Three Essays in Capital Market Studies

by

Haibin Wu

A thesis submitted in partial fulfillment of the requirement for the degree of

Doctor of Philosophy

in

Accounting

Faculty of Business

University of Alberta

Abstract

This thesis consists of three archival studies in capital markets. The introductory chapter briefly summarizes the literature, motivation, research methodology, and main findings in each study. Chapter 2 examines the differential trading activities of small traders (i.e., traders initiating small trades) and large traders (i.e., traders initiating large trades) around earnings announcements by focusing on the effect of sentiment, earnings surprises and firm size. I find that abnormal trading volume is significantly lower in high sentiment periods for small traders, but not for large traders. Both small and larger traders are found to respond more strongly to positive earnings surprises than to negative earnings surprises, and small traders exhibit weaker responses to negative earnings surprises. Finally, small traders trade more actively on small firms, while large traders trade more actively on large firms. Chapter 3 examines when small and large traders use momentum or contrarian trading strategies based on stock returns over the last five years. I find that small traders tend to use contrarian trading strategies based on past year's stock returns, but use momentum trading strategies based on longer horizon returns. Large traders are momentum traders based on past year's stock returns and contrarian traders based on longer horizon returns, though the effects on large traders are not significant. Furthermore, small and large traders tend to sell past year's losers in December, consistent with tax avoidance loss selling or window dressing. In Chapter 4, I examine how financial statement comparability affects corporate investment-cash sensitivity. Building on prior studies, I hypothesize that comparability alleviates the sensitivity of investment to cash, and this effect should be more pronounced in financially constrained firms. The empirical results confirm these conjectures.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

In this thesis, I choose to write three essays in the broad area of capital market studies. The first essay (i.e., Chapter 2) examines the differential trading activities of small traders (i.e., traders initiating small trades) and large traders (i.e., traders initiating large trades) around earnings announcements; the second essay (i.e., Chapter 3) examines when investors use momentum trading strategies (i.e., buying past winners and selling past losers) and when they use contrarian trading strategies (i.e., buying past losers and selling past winners) based on stock returns in the last five years; and the last essay (i.e., Chapter 4) examines the relation between financial statement comparability and the sensitivity of corporate investment to cash holdings. These three essays focus on two broad issues: the effect of behavioral biases on the trading of investors (Chapters 2 and 3), and the real consequences of financial reporting (Chapter 4).

The first two essays investigate whether behavioral biases affect the trading behaviors of small and large traders. The first type of behavioral bias is investor sentiment which is defined as investors' optimism or pessimism about future cash flows not justified by fundamentals. Prior studies argue that sentiment affects investors' processing of public information, and my study provides evidence on whether sentiment affects investors' responses to new public information (i.e., earnings announcements) and whether small traders are more likely to be affected. The second type of behavioral bias is manifested in whether investors' trading is consistent with future stock prices and returns. Prior studies show that small traders' trading on the past year's stock return is not consistent with short-term return momentum, and my study examines whether small traders' trading on long-term past returns is also inconsistent with long-term return

reversals. Thus, these two essays provide new evidence on how behavioral biases affect the trading behaviors of small and large traders differently.

Chapter 2 is based on the first study where I examine the differential trading activities of small and large traders around earnings announcements. This study is motivated by prior studies that investors' belief revision upon receipt of public information depends on their optimism or pessimism such that belief revision decreases in optimism when investors place more weight on private beliefs (or information). Using sentiment as a proxy for investor optimism/pessimism, I examine whether different groups of investors have differential belief revisions and trading volumes in high versus low sentiment periods.

By partitioning transactions based on trade size, I find that investors initiating small trades are more influenced by shifts in investor sentiment than investors initiating large trades. The results suggest that small traders' belief revisions upon receipt of new information are more likely to be affected by sentiment. In addition, I find evidence that earnings surprises affect trading responses by small and large traders differently. Small (large) traders' trading responses are negatively (positively) associated with the magnitude of earnings surprise when the actual earnings fall below analysts' earnings forecasts. On the other hand, when the actual earnings meet or exceed analysts' expectation, trading activities by both small and large traders increase with the magnitude of earnings surprise. Finally, I find that firm size is negatively (positively) associated with the magnitude of trading volume reactions by small (large) traders. This finding casts doubt on whether firm size is a valid proxy for information environment in event studies. Instead, it may reflect the cross-sectional differences in the shareholder composition and the difference in trading behavior between small and large traders.

