THE INTERRELATIONS BETWEEN INVESTOR BELIEFS, INFORMATION AND MARKET LIQUIDITY

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Dedication

I dedicate this work to my family. Without them, this journey would have ended many miles ago.

I am especially grateful to my husband – my very best friend. Thank you for pushing me when it would have been so much easier to simply give up. You've kept me going with all of the early mornings, the late nights and the unending support in between.

I am also very grateful to my parents. Thank you for instilling in me a strong sense of morals and values. I only hope that my efforts have made you proud and that I can share with my own children the wonderful gifts that you have bestowed upon me.

I am grateful too for the love and friendship of my brother and sisters. Although many miles separate us, my love for you is boundless.

Finally, I dedicate this work to my children. I love you with all of my heart.

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Abstract

I use two datasets to test the relation between trading volume, the heterogeneity of beliefs and the heterogeneity of belief revisions. The first dataset allows me to construct two groups that proxy for 'holders' and 'non-holders' of a traded asset. This construct allows me to test the relation between changes in trading volume and changes in the dispersion of beliefs both within and across these two groups. I examine changes in within- and across-group dispersion separately and simultaneously. The second dataset allows me to examine belief revisions more closely by analyzing only those prior and posterior beliefs surrounding an information event. I examine the impact of specific belief revision phenomena on trading volume.

My results provide evidence that without regard to specific information events, trading volume is positively related to any change in within-group or across-group dispersion whether this dispersion is measured separately or simultaneously. Second, I provide evidence that this result holds regardless of the specific characteristics of the belief revisions. This result provides further definition to the findings of Kandel and Pearson (1995) and Bamber, Barron and Stober (1999). Finally, my results suggest that extreme belief revisions such that investors with higher valuations subsequently hold lower valuations ('flips') have a highly positive and significant relation to changes in market liquidity.

Chapter 1: Introduction

As noted by Kandel and Pearson (1995), it is widely accepted in the economics, finance (and accounting) literature that investors trade because of their differing assessments of security value (heterogeneity of agents). Much work has been done to try to uncover the nature of those differences and their impact on trading. Commonly, these differences are related to preferences (risk aversion), priors (endowments of wealth, intellect, etc.) and information. Researchers as far back as Beaver (1968) have focused on differences in prior beliefs and information.

I examine the effect of investor belief revisions on market liquidity. There are many reasons why we need a clear understanding of market liquidity and in particular, its causes. Primarily, it is important to gain a better understanding of the impact of liquidity traders, to determine the level (if any) of information content in market liquidity and to understand the effects of market design on market liquidity. Several studies such as Morse ((1980), (1981)) and Bamber ((1986), (1987)) have documented the impact of investor belief revisions on asset prices, but this paper describes the resulting change in trading volume. Similarly previous researchers have also investigated the information content of market liquidity. A primary focus has been whether or not we can make inferences regarding the level of investor consensus based on the volume reaction to information events. Over time, two schools of thought have emerged. The first school includes Beaver (1968) who argues that a volume response to an information event provides evidence that there is a lack of consensus regarding the implications of the news. Thus, the absence of a volume response suggests that there is total consensus among investors. Stated alternatively, this school of thought contends that there is a positive relation between volume and belief heterogeneity. Karpoff (1986) derives a model wherein trading is caused by investor heterogeneity with respect to their prior beliefs and the way in which they revise those beliefs. This model is supported empirically by both Ajinkya, Atiase and Gift (1991) and Barron (1995). Neither of these empirical studies, however, use data relative to specific information events. Instead, they test changes in volume and investor beliefs over time as information is continuously revealed to the market. In a slightly different type of study, Bamber and Cheon (1995) examine the differing magnitudes of volume (and price) responses to new information. They find that volume increases as the degree of heterogeneity in belief revisions increases. Kandel and Pearson (1995) focus on the common trading model assumption of homogeneous belief revisions. They provide a theory supported by empirical evidence showing that investors do not interpret new information identically. Empirically, they find a positive relation between volume and specific cases of these heterogeneous belief revisions. Bamber, Barron and Stober (1999) provide additional support for Kandel and Pearson (1995).

In the alternative school of thought, Verrecchia (1981) argues that it is not justifiable to infer investor consensus from the absence of a volume response to new information. Ziebart (1990) supports this argument with (weak) evidence that volume, the degree of investor consensus and the magnitude of belief revisions are all positively related. My model and empirical results support Verrecchia (1981) and Ziebart (1990). I find that volume increases as the level of consensus across investors increases. Also, the greater the degree of homogeneity in investor belief revisions, the greater the investor consensus which leads to increased market liquidity.

1.1. Theoretical Model

I develop a theoretical model that seeks to explain market liquidity at a given point in time as well as changes in market liquidity from one period to the next. Assuming a two-period economy with no transactions costs or liquidity traders, I show that at a given point in time, market liquidity is a function of the dispersion of investor beliefs relative to a central region of consensus. Given this foundation, I also show that from one period to the next, changes in market liquidity are a function of the change in dispersion, prior belief heterogeneity and belief revision heterogeneity.

1.2. Empirical Data and Methodology

I use two datasets, both based on analyst forecasts, to empirically test my predictions. In the first dataset, I use a sample of 80,270 analyst forecasts for 4,473 firms from 1990 to 2002. I categorize each forecast as a proxy for a 'holder' or a 'non-holder' based on a comparison of each forecast to the mean value of all forecasts made in the same month for the same firm. I classify forecasts greater than the mean as 'holders' because these analysts represent investors with higher than average expectations of the firm and are therefore likely to own or 'hold' units of the traded asset. I classify forecasts less than or equal to the mean as 'non-holders' because these analysts represent investors with average or less than average expectations of the firm and are therefore not likely to own or 'hold' units of the traded asset. Using this dataset, I test for a relation between market liquidity and belief dispersion. I examine both within-group and across-group dispersion.

In the second dataset, I use a sample of 5,640 observations for 1,364 firms from 1993 to 2002. Each observation corresponds with one earnings announcement. For each earnings announcement, I calculate the mean value of all forecasts for that firm in the 45 days prior to the earnings announcement and the mean value of all forecasts for that firm in the 30 days following the earnings announcement. To be included in the sample, a firm must have volume and return data available on CRSP and at least two analysts making annual forecasts in the 45 days prior to the earnings announcement and the same analysts must make a revised forecast in the 30 days following the earnings announcement. Once I identify all firms that meet these criteria, I search for analysts that make more than one forecast for the same firm in the pre-announcement period, the post-announcement period or both periods. In these cases, I eliminate all but the forecasts closest to the announcement date. I then calculate the grand mean of all of the forecasts. Based on this mean, I calculate the mean of all forecasts above the grand mean and all forecasts below the grand mean. Finally, I classify each observation in three ways: 1) divergent, convergent or constant, 2) consistent or inconsistent and 3) 'flip' or 'no flip'. I define a divergent (convergent) analyst pair as one where the absolute difference in the post-announcement forecasts is greater (less) than the absolute difference in the pre-announcement forecasts. If the absolute difference in the post-announcement forecasts is equal to the absolute difference in the pre-announcement forecasts, I classify this analyst pair as 'constant'. I define a consistent analyst pair as one where both analysts revise in the same direction (either both upward or both downward). In contrast, I classify analyst pairs where one analyst revises his/her forecast upward while the other analyst revises his/her forecast downward as 'inconsistent'. I define a flip as an analyst pair where the analyst with the higher pre-announcement forecast has the lower post-announcement forecast. In cases where the analyst with the higher pre-announcement forecast also has the higher post-announcement forecast, I classify the analyst pair as a ‘no flip’. Also, if either the pre-announcement forecasts or the post-announcement forecasts are equal, I categorize the analyst pair as a ‘no flip’. Using this dataset, I test for a relation between the change in volume over the three day period (-1,+1) relative the quarterly announcement date and these characteristics of the analyst pairings.

1.3. Main Findings and Conclusions

My empirical results support my theoretical predictions. Dispersion and changes in dispersion alone do not fully explain market liquidity. I find that when analyzing ‘holders’ versus ‘non-holders’ any change in within-group or across-group dispersion is positively related to market liquidity. Similarly, after classifying forecast revisions according to the additional characteristics, I find that the convergence of beliefs and the homogeneity of belief revisions are significantly related to market liquidity. One interesting finding is that after separating divergent forecast revision pairs from ‘flipping’ revision pairs there is a significant relation between the ‘flips’ and market liquidity. That is, as investors ‘flip’ their beliefs, market liquidity increases. Kandel and Pearson (1995) and Bamber, Barron and Stober (1999) included these pairs with divergent pairs in their analysis, so such a distinction could not be made. Thus, my main result is that changes in market liquidity can be explained by 1) changes in dispersion both within and across groups of investors, 2) the homogeneity of belief revisions and 3) the ‘flipping’ of beliefs.

1.4. Organization

Chapter Two reviews the theoretical and empirical literature to-date regarding market liquidity. Chapter Three describes the model, the data I use to test it and the empirical tests I perform. Chapter Four presents the results of the univariate and multivariate analysis. Chapter Five summarizes and concludes.

Chapter 2: Review of the Literature

Trading volume has been examined in the academic literature in a variety of contexts. My concern is with the relation between trading volume and information. I consider investor's beliefs before and after information is made public and how investor interpretations of this information impacts trading volume. Many previous studies have addressed similar issues with mixed results. I focus my investigation on the equity markets; however researchers have made significant contributions to the existing literature by examining trading volume in other markets such as the bond market, foreign exchange market, futures markets and options markets.

2.1. Theory

A considerable number of theoretical papers exist that attempt to explain what causes or influences trading volume. Some of these papers focus only on trading volume while others model changes in trading volume in conjunction with changes in price or other factors.

2.1.1. Information Asymmetry

A number of studies consider environments where information asymmetry exists among traders. In general, these studies have shown both theoretically and empirically that traders are able to earn positive abnormal returns by trading on private (insider) information. Also, many of these studies show that investors must rely on specific patterns or levels of trading volume in order to realize these returns. In Morse's (1980) model, this asymmetric information environment is a result of unequal costs of obtaining and processing information and causes trade.

The majority of the current theory suggests that asymmetric information results in an increase in trading volume. Kyle's (1985) single-period model with one informed trader, one uninformed trader and a market maker shows how informed traders 'hide' behind uninformed traders and earn positive abnormal returns at the expense of uninformed traders. Trading strategically, the informed traders gradually release their private information to the market through their order quantity decisions. Later theories such as Holden and Subrahmanyam (1992) extend the Kyle model to one in which multiple informed traders compete for profits and find that the release of information occurs more quickly.

Foster and Viswanathan (1993a) develop a one-period model of market making with informed traders and show three key results. First, the variance of prices and expected trading volume depend on the 'surprise' component contained in public information released at the start of trading. Second, if the decision to become informed is endogenous, the decision rules of the market maker (relative to price) and the insider (relative to quantity) depend on the level of surprise in the public information. Finally, when expanded to multiple periods with multiple insiders who have long-lived private information, informed traders' profits (which are present in the one-period model) disappear. The key difference between this model and the Kyle (1985) model is that volume and volatility are allowed to depend upon the public information that is revealed. That is, if the public information is not complete but is close to investors' expectations, this information has little impact on volume and volatility. However, if the public information differs substantially from investors' expectations, volume and volatility increase.

Wang (1994) models stock trading by investors with heterogeneous prior information who trade for informational and non-informational motives. Wang shows that volume is positively correlated with absolute changes in prices and dividends and that the relation between trading volume and stock returns differs depending on the trader's motive. Further, without asymmetric information, abnormal trading volume is not present.

In an opposite approach, other studies show that trading volume is used by traders to estimate the level of private information in the market and therefore, set their own trading strategy accordingly. Kim and Verrecchia (2001) develop a model in which the firm's returns depend on trading volume when the firm defers disclosure because market makers use volume to draw inferences about better-informed investors' private information on firm value. Therefore, firms that disclose more would find that trading volume has less explanatory power over the firm's stock returns. Suominen (2001) develops a model in which the rates of public and private information arrival are random and the flow of private information, in particular, depends on its availability which also changes randomly over time. Traders, however, estimate the availability of private information based on past period trading volume and trade accordingly.

2.1.2. Volume Response to Public Announcements

Kim and Verrecchia (1991a) assert that differences in the precision of traders' prior information cause them to make different belief revisions triggering positive abnormal trading volume. They provide a theory for how price and volume reactions to a public announcement are related to each other, to the announcement and to the traders' beliefs at the time of the announcement. Their main result is that trading volume is proportional to both the absolute price change and a measure of differential precision across traders. This relation is given in the equation

$$Volume = \left(\frac{1}{2} \int r_i \left| s_i - s \right| di \right) \left| \tilde{P}_2 - \tilde{P}_1 \right| \tag{2.1}$$

where: r_i = trader i's risk tolerance, s_i = the precision of trader i's private information, s = average precision and $\left| \tilde{P}_2 - \tilde{P}_1 \right|$ is the absolute change in price (P).

Then, in this equation, the term $\left(\frac{1}{2} \int r_i \left| s_i - s \right| di \right)$ is the measure of differential precision across traders. The measure of differential precision across traders is the weighted average of the absolute deviations of the precision of traders' private information (s_i) from the average precision (s) and weighted by risk tolerance (r_i). Also, they show that expected volume and variance of price change are increasing functions of the precision of the announced information and decreasing functions of the amount of preannouncement public and private information.

Harris and Raviv (1993) assume that investors have homogeneous prior beliefs and receive the same information, but have different interpretations of that information. Their model shows volume is positively autocorrelated and that absolute price changes and absolute changes in the mean earnings forecasts and volume are positively correlated. Further, they show that, in a speculative market, if investors overestimate (underestimate) the precision of their information, then subsequent price changes will be negatively (positively) serially correlated.

Kim and Verrecchia (1994), theorize that the fact that some traders are able to make better decisions than others based on the same information leads to information asymmetry and positive abnormal trading volume despite a reduction in liquidity. They measure liquidity as $\frac{1}{\lambda}$ where λ is the inverse of Kyle's (1985) market depth parameter. The Kim and Verrecchia (1994) measure, $\frac{1}{\lambda}$, is the order flow necessary to induce prices to rise or fall by one dollar. Therefore, a small λ implies that a trader can buy or sell a large amount of stock for a price that is, on average, close to the current market price. Therefore, the market is said to be liquid. In contrast, a large λ implies an illiquid market. Finally, given the boundary condition $\lambda \geq 0$, if $\lambda = 0$, the market is infinitely deep.

Similarly, other studies conjecture that the trading volume reaction to public announcements is related to the informativeness of the announcement. Holthausen and Verrecchia (1990) argue that this 'informedness effect' and a 'consensus effect' (which measures the extent of agreement among agents at the time of an information release) occur simultaneously and affect both trading volume and price changes.

Karpoff (1986) theorizes that both pre- and post- announcement belief dispersion are related to trading volume. Karpoff models trading volume based on several assumptions. First, market participants revise their beliefs after new information is revealed. Second, trade occurs when buyers and sellers encounter one another at random. Third, short-selling is not allowed. The model explains information-related trading as a function of the market participants' prior beliefs as well as their interpretations of new information.

The Karpoff model considers homogeneous priors with differential interpretations and heterogeneous priors with homogeneous interpretations of information. Kandel and Pearson (1995), however, argue theoretically and empirically that homogeneous interpretations of information are unrealistic. Kim and Verrecchia (2002) wage strong criticism against models that consider only pre-announcement *or* event period information. They argue that a model (such as theirs) that incorporates both types of information is more realistic because it is rare for only one of these types of information (pre-announcement or event-period) to exist. Thus, in their model, volume (which they note is caused by demand change) is related to price change at the time of an earnings announcement. However, trading volume occurs even in the absence of price change.

2.1.3. Stock Price, Stock Returns and Volatility

Karpoff (1987) reviews the existing literature (at the time of the article) that relates trading volume to price changes. One of the key contributions that this paper makes to the literature is that it points out the empirical evidence suggesting that volume is positively related to the magnitude of the price change.

Llorente, Michaely, Saar and Wang (2002) also examine the relation between return and volume of individual stocks. They note that investors trade for three reasons: liquidity, hedging (portfolio rebalancing) or speculation. They develop a model that suggests that hedging activity is marked by price reversals while speculative activity is marked by price continuation.

2.2 Empirical Evidence

2.2.1. Information Asymmetry

Others have specifically examined cases of insider trading and found mixed results. Sanders and Zdanowicz (1992) examine the average abnormal returns, average abnormal trading volume and reported insider trading of corporate control target firms prior to public announcement of the initiation of corporate control transactions. They find no evidence of abnormal trading volume until the first public announcement regarding the transaction. Cornell and Sirri (1992), however, use the case of Anheuser-Busch's 1982 tender offer for Campbell Taggart to analyze insider trading and find that insider trading had a significant impact on the price of the target and overall trading volume rose.

Lang, Litzenberger and Madrigal (1992) provide evidence that the dispersion of private information across traders has an impact on trading volume, but not on price.

To reduce the prevalence of asymmetric information in securities markets, the Securities Exchange Commission (SEC) promotes public disclosure of information and takes action against those who attempt to profit from trading on inside information. Ro (1981) examines a specific SEC mandate, Accounting Series Release No. 190 (ASR 190), which requires footnote disclosure of replacement cost accounting information by certain firms. Ro evaluates the impact of this mandate on transaction volumes of common stock for companies having to comply with this disclosure rule. Ro finds no evidence of a relation between the announcement of ASR 190 and trading volume either through increased total volume or a difference in volume between those firms affected by the ruling and those unaffected by the ruling.

2.2.2. Volume Response to Public Announcements

When examining market activity (typically volume and price movement or returns) in response to public news announcements, researchers have considered a number of different types of news such as dividend information, earnings announcements, macroeconomic announcements, news announcements from specific sources, and general information flow. Market efficiency suggests that the price and volume response to such announcements should be immediate. Current evidence generally supports market efficiency. Researchers have also considered the implications for market consensus based on volume response to public announcements considering that investors simply do not have homogenous interpretations of public announcements.

2.2.2.1. Dividends

With respect to dividend policy announcements, Richardson, Sefcik and Thompson (1986b) investigate the impact of changes in dividend policy on trading volume assuming that such changes have a clientele effect in that the firm's shareholder clientele changes as shareholders have specific dividend preferences due to their personal income tax implications. They find that upon announcing their first cash dividend, sample firms enjoy increased volume *and* value possibly due to the perception that the announcement signals stable future earnings.

2.2.2.2. Earnings Announcements

Most studies examining the relation between trading volume and public announcements examine the market activity surrounding earnings announcements. Beaver's (1968) early study of the information content of earnings announcements examines investor reactions to earnings announcements with respect to volume and price. Using a sample of annual earnings announcements released by 143 firms during the years 1961 through 1965, Beaver finds that both volume and price changes support the contention that earnings announcements are informative. Further, he argues that a simultaneous change in volume and price indicates that the announcement affects the beliefs of the market as a whole. The volume response appears to increase with the amount of surprise in the announcement and the size of the firm. For a sample of firms chosen at random from the Value Line Investment Survey, Bamber (1986) finds a positive relation between volume and the magnitude of surprises and a negative relation between volume and size. Later, Bamber (1987) finds that both the magnitude and the duration of the trading volume reaction to quarterly earnings announcements are increasing functions of unexpected earnings and decreasing functions of firm size.

Generally, there is evidence that investor heterogeneity – or differences in beliefs - impacts trading volume. This heterogeneity can be either prior to the announcement, after the announcement or both.

Atiase and Bamber (1994) support Kim and Verrecchia's (1991a) theory that trading volume is proportional to both the absolute price change and a measure of differential precision across traders.

Ziebart (1990) studies a sample of 611 earnings announcements of 90 NYSE-listed firms. He finds that abnormal trading volume is related to the change in the level of investor consensus (proxied by dispersion in analysts' forecasts) and the absolute value of the percentage change in the consensus forecast as opposed to the level of prior information. That is, trading volume reactions to earnings announcement reflect the surprise in the announcement and the level of consensus of investors' belief revisions. Similarly, Bamber and Cheon (1995) use a sample of price and volume reactions to 8,180 quarterly earnings announcements from 1986 to 1989 by 1,079 firms to compare these volume reactions to their accompanying price reactions. They find that trading volume is likely to be high relative to price reaction when an earnings announcement generates differential belief revisions among investors (as demonstrated by high trading volume), but a limited aggregate market belief revision (as demonstrated by small price change).

Ajinkya, Atiase and Gift (1991) provide empirical evidence in support of Karpoff's (1986) theory that trading volume is positively related to the degree of differing beliefs. Using a sample of 420 firms with a December 31st fiscal year-end, no stock splits or stock dividends during the sample period and at least three analysts reporting forecasts in each sample month they collect analyst forecasts and monthly trading volume from 1978 to 1981. They find a significant positive association between the monthly dispersion in analysts' forecasts of annual earnings per share (EPS) and monthly trading volume[1]. Barron (1995) provides additional support for Karpoff's (1986) prediction that trading is caused by both differential prior beliefs and differential belief revisions. By examining the correlation between the relative positions of individual analysts' current and prior forecasts of earnings to measure differential belief revisions, Barron finds that this variable explains trading volume better than prior dispersion in forecasts. Kandel and Pearson (1995) use quarterly earnings announcements and daily volume and return data surrounding these dates to test their hypothesis that abnormal trading volume during announcement periods occurs because

[1] Ajinkya, Atiase and Gift (1991) measure dispersion as the standard deviation across analysts divided by the absolute value of the mean EPS forecast during the current month. Also, they measure volume as the fraction of outstanding shares traded.

investors have differential interpretations of the announcements. They find that there are economically and statistically significant positive abnormal volumes associated with quarterly earnings announcements even in the absence of price change. Bamber, Barron and Stober (1997) also find that both pre- and post-announcement dispersion are related to trading volume. They take a closer look at investor disagreement (heterogeneous interpretations) and break it into three distinct sources. Those sources of dispersion are: 1) dispersion in prior beliefs – the level of variation in expectations before the earnings announcement, 2) change in dispersion – the difference in the level of dispersion in beliefs after versus before the earnings announcement and 3) belief jumbling – when investors' beliefs change positions relative to each other around the earnings announcement. Bamber, Barron and Stober (1999) take a second look at investor disagreement focusing only on differential interpretations and find two conditions under which differential interpretations play a significant role in explaining trading. These two conditions are 1) trading coincident with small price changes reflects investors' differential interpretations of information and 2) differential interpretations explain a significant amount of the trading occurring in a sample where trading volume is higher than the (firm-specific) non-announcement period average. These results also support Kandel and Pearson (1995).

2.2.2.3. Macroeconomic Announcements

Other studies have investigated the impact of macroeconomic announcements on trading volume. In general, these studies have had mixed results. Castanias (1979) measures the variability of stock prices based on the impact of macroeconomic events and relates these variations to trading volume under the assumption that volume is indicative of the impact of information. Castanias finds a significant relation between macroeconomic announcements by the Fed and stock prices. Jain (1988) also examines trading volume response to macroeconomic announcements, but considers hourly volume responses to announcements about the money supply, the consumer price index (CPI), the producer price index (PPI), industrial production and the unemployment rate. Jain finds that only surprises about the money supply and CPI are significantly associated with price changes in about one hour and, in contrast to Castanias, volume is not significantly affected by *any* of these announcements.

2.2.2.4. Miscellaneous News Announcements

Studies of specific news sources and trading volume have shown a significant relation between the two. Most frequently, researchers have analyzed stocks recommended in regular columns of *The Wall Street Journal* and found a significant but temporary spike in trading volume after publication of the recommendations. Liu, Smith and Syed (1990), Barber and Loeffler (1993) and Bing (1999) examine the impact of specific *The Wall Street Journal* columns on common stock prices and find significant abnormal returns on the publication day coupled with higher trading volume.

The relation between simply the *number* of news announcements and trading volume, however, has been found to be weak. Mitchell and Mulherin (1994) study the relation between the number of news announcements reported daily by Dow Jones & Company (the parent company of *The Wall Street Journal*) and aggregate measures of securities market activity including trading volume and market returns and find that they are directly (but weakly) related. Berry and Howe (1994) also relate the number of news releases to aggregate measures of market activity but examine the Reuter's News Service and consider intraday market activity. They find a positive, moderate relation between public information and trading volume but an insignificant relation to price volatility.

With respect to unanticipated news or events, Lee (1992) separates trading volume into buyer- and seller- initiated activities and examines the volume reaction to good news and bad news. Lee finds that good (bad) news triggers brief, but intense buying (selling) in large trades but any type of news triggers a persistent period of buying activity in small trades. Similarly, Lee, Ready and Seguin (1994) examine the effect of firm-specific NYSE trading halts on volume and price volatility. After comparing volume and price volatility for firms on days where trading was halted to days where trading was not halted, they find that trading halts increase both volume and volatility. Volume is 230% higher after a trading halt than after a firm-matched control period and this increased volume persists into the third post-halt day. Controlling for media coverage reduces the impact, but does not eliminate it completely. Brooks, Patel and Su (2003) examine how the equity markets react to events that are unanticipated in timing and content and find that selling pressure, wider spreads and higher volume remain significant for over an hour.

2.2.3. Trading Volume Patterns

Researchers have also provided evidence of trading volume patterns within the trading day and certain anomalies that are visible when examining trading across the days of the week and months of the year.

2.2.3.1. Day-of-the-week Patterns

The most prominent trading volume patterns show that trading volume is lowest on Mondays when the market is dominated by individual as opposed to institutional investors. Lakonishok and Maberly (1990) consider trading patterns of individual and institutional investors related to the day of the week on the NYSE and find that Monday is the day with the lowest trading volume and the most individual (versus institutional) traders and that trades are more often characterized as sell orders (as opposed to buy orders). Foster and Viswanathan (1993b) find that, consistent with Lakonishok and Maberly's (1990) documentation of the 'Weekend Effect', volume is low and adverse selection costs are high on Monday.

2.2.3.2. Intraday Trading Volume Patterns

Trading volume appears to be highest relative to some very specific market events. Stoll and Whaley (1990) provide evidence of increased intraday trading volume on 'triple-witching' days. 'Triple-witching' days are the third Friday in March, June, September and December when options, index options and futures contracts all expire simultaneously. These days are marked by notoriously heavy program trading (computer-driven buying or selling of baskets of 15 or more stocks by index arbitrage specialists or institutional traders). Stoll and Whaley find evidence of substantially higher volume in the last half hour of expiration days but that price behavior is not significantly different from stocks that are not subject to program trading and that any Friday price declines are typically reversed on the following Monday.

For actively traded firms, trading volume, adverse selection costs, and return volatility are higher in the first half-hour of the day. Kamara (1997) reinvestigates this effect and finds that it declines significantly over the period from 1962 – 1993 for S&P 500 firms and that this decline is positively related to the ratio of institutional to individual trading volume. However, for small stocks, the effect is unchanged over the sample period due to higher trading costs (which are the same for institutions and individuals). Wang, Li and Erickson (1997) provide evidence that this effect occurs primarily in the last two weeks (fourth and fifth weeks) of the month.

2.2.3.3. Tax Trading

Tax trading or buying and selling behavior that is motivated by tax incentives has also allowed researchers to document a prominent pattern in trading volume. Tax trading is most prominent at year-end as investors adjust their portfolios with respect to potential capital gains taxes (credits) owed (due them) based on their investment gains (losses). Many studies provide empirical evidence that there are tax motives to trading.[2]

2.2.4. Stock Price, Stock Returns and Volatility

Although outside the scope of this analysis, a considerable portion of the trading volume literature examines the relation between trading volume and either stock price or stock returns and the associated volatility of these prices and/or returns. Recall from the earlier discussion regarding the relation between trading volume and earnings announcements that several researchers have found a positive relation between trading volume and the absolute price change in response to this new information. However,

[2] See Dyl (1977), Constantinides (1984), Lakonishok and Smidt (1986), Lakonishok and Vermaelen (1986), Lamoureux and Poon (1987), Bolster, Lindsey and Mitrusi (1989), Han (1995), Lasfer (1995), Michaely and Murgia (1995), Michaely and Vila (1995), Bremer and Kato (1996), Seida and Wempe (2000) for examples.

researchers have also found that volume occurs in the absence of price change. Several studies have investigated these relations more closely.

2.2.4.1. Price Impact

Holthausen, Leftwich and Mayers (1987) examine the effect of large block transactions on security prices. After using various definitions of block 'size', they find evidence that seller-initiated trades are associated with a temporary price reduction and buyer-initiated trades are associated with a permanent price increase.

Conrad, Hameed and Niden (1994) test for the relations between trading volume and subsequent returns patterns in individual securities' short-horizon returns and find strong evidence of a relation. Specifically, the authors find that high-transaction securities experience price reversals while the returns of low-transactions securities are positively autocovarying – implying that information on trading activity is an important predictor of the returns of individual securities.

Gervais, Kaniel and Mingelgrin (2001) investigate the idea that extreme trading activity contains information about the future evolution of stock prices. They find that stocks experiencing unusually high (low) trading volume over a day or a week tend to appreciate (depreciate) over the course of the following month.

2.2.4.2. Stock Returns

Hiemstra and Jones (1994) examine the dynamic relation between daily Dow Jones stock returns and percentage changes in New York Stock Exchange trading volume. They find evidence of bidirectional nonlinear causality between returns and volume. They also consider whether the nonlinear causality from volume to returns can be explained by volume serving as a proxy for information flow in the stochastic process generating stock return variance. Beneish and Gardner (1995) also use Dow Jones data, but instead of returns, they investigate the impact of changes in the composition of the Dow Jones Industrial Average (DJIA) on the stock market. However, they find that firms removed from the index experience significant price declines.

Chordia and Swaminathan (2000) find that stock trading volume is a significant determinant of the lead-lag patterns observed in stock returns. Specifically, they find that daily and weekly returns on high volume portfolios lead returns on low volume portfolios after controlling for size and that this is not explained by nonsynchronous trading or low volume portfolio autocorrelations. Instead, they find that their result is due to the fact that returns on low volume portfolios respond more slowly to information in market returns.

Chordia, Subrahmanyam and Anshuman (2001) analyze the relation between expected equity returns and the level as well as the volatility of trading activity. They find a negative and significant cross-sectional relation between stock returns and the variability of dollar trading volume and share turnover after controlling for size, book-to-market ratio, momentum and the level of dollar volume or share turnover.

Chen, Hong and Stein (2001) use trading volume to predict future daily returns in individual stocks. They find that negative skewness in daily returns is most pronounced in stocks that have experienced an increase in trading volume relative to trend over the prior six months and positive returns over the prior 36 months.

Chordia, Roll and Subrahmanyan (2002) examine the relation between returns and trading activity measuring this activity as order imbalance (buy orders minus sell orders). They find that order imbalance increases (decreases) following market declines (increases) and that these imbalances reduce liquidity.

