230	8,234	8,231	8,232	8,233	8,234	8,233
NASDAQ Firms												
84 days												
High	6,981	6,677	6,750	6,395	6,915	6,931	6,790	6,421	6,798	6,734	6,714	6,796
Low	5,849	6,219	7,163	7,434	6,887	7,274	7,797	7,828	7,568	7,816	7,157	7,527
Ordinary	9,705	9,723	9,742	9,748	9,774	9,794	9,792	9,778	9,758	9,758	9,745	9,734
168 days												
High	5,807	5,579	5,685	5,340	5,600	5,633	5,553	5,022	5,787	5,626	5,351	5,561
Low	4,539	4,811	5,824	5,979	4,927	5,557	6,371	6,523	6,609	7,063	5,815	6,340
Ordinary	9,509	9,522	9,528	9,528	9,540	9,550	9,560	9,564	9,563	9,567	9,556	9,547
252 days												
High	5,214	4,977	5,102	4,695	4,781	4,867	4,918	4,415	4,988	4,739	4,519	4,849
Low	3,737	4,144	5,080	5,118	4,080	4,701	5,486	5,726	5,712	6,303	4,853	5,479
Ordinary	9,224	9,234	9,241	9,245	9,254	9,261	9,267	9,271	9,272	9,277	9,277	9,276
504 days												
High	3,747	3,637	3,784	3,570	3,466	3,512	3,532	3,052	3,615	3,491	3,452	3,751
Low	2,355	2,669	3,172	3,142	2,417	2,825	3,475	3,789	4,015	4,628	2,988	3,603
Ordinary	8,207	8,215	8,220	8,220	8,228	8,230	8,234	8,231	8,232	8,233	8,234	8,233

Table 3.3: ANOVA Table for Group Effect on Share Turnover

$$ATOV_{ij} = \mu + G_i + \varepsilon_{ij} \qquad 3.1$$

Where $ATOV_{ij}$ denotes abnormal share turnover for stock *j* the *i*th group. μ denotes the overall mean effect for all three groups (i.e., the high group, the low group or the ordinary group). G_i denotes the effect of different groups, and ε_{ij} denotes the error term.

The following table reports the test statistics for the sample of 168 trading days (test statistics for 84, 252 and 504 days are similar):

Exchanges	Model *F* Value	*P*-Value
NYSE/AMEX	1149.5	<0.0001
NASDAQ	346.7	<0.0001

Table 3.4: Average Abnormal Share Turnover by Group

Trading Period	Event	Average Abnormal Turnover	
		NYSE/AMEX	NASDAQ
84 days	High	0.36%	1.38%
	Low	0.19%	0.86%
	Ordinary	-0.01%	0.22%
168 days	High	0.42%	1.51%
	Low	0.23%	0.95%
	Ordinary	-0.01%	0.22%
252 days	High	0.44%	1.56%
	Low	0.24%	1.00%
	Ordinary	-0.01%	0.22%
504 days	High	0.43%	1.49%
	Low	0.25%	0.75%
	Ordinary	-0.01%	0.22%

High/Low group contains those events that stocks have reached historical high/low prices with a certain number of trading days (i.e., 84, 168, 252, 504 trading days). Ordinary group contains normal trading days for firms in the High/Low group. Average abnormal share turnovers are reported in percentage terms.

Table 3.5: ANOVA Table for Group Effect on Return

$$AR_{ij} = \mu + G_i + \varepsilon_{ij} \qquad 3.2$$

Where AR_{ij} denotes abnormal return for stock *j* the *i*th group. μ denotes the overall mean effect for all three groups (i.e., the high group, the low group or the ordinary group). G_i denotes the effect of different groups, and ε_{ij} denotes the error term.

The following table reports the test statistics for the sample of 84 trading days (test statistics for 168, 252 and 504 days are similar):

Exchanges	Model *F* Value	*P*-Value
NYSE/AMEX	14754.9	<0.0001
NASDAQ	27513.0	<0.0001

Table 3.6: Average Abnormal Return by Group

Trading Period	Event	Average Abnormal Return	
		NYSE/AMEX	NASDAQ
84 days	High	2.37%	4.34%
	Low	-3.87%	-8.16%
	Ordinary	-0.56%	-0.56%
168 days	High	2.27%	3.83%
	Low	-4.02%	-8.75%
	Ordinary	-0.56%	-0.56%
252 days	High	2.23%	3.58%
	Low	-4.13%	-9.15%
	Ordinary	-0.56%	-0.56%
504 days	High	2.36%	3.34%
	Low	-5.39%	-10.75%
	Ordinary	-0.58%	-0.65%

High/Low group contains those events that stocks have reached historical high/low prices with a certain number of trading days (i.e., 84, 168, 252, 504 trading days). Ordinary group contains normal trading days for firms in the High/Low group. Average abnormal share turnovers are reported in percentage terms.

Table 3.7: ANOVA Table for Group Effect on Abnormal Share Turnover or Abnormal Return: Balanced Data

$$ATOV_{ij} = \mu + G_i + \varepsilon_{ij} \quad \text{or} \quad AR_{ij} = \mu + G_i + \varepsilon_{ij}$$

Where $ATOV_{ij}$ and AR_{ij} denotes abnormal share turnover and abnormal return for stock j the ith group, respectively. μ denotes the overall mean effect for all three groups (i.e., the high group, the low group or the ordinary group). G_i denotes the effect of different groups, and ε_{ij} denotes the error term.

The following table reports the test statistics for the sample of 84 trading days (test statistics for 168, 252 and 504 days are similar):

Dependent Variable	Exchanges	Model *F* Value	*P*-Value
Abnormal Turnover $ATOV_{ij}$	NYSE/AMEX	1348.4	<0.0001
	NASDAQ	432.3	<0.0001
Abnormal Return AR_{ij}	NYSE/AMEX	8578.9	<0.0001
	NASDAQ	16247.2	<0.0001

Table 3.8: Average Abnormal Share Turnover and Return by Group for Balanced Data

Trading Period	Event	Average Abnormal Turnover		Average Abnormal Return	
		NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
84 days	High	0.36%	1.38%	2.37%	4.35%
	Low	0.19%	0.86%	-3.87%	-8.16%
	Ordinary	-0.008%	0.23%	-0.55%	-0.56%
168 days	High	0.42%	1.51%	2.27%	3.83%
	Low	0.23%	0.95%	-4.02%	-8.74%
	Ordinary	-0.006%	0.25%	-0.55%	-0.56%
252 days	High	0.44%	1.57%	2.23%	3.58%
	Low	0.24%	1.00%	-4.13%	-9.15%
	Ordinary	-0.001%	0.25%	-0.54%	-0.55%
504 days	High	0.43%	1.49%	2.36%	3.34%
	Low	0.25%	0.75%	-5.39%	-10.75%
	Ordinary	0.003%	0.29%	-0.46%	-0.62%

High/Low group contains those events that stocks have reached historical high/low prices with a certain number of trading days (i.e., 84, 168, 252, 504 trading days). Ordinary group contains normal trading days for firms in the High/Low group. Average share turnovers and returns are reported in percentage terms.

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