Chapter 3 discusses the second study in which I examine the trading by small and large traders based on stock returns in the last five years. Prior studies have documented that while there is short-term stock return momentum and long-term return reversals, small traders are contrarian traders but larger traders are momentum traders when they trade on stock returns in the previous year. My study extends the literature by examining whether past returns over longer horizons affect trading and whether these past returns affect small and large traders differently.

Using monthly net-buy volume for small and large traders, I find that small traders tend to buy more of past year's losers than winners, but they buy more of long-term winners. While large traders tend to buy more of past year's winners and long-term losers, these effects are not significant. Furthermore, both small and large traders are more likely to sell past year's losers in December, consistent with small traders' tax avoidance loss selling and large traders' window dressing motives.

Lastly, Chapter 4 focuses on the real consequences of financial reporting by examining the effect of financial statement comparability on the sensitivity of corporate investment to cash. With capital market imperfection, corporate investment is sensitive to the availability of cash due to costly external finance. This investment-cash sensitivity implies investment inefficiency as cash short firms may need to forgo investment opportunities if it is too costly to obtain external finance. High quality financial reporting reduces such investment inefficiency as firms with better financial reporting have lower cost of external capital. This study provides additional insights that financial statement comparability could improve investment efficiency by reducing the investment-cash sensitivity.

Recent studies document that financial statement comparability improves information analysis and production, alleviates information asymmetry, and reduces costs of obtaining external capital. Building on prior studies, I hypothesize that since financial statement comparability lowers information asymmetry and reduces the cost of external capital, investment should be less sensitive to cash holdings when comparability improves. Furthermore, this effect should be more pronounced in financially constrained firms because financially constrained firms are more likely to face obstacles in obtaining external finance. The empirical results confirm these conjectures. I perform various robustness checks to ensure that the results are robust to endogeneity issue, and to using alternative comparability measures.

To summarize, my thesis provides new evidence that behavioral factors affect trading of small and large traders differently, and there are important real consequences of financial statement comparability.

Chapter 2

Sentiment and Trading Volume Reactions to Earnings Announcements

I Introduction

In this study, we investigate trading volume reactions to earnings announcements by two distinct classes of investors: 1) traders initiating small trades (i.e., small traders) and 2) traders initiating large trades (i.e., large traders). Specifically, we explore how their trading responses to earnings announcements are differentially influenced by shifts in investor sentiment. In addition, we investigate how their trading volume reactions are affected by the sign and magnitude of earnings surprise. We also examine how firm size affects trading volume reactions by these two classes of investors differently.

Our study is motivated by two literatures. First, investors' belief revision upon receipt of new information is affected by behavioral factors. Daniel et al. (1998) argue that investors tend to place more weight on private information and beliefs, and less weight on public information when they are overly optimistic or confident. However, little empirical evidence exists on whether over-optimism reduces investors' belief revision upon the receipt of new information. Trading volume around earnings announcement is a perfect setting for our study for several reasons. First, trading volume is a more accurate measure of belief revision than stock prices and returns because the trading volume reflects the aggregate investor belief revisions (Beaver, 1968). Second, theoretical studies such as Kim and Verrecchia (1991, 1994) show that trading volume around earnings announcements increases in the relative weight of new public information compared to prior private information and beliefs. Third, the use of trading volume allows us to differentiate between different groups of investors and examine how their trading responses are

differentially affected by shifts in investor sentiment. A study of trading volume to earning announcements thus allows us to provide direct evidence on how investor belief revisions and hence trading are affected by sentiment and over-optimism.