Using a sample of NYSE/AMEX stocks, Llorente, Michaely, Saar and Wang (2002) use time-series regression analysis to find the relation between each firm's current return and volume and future return. Using a variety of proxies for the degree of speculative trading, such as market capitalization and bid-ask spread, they compare each firm's return relations (current compared to future) to its degree of speculative trading. They find that small and illiquid firms are often marked by return continuation following high-volume days and large and highly liquid firms have return reversals after high-volume days. These results provide empirical support for their model.

2.2.4.3. Volatility-Volume Relation

Chan and Fong (2000) examine the roles of the number of trades, size of trades and order imbalance in explaining the volatility-volume relation for a sample of NYSE and Nasdaq stocks. They find that the size of the trades has greater importance than the number of trades in explaining the volatility-volume relation in both markets. This confirms the findings of Barclay and Warner (1993) who argue that if informed traders prefer to break up trades so that they can camouflage their trades with liquidity traders, it might be optimal for them to submit medium-sized orders. In that case, the volatility impact of medium-sized trades can be the greatest among trades of different sizes, and we may not be able to detect the volatility–trade size relation using average trade size.

2.2.5. Analyst Forecasts

Finally, many studies consider the impact of financial analysts and their earnings forecasts on stock prices and volume. Studies as early as Givoly and Lakonishok (1979) followed by Womack (1996) find that there is information content in analysts forecasts. Once this was established, the empirical focus switched to determining the usefulness of these forecasts in empirical research as proxies for market expectations. Several studies provided convincing evidence that analyst forecasts beat other proxies such as prediction models based on time series analysis in their predictive abilities.[3] In this examination, researchers also noted that analysts' forecasts become more accurate and less dispersed as the forecast horizon decreases. It is important to note, however, that later studies such as Abarbanell and Bernard (1992) have found some evidence of underreaction by analysts. However, Rajan and Servaes (1997) find that analysts are overoptimistic about the earnings potential and long term growth prospects of recent initial public offering (IPO) firms.

An interesting caveat to the issue of the use of analyst forecasts as a proxy for market expectations exploits the basic assumptions that must be made. Specifically, the researcher must assume that the forecasts reflect analysts' private information in an unbiased manner. Trueman (1994) provides evidence to the contrary. Trueman (1994) shows the tendency of analysts to release forecasts too close to the actual earnings announcement than is appropriate. This tendency necessitates the exclusion of these forecasts in certain empirical research. Also, Trueman (1994) provides evidence that analysts exhibit herding behavior wherein they release forecasts that are similar to

[3] See Fried and Givoly (1982) and O'Brien (1988).

recently released forecasts of other analysts and not necessarily based on their own information. Such a tendency may also skew analyst forecast data if not addressed empirically. A later study by Cooper, Day and Lewis (2001) explores the issue of analyst herding further. The paper divides analysts into leaders (those analysts who publish their reports) and followers (those analysts who publish similar reports after the leader analysts) based on the timeliness of their respective forecasts. They find that lead analysts have a greater impact on stock prices than follower analysts. Recognizing that herding exists, Kim and Pantzalis (2003) find that its existence can be value-reducing for the companies being covered. They found the effect to be more pronounced for diversified firms.

Other studies accept analyst forecasts as proxies for market expectations and examine the changes in consensus surrounding earnings announcements. Morse, Stephan and Stice (1991), for example find that market expectations diverge (consensus decreases) after an earnings announcement. In the spirit of Bamber (1987), they attribute this divergence of opinion to the level of surprise contained in the announcement. They find that there is a greater divergence of forecasts when the earnings announcement contains a bigger surprise.[4] This surprise element appears to have significance in explaining the impact of changes in consensus on trading volume because studies that do not account for surprise find very different results. Barron, Harris and Harris (2001), for example, find changes in uncertainty after an earnings announcement to be negatively related to trading volume. Using the measurement tools developed by Barron, Kim, Lim

[4] Here, surprise is defined as the difference between reported earnings and analysts' prediction of those earnings.

and Stevens (1998), they define consensus as the commonality in individuals' information.

2.3 Conclusion

Trading volume has been a popular subject of theoretical and empirical research in both the accounting and finance literature. The main findings point to many factors that affect trading volume. Namely, researchers have provided theoretical and empirical evidence that the level of information asymmetry present in the market, the precision of investors' information, the level of surprise contained in new information and the amount of pre-event and post-event investor consensus impact trading volume. However, there is not conclusive evidence regarding which of these factors has the greatest impact on volume.

Chapter 3: Data and Methodology

3.1. The Model

3.1.1. Background

Karpoff (1986) shows that the dispersion of beliefs both prior to and following public announcements is related to trading volume. Karpoff (1986) provides two propositions to explain this relation. First, the model proposes that when new information is interpreted differently by market participants, normal liquidity and speculative trading is increased due to an increase in the overall dispersion of beliefs. Second, even if investors interpret new information in the same way, because their prior beliefs differ, individuals will still revise their beliefs in accordance with the new information causing a change in dispersion and an increase in trading volume. Ajinkya, Atiase and Gift (1991) and Barron (1995) provide empirical support for this argument using analyst forecasts. Kim and Verrecchia (1991b) assert that differences in the precision of traders' prior information cause them to make different belief revisions triggering positive abnormal trading volume. Their theory indicates that trading volume is proportional to both the absolute price change and a measure of differential precision across traders and that expected volume and variance of price change are increasing functions of the precision of the announced information and decreasing functions of the amount of preannouncement public and private information. Kim and Verrecchia (1994) show that differential interpretations of information could also be due to the fact that some traders are able to make better decisions than others based on the same information.

With the exception of Kim and Verrecchia (1994), much of this early study of the relation between trading volume and investor beliefs assumed homogeneous interpretations of information across investors. Kandel and Pearson (1995), hereafter KP(1995), focus on heterogeneous interpretations of information. Using analyst forecasts, they document cases in which agents' means move in different directions labeling them 'flips' or 'divergences'. A 'flip' is a case where agent expectations cross such that

$$sign(Y_i - X_i) \neq sign(Y_j - X_j), X_i > X_{j,} Y_i < Y_j \tag{3.1}$$

where X and Y represent agent's prior and posterior belief respectively and i and j represent the agents. A 'divergence' is a case where the agents' belief revisions move in opposite directions such that

$$sign\left(Y_i - X_i\right) \neq sign\left(Y_j - X_j\right), \left|Y_j - Y_i\right| > \left|X_j - X_i\right| \tag{3.2}$$

Table I provides numerical examples of these two phenomena. In both cases, agents i and j have prior beliefs of 8 and 4 respectively and revise these beliefs in opposite directions. In the case of the 'flip', agents i and j have posterior beliefs of 4 and 8 respectively. Here, the agents swap or 'flip' beliefs such that the agent with the lower prior belief has the higher posterior belief. In the case of divergence, the magnitude of the revisions is such that the posterior beliefs (4 and 10) are farther apart than the prior beliefs (8 and 4).

Table I: Examples of a Flip and a Divergence

This table illustrates the phenomena of 'flips' and divergence as defined by Kandel and Pearson (1995) where a 'flip' is a case where $sign(Y_i - X_i) \neq sign(Y_j - X_j), X_i > X_j, Y_i < Y_j$ and a divergence is a case where $sign\left(Y_i - X_i\right) \neq sign\left(Y_j - X_j\right), \left|Y_j - Y_i\right| > \left|X_j - X_i\right|$ where X and Y represent agent's prior and posterior belief respectively and *i* and *j* represent the agents.

Panel A: Flip			
Agent	*Prior Beliefs (X)*	*Posterior Beliefs (Y)*	*Sign(Y – X)*
i	8	4	(-)
j	4	8	(+)
i-j	4	-4	
Panel B: Divergence			
Agent	*Prior Beliefs (X)*	*Posterior Beliefs (Y)*	*Sign(Y – X)*
i	8	4	(-)
j	4	10	(+)
|*j-i*|	4	6	

Bamber, Barron and Stober (1999), hereafter BBS(1999), extend KP(1995) by categorizing equations (3.1) and (3.2) as inconsistent reactions to information where one agent interprets information as 'good' and the other interprets it as 'bad'. BBS(1999), however, show that agents can have consistent reactions to information (both 'good' or both 'bad') but still have flips and divergences in beliefs. In addition, they illustrate the convergence of beliefs in response to new information.

I examine these three types of belief revisions outlined in prior research: 'flips', 'divergences' and 'convergences'. Further, I expand my analysis to address the impact of these belief revisions on market liquidity as opposed to only trading volume. I show that the level of market liquidity following new information is a function of the change in the overlap in the probability distributions that represent buyer and seller reservation prices. This theory provides further definition to prior empirical findings that indicate that differential interpretations of information (whether consistent or inconsistent) alone impact trading volume. Instead, this theory predicts that the change in the degree of belief dispersion predicts market liquidity.

3.1.2. Assumptions

In my two-period model, there is one traded asset that is in fixed supply and three types of market participants: buyers, sellers and a trade-maximizing specialist. This model is loosely based on the model developed in Karpoff (1986). There are no transactions costs, dividends or interest payments. In the first period (t=0), buyers do not own any units of the traded asset while sellers are endowed with one unit. Also, because buyers and sellers can hold only zero or one unit of the traded asset in either period, short-selling is not allowed[5]. The function of the specialist is only to act as an auctioneer or facilitator matching the buy and sell orders. Therefore, the specialist does *not* hold any units of the traded asset in either period and therefore does not buy or sell from his/her own inventory in order to ensure market liquidity or maintain order[6].

Buyers and sellers are heterogeneous in their personal valuation of the asset either due to asymmetric information or differences in the interpretation of identical information across participants. Based on his/her individual valuation of the asset, each buyer and seller sets his/her first-period (t=0) reservation price. Dispersion in initial reservation prices (p_0), therefore, can indicate differences in expectations, risk

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[5] This assumption serves to ensure that the populations strictly represent either buyers or sellers. However, I realize that this assumption is not realistic in a practical sense. Also, according to Miller (1977) and Deither et. al. (2002) whenever market participants with lower valuations of an asset are constrained (that is, they are prohibited from short selling), prices are biased upward because they reflect only the trades of the market participants with higher valuations and volume is therefore biased downward.

[6] This market system is essentially a double call auction market where market participants submit limit orders to the specialist once each period. In continuous time, this assumption can be generalized to liken the market to a double continuous call auction market where the specialist only sets the starting price.

preferences or 'informedness'[7]. Buyers and sellers communicate these reservation prices to the market in the form of limit orders submitted to the specialist. These prices are assumed to be lognormally distributed. If the logarithms of the buyer and seller prices are plotted, they resemble two bell-shaped curves that may or may not overlap. Comparatively, these distributions can be described in terms of their respective means and variances. Therefore, a pair of buyer/seller reservation price (limit order) distributions can be classified in one of four ways: 1) equal means, equal variances, 2) equal means, unequal variances, 3) unequal means, equal variances and 4) unequal means, unequal variances. It is important to note that the case where the two population distributions have equal means and equal variances will have the greatest amount of overlap because the two distributions will be identical. Therefore, this case represents the highest probability of trade.

Figures 1 through 4 provide examples of these cases.

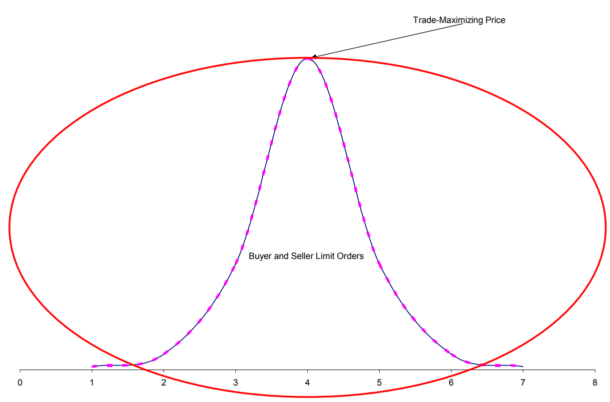

Figure 1: Distributions of Buyer and Seller Orders with Equal Means and Equal Variances

This figure illustrates the distributions of buyer and seller limit orders with equal means and equal variances. The specialist will set the trade-maximizing price at the point where the distributions of buyer and seller limit orders intersect. Only orders that lie in the circled region of overlap between the two distributions will be executed.

[7] See Holthausen and Verrecchia (1990) for a detailed explanation of informedness.

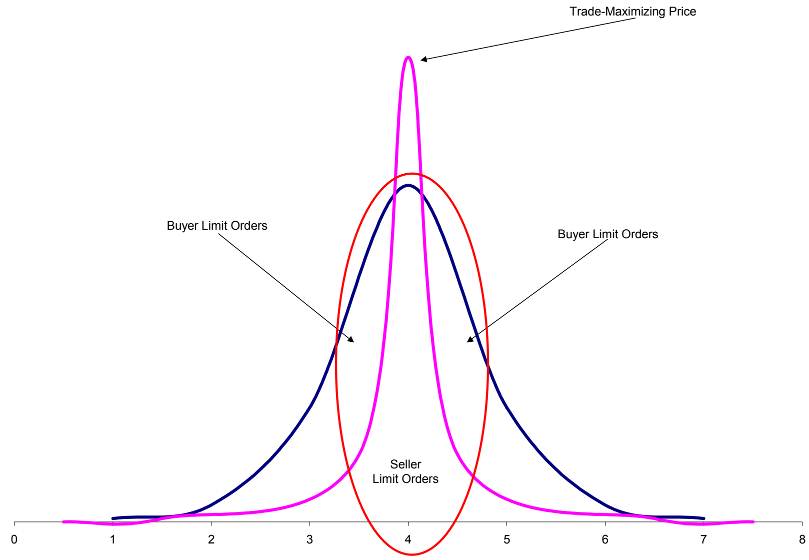

Figure 2: Distributions of Buyer and Seller Orders with Equal Means and Unequal Variances

This figure illustrates the distributions of buyer and seller limit orders with equal means and unequal variances. The specialist will set the trade-maximizing price at the point where the distributions of buyer and seller limit orders intersect. Only orders that lie in the circled region of overlap between the two distributions will be executed.

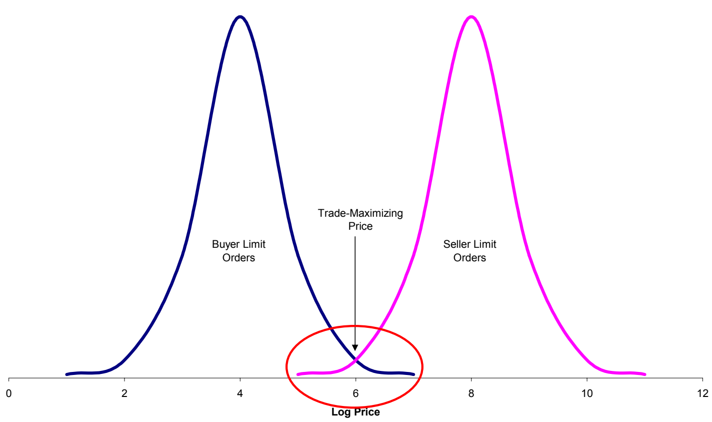

Figure 3: Distributions of Buyer and Seller Orders with Unequal Means and Equal Variances

This figure illustrates the distributions of buyer and seller limit orders with unequal means and equal variances. The specialist will set the trade-maximizing price at the point where the distributions of buyer and seller limit orders intersect. Only orders that lie in the circled region of overlap between the two distributions will be executed.

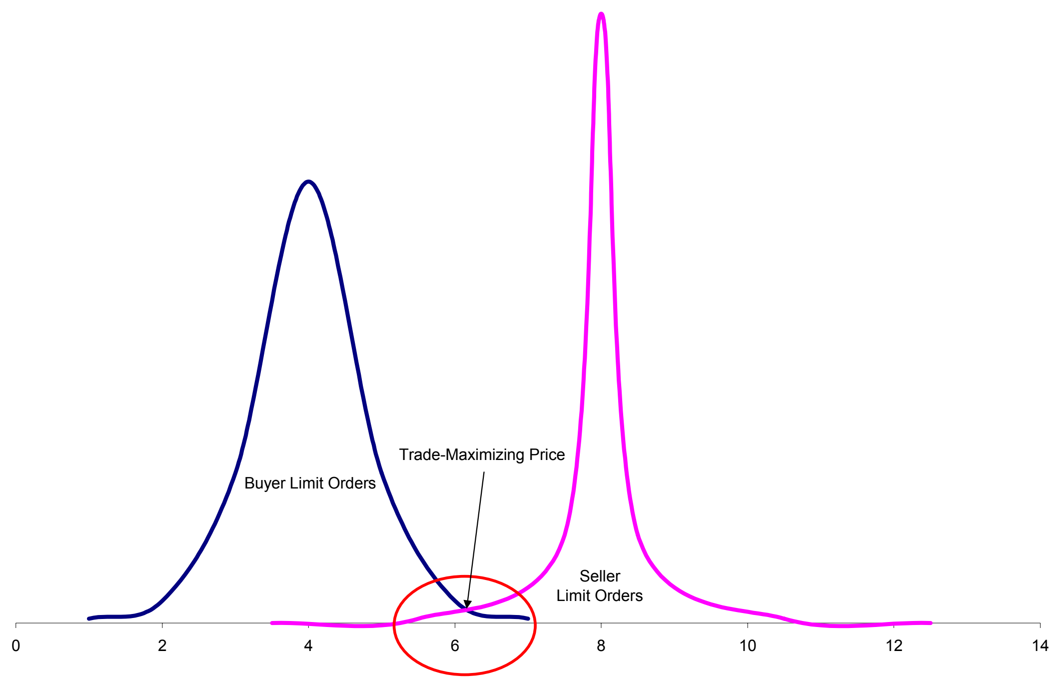

Figure 4: Distributions of Buyer and Seller Orders with Unequal Means and Unequal Variances

This figure illustrates the distributions of buyer and seller limit orders with unequal means and unequal variances. The specialist will set the trade-maximizing price at the point where the distributions of buyer and seller limit orders intersect. Only orders that lie in the circled region of overlap between the two distributions will be executed.

3.1.3. Trading

The specialist compiles the buy and sell orders in a limit order book and executes all marketable trades. The specialist sets a price that will maximize the number of executed orders. I refer to this price as 'trade-maximizing' as opposed to 'market-clearing' to emphasize the fact that not necessarily *all* orders that fall in the region of intersection (R) between buyer and seller orders will be executed. This is because order imbalance (quantity of buy orders not equal to quantity of sell orders) may exist. Alternatively, R can be interpreted as the proportion of total possible trades in the limit order book that actually occur. However, an order will *only* be executed if it lies in this region. In the case depicted in Figure 4, for example, the specialist will set the trade-maximizing price between 5.5 and 7.0. Table II shows a portion of the limit order book that generates the probability distributions depicted in Figure 4.

Table II: Trade-Maximizing Specialist's Limit Order Book

This table gives an example of the ten 'best' orders in the trade-maximizing specialist's limit order book. All buy orders are sorted in descending order from highest bid price to lowest bid price and all sell orders are sorted in ascending order from lowest ask price to highest ask price. The specialist will set a price that maximizes the number of executable trades.

Order Number	*Buy Orders*	*Sell Orders*
1	7.0	5.5
2	6.0	7.5
3	6.0	7.5
4	6.0	7.5
5	6.0	7.5
6	6.0	7.5
7	5.0	7.5
8	5.0	7.5
9	5.0	7.5
10	5.0	7.5

From Table II, it is clear that the prices in R are between 5.5 and 7.0 and the specialist will set the price within this range. Therefore, only the first order in the book will be executed[8]. When the distributions have equal means, the price will be set at that mean value. When the distributions have unequal means, the optimal price can be determined mathematically. Because trade is restricted to R, the area of R represents the probability that a trade will occur. The point at which the two distributions intersect can be determined by setting the probability density functions (pdfs) of the buy and sell order

[8] Of course, the specialist may create a market imbalance depending upon where he/she sets the price. If the specialist were required to maintain 'order' in the market, he/she would have to fill orders using his/her own inventory. That is, if he/she sets the price less than or equal to 6.0 in this example, buy orders two through six would represent unmet demand. The specialist, then, would be required to step in and fill these orders from his own inventory. For simplicity, my model does not impose this requirement on the specialist.

distributions equal to each other and solving for the point at which they intersect (x). Under the assumption of lognormally distributed prices, the pdfs of the logarithms of buyer and seller prices follow the normal distribution which has the following form:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)}, -\infty < x < \infty \tag{3.3}$$

In the example depicted in Figure 4, the logged buyer prices are distributed $N \sim (4,14.06)$ and the logged seller prices are distributed $N \sim (8, 1.18)$. Solving the equation for x

$$\frac{1}{\sqrt{14.06}\sqrt{2\pi}} e^{\left(\frac{-(x-4)^2}{2(14.06)}\right)} = \frac{1}{\sqrt{1.18}\sqrt{2\pi}} e^{\left(\frac{-(x-8)^2}{2(1.18)}\right)} \tag{3.4}$$

gives two results (x = 6.57 and 10.15) indicating that the distributions intersect in two places. The intersection point that lies within the region of consensus must take a value that is between the means of the two distributions. Thus, the trade-maximizing price in this example is 6.57. The area of R is the sum of the area under the intersecting tails of the two distributions. That is,

$$R = \int_{-\infty}^{x} f(x) = \frac{1}{\sigma_S\sqrt{2\pi}} e^{\left(\frac{-(x-\mu_S)^2}{2\sigma_S^2}\right)} dx + \int_{x}^{+\infty} f(x) = \frac{1}{\sigma_B\sqrt{2\pi}} e^{\left(\frac{-(x-\mu_B)^2}{2\sigma_B^2}\right)} dx, -\infty < x < \infty \tag{3.5}$$

where the first integral references the sell order distribution and the second integral references the buy order distribution. In the example depicted in Figure 4, the probability of a transaction as indicated by the area of R is 35%. This results from a 10% probability that a sell order will lie in the lower tail of the seller price distribution and a 25% probability that a buy order will lie in the upper tail of the buyer price distribution.

Because this portion of the two tails overlap or cross, the overall probability that an order will be executed is the sum of these two probabilities which is 35%.

3.1.4. Belief Revisions

Between periods, buyers and sellers receive new information and revise their individual reservation prices accordingly. They communicate these belief revisions to the specialist through new limit orders. The resulting change in market liquidity depends upon the change in the area of R. If the area of R increases (decreases), market liquidity is expected to increase (decrease).

Key characteristics of buyer and seller belief revisions affect trading. These are homogeneity versus heterogeneity, convergence versus divergence and the relative magnitude of the revisions. There are 11 observable combinations of these characteristics. First, homogeneous (consistent) belief revisions indicate that both the buyers and sellers revise their reservation prices in the same manner (either both upward or both downward). Heterogeneous (inconsistent) belief revisions indicate that buyers and sellers revise their reservation prices in opposite directions. Second, the distance between the mean buyer and seller reservation prices (limit orders) can either increase, decrease or remain constant. An increase in this distance indicates that the dispersion across these two groups is increasing -- implying a divergence of beliefs. A decrease in this distance indicates that dispersion across these two groups is decreasing – implying a convergence of beliefs. Third, the magnitude of the belief revisions can be such that the buyers in period t_0 have the higher reservation price for the asset in period t_1. Figures 5 – 15 illustrate these 11 cases. These figures all illustrate belief revisions relative to the same set of prior beliefs which are those depicted in Figure 3. In this case, the buy and sell order distributions have unequal means, but equal variance.

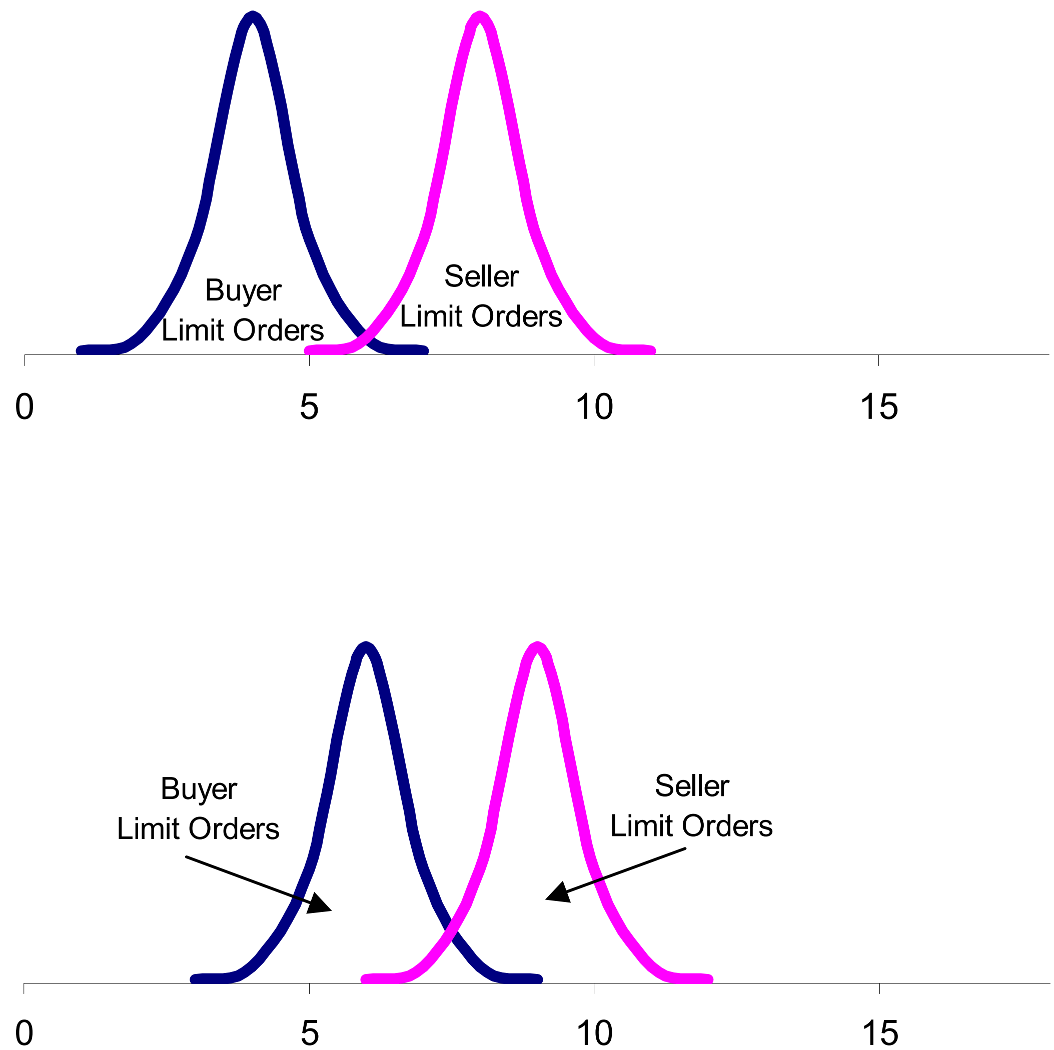

Figure 5: Consistent Convergent Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward) and the distance between the two means decreases.

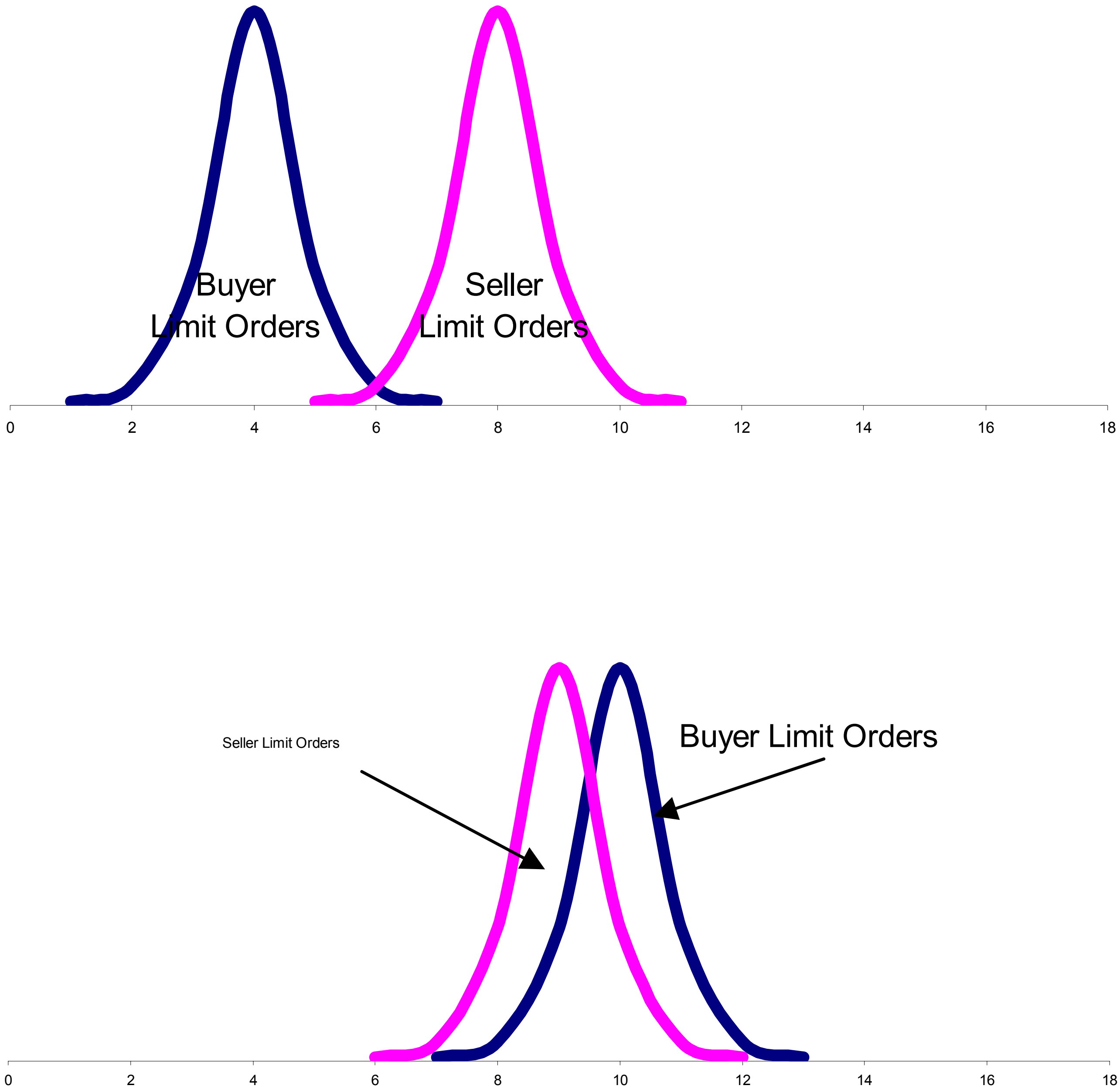

Figure 6: Consistent Convergent Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward) and the distance between the two means decreases. However, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers.