Second, the accounting literature focuses on how differential beliefs among investors affect trading around earnings announcements, but still little is known about the differential trading behavior of small and large traders except that small (individual) investors respond more slowly to earnings news and rely more on seasonal random walk models for earnings forecasts than large investors (Bamber et al., 2011). Our study provides new evidence on the differential trading behavior of small and large traders around earnings announcements.

The efficient market hypothesis asserts that stock prices reflect all publicly available information fully and immediately such that psychological factors have no role in the price discovery processes following corporate news events. Consistent with this view, prior event studies examining trading volume reactions to earnings announcements traditionally ignore behavioral aspects of market reactions.[1] However, recent studies in behavioral finance provide evidence that investor sentiment has significant effects on stock prices and price reactions to earnings news (Conrad et al. 2002; Brown and Cliff 2005; Baker and Wurgler 2006; Lemmon and Portniaguian 2006; Mian and Sankaraguruswamy 2012). Investor sentiment, broadly defined, represents optimism or pessimism about stocks that is not justified by current fundamental information.[2] In high sentiment periods, some investors are excessively optimistic and overconfident (Brown and Cliff 2005; Lemmon and Portniaguian 2006). These overconfident investors place too much weight on their private information and too little weight

[1] See Bamber et al. (2011) for a comprehensive review of research on trading volume around earnings announcements.

[2] For example, the sentiment survey by the American Association of Individual Investors (AAII) measures the percentage of investors who are bullish, bearish, and neutral on the stock market for the next six months.

on public announcements (Daniel, et al., 1998). During high sentiment periods, this tendency reduces the extent of revisions in their beliefs and thus they underreact to earnings announcements. Similarly, during low sentiment periods, these investors are overly pessimistic and tend to place too much weight on public signals. This tendency leads them to excessively revise their beliefs and increase their trading volume reactions to earnings releases. Prior studies in behavioral finance also suggest that individual investors are more influenced by sentiment in valuing stocks than their institutional counterparts (Lee et al. 1991; Barberis et al. 2005; Statman et al. 2006; Kumar and Lee 2006). Given their findings, one may expect that the effect of investor sentiment on trading volume reactions is more pronounced among individual traders than institutional investors. Surprising as it is, no attempt has been made to empirically provide direct evidence that unsophisticated investors cause the underreaction phenomenon in the stock market.

Our study also provides evidence on additional effects of sentiment and which type of investors are more likely to be subject to sentiment. Baker and Wurgler (2006) define sentiment as investor optimism or pessimism not justified by firm fundamentals. We believe that one manifestation of investors' deviation from fundamentals is that they do not make corresponding belief revisions when new public information becomes available, and our findings support this argument. Furthermore, we show that the effects of investment is not uniform across investor groups Instead small traders are more likely to make speculative investment decision not justified by information about firm fundamentals than large traders.

In investigating the effect of investor sentiment on trading volume reactions to earnings announcements, we control for the sign and magnitude of earnings surprise. Prior studies argue and document that the magnitude of earnings surprise is positively associated with trading

volume reactions (e.g., Bamber 1986, 1987; Kim and Verrecchia 1991; Atiase and Bamber 1994). However, more recent studies provide evidence that earnings announcements conveying good news are more informative and result in larger price reactions than announcements conveying bad news (Skinner and Sloan 2002; Conrad et al. 2002; Mian and Sankaraguruswamy 2012). Further, Brown et al. (2008) document that negative (positive) earnings surprises increase (decrease) information asymmetry among investors. Because individual (i.e., small) investors are generally less informed and less able to process public announcements into private information than institutional (i.e., large) investors, we expect that these two classes of investors react differently to earnings surprises.

In our empirical analysis, we also control for firm size that has been used as a proxy for information environment (e.g., Bamber 1986, 1987; Lang and Lundholm 1996). Several studies suggest that the fraction of ownership held by small (large) traders decreases (increases) with firm size (e.g., Kumar and Lee 2006), and thus the composition of shareholders (i.e., small traders versus large traders) should influence trading volume reactions to earnings announcements.

To investigate trading volume reactions to earnings announcements by small traders and large traders, we use the transactions data from the Institute for the Study of Security Markets (ISSM) database and the New York Stock Exchange Trade and Quote (TAQ) database. The use of transaction-level data allows us to partition transactions into two types based on trade size (i.e., small trades and large trades) and to examine whether changes in investor sentiment affect these two classes of trades differently. Using the monthly sentiment index for years 1990 to 2005 from Baker and Wurgler (2006), we provide evidence that, for small traders, abnormal trading volume is significantly lower in high sentiment periods than low sentiment periods, after

controlling for the sign and magnitude of earnings surprise, firm size, and time fixed effects. For large traders, while the association between investor sentiment and abnormal trading volume is also negative, the level of significance is much lower. Prior studies in behavioral finance document that the effect of investor sentiment on valuations and subsequent returns is more pronounced for stocks that are predominantly held and traded by small (or individual) investors (e.g., Statman et al. 2006; Lemmon and Portniaguian 2006). Unlike these studies, we provide direct evidence that small traders are more influenced by investor sentiment than large traders. By partitioning the sample into two sub-samples (speculative sub-sample and non-speculative sub-sample), we also show that this finding is not confined to some particular groups of firms. Instead, our results support the view that small traders are more susceptible to shifts in investor sentiment than large traders in the entire cross-section of firms. As per earnings surprises, we find that small traders' abnormal trading volume is negatively and significantly associated with the magnitude of negative earnings surprises while there is a positive and significant relation between their abnormal trading volume and the magnitude of positive earnings surprises. This finding is consistent with the notion that negative earnings surprises increase information asymmetry (Brown et al. 2008) and small traders, who are aware of their information disadvantages, refrain from trading on earnings news. In contrast, trading volume reactions by large traders increase with the magnitude of earnings surprises irrespective of the news type, implying that large earnings surprises increase the degree to which they revise their beliefs. Thus, our findings on the effect of earnings surprises on abnormal trading volume reinforce the notion that earnings announcements affect different classes of investors differently. Finally, we find that firm size is negatively (positively) associated with the magnitude of trading volume reactions by small (large) traders. This finding casts doubt on whether firm size is a valid proxy

for information environment in event studies. Instead, it may reflect the cross-sectional differences in the shareholder composition and the difference in trading behavior between small and large traders.

This study is also related to the post earnings announcement drift (PEAD) literature. The PEAD literature shows that stock prices will drift in the direction of earnings surprises in the post announcement period, and one important reason for PEAD is that investors tend to under-react to earnings news (e.g., Bernard and Thomas, 1989; Bartov, et al., 2000). A natural question is why investors under-react to earnings news, and several explanations have been proposed. For example, Ball and Bartov (1996) argue that investors do not exploit the correlation in earnings surprises. Hirshleifer, et al. (2009) and DellaVigna and Pollet (2009) show that limited investor attention causes investors to under-react to earnings news. While we do not directly show that PEAD is stronger in high sentiment periods, our findings in this study suggest that investors' trading responds less strongly to earnings news in high sentiment periods.

The rest of this paper is organized as follows. In the next section, we provide the theoretical background. Section III describes the sample. Section IV presents and discusses our empirical results. Section V provides and discusses the results of various robustness checks. Section VI concludes the paper.

II Theoretical Background

In this section, we discuss how earnings surprises, investor sentiment, and firm size affect trading volume reactions to earnings announcements.

II.1 Investor Sentiment

Since Beaver (1968), many studies have examined the impact of earnings announcements on trading volume. These studies attempt to explain the behavior of trading volume within the efficient market hypothesis framework and, hence, they generally ignore the role of psychological factors in explaining trading volume reactions to earnings releases. However, recent studies in behavioral finance document that investor sentiment affects investors' beliefs and stock valuations prior to earnings announcements, and thus price discovery processes in the post-announcement period. In Baker and Wurgler (2006, 2007), investor sentiment is defined as investors' propensity to speculate, which is not justified by fundamentals. They empirically show that sentiment fluctuates over time, and that when sentiment is high, investors become overconfident and tend to chase stocks whose fundamentals are more uncertain or more difficult to evaluate. Brown and Cliff (2005) and Lemmon and Portniaguina (2006) also show that in high sentiment periods, investors become excessively optimistic and their confidence increases.