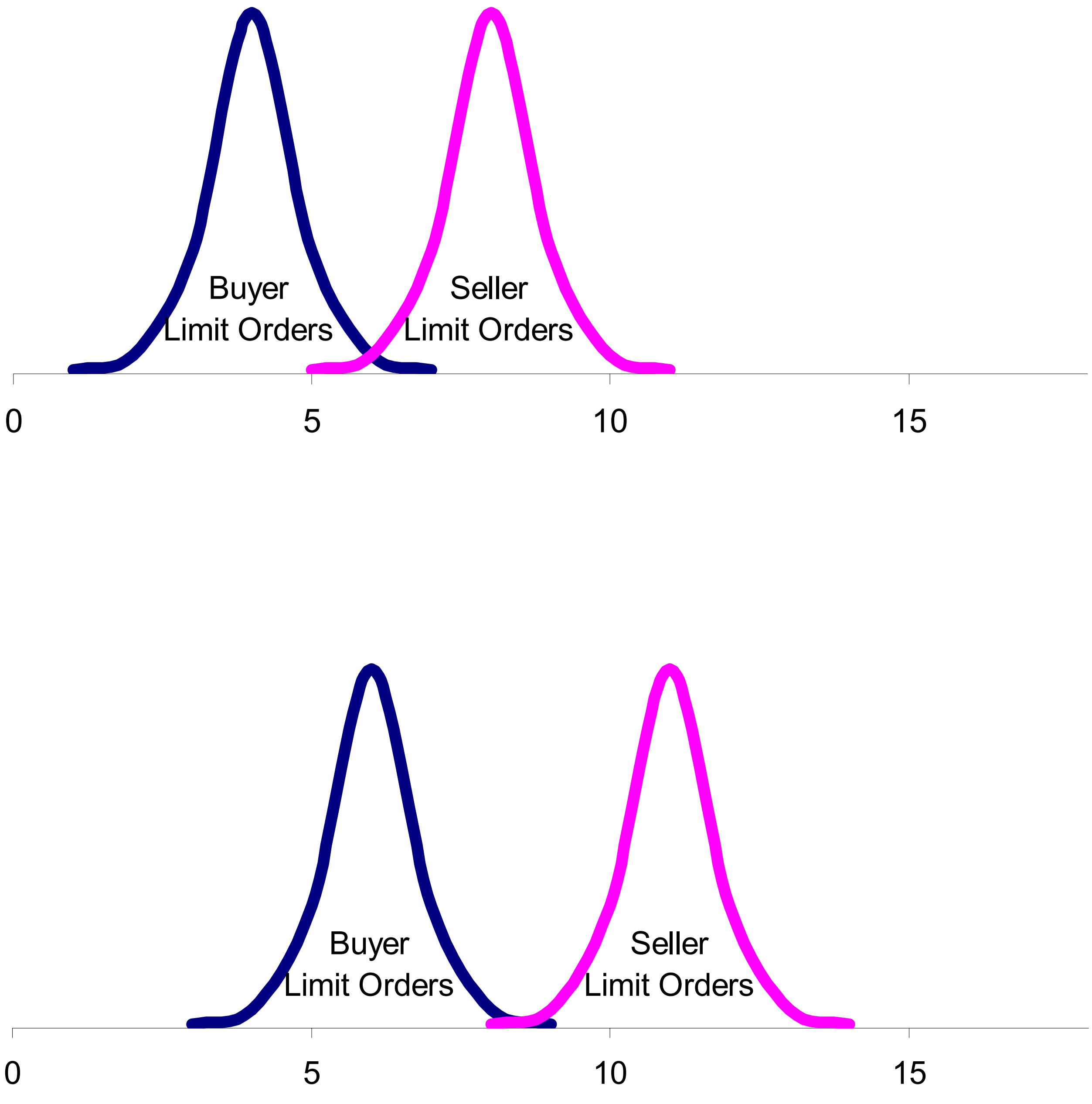

Figure 7: Consistent Divergent Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward) but the distance between the two means increases.

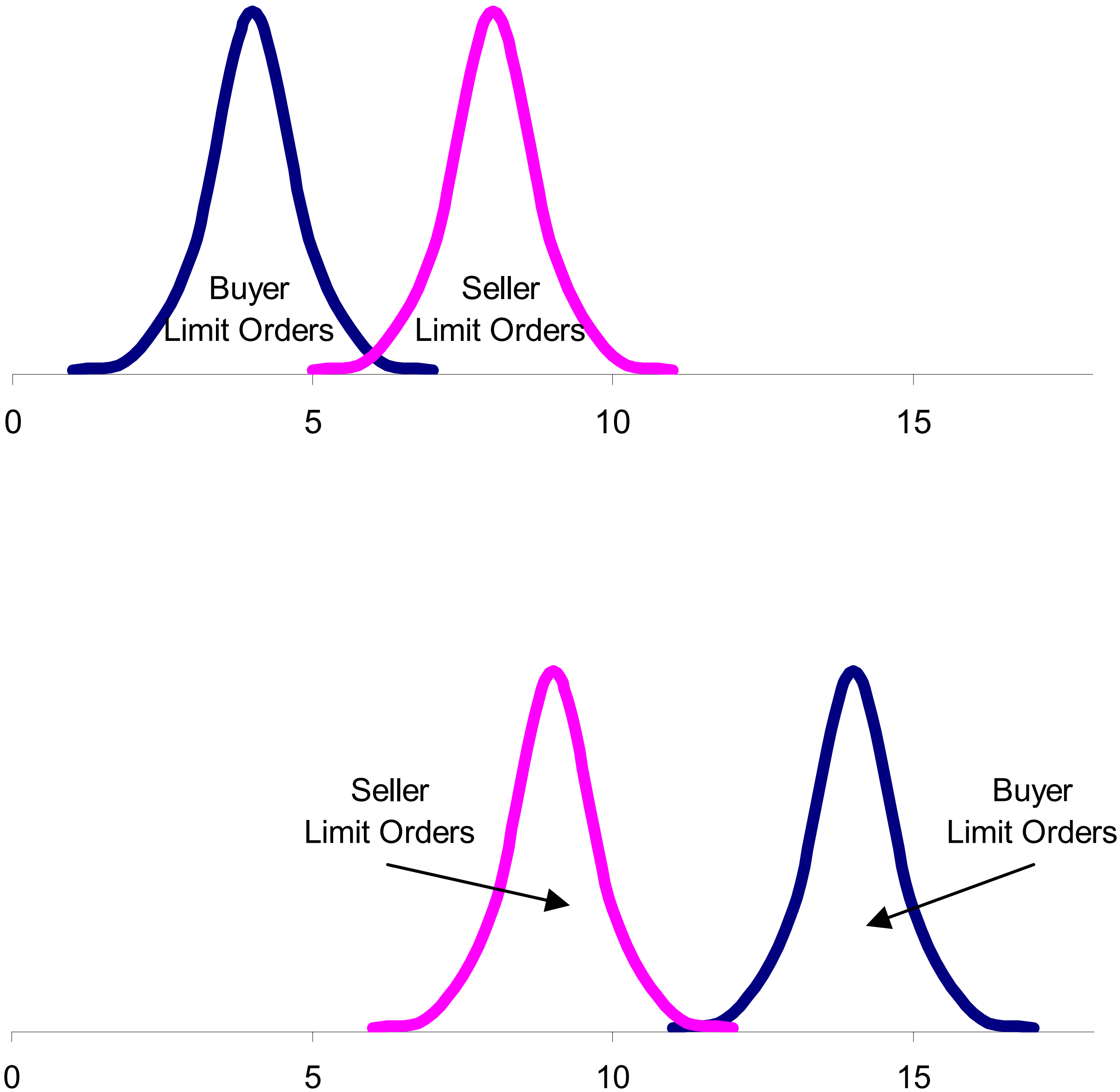

Figure 8: Consistent Divergent Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward) but the distance between the two means increases. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers.

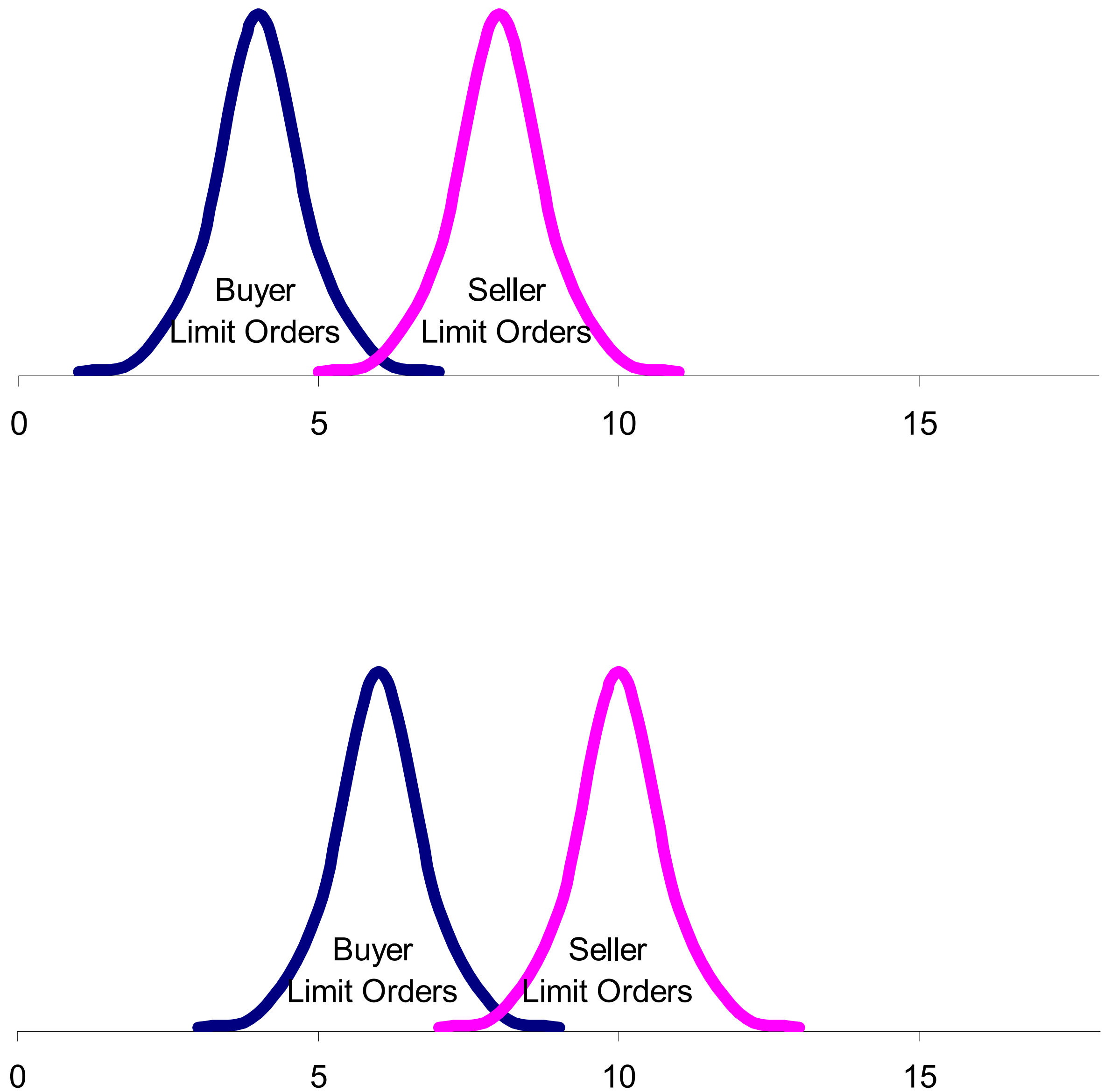

Figure 9: Consistent Constant Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward) and the distance between the two means does not change.

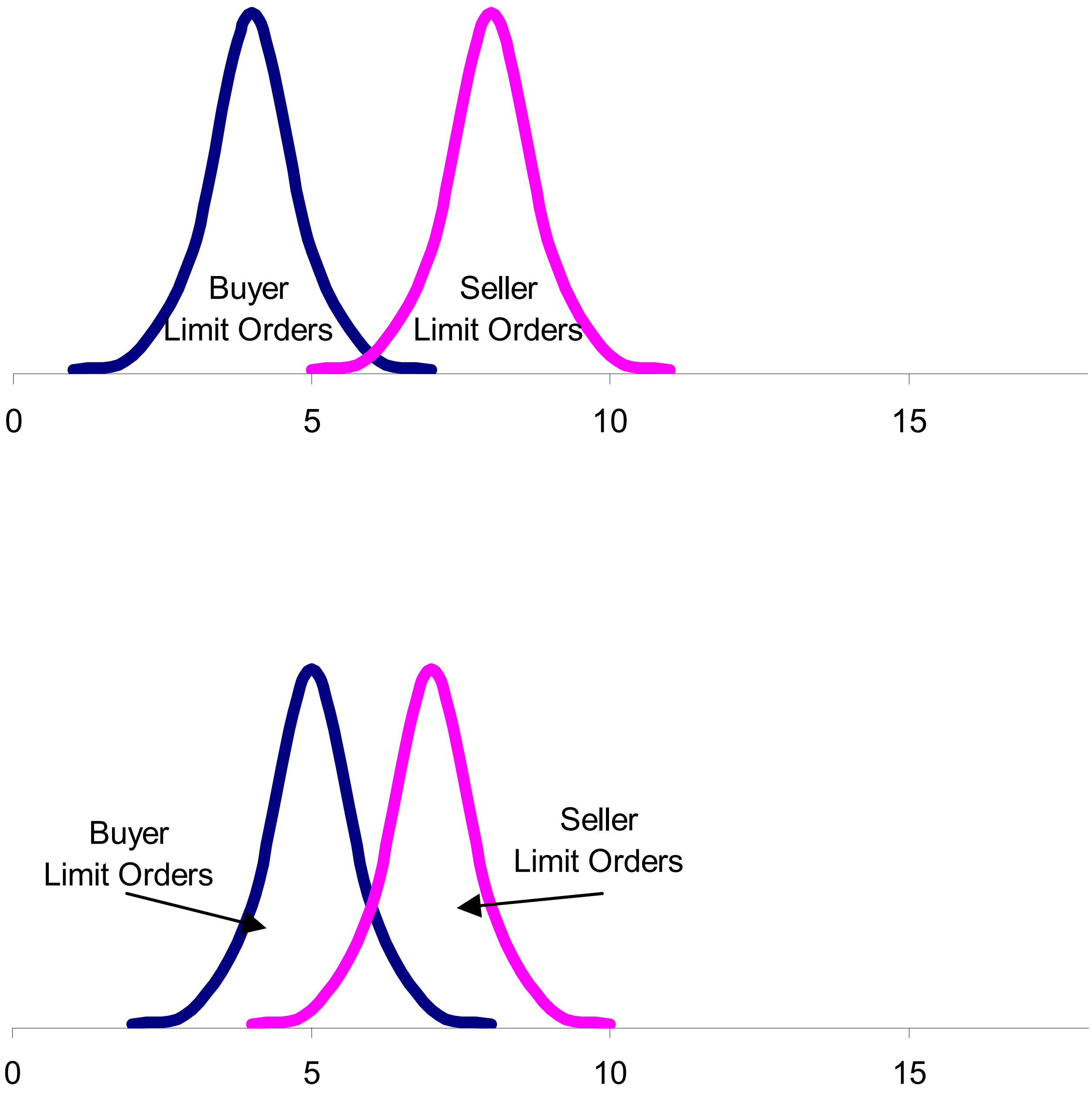

Figure 10: Inconsistent Convergent Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, the distributions move in opposite directions but the distance between the two means decreases. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers

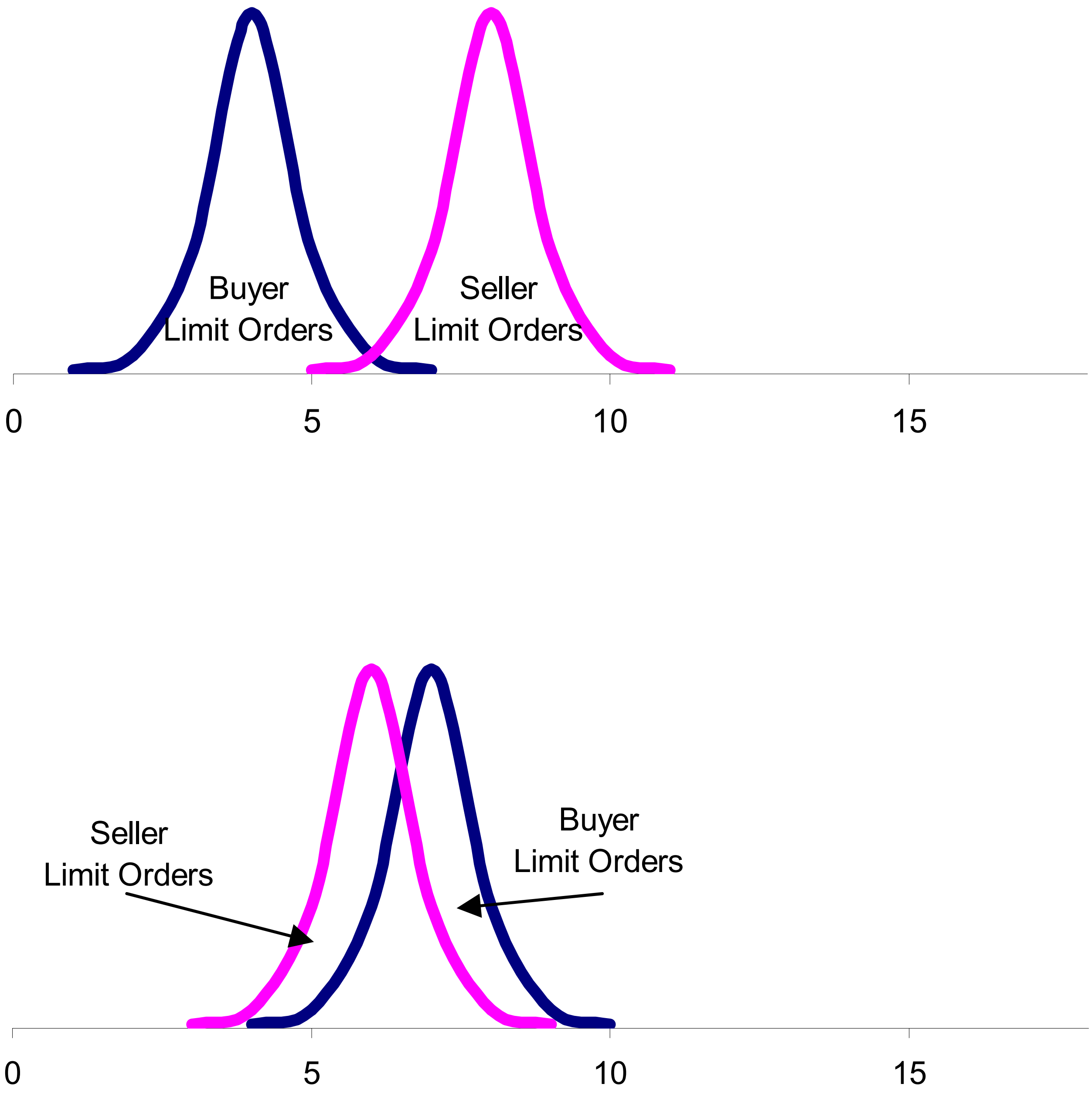

Figure 11: Inconsistent Convergent Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, the distributions move in opposite directions but the distance between the two means decreases. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers

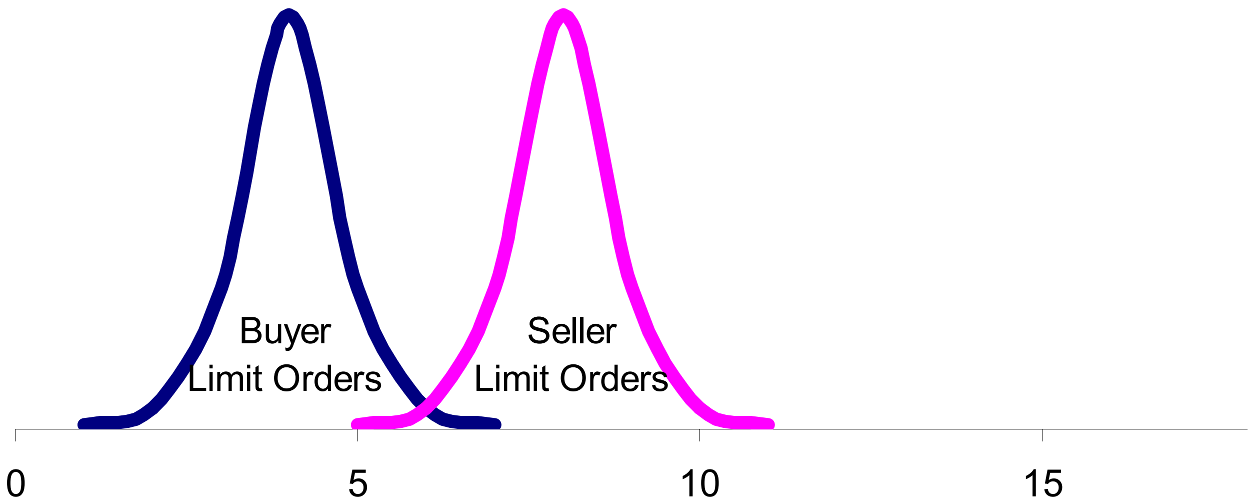

Figure 12: Inconsistent Divergent Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, the distributions move in opposite directions and the distance between the two means increases.

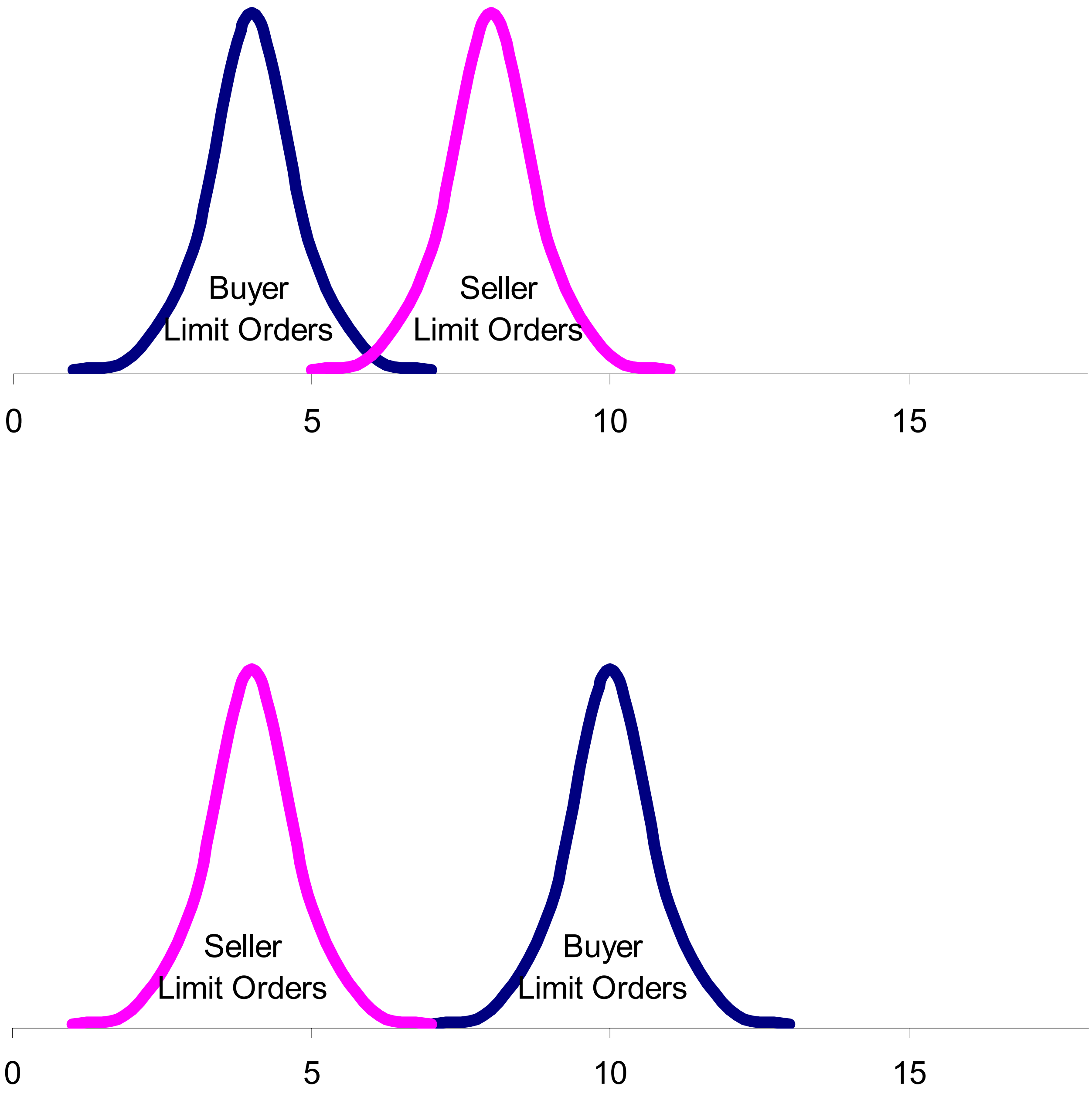

Figure 13: Inconsistent Divergent Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, the distributions move in opposite directions and the distance between the two means increases. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers.

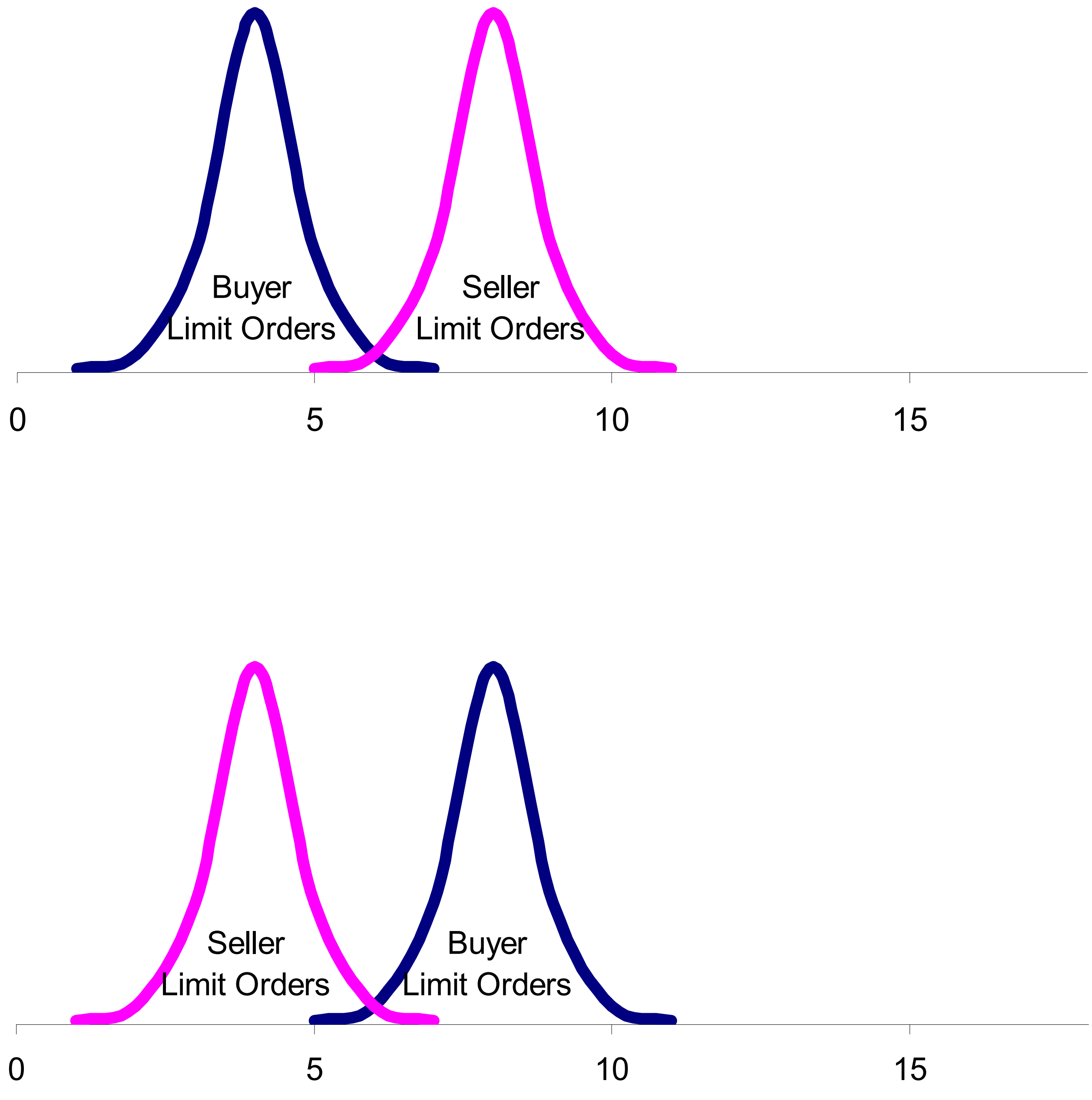

Figure 14: Inconsistent Constant Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, the distributions move in opposite directions but the distance between the two means does not change. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers.

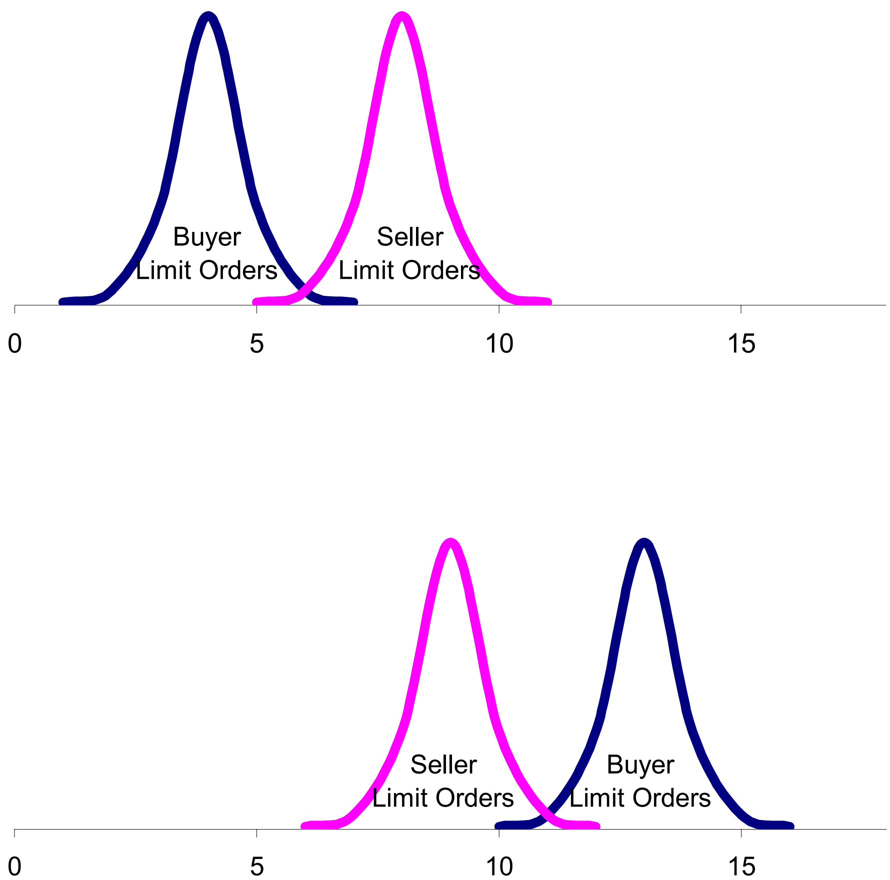

Figure 15: Consistent Constant Flip Belief Revisions

This figure shows investor belief revisions across time periods as represented by their corresponding limit orders. In this case, both distributions move in the same direction (upward), and the distance between the two means does not change. Also, the magnitude of the revisions is such that the buyers have a higher mean posterior belief than the sellers.