In addition, prior studies show that cognitive biases, including overconfidence, affect asset pricing in general and market reactions to public announcements in particular.[3] In Daniel et al. (1998), for example, overconfident investors overestimate the precision of their private information and underestimate the significance of public information signals when they form their posterior beliefs.[4] Thus, when a firm releases earnings news, they underweight the information content of earnings information and underreact to the news.

Another stream of research suggests that investor sentiment affects different types of investors differently. For example, Lee et al. (1991) find that changes in individual investors' sentiment drive fluctuations in discounts of closed-end funds. Barberis et al. (2005) document

[3] Hirshleifer (2001) provides a comprehensive review of how psychological factors affect asset pricing.
[4] Barberis et al. (1998) analytically show that investors subject to conservatism also underweight new information and underreact to public announcements. However, the extent of underreaction is not related to investor sentiment in their model.

sentiment-related return comovements of stocks, which are predominantly held and traded by individual investors. Statman et al. (2006) show that the effects of overconfidence and self-attribution on trading volume are more pronounced when individual investors hold a greater proportion of shares. Lemmon and Portniaguina (2006) report that investor sentiment is associated with misvaluation of stocks that are primarily held by noise traders (i.e., individual investors). They also report that the sentimental component of consumer confidence predicts returns on these stocks. Kumar and Lee (2006) find that individual investors tend to own and trade smaller, lower priced, higher book-to-market, and less institutionally owned firms. They show that these are the firms most sensitive to changes in investor sentiment. Because individual investors tend to make small trades (Chakravarty, 2001; Barber et al., 2009), we predict that the effect of investor sentiment on trading volume around earnings announcements is more evident in small trades than in large trades.

II.2 Sign and Magnitude of Earnings Surprise

Beaver (1968) argues that earnings information induces changes in investors' beliefs, and such changes motivate trading. Unlike price reactions that reflect the average change in investors' beliefs, trading volume reactions reflect the sum of idiosyncratic revisions in their beliefs. Since his seminal work, many studies have examined the impact of earnings announcements on trading volume. For example, Bamber (1986, 1987) empirically documents that trading volume reactions to earnings announcements increase with the magnitude of unexpected earnings. Kim and Verrecchia (1991) analytically show that trading volume around earnings announcements is positively associated with the magnitude of unexpected earnings.

These studies suggest that the greater the magnitude of earnings surprise, the greater the extent of belief revisions among investors, as measured by trading volume.

In extant literature, there is extensive evidence that large investors (i.e., institutional investors) actively trade on earnings news (e.g., Cready 1988; Battalio and Mendenhall 2005; Bushee and Goodman 2006). These studies document that earnings announcements prompt large traders to revise their expectations, and their trading volume is positively associated with the magnitude of earnings surprise. Other studies provide evidence that small traders' responses to earnings announcements differ from those of large traders. Lee (1992), for example, shows that, compared to large traders, small traders are slow to react to earnings releases and they increase buying after both positive and negative earnings surprises. In addition, Hirshleifer et al. (2008) report that individual investors are net buyers following both good news and bad news releases. These studies also argue that net purchases by small traders are consistent with an attention effect. That is, stocks with earnings announcements grab their attention, which causes them to purchase the stocks, while their sell decisions are mainly due to liquidity needs. More recently, Kaniel et al. (2012) provide an alternative explanation to individual traders' behavior following earnings announcements. They document that individual investors aggressively buy (sell) prior to earnings announcements conveying good (bad) news, suggesting pre-announcement information leakage. Following earnings announcements, individual investors profitably reverse positions that they entered into prior to the announcements. Thus, individual investors sell (buy) after positive (negative) earnings surprises. Overall, the aforementioned studies suggest that small traders' reactions to earnings announcements systematically differ from large traders'.