The main predictions of the model (assuming that the means of the buyer and seller price distributions change, but the variances do not) are as follows.

PROPOSITION 1: The probability of a transaction between a buyer and a seller at any point in time is a function of the area of the region of overlap of their corresponding reservation price distributions.

PROPOSITION 2: If buyers and seller revise their reservation prices in a consistent manner the change in volume, is a function of the magnitude of the revisions.

COROLLARY 1: If buyers and sellers revise their reservation prices in a consistent manner, but the difference in their mean reservation prices decreases (because the mean buyer revision is greater than the mean seller revision), volume will increase on the interval t= (0, 1).

This is the case of consistent convergence (depicted in Figure 5) and documents the case of two market participants that both revise their beliefs in the same manner (either both upward or both downward) resulting in a decrease in across-group dispersion.

COROLLARY 2: If buyers and sellers revise their reservation prices in a consistent manner, the difference in their mean reservation prices decreases and the mean buyer price in t=1 is greater than the mean seller price in t=1, volume will increase on the interval t= (0, 1) more so than if the mean buyer price in t=1 is not greater than the mean seller price in t=1 as in Corollary 1.

This is the case of a consistent convergent flip and is depicted in Figure 6. In this case, two market participants revise their beliefs in the same direction and dispersion decreases (consensus increases), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

COROLLARY 3: If buyers and sellers revise their reservation prices in a consistent manner, but the difference in their mean reservation prices increases (because the mean seller revision is greater than the mean buyer revision), volume will decrease on the interval t= (0, 1).

This is the case of consistent divergence (depicted in Figure 7), which documents the case of two market participants that both revise their beliefs in the same manner (either both upward or both downward) resulting in an increase in dispersion.

COROLLARY 4: If buyers and sellers revise their reservation prices in a consistent manner, the difference in their mean reservation prices increases and the mean buyer price in t=1 is greater than the mean seller price in t=1, volume will increase on the interval t= (0, 1).

This is the case of a consistent divergent flip and is depicted in Figure 8. In this case, two market participants revise their beliefs in the same direction and dispersion increases (consensus decreases), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

COROLLARY 5: If seller reservation prices change by the same amount as buyer reservation prices, volume will be unchanged on the interval t=(0,1).

This is the case of a consistent constant revision which is depicted in Figure 9. Here, buyers and sellers revise their reservation prices in the same direction (either both upward or both downward) and by the same amount.

COROLLARY 6: If buyers and sellers revise their reservation prices in a consistent manner, the difference in their mean reservation prices does not change and the mean buyer price in t=1 is greater than the mean seller price in t=1, volume will increase on the interval t= (0, 1).

This is the case of a consistent constant flip and is depicted in Figure 15. In this case, two market participants revise their beliefs in the same direction and dispersion remains constant (the degree of consensus does not change), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

PROPOSITION 3: If buyers and sellers revise their reservation prices in an inconsistent manner, the resulting change in volume is a function of the magnitude of the revisions.

COROLLARY 1: If buyers and sellers revise their reservation prices in an inconsistent manner, but the difference in their mean reservation prices decreases (because the mean buyer revision is greater than the mean seller revision), volume will increase on the interval t= (0, 1).

This is the case of inconsistent convergence which is depicted in Figure 10 and was first noted by KP(1995). It documents the case of two market participants who revise their beliefs such that the participant with the higher valuation of the asset revises his/her valuation downward and the participant with the lower valuation revises upward resulting in a decrease in dispersion.

COROLLARY 2: If buyers and sellers revise their reservation prices in an inconsistent manner, the difference in their mean reservation prices decreases and the mean buyer price in t=1 is greater than the mean seller price in t=1, volume will increase on the interval t= (0, 1) more so than if the mean buyer price in t=1 is not greater than the mean seller price in t=1 as in Corollary 1.

This is the case of an inconsistent convergent flip, depicted in Figure 11 in which the buy order and sell order distributions change places. In this case, two market participants revise their beliefs in opposite directions and dispersion decreases (consensus increases), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

COROLLARY 3: If buyers and sellers revise their reservation prices in an inconsistent manner, but the difference in their mean reservation prices increases (because the mean seller revision is greater than the mean buyer revision), volume will decrease on the interval t= (0, 1).

This explains inconsistent divergence (depicted in Figure 12) and documents the case of two market participants revising their beliefs such that the participant with the higher valuation of the asset revises his/her valuation upward and the participant with the lower valuation revises downward resulting in a decrease in dispersion. The result of this case of belief revisions is an increase in dispersion across groups as the distance between the two belief distributions increases.

COROLLARY 4: If buyers and sellers revise their reservation prices in an inconsistent manner, the difference in their mean reservation prices increases and the mean buyer price in t=1 is greater than the mean seller price in t=1, volume will increase on the interval t= (0, 1).

This is the case of an inconsistent divergent flip, depicted in Figure 13 in which the buy order and sell order distributions change places. In this case, two market participants revise their beliefs in opposite directions and dispersion increases (consensus decreases), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

COROLLARY 5: If sellers revise their reservation prices downward and buyers revise their beliefs upward by an amount exactly equal to the difference in their t=0 reservation prices, volume will be unchanged on the interval t=(0,1).

This is the case of an inconsistent constant flip, depicted in Figure 14 in which the buy order and sell order distributions change places. In this case, two market participants revise their beliefs in opposite directions and dispersion remains constant (the degree of consensus does not change), but the magnitude of the revisions are such that the valuations cross and the participant with the higher prior valuation has the lower posterior valuation and vice versa.

In summary, a pair of belief revisions can be either consistent or inconsistent depending on whether or not the market participants have homogeneous or heterogeneous interpretations of new information and these beliefs can either converge or diverge resulting in a decrease or increase in dispersion respectively. Graphically, consistent (inconsistent) revisions are marked by buyer and seller price distributions with a greater (lesser) amount of overlap than was observable prior to the belief revision. The consistency (or inconsistency) of belief revisions alone does not predict changes in market liquidity. Instead, the joint effect of the consistency of belief revisions and the magnitude of those belief revisions are predictors of changes in market liquidity. Table III shows the change in the probability of trade due to the changes in the distributions of buyer and seller prices in all 11 belief revision cases illustrated in Figures 5 – 15.

Table III: Change in the Probability of Trade due to Specific Types of Belief Revisions

This table documents the change in the probability of trade based on the examples illustrated in Figures 5 – 14.

Panel A: t=0						
Type of Belief Revision	*Mean*		*Standard Deviation*		*Intersection (x)*	*Probability of Trade*
	Buy	*Sell*	*Buy*	*Sell*		
All Cases	4	8	3.75	3.75	6.0	60%
Panel B: t=1						
Type of Belief Revision	*Mean*		*Standard Deviation*		*Intersection (x)*	*Probability of Trade*
	Buy	*Sell*	*Buy*	*Sell*		
Consistent Convergent	6.0	9.0	3.75	3.75	7.5	68%
Consistent Convergent Flip	10.0	9.0	3.75	3.75	9.5	90%
Consistent Divergent	6.0	11.0	3.75	3.75	8.5	50%
Consistent Divergent Flip	14.0	9.0	3.75	3.75	11.5	50%
Consistent Constant	6.0	10.0	3.75	3.75	8.0	60%
Inconsistent Convergent	5.0	7.0	3.75	3.75	6.0	78%
Inconsistent Convergent Flip	7.0	6.0	3.75	3.75	6.5	90%
Inconsistent Divergent	3.0	9.0	3.75	3.75	6.0	42%
Inconsistent Divergent Flip	10.0	4.0	3.75	3.75	7.0	42%
Inconsistent Constant Flip	8.0	4.0	3.75	3.75	6.0	60%
Consistent Constant Flip	13.0	9.0	3.75	3.75	11.0	60%

From these examples, it appears that the convergence of beliefs has the strongest and most consistent impact on the probability of trading. In the four cases of divergent belief revisions, the probability of trading decreases. In the two cases of constant belief revisions, the probability of trading is unchanged. In the four cases of convergent belief revisions, the probability of trading increases. The other two characteristics of belief revisions, consistency versus inconsistency and the flipping phenomena produce unstable results. That is, the impact of these characteristics on the probability of trading is less clear.

3.2. Testable Hypotheses

The propositions discussed in the previous section lead to the following testable hypotheses. First, I address the base notion that there is an inverse relation between market liquidity and overall dispersion. That is, I hypothesize that as the overall variance in investor beliefs increases, market liquidity decreases. The underlying intuition is that market liquidity occurs because actual investor beliefs are clustered around consensus – that point at which all investors have identical beliefs regarding an asset's true value. In the absence of liquidity traders, trading would not occur when there is complete consensus because either all investors have no desire to own the traded asset or all investors wish to own the traded asset. In this rare instance it would be impossible for a transaction to occur. Instead, I hypothesize that investor beliefs tend to cluster *around* consensus. The more tightly these beliefs are clustered, the more investors will transact. As these beliefs stray from consensus, I expect market liquidity to decrease. Therefore, I hypothesize that:

H$_1$: There is an inverse relation between overall dispersion and market liquidity.

An underlying assumption of Karpoff (1986) is that owners of an asset have higher reservation prices for an asset than non-holders. Because this is a necessary and sufficient condition for my hypotheses, this statement is a data requirement for empirical tests. For example, when classifying investors, those with higher reservation prices would then be classified as holders and those with lower reservation prices would be classified as non-holders.

Figure 16 shows a graphic representation of this requirement where non-holders have a mean reservation price of four units and holders have a mean reservation price of eight units.

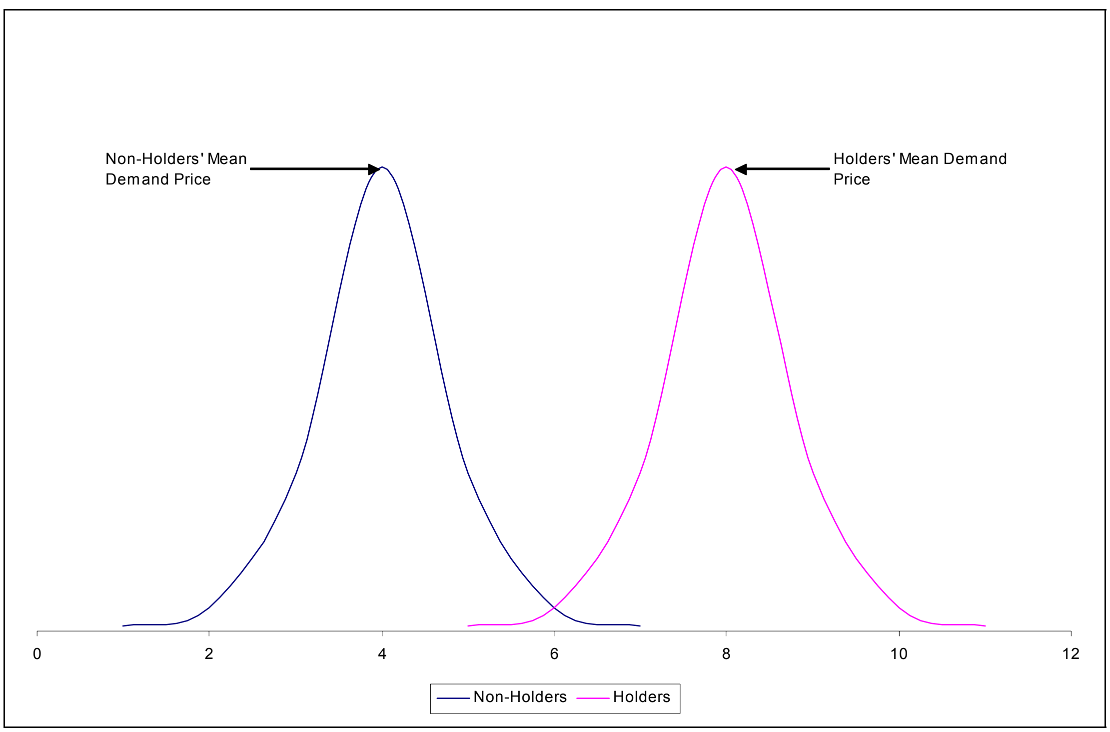

Figure 16: Comparison of Holder versus Non-Holder Reservation Prices

This figure shows the distribution of reservation prices for investors that hold a particular asset as compared to the distribution of reservation prices for investors that do not hold a particular asset.

Karpoff (1986) considers the impact of differential priors and differential interpretations of new information separately. To consider the impact of differential interpretations on trading volume, he assumes homogeneous prior beliefs. Here, a group of individuals with the same beliefs trade because some new piece of information introduced to the market has caused belief dispersion within this group. With respect to the framework of holders and non-holders, this means that within the holders (non-holders) group an increase in the dispersion of beliefs causes trading volume to increase. I expect that increased dispersion within groups increases trading[9]. This argument is the basis for my second hypothesis:

H_2: Within-group dispersion and volume are positively related.

Figure 17 shows a graphic representation of this hypothesis using the non-holders from Figure 16. Recall that this group has a mean reservation price of 4 units. In Figure 17, the variance of the reservation price distribution is initially 4 units, but increases to 6.25 units.

To consider the impact of differential priors, Karpoff (1986) assumes homogeneous interpretations of information. Here, two groups of individuals with different beliefs trade because some new piece of information introduced to the market has caused them to revise their beliefs. That is, the dispersion of beliefs across these two groups has changed. With respect to the framework of holders and non-holders, this means that if non-holders change their beliefs more than holders, volume will increase, and if holders change their beliefs more than non-holders, volume will decrease.

[9] I state this hypothesis with respect to *increased* trading as opposed to simply trading to account for the fact that liquidity (noise) traders are a constant within the framework of this model and therefore some level of trading is always present in the market. Liquidity traders, then, account for part of the "jumbling" of reservation prices in the Karpoff (1995) model.

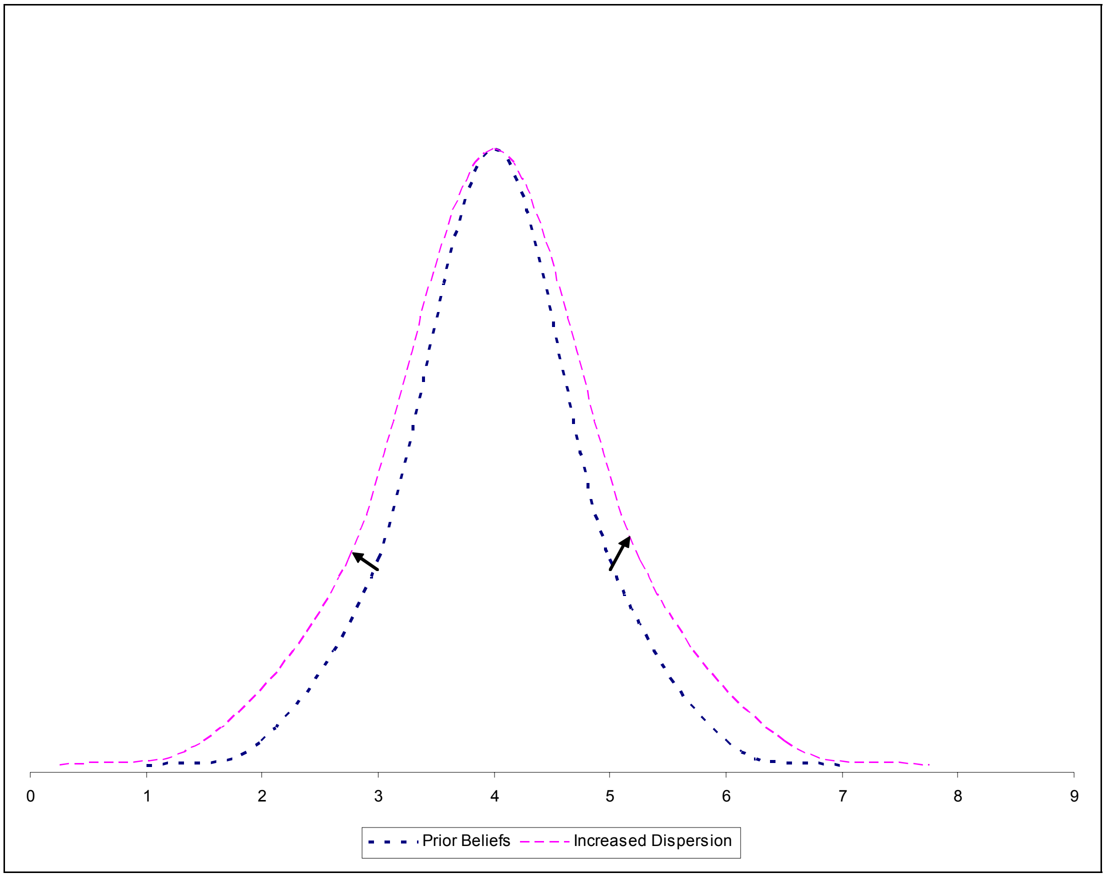

Figure 17: An Increase in Within Group Reservation Price (Belief) Dispersion

This figure shows the change in the distribution of reservation prices for investors that hold a particular asset when the mean reservation price remains constant but the dispersion (standard deviation) increases.

The direction of the revision is also relevant to the change in volume. For example, if holders have an initial valuation of $8 while non-holders have an initial valuation of $4, if both holders and non-holders revise their valuations and the amount of the revision is unequal, there are three possible scenarios:

1) Both could revise upward. If non-holders revise more, say from $4 to $8 while holders revise only from $8 to $10, the difference in valuations across the groups will decrease from $4 to $2 resulting in an increase in volume.

2) Both could revise downward. If non-holders revise from $4 to $0 while holders revise from $8 to $6, in arithmetic terms, holders are revising more than non-holders because -2 are greater than -4. In this case, the difference in valuations across the groups will increase from $4 to $6 resulting in a decrease in volume.

3) The two groups could revise in opposite directions. That is, one group revises upward and one group revises downward. If, for example, non-holders revise from $4 to $8 while holders revise from $8 to $6, in arithmetic terms, non-holders are revising more than holders because +4 is greater than -2. In this case, the difference in valuations will decrease from $4 to $2 resulting in an increase in volume.

In this case, the information is perceived identically, however the volume reaction is due to the differences in the priors of the two groups. That is, holders will react less to good information and more to bad information. Conversely, non-holders will react more to good information and less to bad information. These expected behaviors are due to the fact that good information merely confirms the prior beliefs of the holders and bad information confirms the prior beliefs of the non-holders. Therefore, non-holders are expected to change their beliefs more than holders after good information is introduced to the market and holders are expected to change their beliefs more than non-holders after bad information is introduced to the market. If good information is introduced to the market confirming holders' prior beliefs, non-holders will raise their bid prices substantially while holders will make minimal revisions and therefore the probability of exchange (and subsequently actual market liquidity) between holders and non-holders will increase.

Using across group dispersion as a measure of these belief revisions, this means that an increase in dispersion is related to a decrease in market liquidity and a decrease in dispersion is related to an increase in market liquidity. Therefore, I hypothesize (stated alternatively) that:

> H_3: Changes in the dispersion in beliefs across the holders and non-holders group are related to market liquidity.
>
> > H_{3a}: A decrease in the dispersion of beliefs across the holders and non-holders groups is positively related to market liquidity.
> >
> > H_{3b}: An increase in the dispersion of beliefs across the holders and non-holders groups is negatively related to market liquidity.

Figures 18 and 19 show graphic representations of H_{3a} and H_{3b} respectively assuming upward reservation price revisions by both holders and non-holders. This hypothesis expects that as the difference in means between the two sub-populations (holders and non-holders) becomes smaller, market liquidity increases. Therefore, comparing the difference in means in the prior period to the difference in means in the current period tests this hypothesis. This hypothesis requires that the difference in the differences (or the change in the difference in means) is inversely related to market liquidity.

Kandel and Pearson (1995) and Bamber, Barron and Stober (1997) provide evidence, however, that these homogeneous interpretations of information are unrealistic. They document cases where analysts have heterogeneous interpretations of new information. They label these cases "flips" and "divergences" as discussed previously. H_2, however, would still capture these phenomena, because it considers changes in the actual (not absolute) difference in population means. Figures 18 and 19 illustrate the case of homogeneous interpretations for simplicity.

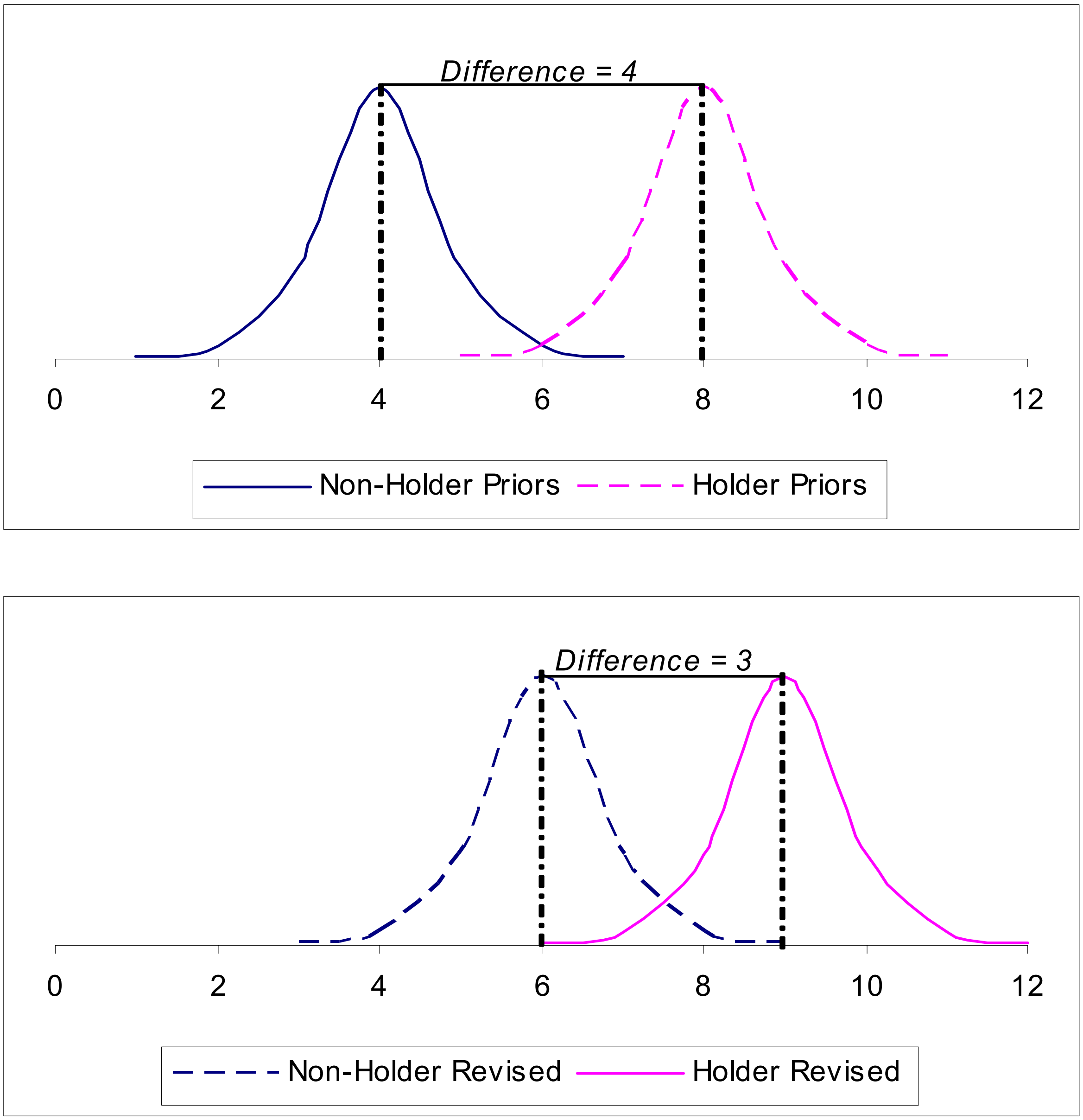

Figure 18: A Decrease in Across Group Reservation Price (Belief) Dispersion

This figure shows the change in the distribution of reservation prices for two groups of investors that hold a particular asset when the within group dispersion (standard deviation) remains constant but the difference between the mean reservation prices for the two groups decreases.

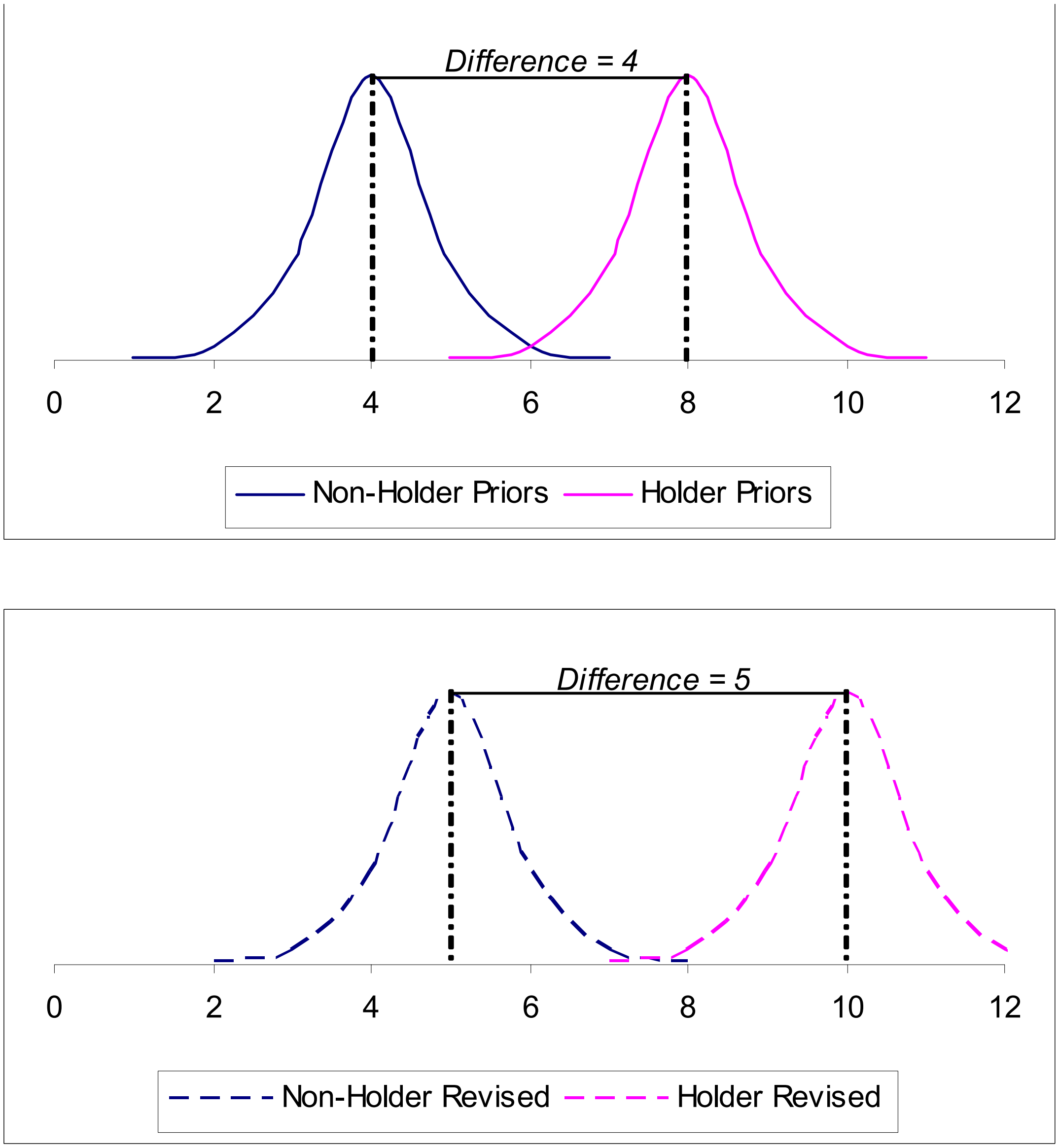

Figure 19: An Increase in Across Group Reservation Price (Belief) Dispersion

This figure shows the change in the distribution of reservation prices for two groups of investors that hold a particular asset when the within group dispersion (standard deviation) remains constant but the difference between the mean reservation prices for the two groups increases.

Specifically, convergences and divergences imply that

H_{3c}: Divergence (convergence) of beliefs is positively (negatively) related to market liquidity.

However, "flips" are a special case in which beliefs begin to converge but investors' belief revisions are so great that the investor with the higher expectation initially becomes the investor with the lower expectation and vice versa. Therefore

> H_{3d}: Flips of beliefs are positively related to market liquidity.

Kim and Verrecchia (1997) argue that while it is the information that investors have regarding the asset that influences investors' reservation price decisions, it is unrealistic to expect that only one type of information (pre-event or event-period) is available to investors. Therefore, I consider simultaneous changes in both within group dispersion and across group dispersion.

> H_4: An increase in within-group dispersion accompanied by a decrease in across-group dispersion is positively related to market liquidity.

For completeness, I consider the case of no change in dispersion.

> H_5: If there is no change in within-group and/or across-group dispersion, there will be no change in market liquidity.

3.3. Data

I test the hypotheses developed in the previous section using analyst forecasts as proxies for investor beliefs and a number of measures of market liquidity. I create a belief dispersion dataset to be used under the assumption of a continuous flow of information. In this dataset, I disaggregate the market into 'buyers' and 'sellers' The dataset contains monthly data from 1990 to 2002 with respect to trading volume, returns and market capitalization. This first dataset uses only volume-related variables from the Center for Research in Securities Prices (CRSP) as measures of market liquidity, while a second dataset also incorporates data from the New York Stock Exchange's (NYSE) Trade and Quote (TAQ) database to measure market liquidity. The second dataset is used under the assumption of a discrete flow of information. It contains daily data from 1990 to 2002 with respect to trading volume, returns and market capitalization as well as average spreads, depth and trade size from 1995 to 1998.

I obtain analyst forecasts from the Institutional Brokers Estimate System (I/B/E/S)[10]. As of March 2003, the I/B/E/S database consists of 7,585,519 forecasts covering 10,951 firms. These forecasts are further subdivided based on periodicity. There are four major periodicity subdivisions. These are annual, semi-annual, quarterly and miscellaneous. These subdivisions are further classified according to the forecast horizon. That is, an analyst estimating a firm's annual earnings per share for the current fiscal year would be classified differently than when the same analyst estimates the same firm's annual earnings for the next fiscal year. Table IV provides a breakdown of the entire I/B/E/S database as of March 2003.

It is important to note that while the number of forecasts for a given periodicity or the entire dataset can be summed to arrive at a total number of forecasts, this is not true for the number of firms. There is not a consistent pattern of continuity for firm representation across periodicities and/or horizons in the database. That is, a firm can be represented in one, several or all horizons within a periodicity or one, several or all periodicities within the database as a whole. Therefore, I analyze the database separately for each periodicity and each horizon to find the number of firms represented.

[10] Note that I use the phrases 'analyst forecast' and 'earnings estimate' interchangeably throughout this paper.

Table IV: I/B/E/S Historical Earnings Estimate Database

This table provides a breakdown of the I/B/E/S historical earnings estimate database as of March 2003 by periodicity and horizon. Periodicity indicates the type of fiscal period reflected in the estimate. Horizon reflects the number of periods between the estimate date and the fiscal period. A horizon of 1 indicates that the estimate reflects the current fiscal period. A horizon of 2 indicates the fiscal period one year after the current fiscal period and so on.

Panel A: Annual Earnings Estimates		
Horizon	*Number of Forecasts*	*Number of Firms*
1	2,093,562	10,907
2	1,689,018	10,773
3	181,373	8,363
4	22,178	3,361
5	11,206	2,010
6	578	339
7	204	146
8	104	79
9	12	10
10	14	10
> 10 fiscal years	1,670	456
Total	3,999,919	10,942
Panel B: Semi-Annual Earnings Estimates		
Horizon	*Number of Forecasts*	*Number of Firms*
1	520	317
2	203	148
3	79	60
4	40	31
> 4 semi-annual periods	4	2
Total	846	321
Panel C: Quarterly Earnings Estimates		
Horizon	*Number of Forecasts*	*Number of Firms*
1	1,262,451	9,488
2	720,602	9,141
3	584,761	8,955
4	456,784	8,739
5	255,973	7,360
6	152,887	6,828
7	90,884	6,260
8	46,070	5,409
> 8 quarters	14,342	2,620
Total	3,584,754	9,595
Panel D: All Earnings Estimates		
Periodicity	*Number of Forecasts*	*Number of Firms*
Annual	3,999,919	10,942
Semi-Annual	846	321
Quarterly	3,584,754	9,595
Total	7,585,519	10,951

The majority (99.9%) of the forecasts in the database reflect either annual or quarterly periodicities. Within these two classifications, there are slightly more annual (52.7%) than quarterly (47.3%) forecasts. Also, almost all firms (99.9%) are represented by the annual forecasts while a much smaller proportion of firms (87.5%) are represented by the quarterly forecasts. In fact, only nine companies in the entire I/B/E/S database do not have at least one annual forecast on file[11]. For these reasons, I use only the annual forecasts in my analysis.

Another trend in the data is that the number of forecasts decreases dramatically as the horizon lengthens. Of the 3,999,919 annual forecasts in the database, the majority (94.6%) of these forecasts are for the current fiscal year and the year following the current fiscal year. Within these two classifications, there are slightly more current fiscal year forecasts (55.3% versus 44.7%). O'Brien (1988) finds evidence that the most current analyst forecast weakly dominates the mean and median forecast with respect to accuracy. This finding is consistent with the idea that information regarding a firm's business operations for a given fiscal year is more plentiful as the fiscal year nears its end. Because analysts rely heavily on this information to prepare their reports (which contain their estimate of the firm's earnings per share), it follows that forecasts with the shortest horizons would be the most accurate. For this reason and the fact that the shortest horizon forecasts are most plentiful in the database, I further restrict my analysis to annual forecasts for the current fiscal year.

Based on the data restrictions described thus far, I next analyze all annual, current fiscal year forecasts. For some forecasts, I/B/E/S cannot identify the analyst making the

[11] These companies are Amerivest Properties, Correctional Properties, Lexford Inc., Inkine Pharmaceuticals, Jamesons Inns, Pan Pac Retail, Select Therapy, Trizec Properties and Cross Media Marketing.

estimate. All forecasts of this type are flagged with an analyst code of ‘0’. Therefore, this code could represent numerous analysts and some of these analysts may already be represented elsewhere in the database. In the parts of my analysis that involve tracking forecast revisions of specific analysts, I cannot use these forecasts. Therefore, I calculate the number of forecasts, analysts and firms by year with and without these forecasts. Table V provides a breakdown of these forecasts by year based on the date of the forecast.

Table V: Annual Current Fiscal Year Earnings Estimates

This table provides a breakdown of all annual current fiscal year earnings per share estimates in the I/B/E/S historical earnings estimate database as of March 2003 by year. The values in parentheses represent frequencies after excluding all forecasts where I/B/E/S cannot determine what analyst made the forecast. The estimates are categorized based on the date that the forecast is made.

Panel A: 1981 - 1989			
Year	*Number of Forecasts*	*Number of Analysts*	*Number of Firms*
1981	30 (29)	30 (29)	24 (24)
1982	8,638 (8,453)	1,628(1,627)	1,559(1,546)
1983	57,248 (55,423)	2,287(2,286)	2,227(2,215)
1984	68,977 (67,728)	2,289(2,288)	2,517(2,509)
1985	85,033 (83,031)	2,499(2,498)	2,851(2,830)
1986	88,362 (85,939)	2,482(2,481)	3,041(3,022)
1987	90,653 (88,841)	2,507(2,506)	3,285(3,265)
1988	89,740 (87,414)	2,424(2,423)	3,314(3,286)
1989	87,721 (84,824)	2,681(2,680)	3,317(3,242)
Total	576,402(561,682)	6,042(6,041)	4,501(4,465)
Panel B: 1990 - 1999			
Year	*Number of Forecasts*	*Number of Analysts*	*Number of Firms*
1990	90,541 (88,719)	2,536(2,535)	3,361(3,274)
1991	90,983 (88,754)	2,307(2,306)	3,341(3,273)
1992	92,067 (89,967)	2,180(2,179)	3,484(3,448)
1993	96,985 (93,735)	2,408(2,407)	3,751(3,739)
1994	97,978 (95,133)	2,775(2,774)	4,280(4,233)
1995	107,358 (105,250)	3,033(3,032)	4,648(4,610)
1996	113,161 (111,131)	3,402(3,401)	5,309(5,271)
1997	119,652 (118,169)	3,890(3,889)	5,798(5,778)
1998	133,698 (132,810)	4,278(4,277)	5,910(5,884)
1999	134,737 (133,092)	4,425(4,424)	5,933(5,894)
Total	1,077,160(1,056,760)	8,204(8,203)	8,659(8,609)

table continued

Panel C: 2000 - 2002			
Year	*Number of Forecasts*	*Number of Analysts*	*Number of Firms*
2000	131,733(129,980)	4,581(4,580)	5,754(5,730)
2001	140,961(134,614)	4,361(4,360)	5,071(5,002)
2002	136,266(134,829)	4,590(4,589)	4,961(4,916)
Total	408,960(399,423)	6,959(6,958)	6,616(6,562)
Panel D: 2003			
Year	*Number of Forecasts*	*Number of Analysts*	*Number of Firms*
2003	31,040(29,868)	3,299(3,298)	4,052(3,971)
Panel E: All Years			
Year	*Number of Forecasts*	*Number of Analysts*	*Number of Firms*
1981 – 1989	576,402 (561,682)	6,042(6,041)	4,501 (4,465)
1990 – 1999	1,077,160(1,056,760)	8,204(8,203)	8,659 (8,609)
2000 – 2002	408,960 (399,423)	6,959(6,958)	6,616 (6,562)
2003	31,040 (29,868)	3,299(3,298)	4,052 (3,971)
Total	2,093,562(2,047,733)	15,325(15,324)	10,907(10,824)

Note that as with the number of firms represented in a given time period, the number of analysts cannot be summed to arrive at a total number of analysts represented. Again, there is not a consistent pattern of continuity for firm or analyst representation across years in the database. That is, a firm or analyst can be represented in one, several or all years within the database. Therefore, I analyze the database separately for each year and subset of years to find the number of firms and analysts represented.

The number of forecasts, analysts and firms in the I/B/E/S database grows fairly steadily from 1981 to 1989. There are over nine times as many forecasts made in 1989 (87,721) as there are forecasts made in 1982 (8,638) representing a 64.6% increase in the number of analysts represented and a 112.8% increase in the number of firms represented. Over the period from 1990 to 1999, the increases in the size and representation of the database are significant, with the bulk of the growth focused on the representation of analysts and firms as compared to the previous decade. The number of forecasts increases by 48.8% while the number of analysts and firms increases by 223.5%

and 157.6% respectively. In 2000, as the United States stock markets begin to decline, the number of forecasts and firms represented in the I/B/E/S database falls as well. Most noticeably, the average number of firms represented in the database declines significantly from an actual level of 5,933 firms represented in 1999 to an average of 5,223 firms represented in the years 2000 through 2002.

Tables IV and V relate the number of forecasts, analysts and firms using ratios between these elements of the data by year and by month respectively. The number of forecasts per analyst and the number of forecasts per firm reflect the ratio of total forecasts in a given year to the total number of unique analysts and firms, respectively. However, I calculate the number of firms per analyst and the number of analysts per firm in a more complex manner. This is because one analyst may cover more than one firm and a simple ratio of unique firms to unique analysts would not capture this overlap. Instead, for each year I obtain the number of analysts following each unique firm such that each unique firm (i) in a sample year is followed by N_i analysts where $i \in (1, 2, \ldots, n)$ *and* $N_i \in (1, 2, \ldots, N)$. I then sum this figure across all firms and divide the total by the number of unique firms in that year. In other words, I calculate the average number of analysts per firm as:

$$\overline{analysts / firm} = \frac{\sum_i N_i}{n} \tag{3.6}$$

Similarly, to obtain the number firms that each analyst covers, I obtain the number of firms covered by each unique analyst such that each unique analyst ($_j$) in a sample year covers n_j firms where $j \in (1, 2, \ldots, N)$ *and* $n_j \in (1, 2, \ldots, n)$. I then sum this figure across all analysts and divide the total by the number of unique analysts in that year. In other words, I calculate the average number of firms per analyst as:

$$\overline{firms / analyst} = \frac{\sum_j n_j}{N} \tag{3.7}$$

Finally, I calculate the average number of forecasts per analyst per firm as:

$$\overline{forecasts / analyst / firm} = \frac{\overline{forecasts}}{analyst} \Big/ \frac{\overline{firms}}{analyst} \tag{3.8}$$

Table VI: Annual Relations Between the Number of Forecasts, Analysts and Firms

This table provides a breakdown of the ratios between the number of forecasts and analysts, the number of forecasts and firms and the number of analysts and firms in the I/B/E/S historical earnings estimate database as of March 2003 by year. The estimates are categorized based on the date that the forecast is made.

Year	*Average Number of Forecasts per Analyst*	*Average Number of Firms per Analyst*	*Average Number of Forecasts per Analyst per Firm*	*Average Number of Forecasts per Firm*	*Average Number of Analysts per Firm*
1981	1.00	1.00	1.00	1.21	1.21
1982	5.20	5.04	1.03	5.47	5.30
1983	24.24	11.00	2.20	25.02	11.36
1984	29.60	11.37	2.60	26.99	10.37
1985	33.24	12.39	2.68	29.34	10.93
1986	34.64	13.21	2.62	28.44	10.84
1987	35.45	12.83	2.76	27.21	9.85
1988	36.08	12.69	2.84	26.60	9.35
1989	31.65	11.74	2.70	26.16	9.70
1990	35.00	10.87	3.22	27.10	8.42
1991	38.49	11.38	3.38	27.12	8.02
1992	41.29	12.27	3.37	26.09	7.76
1993	38.94	12.65	3.08	25.07	8.15
1994	34.29	11.54	2.97	22.47	7.56
1995	34.71	11.19	3.10	22.83	7.36
1996	32.68	10.78	3.03	21.08	6.96
1997	30.39	10.06	3.02	20.45	6.77

table continued

1998	31.05	9.60	3.23	22.57	6.98
1999	30.08	9.53	3.16	22.58	7.15
2000	28.38	9.14	3.11	22.68	7.31
2001	30.87	8.84	3.49	26.91	7.70
2002	29.38	8.45	3.48	27.43	7.89
2003	9.06	6.39	1.42	7.52	5.31

Table VII: Monthly Relations Between the Number of Forecasts, Analysts and Firms

This table provides a breakdown of the ratios between the number of forecasts and analysts and the number of forecasts and firms per month in the I/B/E/S historical earnings estimate database as of March 2003 by year. The estimates are categorized based on the date that the forecast is made.

Year	*Number of Forecasts per Analyst per Month*	*Number of Forecasts per Firm per Month*
1981	0.08	0.10
1982	0.43	0.46
1983	2.02	2.09
1984	2.47	2.25
1985	2.77	2.45
1986	2.89	2.37
1987	2.95	2.27
1988	3.01	2.22
1989	2.64	2.18
1990	2.92	2.26
1991	3.21	2.26
1992	3.44	2.17
1993	3.24	2.09
1994	2.86	1.87
1995	2.89	1.90
1996	2.72	1.76
1997	2.53	1.70
1998	2.59	1.88
1999	2.59	1.88
2000	2.37	1.89
2001	2.57	2.24
2002	2.45	2.29
2003	3.02	2.51

Taken together (and excluding 1981, 1982 and 2003 as outliers due to incomplete data), Tables VI and VII show interesting trends in analyst coverage. The average analyst reports two to four forecasts per month while the average firm is reported on by one to three analysts each month. Also, during the sample period, over the course of one year, the average analyst follows a minimum of 8.45 firms in 2002 and a maximum of 13.21 firms in 1986. A minimum of 6.77 analysts cover each firm in 1997 and a maximum of 11.36 analysts follow each firm in 1983.

In order to limit the number of observations in my final sample, I prefer to analyze only 10 full years of data ending with the most recent year of complete data. This requirement would restrict my dataset to the years 1993 through 2002. However, because of the state of the stock market (and the economy as a whole) in the United States throughout all of the 1990s, I extend this dataset to include all forecasts made during the years 1990 through 2002.

3.3.1. Belief Dispersion Dataset

Because I require stock return data for my analysis, I next match the I/B/E/S database to the Center for Research in Securities Prices (CRSP) database. Because I/B/E/S and CRSP use different unique identifiers (I/B/E/S ticker and PERMNO respectively) in their databases to distinguish between firms, this matching is a multi-step process.

First, I generate a list of unique I/B/E/S tickers represented for each year of the sample period. I compare these lists to the I/B/E/S identifier file in order to find the official ticker symbol for each company. I match these files on an annual basis in order to automate the process. I separate the I/B/E/S identifier file into 13 overlapping smaller files each corresponding with a different year of my sample (1990 – 2002). Thus, the smaller files grow increasingly larger as the identifier file reflects changes made to company's CUSIP numbers, official ticker symbols or official names. Official tickers change over time while I/B/E/S tickers do not. Therefore, I sort each I/B/E/S identifier sub-file in descending order such that for each I/B/E/S ticker, the first entry in the file is actually the most current entry for the respective year. Then, I use an automated lookup function to search the file for the first record for each I/B/E/S ticker. The function then returns the most recent official ticker for the firm as of the end of the sample year. After matching all I/B/E/S tickers to their official ticker symbols for each year of the sample, I follow the same process to match the official ticker symbols to their respective CRSP PERMNOs.

Next, I aggregate the forecast data by firm, by the fiscal year estimated and by the month and year that the estimates are made. This step redefines an observation as a firm-month as opposed to an individual forecast. Thus, the number of observations is greatly reduced and each observation now reflects the mean value of all forecasts made in a specific month for a specific fiscal year for a specific firm. Table VIII reports the corresponding reductions in the number of observations in each year of the sample as I aggregate the forecasts by firm-month.

Once the forecasts are aggregated into firm-months, I impose several restrictions on the data to generate the final dataset. First, recall that I am interested in examining the effect of belief dispersion on market liquidity using analyst forecasts as a proxy for investor beliefs. Therefore, in order to have dispersion among analysts (investors), there must be at least two forecasts per firm-month.

Table VIII: Aggregation of Analyst Forecasts			
This table reports the results of aggregating all forecasts by firm and the month that the forecast is made. All forecasts made in the same month for the same firm result in one firm-month.			
Year	*Total Number of Forecasts*	*Total Number of Firm-Months*	*Average Number of Forecasts per Firm-Month*
1990	90,541	26,798	3.38
1991	90,983	26,768	3.40
1992	92,067	28,014	3.29
1993	96,985	29,282	3.31
1994	97,978	31,533	3.11
1995	107,358	34,611	3.10
1996	113,161	36,812	3.07
1997	119,652	39,922	3.00
1998	133,698	40,674	3.29
1999	134,737	39,064	3.45
2000	131,733	37,523	3.51
2001	140,961	33,189	4.25
2002	136,266	32,924	4.14

Second, because I am interested in studying the interactions between potential buyers and sellers of a traded asset, I distinguish those forecasts that proxy for potential buyers from those forecasts that proxy for potential sellers. I can do this in a number of ways.

I can match the analysts' forecasts to their corresponding recommendation. It would be reasonable to expect that analysts making 'buy' recommendations have higher valuations for a traded asset than analyst making 'sell' recommendations for that same traded asset. Recall that 'holders' ('non-holders') are defined as investors who own (do not own) the traded asset and are thus assumed to have higher (lower) valuations for the asset. It follows, then, that analysts making 'buy' recommendations proxy for 'holders' and analysts making 'sell' recommendations proxy for 'non-holders'. Many recent studies, however, have shown that buy-side analysts exhibit considerable bias in issuing recommendations primarily due to conflicts of interest and the way in which they are compensated. Analysts employed by brokerage firms that underwrite the securities offerings of the traded companies that they follow have an incentive to issuing more positive recommendations for these firms than if this investment banking relationship did not exist. Also, buy-side analysts typically follow firms whose securities they or others within their brokerage firm attempt to sell to firm clients. The securities issued by a traded company with a favorable recommendation are easier to sell than the securities issued by a traded company with an unfavorable recommendation. Finally, representatives of traded companies may be less inclined to provide information to analysts who give unfavorable recommendations for their company. The possibility of limited information upon which to base their financial analysis may also deter an analyst from issuing an unfavorable recommendation for a traded company. All of these issues represent potential reasons for bias in analyst forecasts. Also, there is significant empirical evidence that this upward bias does, in fact, exist. Trueman (1994), for example, provides evidence that analyst forecasts are not necessarily unbiased reflections of analysts' private information. A principal result of Trueman (1994) is that analysts tend to issue earnings forecasts that are close to prior earnings expectations even if their own research suggests that the firm's earnings may differ significantly from prior expectations. The existence of this bias in forecasts makes the use of analyst recommendations an undesirable means for distinguishing potential buyers from potential sellers.

Alternatively, I can base the distinction between 'holders' and 'non-holders' on the assumption that 'holders' have higher valuations of the traded asset than 'non-holders'. Therefore, it is reasonable to calculate the mean or median value of all forecasts for a given firm in a given month and classify all forecasts that are higher than the mean (or median) as 'holders' and all forecasts below the mean (or median) as 'non-holders'. I use this method of differentiating 'holders' and 'non-holders'. This methodology is consistent with the practice whereby investors observe the 'consensus' forecast and make investment decisions accordingly. Typically, the 'consensus' forecast is the mean value of all forecasts made for a given firm in a given time period. Therefore, I classify all forecasts that are greater than the mean forecast value for a firm-month as 'holders' and all forecasts that are less than or equal to the mean forecast value for a firm-month as 'non-holders'. Again, because dispersion of beliefs is my primary concern in this study, I require that within the 'holder' and 'non-holder' groups there exists at least two forecasts so that I can observe dispersion within each group.

Next, I obtain monthly data from CRSP for each firm in the sample and match it to the remaining observations. In order to match the CRSP data to the I/B/E/S data, I first match the forecast data to the identifier file described previously. This file contains the I/B/E/S ticker, official ticker symbol and CRSP PERMNO for every firm represented in the dataset. I match this file to the forecast file by I/B/E/S ticker and then match this new file to the CRSP data by CRSP PERMNO. Table IX reports the number of firms lost at each step of this matching process.

Table IX: Creation of the Final Dataset

This table documents the beginning number of observations (firm-months), the reasons for dropping observations from the sample and the final number of observations remaining when creating the final dataset.

Year	*Beginning Number of Observations*	*Reason for Dropping Observations from the Sample*			*Total Number (Percentage) of Observations Lost*	*Final Number of Observations*
		One Forecast per Firm-Month	*One Holder/Non-Holder Forecast per Firm-Month*	*CRSP Data not available*		
1990	26,798	10,520	9,598	1,732	21,850(81.5)	4,948
1991	26,768	10,377	9,681	1,671	21,729(82.1)	5,039
1992	28,014	10,885	10,343	1,716	22,944(81.9)	5,070
1993	29,282	10,886	11,422	1,740	24,048(82.1)	5,234
1994	31,533	12,394	12,300	1,597	26,291(83.4)	5,242
1995	34,611	13,749	13,540	1,851	29,140(84.2)	5,471
1996	36,812	15,024	14,221	1,898	31,143(84.6)	5,669
1997	39,922	17,001	14,999	1,859	33,859(84.8)	6,063
1998	40,674	16,681	15,062	2,186	33,929(83.4)	6,745
1999	39,064	16,076	14,019	1,878	31,973(81.8)	7,091
2000	37,523	15,254	13,556	1,468	30,278(80.7)	7,245
2001	33,189	12,083	11,292	1,408	24,783(74.7)	8,406
2002	32,924	12,257	11,104	1,316	24,677(75.0)	8,247

There are four reasons why observations are dropped from the final sample. First, if there is only one forecast for a firm-month, I cannot calculate overall dispersion. Therefore, all firm-months with only one forecast are dropped from the final sample. I drop, on average, 40 percent of all observations in each sample year due to this restriction. Second, once ‘holder’ forecasts are differentiated from ‘non-holder’ forecasts, I drop all firm-months that do not represent at least two ‘holder’ and two ‘non-holder’ forecasts. This data requirement allows me to calculate dispersion within both the ‘holder’ and ‘non-holder’ group for each firm-month. I drop, on average, an additional 37 percent of all observations in each sample year due to this restriction. Taken together, these two restrictions require a firm to have at least four forecasts in a given month with at least two of them being above the mean and two below the mean in order to be included in the final sample. I drop, on average, 76 percent of all observations in each sample year due to these dispersion requirements.

Third, I drop all observations where complete data is not available from CRSP. There are four reasons why firms are dropped from the sample at this stage. First, if the I/B/E/S identifier file does not contain an official ticker symbol for a firm, this firm cannot be matched with a CRSP PERMNO and is therefore dropped from the sample. Second, because stock exchanges reissue ticker symbols, but I/B/E/S tickers are unique, in some cases an I/B/E/S ticker corresponds to more than one official ticker symbol. To avoid the possibility of matching these firms incorrectly in CRSP, all I/B/E/S tickers that can be matched to more than one official ticker symbol in a given year are dropped from the sample. Third, firms are dropped from the sample because they are not found in the CRSP database. A cursory review of a sample of firms not found in CRSP reveals that these firms are typically either no longer trading, are trading via 'pink sheets' or are traded in the over-the-counter (OTC) market[12]. Finally, CRSP data is incomplete or contains error codes for some firms. On average, I drop an additional five percent of the total observations due to difficulties in matching the forecast file to CRSP.

In summary, these three issues, the number of forecasts per firm-month, the number of holder and non-holder forecasts per firm-month and the availability of matching CRSP data result in the loss of 82 percent of the total observations.

[12] Pink Sheets (whose name is based on the fact that they were originally printed on pink paper) are a daily publication compiled by the National Quotation Bureau containing price quotations for over-the-counter stocks. Unlike a stock exchange, companies quoted on the pink sheets system are not required to meet minimum standards.

3.3.2. Belief Revision Dataset

In order to study the impact of the various patterns of belief revisions, I create a second dataset. I restrict this dataset to firms whose fiscal year ends in December. Also, I examine only annual forecasts and annual forecast revisions made around the *quarterly* earnings announcements. Table X describes the I/B/E/S actual earnings database.

Table X: I/B/E/S Historical Actual Earnings Database

This table provides a breakdown of the I/B/E/S historical actual earnings database as of March 2003 by fiscal year.

Fiscal Year	*Number of Annual Announcements*	*Number of Semi-Annual Announcements*[13]	*Number of Quarterly Announcements*
1976	2,448	0	0
1977	2,749	0	1
1978	3,012	0	0
1979	3,266	0	0
1980	3,418	0	5
1981	3,430	0	22
1982	4,337	0	299
1983	4,647	0	9,845
1984	4,835	0	13,797
1985	4,828	0	14,927
1986	5,457	0	19,971
1987	5,926	0	25,081
1988	5,957	0	27,433
1989	5,912	0	26,491
1990	6,124	0	25,353
1991	6,117	0	24,231
1992	6,167	6	23,473
1993	6,796	3	24,029
1994	7,426	0	27,242
1995	8,342	0	29,451
1996	8,930	0	31,937

table continued

[13] There are 44 semi-annual announcements in the actual earnings database. These announcements represent 13 firms: British Steel PLC, Fujitsu, Grand Met PLC, Imperial Tobacco, Mandarin Orient, Marui Co., Overseas Un Bank, Polygram, Reuters, Sumitomo Mitsui, Trinity Biotech, Terremark World and Westpac Banking. However, no actual earnings data is available for Trinity Biotech or Terremark World.

1997	8,981	3	33,877
1998	8,799	11	33,392
1999	8,309	10	31,937
2000	7,540	8	29,101
2001	6,871	3	26,457
2002	5,174	0	23,054
2003	139	0	425
Total	156,317	44	501,831

Table XI: Annual Forecasts Before and After Quarterly Earnings Announcements

This table reports the number of annual forecasts in the I/B/E/S database in the period from 45 days prior to the quarterly earnings announcement to 30 days after the quarterly earnings announcement relative to each quarter from the period beginning January 1983 and ending December 2002.

Year	*First Quarter*	*Second Quarter*	*Third Quarter*	*Fourth Quarter*
1983	6,083	6,693	3,202	2,158
1984	7,302	6,845	6,951	2,936
1985	8,695	6,582	9,598	2,599
1986	7,037	8,433	8,271	2,761
1987	8,701	9,193	8,842	2,845
1988	10,269	9,130	9,973	3,117
1989	10,222	10,831	11,695	3,338
1990	11,951	11,373	13,182	3,535
1991	13,749	12,969	13,843	3,576
1992	12,702	13,763	14,781	3,843
1993	13,416	14,238	14,849	5,291
1994	14,295	13,424	14,225	5,765
1995	14,565	14,875	16,237	5,856
1996	16,005	16,574	18,026	5,742
1997	17,053	18,028	19,596	6,183
1998	18,927	21,225	22,270	6,808
1999	20,944	21,035	22,329	5,802
2000	20,233	20,011	20,201	5,958
2001	20,667	20,460	25,403	5,678
2002	19,964	20,918	22,450	5,844

I extract only those forecasts made 45 days prior to and 30 days following the quarterly earnings announcements for firms whose fiscal year ends in December[14]. Table XI reports the number of forecasts that fall within this time frame relative to each of the 160 quarters from the quarter beginning January 1983 to the quarter ending December 2002.

Table XII separates the forecasts that are made during the window (-45,+30) relative to the quarterly earnings announcement with respect to the number of forecasts made prior to the quarterly earnings announcement and the number made after the quarterly earnings announcement.

Table XII: Annual Forecasts Before and After Quarterly Earnings Announcements

This table reports the number of annual forecasts in the I/B/E/S database in the period from 45 days prior to the quarterly earnings announcement and the period 30 days after the quarterly earnings announcement relative to each quarter from the period beginning January 1983 and ending December 2002. Forecasts made on the quarterly earnings announcement date are included in the pre-announcement ('prior') window.

	First Quarter		*Second Quarter*		*Third Quarter*		*Fourth Quarter*	
Year	*Prior*	*Post*	*Prior*	*Post*	*Prior*	*Post*	*Prior*	*Post*
1983	3,100	2,983	3,503	3,190	1,539	1,663	2,158	0
1984	4,075	3,227	3,653	3,192	3,797	3,154	2,925	11
1985	5,194	3,511	4,330	2,252	4,636	4,962	2,586	13
1986	4,602	2,435	4,354	4,079	3,857	4,414	2,761	0
1987	4,678	4,023	4,653	4,540	4,070	4,772	2,842	3
1988	5,438	4,831	4,354	4,776	4,648	5,325	3,114	3
1989	5,329	4,893	5,378	5,453	5,161	6,534	3,337	1
1990	6,103	5,848	5,044	6,329	6,034	7,148	3,535	0
1991	7,470	6,279	6,194	6,775	5,977	7,866	3,576	0
1992	6,142	6,160	6,346	7,417	6,853	7,928	3,838	5
1993	6,599	6,817	6,261	7,977	6,449	8,400	5,291	0
1994	6,635	7,660	5,446	7,978	5,786	8,439	5,765	0
1995	6,606	7,959	6,341	8,534	7,033	9,204	5,854	2
1996	7,511	8,494	7,222	9,352	7,743	10,283	5,735	7

table continued

[14] I use a 45-day pre-announcement window (as opposed to 30 days) because, as noted by Bamber, Barron and Stober (1999), Stickel (1989) shows that analysts are less likely to report annual earnings forecasts shortly before quarterly earnings announcements.

1997	7,850	9,203	7,475	10,553	8,367	11,229	6,170	13
1998	8,426	10,501	9,399	11,826	9,860	12,410	6,742	66
1999	8,903	12,041	8,602	12,433	9,557	12,772	5,696	106
2000	8,436	11,797	7,644	12,367	8,007	12,194	5,817	141
2001	9,804	10,863	9,829	10,631	11,803	13,600	5,608	70
2002	7,967	11,997	8,077	12,841	8,900	13,550	5,730	114

In order to examine differences in belief revisions, I impose additional data restrictions. In many cases, one analyst reports more than one forecast for the same firm in either the pre-announcement window or the post-announcement window. I include only the forecasts reported closest to the announcement date for each analyst in both windows. That is, if an analyst reports more than one forecast for the same firm in either the pre-announcement window or the post-announcement window, I include only the forecast made on the event date with the lowest absolute value. Further, I assume that an analyst making a forecast on the announcement date has no knowledge of the content of the earnings announcement at the time he/she makes his forecast. Therefore, I include forecasts made on the announcement date in the pre-announcement window. However, for robustness, I later create an alternate dataset where I omit all forecasts made on the quarterly earnings announcement date. This dataset will eliminate any potential bias caused by analysts who base their forecast on the earnings announcement.