In addition, prior studies suggest that market reactions to earnings news are affected not only by the magnitude of earnings surprise but also by the sign of the surprise. For example, Skinner and Sloan (2002) find that positive negative earnings surprises yield significantly larger price changes than negative earnings surprises. Brown et al. (2009) document that negative (positive) earnings surprises increase (reduce) information asymmetry among investors, as measured by the probability of informed trading. To the extent that small traders are generally less informed than large traders (Lev 1988; Shiller and Pound 1989; Kim and Verrecchia 1994), one may argue that increased information asymmetry caused by negative earnings surprises will discourage small traders from trading on earnings news. Thus, we expect that, for small traders, their trading responses to earnings announcements decrease with the magnitude of negative earnings surprise while the abnormal volume for large traders increases with the magnitude of earnings surprise irrespective of the news type.

II.3 Firm Size

Previous research shows that firm size is an important determinant of trading volume reactions to earnings announcements. For example, Bamber (1986, 1987) reports that the magnitude of trading volume reaction to an earnings announcement is inversely associated with firm size. However, Barron et al. (2011) find that the relation between the abnormal trading volume and firm size has reversed in recent years, and that earnings announcements by larger firms result in more intense trading responses than those by smaller firms. Possible factors that attribute to the intertemporal relation between firm size and trading volume reactions may include the difference in trading behavior between small and large traders, the cross-sectional differences in the shareholder composition, and the change in shareholder composition over time.

Cready (1988) and Lee (1992) find that large traders respond more quickly and more

intensely to earnings news than small traders. Moreover, Hvidkjaer (2006) shows that momentum is driven by initial underraction followed by delayed reaction among small traders. These studies suggest that the magnitude of trading volume reaction is influenced by the composition of shareholders. In addition, Lee et al. (1991) and Kumar and Lee (2006) argue that small firms are habitats of individual investors while the dominance of institutional investors increases with firm size. Further, institutions have become increasingly dominant equity investors in the U.S. over time. According to the 2010 Institutional Investment Report, their equity holdings increased from $436.2 billion (representing 28.4% of total outstanding equity) in 1980 to $11,005.5 billion (representing 53.3% of total outstanding equity) in 2005. They also control 67.9% of top 1,000 U.S. corporations at the end of 2005. Thus, the increase in firm size reduces not only the fraction of shares owned by small traders but also the relative importance of their trading activities around earnings news. On the other hand, the increase in firm size has the exactly opposite effects on trading volume reactions to earnings announcements for large traders. Thus, we expect that firm size is negatively (positively) associated with trading volume reactions for small (large) trades.

III Data, Variable Description, and Descriptive Statistics

III.1 Data Sources

Our sample includes quarterly earnings announcements made by firms listed on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) during the sample period 1990-2005 (16 years). From COMPUSTAT, we obtain earnings announcement dates and various accounting variables. We collect stock prices, returns, and numbers of shares outstanding from the CRSP while analysts' earnings forecasts are from the I/B/E/S detail history

database. Intraday transaction data come from the Institute for the Study of Security Markets (ISSM) database for the period 1990-1992 and the NYSE's Trade and Quote (TAQ) database for the period 1993-2005. Our final sample consists of 55,183 firm-quarter observations.

III.2 Investor Sentiment

For each month during the sample period, we obtain the level of investor sentiment from Jeffrey Wurgler's website. Baker and Wurgler (2006, 2007) identify six proxies which are known to be closely related to investor sentiment. These proxies include the closed-end fund discount, NYSE share turnover, the number and average first-day returns on initial public offerings, the equity share in new issues, and the dividend premium. Using these proxies, they construct two composite measures of investor sentiment. The first one is based on the first principal component of six (standardized) sentiment proxies. The second measure is based on the first principal component of six (standardized) sentiment proxies, where each of the proxies has first been orthogonalized with respect to a set of macroeconomic conditions. These macroeconomic conditions include the growth in industrial production, the growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions. In this study, we use the second measure because Baker and Wurgler (2006) suggest that it may be a cleaner measure of investor sentiment. We have repeated our empirical procedures by using the first index. However, the use of this alternative sentiment index measure does not alter our conclusions.