I require that each firm in the sample has forecasts from at least two different analysts and that both analysts make at least one forecast no more than 45 days before the quarterly earnings announcement *and* at least one forecast within 30 days after the quarterly earnings announcement.

Next, I create one observation for each firm-announcement date. That is, every earnings announcement by an individual firm represents a different observation. For each firm-announcement, I collect various analyst forecast data. Specifically, I calculate the descriptive statistics of all analyst forecasts made in the 45 days prior to the earnings announcement and the descriptive statistics of all analyst forecasts made in the 30 days following the announcement. Based on the pre- and post-announcement mean analyst forecasts, I categorize all analyst forecasts as 'optimists' or 'pessimists' based on the individual forecast value relative to the mean of all forecasts. Thus, all individual forecasts that are greater than the mean forecast are classified as 'optimists' while all individual forecasts that are less than the mean forecast are classified as 'pessimists'. For each observation I record the I/B/E/S ticker and the mean and variance of all forecasts reported for in the pre- and post-announcement windows.

I obtain volume data from CRSP for each sample firm and incorporate this data into the final dataset. After deleting firms for whom CRSP data is incomplete or unavailable, this results in a final dataset with 5,640 observations representing 1,364 firms. Finally, for the observations from 1995 to 1998 I add additional data from TAQ as described later in this chapter[15]. This subset contains 1,850 observations representing 639 firms.

3.4. Methodology

3.4.1. Key Variables

The dependent variable in all of my regression models is a form of market liquidity. Market liquidity can be defined in a number of ways. I examine several commonly used measures: trading volume, effective spread, quoted spread, order

[15] The TAQ data is limited to the period 1995-1998 due to availability.

imbalance, trade imbalance, market depth and average trade size. It is important to note that the relation between these variables and market liquidity may differ. For example, a high level of trading volume is indicative of a liquid market whereas a large spread (either effective or quoted) would indicate an illiquid market.

With respect to trading volume, I specifically examine turnover. I calculate abnormal turnover according to the simple model of Tkac (1999) which argues that firm turnover should equal market turnover under normal circumstances. This argument is based on the theoretical prediction that market-wide trading translates into trading in each asset according to its relative value in the market. According to Tkac, although this model is simple, it should isolate idiosyncratic trading activity. Further, Tkac attributes undertrading (overtrading) possibly to less (more) non-rebalancing activity. In other words, fewer (more) investors are trading these stocks based on firm-specific information. In the context of informed versus uninformed traders, this model separates the informed from the uninformed traders so that an analysis of the resulting abnormal (idiosyncratic) volume actually allows me to examine the behavior of informed traders. Therefore, I measure turnover ($Turnover$) for an individual firm as

$$Turnover = \frac{\text{shares traded}}{\text{shares outstanding}} \tag{3.9}$$

I measure market turnover using data from all firms (i) in the CRSP database. I calculate market turnover ($MktTurnover$) as

$$MktTurnover = \frac{\sum_i (\text{shares traded})_i}{\sum_i (\text{shares outstanding})_i} \tag{3.10}$$

I calculate abnormal turnover, then, as

$$AbnormalTO = Turnover - MktTurnover \tag{3.11}$$

I test my hypothesis regarding belief revision characteristics using volume as well as alternative measures of market liquidity. Specifically, I use the difference in the pre- and post-announcement averages of several alternative dependent variables: *EffectiveSpread*, *QuotedSpread*, *OrderImbalance*, *TradeImbalance*, *MarketDepth* and *TradeSize*. *EffectiveSpread* is the difference between the execution price and the mid-point of the prevailing bid-ask spread. *QuotedSpread* is the quoted offer (bid) price less the quoted ask price prevailing at the time of the trade[16]. *OrderImbalance* is the difference between the offer size and the bid size prevailing at the time of the trade. *MarketDepth* is the average of the bid size and the offer size[17]. *TradeSize* is the actual number of shares exchanged.

I use several explanatory variables related to belief dispersion and the characteristics of belief revisions. With respect to belief dispersion, I first address overall dispersion followed by dispersion within groups of investors. These groups, 'holders' and 'non-holders', represent investors that own or do not own the traded asset, respectively. I measure dispersion within the 'holder' ('non-holder') group as the coefficient of variation in the forecasts greater than (less than) the mean value of all forecasts for the same firm in the same month or

$$HDisp_{jt} = \frac{\sigma_{forecasts_{jt} > \mu}}{\mu_{forecasts_{jt} > \mu}} \tag{3.12}$$

[16] *PercentageQuotedSpread* is also used and is calculated as the quoted spread as a percentage of the midpoint of the prevailing bid-ask spread.
[17] *DollarDepth* is also captured by multiplying the bid size and the offer size by their respective prices.

$$NHDisp_{jt} = \frac{\sigma_{forecasts_{jt} < \mu}}{\mu_{forecasts_{jt} < \mu}} \tag{3.13}$$

I also address dispersion across the two sub-groups of investors. I calculate this variable, *Across*, as simply the difference in the mean forecasts for the two groups or

$$Across = \mu_H - \mu_{NH} \tag{3.14}$$

When examining the characteristics of belief revisions on market liquidity, I first examine the magnitude of the revisions themselves. Using the Holder/Non-Holder dataset, I construct dummy variables that indicate, on average, whether the 'holder' or 'non-holder' group revised their forecasts (beliefs) more. Therefore, *DHold* is a dummy variable that is set to 1 if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to 1 if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise. Because 'holders' have higher valuations than 'non-holders', if these investors revise their beliefs more, across group dispersion will increase and market liquidity should therefore decrease. It is also important to note that both the *DHold* and *DNon* variables are needed in analysis because these cases are not mutually exclusive. That is, it is possible for the holders and non-holders to revise their beliefs by exactly the same amount. In that case, both the *DHold* and *DNon* variables would be set to zero.

Alternatively, I measure dispersion and the magnitude of belief revisions in the two-dimensional XY space where the X-axis indicates holder demand prices and the Y-axis indicates non-holder demand prices. This representation is shown in Figure 20.

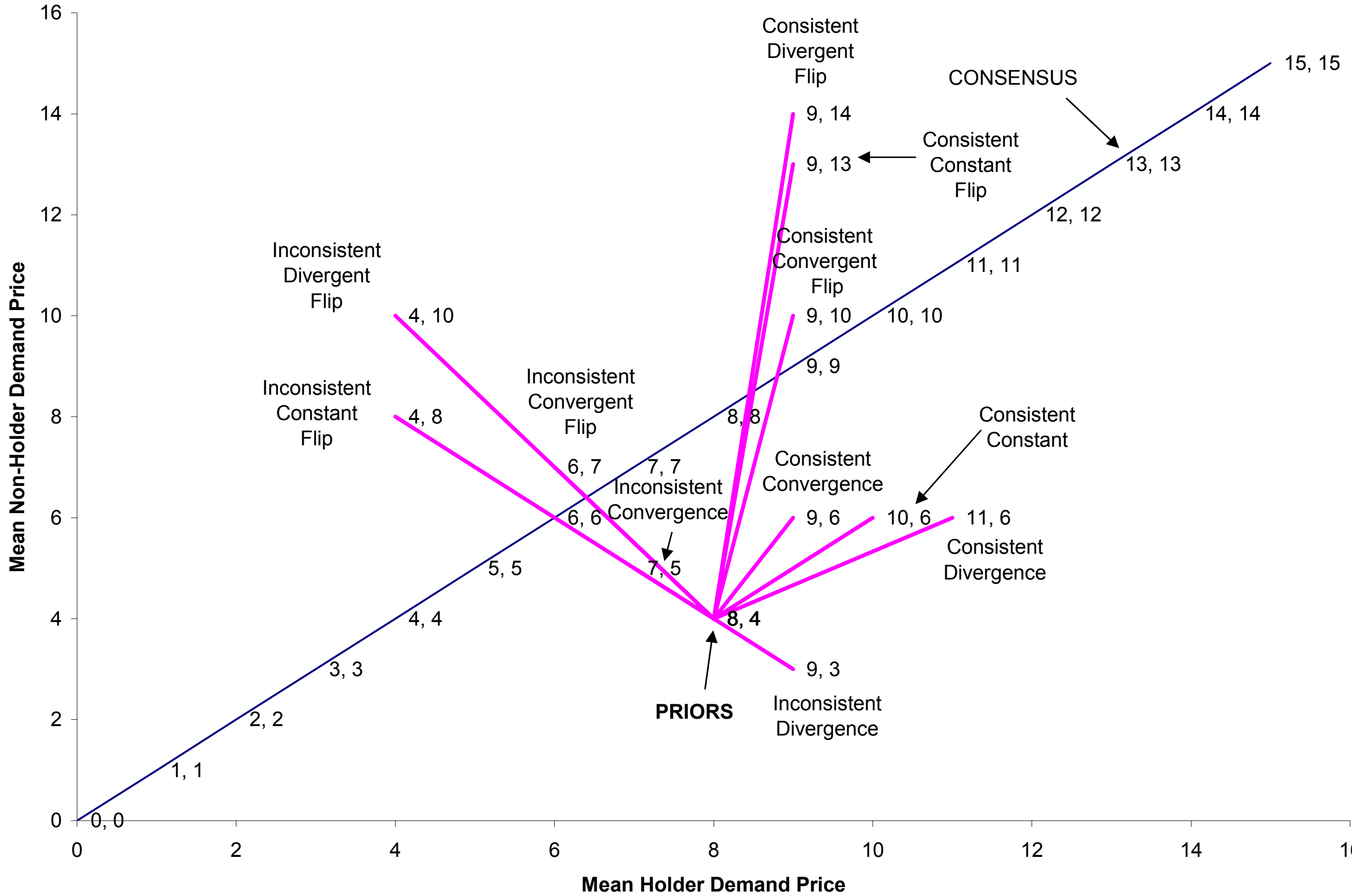

Figure 20: Belief Revisions in the XY Plane

This figure represents pairings of mean holder and non-holder beliefs both prior to and following the announcement of new information.

A given point in this space represents the combination of holder and non-holder demand prices. That is, the point (8,4) represents a mean holder demand price of $8 and a mean non-holder demand price of $4. Consensus across the two groups, is represented by the 45-degree line where all X-values and Y-values are equal. Given this representation of holder and non-holder demand prices, I measure across-group dispersion as the distance between the intersection of the mean holder and mean non-holder forecasts (any given point in the XY plane) and consensus or

$$\text{Distance} = \sqrt{\left(\mu_H - \mu\right)^2 + \left(\mu_{NH} - \mu\right)^2} \tag{3.15}$$

Also, I calculate the length and the slope of the revision path that represents the change in the intersection of the mean holder and mean non-holder forecasts. I calculate these variables as:

$$Slope = \frac{\Delta\mu_{NH}}{\Delta\mu_H} \tag{3.16}$$

$$PathLength = \sqrt{\left(\Delta\mu_H\right)^2 + \left(\Delta\mu_{NH}\right)^2} \tag{3.17}$$

In order to address simultaneous changes in across group and within group dispersion, I use the belief dispersion dataset to construct additional dummy variables and that capture the possibility of 'holder' group dispersion increasing or decreasing (*DHInc* and *DHDec*) and 'non-holder' group dispersion increasing or decreasing (*DNHInc* and *DNHDec*). Again, both of these variables are necessary as they are not mutually exclusive. That is, it is possible for dispersion to remain constant rather than increase or decrease following the introduction of new information.

I create three additional dummy variables using the belief revision dataset to capture characteristics of belief revisions. *Diverge* indicates whether the absolute difference between a pair of analysts' forecasts is increasing or decreasing. If the difference in the post-announcement forecasts is greater than the difference in the pre-announcement forecasts, this variable is set to one and is zero otherwise. *Consistent* indicates whether or not a pair analysts revise their forecast in the same direction. That is, if both analysts revise upward or downward, this variable is set to one and is zero otherwise. *Flip* indicates whether a pair of analysts revise their forecasts in such a way that the analyst with the higher pre-announcement forecast has the lower post-announcement forecast. In this case, the variable *Flip* is set to one and is zero otherwise.

The control variables I use in the model are intended to capture the effect of other factors beyond the dispersion of beliefs. Specifically, I include $|r_{jt}|$, the absolute magnitude of stock returns, to account for the positive association between market liquidity and the absolute magnitude of price changes found by Crouch (1970), Westerfield (1977), Cornell (1981), Wood, McInish and Ord (1985), Harris (1986), Richardson, Sefcik and Thompson (1986a) and others. Firm size ($Size_{jt}$) is measured as the total market value of equity (market capitalization). I include it as a control variable because more news is typically available about larger firms than smaller firms. Thus, it is reasonable to assume that there is less investor disagreement (dispersion of beliefs) regarding larger firms than smaller firms and therefore, larger firms will experience higher volume after news announcements than smaller firms simply due to the size differential. Also, it is important to note that due to the sample selection criteria (outlined previously), the sample is biased toward large firms. *PriceChange* accounts for the dollar change in a firm's stock price coincident with an earnings announcement. Karpoff (1987) points to empirical evidence suggesting that volume is positively related to the magnitude of the price change. Similarly, Bamber, Barron and Cheon (1999) studied small price change firms and concluded that coincident trading reflects investors' differential interpretations of information. I calculate *PriceChange* as the natural logarithm of the absolute value of the difference between the stock price on the day following the quarterly earnings announcement and the stock price on the day prior to the quarterly earnings announcement. Consistent with Karpoff, I predict a positive coefficient for this variable. Finally, I use *Surprise* to account for the degree of surprise contained in a firm's actual earnings announcement. I calculate this variable as the difference between the mean pre-announcement forecast and the actual earnings. Bamber (1986) finds evidence that the degree of surprise associated with an earnings announcement is positively related to trading volume.

3.4.2 .Empirical Tests[18]

In all of the empirical tests that follow, the abnormal turnover emphasis varies slightly depending upon the dataset used. In the first dataset where no firm specific information is introduced, abnormal turnover is measured as the percentage of outstanding shares traded for a given firm (j) in a given month (t) minus the percentage of outstanding shares traded for all firms in the CRSP database in that month. With this data, I observe and analyze the level of abnormal turnover relative to the level of dispersion both across and within groups (holders and non-holders). In addition, as holder and non-holder beliefs change from month to month, I analyze the change in turnover relative to the change in dispersion.

In the second dataset where I examine changes in market liquidity relative to the firm's earnings announcement, abnormal turnover is measured in the same way, but the change is observed as the difference between the abnormal turnover on the day after the announcement less the abnormal turnover on the day before the announcement.

[18] Note that in all regression equations that follow, I list only the key variables individually and aggregate the control variables in a vector denoted 'CONTROL'.

3.4.2.1. Hypothesis One

To test H_1 regarding the relation between overall dispersion and market liquidity, I use the Holder/Non-Holder dataset and estimate the following panel data regression models (with the predicted signs of the coefficients given in parentheses):

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1} Disp_{jt} + CONTROL_{jt} + \varepsilon \quad (3.18)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1} \text{Distance}_{\text{jt}} + CONTROL_{jt} + \varepsilon \quad (3.19)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1} Disp_{jt} + \underset{(-)}{b_2} \text{Distance}_{\text{jt}} + CONTROL_{jt} + \varepsilon \quad (3.20)$$

If there is a relation between market liquidity and overall dispersion, I expect that market liquidity will increase as dispersion decreases until investors reach consensus. Therefore, in Equations (3.18), (3.19) and (3.20) I expect negative coefficients for the key variables *Disp* and *Distance*. Both variables measure overall dispersion. *Disp* is the coefficient of variation for all forecasts made in the same month for a given firm. *Distance* is the geometric difference between the point of intersection of mean holder and non-holder beliefs and consensus. Consensus is the point where mean holder beliefs are equal to mean non-holder beliefs and is represented by the line $Y = X$ in the *XY* plane.

3.4.2.2. Hypothesis Two

To test H_2 regarding the relation between within-group dispersion and market liquidity, I use the belief dispersion dataset and estimate the following regression models (with the predicted signs of the coefficients given in parentheses):

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(+)}{b_1 \Delta HDisp_j} + \underset{(+)}{b_2 \Delta NHDisp_j} + CONTROL_j + \varepsilon \quad (3.21)$$

If there is a relation between changes in market liquidity and changes in within group dispersion, I expect that market liquidity will increase as the dispersion within either the Holder or Non-Holder group increases. This is because an increase in within group dispersion would stretch the distribution of beliefs for that group such that it increases the overlap in the distributions of both groups. Because trading occurs where the two population distributions overlap, an increase in the dispersion of *either* distribution (not necessarily *both* distributions) should be positively related to an increase in market liquidity. Therefore, in Equation (3.21), I expect positive coefficients for the key variables *ΔHDisp* and *ΔNHDisp* which measure the change in Holder dispersion and Non-Holder dispersion, respectively.

3.4.2.3. Hypothesis Three

To test H_{3a} and H_{3b} regarding the relation between across-group dispersion and market liquidity, I use the Holder/Non-Holder dataset and estimate the following regression model (with the predicted signs of the coefficients given in parentheses):

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1 Across_{jt}} + CONTROL_{jt} + \varepsilon \quad (3.22)$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1 \Delta Across_j} + CONTROL_j + \varepsilon \quad (3.23)$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1 DHold_j} + \underset{(+)}{b_2 DNon_j} + CONTROL_j + \varepsilon \quad (3.24)$$

Equation (3.22) tests the relation between market liquidity and the *level* of across-group dispersion while Equations (3.23) and (3.24) test the relation between changes in market liquidity and *changes* in across-group dispersion. *Across* measures the difference in the means of (or the distance between) the two distributions; Holders and Non-Holders. If market liquidity is inversely related to the level of across-group dispersion, I expect a negative coefficient for the variable *Across*. I measure the change in across-group dispersion as the change in the difference in the Holder mean and the Non-Holder mean. Therefore, a positive (negative) value for the variable *ΔAcross* indicates an increase (decrease) in across-group dispersion. If changes in market liquidity are inversely related to changes in across-group dispersion, I expect a negative coefficient for the variable *ΔAcross.*

Alternatively, I use the qualitative variables *DHold* and *DNon* to measure changes in across-group dispersion. These variables indicate which of the two groups revised its beliefs more. These variables are based on the foundation that the Holder population has a higher mean than the Non-Holder population. For example, if the means of both populations increase (decrease), but the Holder mean increases (decreases) more than the Non-Holder mean, the population distributions will move farther apart (closer together) which decreases (increases) the overlap in the distributions and leads to a decrease (an increase) in market liquidity. Also, if the mean of the Holder population increases (decreases) while the mean of the Non-Holder population decreases (increases) the population distributions will again move farther apart (closer together) which decreases (increases) the overlap in the distributions and leads to a decrease (an increase) in market liquidity. If changes in market liquidity are inversely related to changes in across-group dispersion, I expect a negative coefficient for the variable *DHold* and a positive coefficient for the variable *DNon*.

It is important to note that I base this analysis on the actual value of the changes in means as opposed to the absolute value of the change. For example, consider the case with prior Holder and Non-Holder means of $6 and $3 respectively. If the means decrease by $2 and $1 respectively, the posterior means are $4 and $2. The difference in means decreases from $3 to $2. The change in the Holder mean is -$2 and the change in the Non-Holder mean is -$1. Therefore, in this case, the Non-Holder belief revision (-$1) is greater than the Holder belief revision (-$2).

To test H_{3c} and H_{3d} regarding the relations between the characteristics of belief revisions and market liquidity, I first use the Holder/Non-Holder dataset. I estimate the following regression models (with the predicted signs of the coefficients given in parentheses):

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1 Slope_j * DHold_j} + CONTROL_j + \varepsilon \tag{3.25}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(+)}{b_1 Slope_j * DNon_j} + CONTROL_j + \varepsilon \tag{3.26}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1 Slope_j * DHold_j} + \underset{(+)}{b_2 PathLength_j} + CONTROL_j + \varepsilon \tag{3.27}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(+)}{b_1 Slope_j * DNon_j} + \underset{(+)}{b_2 PathLength_j} + CONTROL_j + \varepsilon \tag{3.28}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1 DHold_j} + \underset{(+)}{b_2 DNon_j}$$
$$+ \underset{(+)}{b_3 PathLength_j} + \underset{(?)}{b_4 Slope_j} + CONTROL_j + \varepsilon \tag{3.29}$$

In Equations (3.25) through (3.29), I examine the belief revisions between the intersection of the prior Holder and Non-Holder beliefs and the intersection of the posterior Holder and Non-Holder beliefs. I identify the line that connects these two points as the 'Revision Path', RP. The length of RP (*PathLength*) indicates the magnitude of the belief revision. The relation between market liquidity and the magnitude of belief revisions is expected to be positive. Therefore, I expect the sign of the coefficient for the variable *PathLength* to be positive.

The slope of RP (*Slope*) indicates the ratio of the change in Non-Holder beliefs to the change in Holder beliefs. A *Slope* greater (less) than one indicates that Non-Holders are revising their beliefs more (less) than Holders. As explained previously, this implies a convergence (divergence) of beliefs. A positive *Slope* indicates that both Holders and Non-Holders are revising their beliefs in a homogenous manner (either positively or negatively). A negative *Slope* indicates that Holders and Non-Holders are revising their beliefs in a heterogeneous manner (one positively and one negatively). However, I hypothesize that market liquidity is a function of both the homogeneity of belief revisions and the convergence of beliefs. Therefore, because a positive *Slope* could indicate either a convergence or a divergence of beliefs, the relation between market liquidity and *Slope* is indeterminate. However, a positive (negative) coefficient on the *Slope* variable would clearly indicate that the homogeneity of belief revisions is positively (inversely) related to market liquidity.

To account for the convergence of beliefs, I test the relation between market liquidity and the joint relations between homogeneous belief revisions and the convergence of beliefs. Recalling that the variable *DHold* indicates a divergence of beliefs and *DNon* indicates a convergence of beliefs, the variables *Slope*DHold* and *Slope*DNon* indicate consistent/inconsistent divergence and convergence, respectively. A positive (negative) *Slope*DHold* would indicate homogeneous divergence (heterogenous divergence). A positive (negative) *Slope*DNon* would indicate homogeneous convergence (heterogeneous convergence). I expect a negative coefficient for *Slope*DHold* and a positive coefficient for *Slope*DNon*.

Next, I use the belief revisions dataset and estimate the following regression models (with the predicted signs of the coefficients given in parentheses) that test the relation between volume and the change in the level of consensus:

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1} Diverge_{jt} + CONTROL_{jt} + \varepsilon \tag{3.30}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Converge_{jt} + CONTROL_{jt} + \varepsilon \tag{3.31}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(?)}{b_1} \mathrm{Constant}_{\mathrm{jt}} + CONTROL_{jt} + \varepsilon \tag{3.32}$$

Next, I test the relation between volume and the heterogeneity of investor belief revisions by estimating the following regression models (with the predicted signs of the coefficients given in parentheses):

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Consistent_{jt} + CONTROL_{jt} + \varepsilon \tag{3.33}$$

Finally, I test the relation between volume and the phenomena wherein investors revise their beliefs such that those with lower pre-event valuations have higher post-event valuations and vice versa. To do so, I estimate the following regression model (with the predicted signs of the coefficients given in parentheses):

$$AbnormalTO_{jt} = a_0 + \underset{(+)}{b_1} Flip_{jt} + CONTROL_{jt} + \varepsilon \tag{3.34}$$

After examining the relation between volume and each possible characteristic of belief revisions individually, I test the relation between volume and each of the 11 possible combinations of these characteristics. To do so, I estimate the following regression models (with the predicted signs of the coefficients given in parentheses):

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1 Consistent_{jt} * Converge_{jt}} * NoFlip_{jt} + CONTROL_{jt} + \varepsilon \tag{3.35}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1 Consistent_{jt} * Converge_{jt}} * Flip_{jt} + CONTROL_{jt} + \varepsilon \tag{3.36}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1 Consistent_{jt} * Diverge_{jt}} * NoFlip_{jt} + CONTROL_{jt} + \varepsilon \tag{3.37}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1 Consistent_{jt} * Diverge_{jt}} * Flip_{jt} + CONTROL_{jt} + \varepsilon \tag{3.38}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(0)}{b_1 Consistent_{jt} * \mathrm{Constant}_{\mathrm{jt}}} * NoFlip_{jt} + CONTROL + \varepsilon \tag{3.39}$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Inconsistent_{jt} * Converge_{jt} * NoFlip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.40)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Inconsistent_{jt} * Converge_{jt} * Flip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.41)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(-)}{b_1} Inconsistent_{jt} * Diverge_{jt} * NoFlip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.42)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Inconsistent_{jt} * Diverge_{jt} * Flip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.43)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Inconsistent_{jt} * \mathrm{Constant}_{\mathrm{jt}} * Flip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.44)$$

$$AbnormalTO_{jt} = \underset{(?)}{a_0} + \underset{(+)}{b_1} Consistent_{jt} * \mathrm{Constant}_{\mathrm{jt}} * Flip_{jt} + CONTROL_{jt} + \varepsilon \quad (3.45)$$

Equations (3.30) through (3.45) examine the characteristics of pairs of annual analyst forecasts made both before and after a quarterly earnings announcement. Each pair is classified using three qualitative variables. *Consistent* indicates that the pair of analysts revise their beliefs in the same direction (either both upward or both downward). A *Consistent* pair in the Analyst Pairings dataset is indicative of homogenous belief revisions similar to a firm-month in the Holder/Non-Holder dataset with a positive *Slope*. As I mentioned previously, I hypothesize that market liquidity is a function of both the homogeneity of belief revisions and the convergence of beliefs. Therefore, because a *Consistent* pair could indicate either a convergence or a divergence of beliefs, the relation between market liquidity and *Consistent* is indeterminate. However, a positive (negative) coefficient on the *Consistent* variable would clearly indicate that the homogeneity of belief revisions is positively (inversely) related to market liquidity.

To account for the convergence of beliefs, I test the relation between market liquidity and the joint relations between homogeneous belief revisions and the convergence of beliefs. *Diverge* indicates that the difference in the two analysts' post-announcement forecasts is greater than the difference in their pre-announcement forecasts[19]. A *Diverge* pair in the Analyst Pairings dataset is indicative of an increase in across-group dispersion (divergence of beliefs) similar to a *DHold* firm-month in the Holder/Non-Holder dataset. *Consistent*Diverge* indicates the pair of analysts revise their beliefs in the same direction (either both upward or both downward) *and* the difference in the two analysts' post-announcement forecast is greater than the difference in their-pre-announcement forecasts. I expect that the coefficients for both *Diverge* and *Consistent*Diverge* will be negative indicating an inverse relation between changes in market liquidity and the divergence of beliefs regardless of if analysts (investors) revise their beliefs in a homogeneous manner.

Kandel and Pearson (1995) are the first to document an interesting phenomenon with respect to belief revisions which they label 'flips'. A flip occurs when the analyst reporting the higher pre-announcement forecast subsequently reports the lower post-announcement forecast. Kandel and Pearson (1995) followed by Bamber, Barron and Stober (1999) provide evidence of the existence of flips, divergence and inconsistencies

[19]This difference in forecasts is measured in actual terms as opposed to absolute terms.

in analyst forecasts around quarterly earnings announcements. These phenomena, and additional evidence of a positive relation between these unexpected behaviors and trading volume, they argue, refute the notion of homogeneous belief revisions. In both of these studies, the authors aggregate pairs that I label as inconsistent, divergent or a flip into one measure. This measure, KP(1995), is the proportion of all pairs for the same firm that fit any of these criteria. I test inconsistent, divergent and flip pairs separately in order to determine the impact of each of these characteristics individually. Therefore, the third qualitative variable with respect to the Analyst Pairings dataset is *Flip*. *Flip* indicates that the analyst reporting the higher pre-announcement forecast subsequently reports the lower post-announcement forecast. The relation between changes in market liquidity and *Flip* is expected to be positive.

I also test the relation of the three possible pairs of these characteristics (*Consistent*Diverge*, *Consistent*Flip* and *Diverge*Flip*) on changes in market liquidity. Finally, I test the relation between pairs that exhibit all three characteristics (*Consistent*Diverge*Flip*) and changes in market liquidity. I expect a negative coefficient for the variable *Consistent*Diverge*, but the relations between *Consistent*Flip*, *Diverge*Flip* and changes in market liquidity are indeterminate.

3.4.2.4. Hypothesis Four

To test H_4 regarding simultaneous changes in both within group dispersion and across group dispersion, I use the belief dispersion dataset and estimate the following regression model:

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DHold_j * DHInc_j * DNHInc_j + CONTROL_j + \varepsilon \tag{3.46}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DHold_j * DHInc_j * DNHDec_j + CONTROL_j + \varepsilon \tag{3.47}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DHold_j * DHDec_j * DNHInc_j + CONTROL_j + \varepsilon \tag{3.48}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(-)}{b_1} DHold_j * DHDec_j * DNHDec_j + CONTROL_j + \varepsilon \tag{3.49}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(+)}{b_1} DNon_j * DHInc_j * DNHInc_j + CONTROL_j + \varepsilon \tag{3.50}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DNon_j * DHInc_j * DNHDec_j + CONTROL_j + \varepsilon \tag{3.51}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DNon_j * DHDec_j * DNHInc_j + CONTROL_j + \varepsilon \tag{3.52}$$

$$\Delta AbnormalTO_j = \underset{(?)}{a_0} + \underset{(?)}{b_1} DNon_j * DHDec_j * DNHDec_j + CONTROL_j + \varepsilon \tag{3.53}$$

$$
\begin{aligned}
\Delta AbnormalTO_j = \underset{(?)}{a_0} &+ b_1 DHold_j * \underset{(?)}{DHInc_j} * DNHInc_j \\
&+ b_2 DHold_j * \underset{(?)}{DHInc_j} * DNHDec_j \\
&+ b_3 DHold_j * \underset{(?)}{DHDec_j} * DNHInc_j \\
&+ b_4 DHold_j * \underset{(-)}{DHDec_j} * DNHDec_j \\
&+ b_5 DNon_j * \underset{(+)}{DHInc_j} * DNHInc_j \\
&+ b_6 DNon_j * \underset{(?)}{DHInc_j} * DNHDec_j \\
&+ b_7 DNon_j * \underset{(?)}{DHDec_j} * DNHInc_j \\
&+ b_8 DNon_j * \underset{(?)}{DHDec_j} * DNHDec_j + CONTROL_j + \varepsilon
\end{aligned}
\tag{3.54}
$$

I model all possible combinations of simultaneous changes in within-group and across-group dispersion. Recall that *DHold* indicates an increase in across-group dispersion (belief divergence) and *DNon* indicates a decrease in across-group dispersion (belief convergence). To account for changes in within-group dispersion, *DHInc* and *DHDec* account for increases and decreases in Holder group dispersion while *DNHInc* and *DNHDec* account for increases and decreases in Non-Holder group dispersion. The eight interaction variables tested separately in Equations (3.46) through (3.53) and together in Equation (3.54) represent all of the possible combinations of across-group and within-group dispersion. I expect that a decrease in across group dispersion is related to an increase in market liquidity because of an increase in the overlap between the two population distributions. I expect that an increase in the dispersion within either (or both) groups is related to an increase in market liquidity because stretching either (or both) population distributions also increases the overlap between the two populations. However, in some cases, it is unclear how simultaneous changes in across group and within-group dispersion are related to market liquidity. For example, if across group dispersion increases, market liquidity could either increase or decrease depending upon whether or not the individual population distributions stretch enough to cover the added distance between the two population means. Also, if across group dispersion decreases, but within-group dispersion also decreases (in one or both of the populations), market liquidity could either increase or decrease depending upon if the distributions collapse more than enough to overcome the shortened distance between the two population means. Therefore, I can only predict the signs of the coefficients of the variables that represent the two extreme cases: *DHold*DHDec*DNHDec* and *DNon*DHInc*DNHInc*. *DNon*DHInc*DNHInc* indicates a decrease in across-group dispersion (convergence of beliefs) and an increase in the dispersion within *both* the Holder and the Non-Holder groups. I expect that this case is positively related to market liquidity and therefore expect a positive coefficient for this variable. *DHold*DHDec*DNHDec* indicates an increase in across-group dispersion (divergence of beliefs) and a decrease in the dispersion within *both* the Holder and the Non-Holder groups. I expect that this case is inversely related to market liquidity and therefore expect a negative coefficient for this variable.