Insert Table 2-1 about here

Table 2-1 presents the distribution of investor sentiment index during the sample period. The table also shows the distribution of our sample over time. It can be seen that the sentiment index fluctuates substantially over time. For the first six years of our sample period (i.e., from 1990 to 1995), the sentiment index was, in general, low. The sentiment index was higher than the sample median value of -0.06 in only 14 months out of 72 months. Further, the mean value of the sentiment index was -0.29 during the six-year period which was substantially lower than the sample mean of 0.07. However, from 1996 to 2001, the index was typically higher than the sample mean and median values. It should be noted that during this time period, the stock market experienced a speculative upsurge led by the high-tech industry.[5] Further, the U.S. economy experienced a long stretch of economic expansion until the first quarter of 2001.[6] Thus, it is not surprising that investor sentiment was high during this time period. Subsequent to the 2001 recession in the U.S. economy, the sentiment index remained at low levels until December 2005. Thus, our sample period includes two extended periods of bearish sentiment as well as one extended period of bullish sentiment.

III.3 Abnormal Trading Volume

Consistent with prior studies (Barclay et al. 1993; Chakravarty 2001; Battalio and Medenhall 2005), we categorize transactions into two distinct classes, small trades and large

[5] Shiller (2005) describes this period as the biggest historical example of a speculative upsurge in the stock market. Further, On December 5, 1996, Alan Greenspan first used the term 'irrational exuberance' to describe the behavior of investors in the stock market.

[6] On November 26, 2001, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) determined that a peak in business activity occurred in the U.S. economy in March 2001. This peak marked the beginning of the 2001 recession that lasted 8 months until November, 2001.

trades, on the basis of trade size. We classify a trade with 500 shares or fewer as small, whereas a trade with more than 500 shares is classified as large.[7]

For each trading day and each firm, we calculate the daily trading volume for trade size group *k* as:

$$VOL\_\_k = 1000 \times \frac{Number\ of\ Shares\ Traded\ \_\_k}{Number\ of\ Shares\ Outanding}. \quad (1)$$

For each firm-quarter observation, we define the event window as day 0 and day +1 and the benchmark period as day -50 to day -11 (i.e., 40 trading days) where day 0 is the earnings announcement date. Then, we measure the trading volume reaction for each trade size group as the average daily trading volume during the event window minus the average daily trading volume during the benchmark period. That is,

$$AVOL\_\_k = \frac{1}{2} \sum_{t=0}^{1} VOL\_\_k_t - \frac{1}{40} \sum_{t=-50}^{-11} VOL\_\_k_t. \quad (2)$$

We winsorize each abnormal trading volume measure at 99% and 1% to mitigate problems with outliers.

On the NYSE and AMEX, trading commences with an auction in which the specialist observes electronically submitted orders and interests represented on the floor. Then, these orders are taken as simultaneous and the specialist sets one single opening price that clears the market. Because this opening transaction, by nature, cannot be categorized as a small or large trade, we exclude them when we measure the trading volume.

In addition, we calculate the abnormal buyer-initiated and seller-initiated trading volume for each trade size group. In doing so, we first classify each trade as a buyer-initiated or seller-initiated trade using the Lee and Ready (1991) algorithm. We then summarize all buyer-initiated

[7] We augment our empirical analyses by using 1,000 shares as the cut-off point. However, the use of this alternative cut-off point does not alter our results in any meaningful way.

(seller-initiated) trades each trading day and for each size group. We divide each of these measures by the number of shares outstanding to obtain the daily measure of buyer-initiated (seller-initiated) trading volume. Finally, the abnormal buyer-initiated (seller-initiated) trading volume for each trade size group is given by the average daily volume during the event window minus the average daily volume during the benchmark period.