3.4.2.5. Hypothesis Five

To test H_5 regarding no change in dispersion, I examine the intercepts of regression Equations (3.21), (3.23) and (3.24). Equation (3.21) tests the relation between changes in market liquidity and changes in within-group dispersion. Equations (3.23) and (3.24) test the relation between changes in market liquidity and changes in across-group dispersion. The impact of observations that reflect no change in dispersion would be captured in the intercept terms of these equations. Recalling that I remove the impact of liquidity traders and 'portfolio rebalancers' by using abnormal turnover as my dependent variable, I expect that there would be no change in market liquidity in the absence of a change in dispersion[20]. Therefore, I expect the coefficients of the intercept terms in regression Equations (3.21), (3.23) and (3.24) to be insignificantly different from zero.

[20] See Tkac (1999) for a detailed discussion of the impact of portfolio rebalancing on trading volume.

Chapter 4: Results and Discussion

4.1. Univariate Analysis

I use two panel datasets in my analysis. The first dataset aggregates all analyst forecasts made in the same month for the same firm for 4,473 firms over the time period from 1990 to 2002. Additionally, it contains two subsets: 'holder' and 'non-holder' forecasts which proxy for the beliefs of investors who hold or do not hold the traded asset. This dataset contains 80,470 firm-month observations. The second dataset includes mean values of analysts forecasts made 45 days prior to a firm's quarterly earnings announcement and revised within 30 days following the earnings announcement. This dataset covers the 40 quarters beginning January 1993 and ending December 2002. This dataset contains 5,640 observations representing forecast revisions relative to quarterly earnings announcements for 1,364 firms.

4.1.1. Holder/Non-holder Dataset

Table XIII reports descriptive statistics for the key quantitative variables in the dataset. Median abnormal turnover is less than mean abnormal turnover in the full dataset and both subsets indicating a positively skewed distribution. This distribution indicates that many firms in the sample experience low (or even negative) abnormal turnover while a small number of firms experience extremely high abnormal turnover. However, both the mean and median values are positive indicating that the sample firms are overtrading the market. This is especially pronounced in the sub-period from 2000 to 2002 where mean (median) abnormal turnover is 10.86% (1.47%).

Table XIII: Holder/Non-Holder Descriptive Statistics

This table presents the descriptive statistics for all key quantitative variables from the Holder/N on-Holder dataset used in regression equations. $AbnormalTO_{jt}$ is defined as the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $\Delta AbnormalTO_{jt}$ is defined as the change in the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $Disp_{jt}$ is defined as the coefficient of variation in all forecasts for firm *j* in month *t*. *Across* is defined as the difference in the mean holder forecast and the mean non-holder forecast. *ΔAcross* is defined as the change in the difference in the mean holder forecast and the mean non-holder forecast. $\Delta HDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts greater than the consensus forecast for firm *j* in month *t*. $\Delta NHDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts less than or equal to the consensus forecast for firm *j* in month *t*. *Distance* is defined as $\sqrt{(\mu_H - \mu)^2 + (\mu_{NH} - \mu)^2}$. *PathLength* is defined as $\sqrt{(\Delta\mu_H)^2 + (\Delta\mu_{NH})^2}$. Slope is defined as $\frac{\Delta\mu_{NH}}{\Delta\mu_H}$.
DHold is a dummy variable that is set to 1 if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to 1, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise.

Panel A: 1990 – 1999 (N = 56,572)					
Variable	*Minimum*	*Maximum*	*Mean*	*Median*	*Std. Dev.*
AbnormalTO	-0.1379	109.5102	0.0641	0.0003	0.5129
ΔAbnormalTO	-7.1551	2.2788	-0.0021	-0.0014	0.1261
Disp	0.0012	NM[21]	NM	0.0465	NM
Across	0.0100	34.0875	0.2750	0.1300	0.7384
ΔAcross	-33.9195	31.8613	-0.0080	-0.0075	0.6828
ΔHDisp	NM	NM	NM	-0.0003	NM
ΔNHDisp	NM	NM	NM	-0.0008	NM
Distance	0.0071	24.3482	0.2007	0.0943	0.5495
PathLength	0.0000	35.4574	0.3553	0.1444	0.9209
Slope	NM	NM	NM	0.7647	NM
*DHold*Slope*	NM	NM	NM	0.0000	NM
*DNon*Slope*	NM	NM	NM	0.0000	NM
Panel B: 2000 – 2002 (N = 23,898)					
Variable	*Minimum*	*Maximum*	*Mean*	*Median*	*Std. Dev.*
AbnormalTO	-0.1954	49.1659	0.1086	0.0147	0.4821
ΔAbnormalTO	-32.6467	6.1572	-0.0040	-0.0002	0.3471
Disp	0.0007	NM	NM	0.0467	NM
Across	0.0100	63.3333	0.1992	0.0811	0.8073
ΔAcross	-18.7983	19.5983	-0.0094	-0.0070	0.5611
ΔHDisp	NM	NM	NM	-0.0010	NM
ΔNHDisp	NM	NM	NM	-0.0015	NM
Distance	0.0071	45.6703	0.1457	0.0589	0.5995
PathLength	0.0000	58.1355	0.3287	0.1324	0.9519
Slope	NM	NM	NM	0.8816	NM

table continued

[21] NM (Not Meaningful) indicates a statistic that is unusually high or low. These values occur in ratios where either the numerator or denominator is very close to zero.

*DHold*Slope*	NM	NM	NM	0.0000	NM
*DNon*Slope*	NM	NM	NM	0.0000	NM
Panel C: 1990 – 2002 (N = 80,470)					
Variable	*Minimum*	*Maximum*	*Mean*	*Median*	*Std. Dev.*
AbnormalTO	-0.1954	109.5102	0.0773	0.0029	0.5043
ΔAbnormalTO	-32.6467	6.1572	-0.0026	-0.0012	0.2150
Disp	0.0007	NM	NM	0.0466	NM
Across	0.0100	63.3333	0.2525	0.1150	0.7603
ΔAcross	-33.9195	31.8613	-0.0080	-0.0075	0.6828
ΔHDisp	NM	NM	NM	-0.0005	NM
ΔNHDisp	NM	NM	NM	-0.0010	NM
Distance	0.0071	45.6703	0.1844	0.0829	0.5654
PathLength	0.0000	58.1355	0.3476	0.1413	0.9301
Slope	NM	NM	NM	0.8033	NM
*DHold*Slope*	NM	NM	NM	0.0000	NM
*DNon*Slope*	NM	NM	NM	0.0000	NM

Table XIV reports frequency data for the key qualitative variables in the dataset. In all samples, the majority of firm-months (42% versus 32-34%) are marked by a convergence of beliefs as indicated by the variables *DHold* and *DNon*. Similarly, within-group dispersion also appears to be decreasing more often than increasing (63-66% versus 33-36%) as indicated by the variables *DHInc*, *DHDec*, *DNHInc* and *DNHDec*. This decrease in within-group dispersion is evident in both the holder and non-holder groups. In addition, more observations are marked by no change in across-group (approximately 25%) dispersion than no change in within-group (approximately 1%) dispersion.

Table XIV: Frequency of Holder/Non-Holder Qualitative Variables

This table reports the percentage of all observations in the Holder/Non-Holder dataset that exhibit the specified characteristics. *DHold* is a dummy variable that is set to one if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to one, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise. *DHInc* is a qualitative variable that is set to one if the coefficient of variation for the holder group increases relative to the prior period and is zero otherwise. *DHDec* is a qualitative variable that is set to 1 if the coefficient of variation for the holder group decreases relative to the prior period and is zero otherwise. *DNHInc* is a qualitative variable set to one if the coefficient of variation of the non-holder group increases relative to the prior period and is zero otherwise. *DNHDec* is a qualitative variable set to one if the coefficient of variation of the non-holder group decreases relative to the prior period and is zero otherwise.

table continued

Panel A: 1990 – 1999 (N = 56,572)		
Variable	*Sum*	*Percentage of Total Observations*
DHold	19,299	34.11
DNon	23,732	41.95
DHInc	20,606	36.42
DHDec	35,356	62.50
DNHInc	20,272	35.83
DNHDec	35,797	63.28
*DHold*DHInc*	13,222	23.37
*DHold*DHDec*	5,834	10.31
*DHold*DNHInc*	13,113	23.18
*DHold*DNHDec*	5,997	10.60
*DNon*DHInc*	7,323	12.94
*DNon*DHDec*	16,077	28.42
*DNon*DNHInc*	7,099	12.55
*DNon*DNHDec*	16,353	28.91
*DHInc*DNHInc*	11,718	20.71
*DHInc*DNHDec*	8,695	15.37
*DHDec*DNHInc*	8,300	14.67
*DHDec*DNHDec*	26,799	47.37
*DHold*DHInc*DNHInc*	9,211	16.28
*DHold*DHInc*DNHDec*	3,895	6.89
*DHold*DHDec*DNHInc*	3,725	6.58
*DHold*DHDec*DNHDec*	2,046	3.62
*DNon*DHInc*DNHInc*	2,479	4.38
*DNon*DHInc*DNHDec*	4,771	8.43
*DNon*DHDec*DNHInc*	4,548	8.04
*DNon*DHDec*DNHDec*	11,340	20.05
Panel B: 2000 – 2002 (N = 23,898)		
Variable	*Sum*	*Percentage of Total Observations*
DHold	7,547	31.58
DNon	10,012	41.89
DHInc	8,169	34.18
DHDec	15,531	64.99
DNHInc	7,993	33.45
DNHDec	15,763	65.96
*DHold*DHInc*	5,321	22.27
*DHold*DHDec*	2,151	9.00
*DHold*DNHInc*	5,261	22.01
*DHold*DNHDec*	2,226	9.31
*DNon*DHInc*	2,822	11.81

table continued

*DNon*DHDec*	7,082	29.63
*DNon*DNHInc*	2,714	11.36
*DNon*DNHDec*	7,234	30.27
*DHInc*DNHInc*	4,785	20.02
*DHInc*DNHDec*	3,319	13.89
*DHDec*DNHInc*	3,134	13.11
*DHDec*DNHDec*	12,338	51.63
*DHold*DHInc*DNHInc*	3,825	16.01
*DHold*DHInc*DNHDec*	1,448	6.06
*DHold*DHDec*DNHInc*	1,384	5.79
*DHold*DHDec*DNHDec*	759	3.18
*DNon*DHInc*DNHInc*	950	3.98
*DNon*DHInc*DNHDec*	1,857	7.77
*DNon*DHDec*DNHInc*	1,743	7.29
*DNon*DHDec*DNHDec*	5,291	22.14
Panel C: 1990 – 2002 (N = 80,470)		
Variable	*Sum*	*Percentage of Total Observations*
DHold	26,846	33.36
DNon	33,744	41.93
DHInc	28,775	35.76
DHDec	50,887	63.24
DNHInc	28,265	35.12
DNHDec	51,560	64.07
*DHold*DHInc*	18,543	23.04
*DHold*DHDec*	7,985	9.92
*DHold*DNHInc*	18,374	22.83
*DHold*DNHDec*	8,223	10.22
*DNon*DHInc*	10,145	12.61
*DNon*DHDec*	23,159	28.78
*DNon*DNHInc*	9,813	12.19
*DNon*DNHDec*	23,587	29.31
*DHInc*DNHInc*	16,503	20.51
*DHInc*DNHDec*	12,014	14.93
*DHDec*DNHInc*	11,434	14.21
*DHDec*DNHDec*	39,137	48.64
*DHold*DHInc*DNHInc*	13,036	16.20
*DHold*DHInc*DNHDec*	5,343	6.64
*DHold*DHDec*DNHInc*	5,109	6.35
*DHold*DHDec*DNHDec*	2,805	3.49
*DNon*DHInc*DNHInc*	3,429	4.26
*DNon*DHInc*DNHDec*	6,628	8.24
*DNon*DHDec*DNHInc*	6,291	7.82
*DNon*DHDec*DNHDec*	16,631	20.67

Table XV reports the correlations between the key quantitative variables.

Table XV: Correlation Matrix

This table displays the estimated Pearson correlation coefficients using monthly data with two-tailed probability values given in parentheses. $AbnormalTO_{jt}$ is defined as the percentage of outstanding shares traded for firm j in month t minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $\Delta AbnormalTO_{jt}$ is defined as the change in the percentage of outstanding shares traded for firm j in month t minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $Disp_{jt}$ is defined as the coefficient of variation in all forecasts for firm j in month t. *Across* is defined as the difference in the mean holder forecast and the mean non-holder forecast. $\Delta HDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts greater than the consensus forecast for firm j in month t. $\Delta NHDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts less than or equal to the consensus forecast for firm j in month t. *Distance* is defined as $\sqrt{(\mu_H - \mu)^2 + (\mu_{NH} - \mu)^2}$. *PathLength* is defined as $\sqrt{(\Delta\mu_H)^2 + (\Delta\mu_{NH})^2}$. Slope is defined as $\frac{\Delta\mu_{NH}}{\Delta\mu_H}$. *DHold* is a dummy variable that is set to 1 if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to 1, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise.

Panel A: 1990 – 1999

	Abnormal TO	*ΔAbnormal TO*	*Disp*	*Across*	*ΔAcross*	*ΔHDisp*	*ΔNHDisp*	*Distance*	*Path Length*	*Slope*	*DHold *Slope*	*DNon *Slope*
Abnormal TO	1.0000 (0.0000)											
ΔAbnormal TO	0.3051 (<-0.0001)	1.0000 (0.0000)										
Disp	0.0008 (0.8502)	-0.0036 (0.4508)	1.0000 (0.0000)									
Across	0.0075 (0.0737)	0.0073 (0.1292)	0.0037 (0.3785)	1.0000 (0.0000)								
ΔAcross	0.0132 (0.0059)	0.0149 (0.0019)	0.0055 (0.2503)	0.5086 (<0.0001)	1.0000 (0.0000)							
ΔHDisp	-0.0017 (0.7234)	-0.0018 (0.7052)	-0.0000 (0.9933)	-0.0009 (0.8450)	0.0002 (0.9603)	1.0000 (0.0000)						
ΔNHDisp	-0.0027 (0.5814)	0.0010 (0.8405)	-0.0000 (0.9953)	0.0002 (0.9649)	0.0004 (0.9394)	-0.0000 (0.9968)	1.0000 (0.0000)					
Distance	0.0079 (0.0615)	0.0078 (0.1068)	0.0037 (0.3797)	0.9983 (<0.0001)	0.5095 (<0.0001)	-0.0010 (0.8437)	-0.0000 (0.9944)	1.0000 (0.0000)				
Path Length	0.0493 (<0.0001)	0.0030 (0.5377)	0.0063 (0.1877)	0.5383 (<0.0001)	0.0282 (<0.0001)	0.0026 (0.5939)	0.0002 (0.9725)	0.5361 (<0.0001)	1.0000 (0.0000)			
Slope	-0.0016 (0.7441)	0.0011 (0.8163)	-0.0001 (0.9919)	0.0005 (0.9217)	-0.0007 (0.8888)	-0.0000 (0.9945)	-0.0000 (0.9962)	0.0005 (0.9116)	-0.0003 (0.9519)	1.0000 (0.0000)		
*DHold *Slope*	-0.0036 (0.4517)	0.0005 (0.9209)	-0.0001 (0.9889)	0.0061 (0.2086)	0.0065 (0.1809)	-0.0001 (0.9925)	-0.0000 (0.9947)	0.0062 (0.1994)	0.0017 (0.7273)	0.1560 (<0.0001)	1.0000 (0.0000)	
*DNon *Slope*	-0.0010 (0.8324)	0.0011 (0.8262)	-0.0000 (0.9935)	-0.0005 (0.9210)	-0.0017 (0.7241)	-0.0000 (0.9956)	-0.0000 (0.9969)	-0.0004 (0.9280)	-0.0006 (0.9076)	0.9877 (<0.0001)	-0.0000 (0.9928)	1.0000 (0.0000)

table continued

Panel B: 2000 – 2002												
	Abnormal TO	*ΔAbnormal TO*	*Disp*	*Across*	*ΔAcross*	*ΔHDisp*	*ΔNHDisp*	*Distance*	*Path Length*	*Slope*	*DHold *Slope*	*DNon *Slope*
Abnormal TO	1.0000 (0.0000)											
ΔAbnormal TO	-0.0488 (<0.0001)	1.0000 (0.0000)										
Disp	-0.0005 (0.9417)	-0.0062 (0.4096)	1.0000 (0.0000)									
Across	0.0253 (<0.0001)	0.0117 (0.1221)	-0.0020 (0.7597)	1.0000 (0.0000)								
ΔAcross	0.0088 (0.2419)	0.0149 (0.0483)	-0.0005 (0.9437)	0.4144 (<0.0001)	1.0000 (0.0000)							
ΔHDisp	0.0003 (0.9673)	-0.0015 (0.8428)	0.0001 (0.9945)	0.0004 (0.9549)	0.0023 (0.7602)	1.000 (0.0000)						
ΔNHDisp	0.0046 (0.5393)	0.0021 (0.7823)	-0.0001 (0.9940)	-0.0012 (0.8760)	-0.0002 (0.9763)	0.0000 (0.9974)	1.0000 (0.0000)					
Distance	0.0256 (<0.0001)	0.0121 (0.1093)	-0.0020 (0.7620)	0.9980 (<0.0001)	0.4154 (<0.0001)	0.0004 (0.9530)	-0.0012 (0.8780)	1.0000 (0.0000)				
Path Length	0.0590 (<0.0001)	-0.0011 (0.8799)	-0.0023 (0.7648)	0.4215 (<0.0001)	0.0782 (<0.0001)	0.0003 (0.9719)	-0.0005 (0.9500)	0.4176 (<0.0001)	1.0000 (0.0000)			
Slope	0.0001 (0.9849)	0.0002 (0.9745)	-0.0001 (0.9919)	0.0006 (0.9333)	0.0016 (0.8307)	0.0000 (0.9965)	-0.0000 (0.9961)	0.0001 (0.9425)	-0.0015 (0.8396)	1.0000 (0.0000)		
*DHold *Slope*	0.0001 (0.9881)	0.0003 (0.9688)	-0.0001 (0.9917)	0.0006 (0.9375)	0.0016 (0.8284)	0.0000 (0.9964)	-0.0000 (0.9960)	0.0005 (0.9466)	-0.0016 (0.8326)	0.9995 (<0.0001)	1.0000 (0.0000)	
*DNon *Slope*	0.0010 (0.8928)	-0.0018 (0.8115)	0.0001 (0.9939)	0.0013 (0.8607)	-0.0007 (0.9228)	-0.0000 (0.9973)	0.0000 (0.9971)	0.0013 (0.8638)	0.0022 (0.7702)	0.0303 (<0.0001)	0.0000 (0.9960)	1.0000 (0.0000)

Panel C: 1990 – 2002												
	Abnormal TO	*ΔAbnormal TO*	*Disp*	*Across*	*ΔAcross*	*ΔHDisp*	*ΔNHDisp*	*Distance*	*Path Length*	*Slope*	*DHold *Slope*	*DNon *Slope*
Abnormal TO	1.0000 (0.0000)											
ΔAbnormal TO	0.0581 (<0.0001)	1.0000 (0.0000)										
Disp	0.0004 (0.9173)	-0.0055 (0.1716)	1.0000 (0.0000)									
Across	0.0110 (0.0018)	0.0085 (0.0355)	0.0004 (0.9042)	1.0000 (0.0000)								
ΔAcross	0.0102 (0.0120)	0.0123 (0.0024)	0.0025 (0.5459)	0.4846 (<0.0001)	1.0000 (0.0000)							

table continued

ΔHDisp	-0.0008 (0.8355)	-0.0016 (0.7006)	-0.0000 (0.9993)	-0.0000 (0.9949)	0.0010 (0.8123)	1.0000 (0.0000)						
ΔNHDisp	-0.0011 (0.7930)	0.0008 (0.8453)	-0.0000 (0.9941)	0.0001 (0.9736)	0.0003 (0.9395)	-0.0000 (0.9997)	1.0000 (0.0000)					
Distance	0.0114 (0.0013)	0.0089 (0.0277)	0.0004 (0.9011)	0.9982 (<0.0001)	0.4853 (<0.0001)	-0.0000 (0.9945)	-0.0000 (0.9856)	1.0000 (0.0000)				
Path Length	0.0495 (<0.0001)	0.0007 (0.8569)	0.0017 (0.6732)	0.5045 (<0.0001)	0.0402 (<0.0001)	0.0014 (0.7278)	0.0001 (0.9791)	0.5018 (<0.0001)	1.0000 (0.0000)			
Slope	-0.0003 (0.9517)	0.0005 (0.9042)	-0.0001 (0.9896)	0.0004 (0.9286)	0.0002 (0.9606)	-0.0000 (0.9995)	-0.0000 (0.9957)	0.0004 (0.9285)	-0.0009 (0.8336)	1.0000 (0.0000)		
*DHold *Slope*	0.0003 (0.9366)	0.0003 (0.9492)	-0.0000 (0.9922)	0.0006 (0.8782)	0.0014 (0.7326)	-0.0000 (0.9996)	-0.0000 (0.9967)	-0.0006 (0.8827)	-0.0008 (0.8474)	0.8033 (<0.0001)	1.0000 (0.0000)	
*DNon *Slope*	-0.0009 (0.8345)	0.0005 (0.9076)	-0.0000 (0.9931)	-0.0002 (0.9551)	-0.0015 (0.7056)	-0.0000 (0.9996)	-0.0000 (0.9971)	-0.0002 (0.9613)	-0.0004 (0.9258)	0.5956 (<0.0001)	-0.0000 (0.9962)	1.0000 (0.0000)

The *Across*, *ΔAcross, Distance* and *PathLength* variables are all highly correlated with the dependent variables *AbnormalTO* and *ΔAbnormalTO.* This gives a preliminary indication that across-group dispersion and the magnitude of belief revisions may have some explanatory power with respect to trading volume. The *Distance* and *PathLength* variables are also highly correlated with *Across* and with each other. The correlation between the variables *Across*, *ΔAcross*, *Slope* and *DHold*Slope* and *Slope* and *DNon*Slope* is to be expected. To prevent interpretation errors due to multicollinearity, I do not include combinations of these variables in my regression models.

4.1.2. Belief Revisions Dataset

In the full belief revisions dataset, pre-announcement abnormal turnover ranges from -11.52 % to 216.16% with a mean value of 3.09%. However, after the quarterly earnings announcement, abnormal turnover rises to a range of -10.35 % to 788.04% with a mean value of 9.66 %.

The market capitalization of the firms in the sample ranges from \$3,094,410 to \$498,415,940,000 with a mean of \$10,030,096,780. The post-announcement returns relative to the quarterly earnings announcement for firms in the sample range from -0.58% to +0.78% with a mean of 0.00%.

In the 1995-1998 subset of the belief revisions dataset, pre-announcement abnormal turnover ranges from -6.63 % to 161.34% with a mean value of 2.45%. However, after the quarterly earnings announcement, abnormal turnover rises to a range of -6.14% to 349.83% with a mean value of 7.41%. The market capitalization of the firms in the sample ranges from \$3,094,410 to \$188,596,271,000 with a mean of \$8,792,683,380. The post-announcement returns relative to the quarterly earnings announcement for firms in the sample range from -0.33% to +0.38% with a mean of 0.00%.

Tables XVI and XVII report frequency data for the key qualitative variables in the dataset. This data exhibits high occurrences of divergence of beliefs (12%/13%), inconsistent belief revisions (26%) and 'flips' (17%). Kandel and Pearson (1995) report that on average, 13.4% of their sample observations exhibit both inconsistent belief revisions and either flip or diverge. Bamber, Barron and Stober (1999) report a slightly lower occurrence rate of 12.4% in their full sample. In the full sample, 7.69% of all observations exhibit inconsistent belief revisions *and* either flip or diverge. In the 1995-1998 subset, 8.7% of all observations fit this criteria.

These tables show that the pairs of analysts in the sample tend to agree more after the quarterly earnings announcement by revising their forecasts in the same direction. However, the magnitude of these changes tends not to be such that analysts with the lower forecasts before the announcement have higher forecasts after the announcement. Thus, analysts in this sample tend to revise their forecasts in a homogeneous manner.

Table XVI: Frequency of Analyst Pairings Qualitative Variables

This table reports the percentage of all observations in the Analyst Pairings dataset that exhibit the specified characteristics. There are 5,640 total observations in the dataset. *Diverge* (*Converge*) is a qualitative variable set to one if the difference in the post-announcement forecasts is greater (less) than the difference in the pre-announcement forecasts and is zero otherwise. *Consistent* is a qualitative variable set to one if a pair of analysts revise their forecast in the same direction and is zero otherwise. *Inconsistent* is a qualitative variable set to one if a pair of analysts revises their forecast in opposite directions and is zero otherwise. *Flip* (*NoFlip*) is a qualitative variable set to one if a pair of analysts revises their forecasts in such a way that the analyst with the higher pre-announcement forecast has the lower (higher) post-announcement forecast and is zero otherwise.

Panel A: Full Dataset		
Variable	*Sum*	*Percentage of Total Observations*
Do the Analysts Agree More After the Announcement?		
Converge (Yes)	4,926	87.34
Diverge (No)	677	12.00
Constant (No Change)	37	0.66
Total	5,640	100.00
Do the Analysts Revise in the Same Direction?		
Consistent (Yes)	4,194	74.36
Inconsistent (No)	1,446	25.64
Total	5,640	100.00
Does the Higher Pre-Event Analyst Become the Lower Post-Event Analyst?		
Flip (Yes)	948	16.81
No Flip (No)	4,692	83.19
Total	5,640	100.00
Panel B: 1995 – 1998 Subset		
Variable	*Sum*	*Percentage of Total Observations*
Do the Analysts Agree More After the Announcement?		
Converge (Yes)	1,596	86.27
Diverge (No)	242	13.08
Constant (No Change)	12	0.65
Total	1,850	100.00
Do the Analysts Revise in the Same Direction?		
Consistent (Yes)	1,371	74.11
Inconsistent (No)	479	25.89
Total	1,850	100.00
Does the Higher Pre-Event Analyst Become the Lower Post-Event Analyst?		
Flip (Yes)	312	16.86
No Flip (No)	1,538	83.14
Total	1,850	100.00

Table XVII: Frequency of Specific Types of Belief Revisions

This table reports the percentage of all observations in the Analyst Pairings dataset that exhibit the specified characteristics. There are 5,640 total observations in the dataset. *Diverge* (*Converge*) is a qualitative variable set to one if the difference in the post-announcement forecasts is greater (less) than the difference in the pre-announcement forecasts and is zero otherwise. *Consistent* is a qualitative variable set to one if a pair of analysts revise their forecast in the same direction and is zero otherwise. *Inconsistent* is a qualitative variable set to one if a pair of analysts revises their forecast in opposite directions and is zero otherwise. *Flip* (*NoFlip*) is a qualitative variable set to one if a pair of analysts revises their forecasts in such a way that the analyst with the higher pre-announcement forecast has the lower (higher) post-announcement forecast and is zero otherwise.

Panel A: Full Dataset

Variable	*Sum*	*Percentage of Total Observations*
Consistent Convergent	3,056	54.18
Consistent Convergent Flip	525	9.31
Consistent Divergent	524	9.29
Consistent Divergent Flip	53	0.94
Consistent Constant	32	0.57
Consistent Constant Flip	4	0.07
Inconsistent Convergent	1,013	17.96
Inconsistent Convergent Flip	332	5.89
Inconsistent Divergent	67	1.19
Inconsistent Divergent Flip	33	0.59
Inconsistent Constant Flip	1	0.02
Total	5,640	100.00

Panel B: 1995 – 1998 Subset

Variable	*Sum*	*Percentage of Total Observations*
Consistent Convergent	1,005	54.32
Consistent Convergent Flip	151	8.16
Consistent Divergent	182	9.84
Consistent Divergent Flip	21	1.14
Consistent Constant	9	0.49
Consistent Constant Flip	3	0.16
Inconsistent Convergent	318	17.19
Inconsistent Convergent Flip	122	6.59
Inconsistent Divergent	24	1.30
Inconsistent Divergent Flip	15	0.81
Inconsistent Constant Flip	0	0.00
Total	1,850	100.00

4.2. Multivariate Analysis

4.2.1. Hypothesis One

Table XVIII reports the average estimates and t-statistics of each coefficient using the methodology of Fama and MacBeth (1973) in the three regressions used to test H_1.

Table XVIII: Relations Between Trading Volume and Overall Dispersion

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses. Regressions are performed by fiscal year and by month. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. The dependent variable in all models is $AbnormalTO_{jt}$. $AbnormalTO_{jt}$ is defined as the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $Disp_{jt}$ is defined as the coefficient of variation in all forecasts for firm *j* in month *t*. *Distance* is defined as $\sqrt{(\mu_H - \mu)^2 + (\mu_{NH} - \mu)^2}$.

Panel A: 1990 – 1999				
Intercept	?	0.4919(3.63)***	0.4322(4.51)***	
Disp	-	0.3109(0.83)		
Distance	-		0.3134(1.51)	
Panel B: 2000 – 2002				
Intercept	?	0.4201(18.28)***	0.4020(17.64)***	
Disp	-	0.4859(2.81)***		
Distance	-		0.4781(1.74)*	
Panel C: 1990 – 2002				
Intercept	?	0.4748(4.59)***	0.4250(5.81)***	
Disp	-	0.3527(1.22)		
Distance	-		0.3527(2.06)**	

In all three models and all three sample periods the signs of the coefficients are the opposite of what I predict. This indicates a weak, positive relation between overall dispersion and trading volume. That is, as there is more disagreement among investors, in general, market liquidity (as measured here by abnormal turnover) increases.

4.2.2. Hypothesis Two

Table XIX reports the average estimates and t-statistics of each coefficient using the methodology of Fama and MacBeth (1973) in the three regressions used to test H_2.

Table XIX: Relations Between Trading Volume and Within-Group Dispersion

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses. Regressions are performed by fiscal year and by month. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. The dependent variable in all models is $\Delta AbnormalTO_{jt}$. $\Delta AbnormalTO_{jt}$ is defined as the change in the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. $\Delta HDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts greater than the consensus forecast for firm *j* in month *t*. $\Delta NHDisp_{jt}$ is defined as the change in the coefficient of variation in forecasts less than or equal to the consensus forecast for firm *j* in month *t*.

Panel A: 1990 – 1999				
Intercept	?	-0.0078(-0.19)	-0.2671(-0.95)	
ΔHDisp	+	0.3743(1.69)*		
ΔNHDisp	+		0.6833(1.34)	
Panel B: 2000 – 2002				
Intercept	?	0.0606(3.69)***	0.4139(0.98)	
ΔHDisp	+	0.4605(1.80)*		
ΔNHDisp	+		0.9156(2.06)**	
Panel C: 1990 – 2002				
Intercept	?	0.0086(0.27)	-0.1037(-0.44)	
ΔHDisp	+	0.3950(2.20)**		
ΔNHDisp	+		0.7390(1.84)*	

The signs of the coefficients for *ΔHDisp* and *ΔNHDisp* are positive in all models and all sample periods. This indicates that a change in the dispersion of either group (holders or non-holders) is positively related to trading volume.

4.2.3. Hypothesis Three

Table XX reports the average estimates and t-statistics of each coefficient using the methodology of Fama and MacBeth (1973) in the regression equation used to test H_{3a} and H_{3b}. All right-hand-side variables are positive in all regression equations. This indicates that *any* change in across-group dispersion is positively related to trading volume. *DHold* and *DNon* appear to have greater explanatory power than *Across* and *ΔAcross*.

Table XXI reports the average estimates and t-statistics of each coefficient using the methodology of Fama and MacBeth (1973) in the regression equations based on the Holder/Non-Holder dataset used to test H_{3c} and H_{3d}.

Table XX: Relations Between Trading Volume and Across-Group Dispersion

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses. Regressions are performed by fiscal year and by month. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. The dependent variable in all models is $AbnormalTO_{jt}$. $AbnormalTO_{jt}$ is defined as the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. *Across* is defined as the difference in the mean holder forecast and the mean non-holder forecast. *ΔAcross* is defined as the change in the difference in the mean holder forecast and the mean non-holder forecast. *DHold* is a dummy variable that is set to one if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to one, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise.

Panel A: 1990 – 1999					
	Intercept	*Across*	*ΔAcross*	*DHold*	*DNon*
Predicted Sign	?	-	-	-	+
	0.5658 (2.49)**	0.2297 (1.13)			
	0.0551 (3.59)***		0.2640 (1.29)		
	0.0065 (0.17)			0.1105 (5.57)***	0.0167 (3.91)***
Panel B: 2000 – 2002					
	Intercept	*Across*	*ΔAcross*	*DHold*	*DNon*
Predicted Sign	?	-	-	-	+
	0.3988 (16.49)***	0.3866 (1.83)*			
	0.0424 (1.80)*		0.4266 (1.26)		
	0.0188 (0.77)			0.1667 (6.53)***	0.0296 (2.85)***
Panel C: 1990 – 2002					
	Intercept	*Across*	*ΔAcross*	*DHold*	*DNon*
Predicted Sign	?	-	-	-	+
	0.5259 (3.03)***	0.2671 (1.64)			
	0.0520 (4.02)***		0.3030 (1.72)*		
	0.0094 (0.32)			0.1240 (7.62)***	0.0198 (4.84)***

Table XXI: Relations Between Trading Volume and Belief Revision Magnitude

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses. Regressions are performed by fiscal year and by month. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. The dependent variable in all models is $\Delta AbnormalTO_{jt}$. $\Delta AbnormalTO_{jt}$ is defined as the change in the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. *PathLength* is defined as $\sqrt{(\Delta\mu_H)^2 + (\Delta\mu_{NH})^2}$. Slope is defined as $\frac{\Delta\mu_{NH}}{\Delta\mu_H}$. *DHold* is a qualitative variable that is set to one if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a qualitative variable that is set to one, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise.

Panel A: 1990 – 1999							
	Intercept	*PathLength*	*Slope*	*Slope*DHold*	*Slope*DNon*	*DHold*	*DNon*
	?	?	?	-	+	-	+
	0.0221 (0.51)			0.1280 (3.83)***			
	0.0375 (1.98)**				0.0860 (3.95)***		
	0.0628 (4.19)***	0.1081 (1.89)*		0.1118 (5.22)***			
	0.0629 (3.71)***	0.0931 (1.66)*			0.1186 (3.68)***		
	0.0754 (2.83)***	0.0741 (1.08)	0.0765 (4.56)***			0.1167 (3.35)***	0.0123 (1.03)
Panel B: 2000 – 2002							
	Intercept	*PathLength*	*Slope*	*Slope*DHold*	*Slope*DNon*	*DHold*	*DNon*
	?	?	?	-	+	-	+
	0.0355 (1.08)			0.1547 (5.61)***			
	0.0535 (3.61)***				0.0641 (2.03)**		
	0.0699 (1.17)	0.0508 (0.16)		0.1354 (2.54)**			
	0.0393 (0.78)	0.2495 (0.75)			0.0900 (1.73)*		
	0.0040 (0.08)	0.0877 (0.34)	0.1195 (5.81)***			0.1649 (6.68)***	0.0442 (3.31)***
Panel C: 1990 – 2002							
	Intercept	*PathLength*	*Slope*	*Slope*DHold*	*Slope*DNon*	*DHold*	*DNon*
	?	?	?	-	+	-	+
	0.0253 (0.74)			0.1344 (5.13)***			
	0.0413 (2.79)***				0.0807 (4.44)***		
	0.0645 (3.48)***	0.0939 (1.03)		0.1176 (5.65)***			
	0.0571 (3.22)***	0.1315 (1.43)			0.1116 (4.06)***		
	0.0574 (2.44)**	0.0775 (0.94)	0.0873 (6.42)***			0.1287 (4.79)***	0.0203 (2.14)**

Again, the coefficients for all right-hand-side variables are positive. This indicates that any change in across-group dispersion is positively related to trading volume. *PathLength*, which measures, the magnitude of the belief revision, appears to have little explanatory power. *Slope*, which measures both the consistency of the belief revision and the relative magnitude of the belief revisions across groups, appears to have a high level of explanatory power. The positive, significant coefficients in all regression equations indicate that the consistency of belief revisions is positively related to trading volume. When combined with *DHold* and *DNon*, *Slope* indicates whether consistent belief revisions marked by divergence or convergence are related to trading volume. The positive, significant coefficients for the variables *DHold**Slope* and *DNon**Slope* in all regression equations indicate that regardless of the change in across-group dispersion, consistency of belief revisions is positively related to trading volume.

Table XXII reports the average estimates and t-statistics of each coefficient in the regression equations based on the Analyst Pairings dataset used to test H_{3c} and H_{3d}.

Certain characteristics of belief revisions tend to explain changes in market liquidity. When investors revise their beliefs in the same manner (either both upward or both downward) resulting in increased consensus, market liquidity tends to increase when measured as the change in abnormal turnover or depth. In these models, *Consistent*Convergent* is positive and significant. However, when trade-weighted or quoted spreads are used as measures of liquidity, spreads tend to widen in response to these characteristics indicating a less liquid market for the security. In these models, *Consistent*Convergent* is also positive and significant.

Flips, as previously described, are indicative of a dramatic change in beliefs whereby pessimistic investors become optimistic investors and vice versa.

Table XXII: Relations Between Trading Volume and Belief Revision Characteristics

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses based on Ordinary Least Squares (OLS). Regressions are performed by fiscal year and quarter. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. *Diverge* (*Converge*) is a qualitative variable set to one if the difference in the post-announcement forecasts is greater (less) than the difference in the pre-announcement forecasts and is zero otherwise. *Consistent* is a qualitative variable set to one if a pair of analysts revise their forecast in the same direction and is zero otherwise. *Inconsistent* is a qualitative variable set to one if a pair of analysts revises their forecast in opposite directions and is zero otherwise. *Flip* (*NoFlip*) is a qualitative variable set to one if a pair of analysts revises their forecasts in such a way that the analyst with the higher pre-announcement forecast has the lower (higher) post-announcement forecast and is zero otherwise. *PriceChange* is the natural logarithm of the absolute value of the difference between the stock price on the day following the quarterly earnings announcement and the stock price on the day prior to the quarterly earnings announcement. *Surprise* is the difference between the mean pre-announcement forecast and the actual earnings. *Size* is the natural logarithm of average market capitalization over the period (-1,+1) relative to the quarterly earnings announcement.

Panel A: Dependent Variable is Abnormal Turnover

Intercept	*Consistent Convergent*	*Consistent Convergent Flip*	*Consistent Divergent*	*Consistent Divergent Flip*	*Consistent No Change*	*Inconsistent Convergent*	*Inconsistent Convergent Flip*	*Inconsistent Divergent*	*Inconsistent Divergent Flip*	*Inconsistent No Change Flip*	*Consistent No Change Flip*	*Price Change*	*Surprise*	*Size*
?	+	+	-	+	?	+	+	-	+	?	?	+	+	-
24.7593 (8.90)***	0.7692 (1.88)*											4.0483 (13.52)***	0.7524 (6.64)***	-1.2709 (-6.54)***
24.9397 (8.84)***		1.4769 (1.87)*										4.0552 (13.39)***	0.7351 (6.51)***	-1.2856 (-6.56)***
24.9699 (8.90)***			1.1025 (1.59)									4.0463 (13.55)***	0.7324 (6.45)***	-1.2902 (-6.61)***
24.8433 (8.86)***				6.0187 (2.63)***								4.0282 (13.56)***	0.7164 (6.61)***	-1.2794 (-6.56)***
24.9887 (8.95)***					1.8943 (0.87)							4.0685 (13.61)***	0.7452 (6.65)***	-1.2945 (-6.66)***
24.9552 (8.86)***						-0.1972 (-0.39)						4.0258 (13.51)***	0.7551 (6.68)***	-1.2672 (-6.50)***
24.8428 (8.86)***							2.2872 (2.24)**					4.0535 (13.54)***	0.7476 (6.63)***	-1.2788 (-6.56)***
24.9205 (8.86)***								2.6449 (1.34)				4.0424 (13.51)***	0.7116 (6.28)***	-1.2875 (-6.58)***
25.0511 (8.88)***									2.9625 (1.42)			4.0580 (13.51)***	0.7406 (6.57)***	-1.2924 (-6.59)***
24.9785 (9.02)***										0.3158 (0.64)		4.0714 (13.62)***	0.7463 (6.68)***	-1.2986 (-6.74)***
24.9736 (9.02)***											-0.3767 (-0.44)	4.0734 (13.62)***	0.7458 (6.67)***	-1.2980 (-6.74)***

table continued

Panel B: Dependent Variable is Trade-Weighted Spread															
	8.5530	10.0042											1.3042	1.6894	1.9158
	(0.33)	(2.39)**											(0.63)	(1.33)	(1.09)
	18.2031		-1.0734										1.6878	1.8295	1.6235
	(0.67)		(-0.15)										(0.81)	(1.43)	(0.89)
	14.3944			0.4213									1.5943	1.7135	1.8055
	(0.56)			(0.06)									(0.78)	(1.34)	(1.02)
	14.3279				-6.2430								1.4524	1.7239	1.7692
	(0.56)				(-0.65)								(0.70)	(1.36)	(1.01)
	13.4676					13.7551							1.5058	1.6817	1.7974
	(0.53)					(1.32)							(0.74)	(1.34)	(1.03)
	12.9101						1.4376						1.4502	1.4998	1.8891
	(0.50)						(0.25)						(0.70)	(1.17)	(1.06)
	12.6547							4.3322					1.5547	1.6822	1.9007
	(0.49)							(0.54)					(0.75)	(1.32)	(1.08)
	14.3125								8.9206				1.5233	1.6696	1.7743
	(0.55)								(0.37)				(0.74)	(1.31)	(1.00)
	13.4742									5.7279			1.5715	1.7159	1.8301
	(0.52)									(0.57)			(0.77)	(1.35)	(1.04)
	14.1732											8.4524	1.5546	1.6805	1.7632
	(0.55)											(0.25)	(0.76)	(1.33)	(1.01)
Panel C: Dependent Variable is Average Quoted Spread															
	-12.4734	4.0143											1.2010	0.0830	1.8667
	(-1.16)	(2.07)**											(1.20)	(0.20)	(2.69)***
	-10.6521		1.5895										1.3360	0.0633	1.8557
	(-1.00)		(0.45)										(1.33)	(0.15)	(2.67)***
	-10.0031			3.5766									1.3884	0.0225	1.7976
	(-0.94)			(1.10)									(1.37)	(0.05)	(2.58)**
	-8.5578				-47.1188								0.3951	0.0000	1.4557
	(-1.01)				(-1.56)								(0.54)	(0.00)	(2.66)***
	-9.9260					2.6967							1.3432	0.0251	1.7880
	(-0.94)					(0.72)							(1.34)	(0.06)	(2.59)**
	-11.3805						-0.0284						1.2931	0.1308	1.9232
	(-1.06)						(-0.01)						(1.28)	(0.31)	(2.71)***
	-11.0945							5.3985					1.4240	0.0252	1.8754
	(-1.03)							(1.12)					(1.39)	(0.06)	(2.66)***
	-10.0288								7.6210				1.3827	0.0399	1.8004
	(-0.95)								(1.30)				(1.36)	(0.10)	(2.59)**
	-9.9429									7.4501			1.3672	0.0421	1.8081
	(-0.93)									(0.62)			(1.34)	(0.10)	(2.56)**
	-9.9065											0.9660	1.3434	0.0251	1.7867
	(-0.94)											(0.53)	(1.34)	(0.06)	(2.58)**

Panel D: Dependent Variable is Average Depth															
	5.2294	37.5331											14.3928	2.4871	5.9534
	(0.06)	(2.22)**											(1.62)	(0.71)	(0.96)
	18.0208		15.2575										15.3094	2.6061	6.3134
	(0.19)		(0.58)										(1.71)*	(0.75)	(0.99)
	18.2362			25.7776									15.4094	2.5651	6.1530
	(0.20)			(0.79)									(1.71)*	(0.73)	(0.98)
	35.4976				-635.466								3.5305	2.2822	2.0119
	(1.05)				(-1.71)*								(1.25)	(1.46)	(0.88)
	17.8899					12.9666							15.1626	2.4891	6.1322
	(0.19)					(0.37)							(1.69)*	(0.72)	(0.99)
	15.4241						5.3773						14.9403	3.0539	6.5035
	(0.17)						(0.27)						(1.66)	(0.86)	(1.04)
	24.0422							18.1163					15.2444	2.4022	5.7572
	(0.26)							(0.56)					(1.67)*	(0.69)	(0.92)
	16.3638								59.3323				15.6883	2.5618	6.2736
	(0.18)								(0.94)				(1.70)*	(0.73)	(1.00)
	18.3972									54.8425			15.2876	2.6213	6.2326
	(0.20)									(0.51)			(1.67)	(0.69)	(0.98)
	17.7622											5.7987	15.1478	2.4830	6.1309
	(0.19)											(0.47)	(1.69)*	(0.71)	(0.99)
Panel E: Dependent Variable is Average Trade Size															
	14576.75	231.697											-285.074	147.810	-601.967
	(5.46)***	(0.57)											(-1.34)	(1.26)	(-3.13)***
	14042.85		1474.21										-307.196	152.769	-578.974
	(5.54)***		(1.97)*										(-1.47)	(1.31)	(-3.07)***
	14477.09			759.909									-295.528	148.841	-605.222
	(5.53)***			(1.07)									(-1.43)	(1.28)	(-3.17)***
	14096.89				5494.52								-232.484	146.766	-589.498
	(5.63)***				(1.82)*								(-1.16)	(1.28)	(-3.21)***
	14169.72					152.424							-301.291	152.710	-587.438
	(5.47)***					(0.10)							(-1.45)	(1.33)	(-3.11)***
	14391.86						-227.208						-342.503	145.626	-590.352
	(5.49)***						(-0.40)						(-1.59)	(1.25)	(-3.09)***
	14616.70							2197.73					-267.266	171.704	-618.019
	(5.63)***							(2.27)**					(-1.30)	(1.48)	(-3.25)***
	14451.16								-483.528				-321.245	147.847	-602.980
	(5.49)***								(-0.27)				(-1.52)	(1.27)	(-3.15)***
	14347.50									622.554			-303.079	154.607	-594.865
	(5.48)***									(0.29)			(-1.45)	(1.31)	(-3.11)***
	14166.37											392.917	-301.529	153.051	-587.302
	(5.47)***											(0.36)	(-1.46)	(1.33)	(-3.11)***

table continued

Panel F: Dependent Variable is Average Effective Spread

	2.8752 (0.71)	0.3473 (0.55)											-0.3936 (-1.01)	0.2203 (1.12)	0.3517 (1.26)
	3.0162 (0.73)		-1.3609 (-1.08)										-0.4244 (-1.06)	0.2286 (1.17)	0.3402 (1.19)
	2.4897 (0.61)			0.8567 (0.75)									-0.4542 (-1.15)	0.2019 (1.03)	0.3632 (1.29)
	1.7165 (0.44)				11.9042 (2.27)**								-0.3118 (-0.84)	0.1880 (0.97)	0.3954 (1.47)
	2.6754 (0.66)					2.7525 (1.35)							-0.4421 (-1.13)	0.1966 (1.01)	0.3434 (1.23)
	2.8164 (0.69)						1.7074 (1.91)*						-0.4569 (-1.13)	0.1763 (0.89)	0.3267 (0.49)
	1.9666 (0.49)							3.2557 (1.76)*					-0.3541 (-0.91)	0.1991 (1.02)	0.3891 (1.39)
	2.5315 (0.63)								1.3312 (0.70)				-0.4478 (-1.13)	0.2039 (1.05)	0.3606 (1.29)
	2.8813 (0.71)									-2.2315 (-0.62)			-0.4447 (-1.13)	0.1856 (0.95)	0.3265 (1.17)
	2.6513 (0.66)											2.7291 (1.47)	-0.4519 (-1.15)	0.1970 (1.01)	0.3434 (1.23)

In order for investors to rebalance their portfolios to reflect these changes in beliefs, a significant amount of trading must occur. This argument is reflected in the positive and significant regression coefficients for the variables *Consistent*Convergent*Flip*, *Consistent*Divergent*Flip* and *Inconsistent*Convergent*Flip* when abnormal turnover and average trade size are used as measures of liquidity.

Finally, as predicted, the control variables *PriceChange*, *Surprise* and *Size* do explain a significant portion of the change in liquidity in most models but most notably in those using abnormal turnover as a measure of liquidity. Specifically, the change in price, which Bamber and Cheon (1995) argue indicates the aggregate belief revision, is positive and significant. This indicates that the change in liquidity increases as price change increases. The change in liquidity also increases as the degree of surprise in the earnings announcement increases. Thus, as earnings differ more from what investors expect, investors must engage in more trading to rebalance their portfolios in response to this new information. Finally, I use size as a proxy for information asymmetry. That is, larger firms are expected to have less information asymmetry because there is more public information available to investors regarding these firms. As predicted, the change in liquidity decreases as size increases. Liquidity changes less in large firms than small firms because the marginal impact of an individual piece of information is less than in a small firm.

4.2.4. Hypothesis Four

Table XXIII reports the average estimates and t-statistics of each coefficient using the methodology of Fama and MacBeth (1973) in the regression equations based on the Holder/Non-Holder dataset used to test H_4.

Previously presented results showed a positive relation between volume and any independent change in across-group and within-group dispersion. Here, simultaneous changes in dispersion both within and across groups (holders and non-holders) are examined. All coefficients are positive and significant. These results indicate that any simultaneous change in across-group and within-group dispersion is positively related to trading volume.

Table XXIII: Relations Between Trading Volume and Simultaneous Changes in Within-Group and Across-Group Dispersion

This table reports the average estimates of each coefficient in the regression equation with t-statistics given in parentheses. Regressions are performed by fiscal year and by month. Average coefficients and t-statistics are calculated using Fama and MacBeth (1973) methodology. The dependent variable in all models is $\Delta AbnormalTO_{jt}$. $\Delta AbnormalTO_{jt}$ is defined as the change in the percentage of outstanding shares traded for firm *j* in month *t* minus the percentage of outstanding shares traded for all firms in the CRSP database in month t. *DHold* is a dummy variable that is set to one if the mean price revision of the holder group is greater than that of the non-holder group and is zero otherwise. *DNon* is a dummy variable that is set to one, if the mean price revision of the non-holder group is greater than that of the holder group and is zero otherwise. *DHInc* is a qualitative variable that is set to one if the coefficient of variation for the holder group increases relative to the prior period and is zero otherwise. *DHDec* is a qualitative variable that is set to 1 if the coefficient of variation for the holder group decreases relative to the prior period and is zero otherwise. *DNHInc* is a qualitative variable set to one if the coefficient of variation of the non-holder group increases relative to the prior period and is zero otherwise. *DNHDec* is a qualitative variable set to one if the coefficient of variation of the non-holder group decreases relative to the prior period and is zero otherwise.

Panel A: 1990 – 1999										
Intercept	?	-0.0285 (-0.72)	-0.0011 (-0.03)	0.0085 (0.23)	0.0143 (0.40)	0.0037 (0.10)	0.0059 (0.16)	0.0337 (2.22)**	0.0524 (3.47)***	0.0244 (0.72)
*DHold*DHInc*DNHInc*	?	0.1520 (8.68)***								0.1398 (5.30)***
*DHold*DHInc*DNHDec*	?		0.0545 (2.30)**							0.1162 (3.99)***
*DHold*DHDec*DNHInc*	?			0.0771 (5.34)***						0.1105 (4.54)***
*DHold*DHDec*DNHDec*	-				0.0409 (2.11)**					0.0436 (0.87)
*DNon*DHInc*DNHInc*	+					0.0749 (7.99)***				0.0795 (4.05)***
*DNon*DHInc*DNHDec*	?						0.0487 (4.44)***			0.0533 (3.48)***
*DNon*DHDec*DNHInc*	?							0.0730 (3.30)***		0.0779 (4.44)***
*DNon*DHDec*DNHDec*	?								0.0546 (5.42)***	0.0530 (6.34)***
Panel B: 2000 - 2002										
Intercept	?	0.0011 (0.05)	0.0451 (2.82)***	0.0332 (1.43)	0.0318 (1.38)	0.0240 (1.04)	0.0576 (3.39)***	0.0364 (1.53)	0.0660 (2.76)***	0.0360 (0.21)
*DHold*DHInc*DNHInc*	?	0.1741 (9.00)***								0.0481 (0.45)
*DHold*DHInc*DNHDec*	?		0.1196 (7.13)***							0.2585 (1.87)*

table continued

*DHold*DHDec*DNHInc*	?			0.0699 (3.03)***						0.2457 (1.54)
*DHold*DHDec*DNHDec*	-				0.0707 (3.46)***					0.2000 (1.38)
*DNon*DHInc*DNHInc*	+					0.0585 (2.11)**				0.0221 (0.39)
*DNon*DHInc*DNHDec*	?						0.0754 (3.68)***			0.2470 (1.57)
*DNon*DHDec*DNHInc*	?							0.0637 (2.88)***		-0.0273 (-0.26)
*DNon*DHDec*DNHDec*	?								0.0249 (1.21)	0.0260 (0.93)
Panel C: 1990 – 2002										
Intercept	?	-0.0215 (-0.70)	0.0098 (0.34)	0.0144 (0.49)	0.0184 (0.66)	0.0085 (0.30)	0.0180 (0.63)	0.0343 (2.66)***	0.0556 (4.34)***	0.0272 (0.55)
*DHold*DHInc*DNHInc*	?	0.1573 (11.14)***								0.1175 (3.60)***
*DHold*DHInc*DNHDec*	?		0.0701 (3.79)***							0.1512 (3.74)***
*DHold*DHDec*DNHInc*	?			0.0754 (6.13)***						0.1433 (3.35)***
*DHold*DHDec*DNHDec*	-				0.0482 (3.10)***					0.0823 (1.59)
*DNon*DHInc*DNHInc*	+					0.0710 (7.32)***				0.0656 (3.23)***
*DNon*DHInc*DNHDec*	?						0.0552 (5.70)***			0.1010 (2.50)**
*DNon*DHDec*DNHInc*	?							0.0707 (4.04)***		0.0516 (1.74)*
*DNon*DHDec*DNHDec*	?								0.0474 (5.21)***	0.0467 (5.09)***

4.2.5. Hypothesis Five

For completeness, H_5 predicts that if there is no change in dispersion, there will be no change in trading volume. To test this hypothesis, I examine the intercepts of the models that isolate the variables ΔHDisp, ΔNHDisp, ΔAcross, DHold and DNon where ΔHDisp and ΔNHDisp examine within group dispersion while ΔAcross, DHold and DNon examine across group dispersion. The impact of observations that reflect no change in dispersion are captured in the intercept terms of these equations. In all but one model that analyzes within-group dispersion, the intercept term is not significantly different from zero. This indicates that the change in trading volume is primarily explained by changes in within group-dispersion and not by firm-months where there is no change in within-group dispersion. The intercept in the equations that use ΔAcross to measure across-group dispersion is significantly different from zero in all samples. However, the variable I use to measure changes in across-group dispersion, ΔAcross, does not appear to explain the variation in changes in trading volume. When I use DHold and DNon to measure changes in across-group dispersion, the intercept is not significantly different from zero. This indicates that the change in trading volume is primarily explained by changes in across-group dispersion and not by firm-months where there is no change in across-group dispersion.

Chapter 5: Summary and Conclusions

5.1. Summary

I use two datasets to test the relation between market liquidity, the heterogeneity of beliefs and the heterogeneity of belief revisions. The first dataset allows me to construct two groups that proxy for 'holders' and 'non-holders' of a traded asset. This construct allows me to test the relation between changes in trading volume (as a measure of market liquidity) and changes in the dispersion of beliefs both within and across these two groups. I examine changes in within- and across-group dispersion separately and simultaneously. The second dataset allows me to examine belief revisions more closely by analyzing only those prior and posterior beliefs surrounding an information event. I examine the impact of specific belief revision phenomena on trading volume. I find that a change in dispersion within either group (holders or non-holders) is positively related to market liquidity. However, contrary to my expectations, I find that any change in across-group dispersion is also positively related to market liquidity. That is, regardless of which group (holders or non-holders) revises more (or the specific characteristics of their belief revisions), any change in beliefs prompting a change in belief dispersion is positively related to market liquidity. Also, when within-group and across-group dispersion change simultaneously – regardless of the direction or magnitude of the change, market liquidity increases. It is possible that in the aggregate, market participants change their beliefs in an offsetting manner. That is, the aggregate dispersion (either within a particular group or across the two groups) prior to and following a news announcement may be quantitatively equal. I find that my results are not driven by these instances. Finally, I find that the characteristics of market participants' belief revisions relative to one another (consistent or inconsistent, convergent or divergent, etc.) provide little additional insight into changes in market liquidity relative to belief revisions surrounding news announcements. One exception, however, is the case of 'flips'. In this case, belief revisions across groups are so extreme that essentially holders and non-holders change positions such that sellers become buyers and buyers become sellers. In this extreme case, market liquidity is positively impacted.

5.2. Conclusion and Future Extensions

My results provide evidence that without regard to specific information events, trading volume is positively related to any change in within-group or across-group dispersion whether this dispersion is measured separately or simultaneously. Second, I provide evidence that suggests that both the convergence and homogeneity of belief revisions are positively related to changes in trading volume. Finally, my results suggest that belief revisions such that investors with higher valuations subsequently hold lower valuations ('flips') have a significant (positive) relation to changes in trading volume.

These results warrant further examination of the relation between belief revisions and market liquidity. My findings are based on the careful examination of changes in the means of distributions of buyer and seller demand prices. For much of this analysis, however, I have assumed little or no change in the variance of these distributions. However, many interesting empirical questions remain. For example, if changes in market liquidity are, indeed, influenced by changes in the overlap in buyer and seller demand price distributions, in what other ways can this overlap change shape besides a change in the means of the distributions? For computational ease, I assume normal distributions, but certainly buyer and seller prices can be represented in other ways. In fact, these distributions could shift so dramatically that they 'lose' there normality after certain extreme changes in one or both distributions. Particularly, close examination of those observations in the tails of the distributions is in order. What would be the impact on market liquidity of 'holdout' investors whose demand prices are represented in the (upper or lower) tails of the distribution? Consider, for example, sellers who harbor a strong desire to liquidate their position in an asset despite general market exuberance with regard to the asset that tends to drive the mean price upwards. These 'holdouts' could effect a shift in the shape of the distribution such that it could exhibit leptokurtosis due to the 'fatness' of the tails of the distribution. Also, a certain degree of negative skewness could also result if these 'holdouts' occur only in the left tail of the distribution (due to their low demand prices) and are not present in the right tail of the distribution. Thus, a review of the higher moments of the demand price distributions may shed more light on the relation between market liquidity and trading volume.

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Professor Rauterkus' research interests span a wide variety of topics in finance including investments, market microstructure, financial distress and real estate. Professor Rauterkus has earned a research grant from the United States Department of Housing and Urban Development (HUD) to study the attitudes and awareness of reverse mortgage programs. Similarly, Professor Rauterkus has conducted research on behalf of several municipalities such as the cities of New York, Boston and Miami to determine the feasibility of shared equity program designed to make housing more affordable to low income families. Professor Rauterkus serves as an ad hoc reviewer for the Quarterly Review of Economics and Finance. Professor Rauterkus has made several presentations at national and regional conferences. She has also discussed numerous papers at conferences and served as session chair.

Professor Rauterkus' teaching interests are primarily in investments, multinational finance and corporate finance. She has earned a research grant from Siena College to assess information literacy in finance majors at the College. In addition, she has earned a grant from Salomon Smith Barney to educate inner city middle school students on financial literacy.

Professor Rauterkus performs service both within the Siena College community and externally. She serves on Information Technology Master Plan Committee as well as the Siena College Council of Administrators. In addition, she is very active with PhD Project, a mentoring organization for minority doctoral students in business. Professor Rauterkus speaks annually at the organization's fall conference as well as the Finance Doctoral Students Association annual conference.