III.4 Earnings Surprises

For each firm-quarter, we obtain the latest individual analysts' earnings forecasts prior to the earnings announcement from the I/B/E/S detail history database, and estimate their mean value.[8] Then, the earnings forecast error (*FE*) is measured as the actual earnings per share (EPS) minus the mean EPS forecast, scaled by the stock price at the end of the fiscal quarter: [9]

$$FE = 100 \times \frac{(Actual\ EPS - Mean\ EPS\ Forecast)}{Stock\ Price}. \quad (3)$$

We winsorize this variable at 99% and 1% level. To examine the differential effects of the sign and magnitude of earnings surprise on trading volume reactions, we differentiate between positive and negative earnings surprises. Specifically, FE^+ is equal to $|FE|$ if it is zero or positive; zero, otherwise. FE^- is equal to $|FE|$ if it is negative; zero, otherwise. Thus, FE^+ is the magnitude of earnings surprise when the actual earnings meet or exceed the mean value of analysts' forecasts (i.e., 'good news' announcement). FE^- is the magnitude of earnings surprise when the actual earnings fall below the mean value of analysts' forecasts (i.e., 'bad news' announcement).

[8] The use of median analyst forecasts yields similar results.
[9] We augment our empirical analyses by using the mean value in measuring the earnings forecast error. However, the use of mean value does not alter our results in any meaningful way.

III.5 Descriptive Statistics

Table 2-2 provides the descriptive statistics. During the benchmark period (i.e., day -50 to day -11 where day 0 is the earnings announcement date), the average daily trading volume is 0.70 for small trades while it is 2.98 for large trades.[10] Thus, small (large) trades represent, on average, 18.92% (81.08%) of the total trading volume during the benchmark period. For the event window of day 0 and day +1, the average daily abnormal trading volume is 0.33 (2.32) for small (large) trades, representing 12.45% (87.55%) of the total abnormal trading volume. This means that the trading volume increases by 47.14% for small trades and by 77.85% for large trades during the earnings announcement period. Thus, investors initiating large trades respond more intensely to earnings news than those initiating small trades, as documented in prior studies (Cready, 1988; Lee, 1991).

Insert Table 2-2 about here

IV Empirical Findings

IV.1 Investor Sentiment, Forecast Errors, and Trading Volume Reactions

Figure 2-1 shows the trading volume reactions to earnings announcements for small trades while Panel A of Table 2-3 reports their values. For each investor sentiment quartile, the first bar in the figure represents the total abnormal trading volume. The second (third) bar shows the abnormal buyer-initiated (seller-initiated) abnormal trading volume.

[10] These two values jointly give the annualized turnover rate of 92.74% relative to the number of shares outstanding.

Insert Figure 2-1 and Table 2-3 about here

Figure 2-1 and Table 2-3 reveal several interesting patterns of the abnormal trading volume for small trades during the event window. First, the abnormal trading volume for small trades monotonically decreases with the level of sentiment. The mean values are also significantly different across sentiment index quartiles (F-statistic = 812.73 for good news announcements and F-statistic = 303.80 for bad news announcements). On the other hand, the magnitude of analysts' forecast errors varies little across sentiment index quartiles (F-statistic = 7.09 for good news announcements and F-statistic = 4.18 for bad news announcements). For example, with good news announcements, the abnormal trading volume (*AVOL_S*) for the 1st sentiment index quartile is 121.74% higher than that for the 4th sentiment index quartile (0.51 versus 0.23), whereas the average value of absolute earnings surprises (|*FE*|) is the same for these two quartiles. This implies that investors initiating small trades tend to respond more intensely to earnings releases in low sentiment periods than high sentiment periods, consistent with our prediction. Second, the abnormal trading volume is significantly higher for good news announcements than it is for bad news announcements in all four sentiment index quartiles. For example, the mean abnormal trading volume is 64.52% higher for positive earnings surprises than negative earnings surprises (0.51 versus 0.31) for the 1st sentiment index quartile although the magnitude of earnings surprises is greater for bad news announcements than good news announcements (0.19 versus 0.31). The difference in the abnormal trading volume between these two news types is significant at any conventional level. Thus, our result implies that the trading volume responses to earnings changes diminish when the surprises are negative. Third, across all sentiment index quartiles, the abnormal buyer-initiated trading volume (*ABUY_S*) is

higher than the abnormal seller-initiated trading volume (*ASELL_L*) for both positive and negative earnings surprises. This suggests that buyers place their orders more aggressively than sellers regardless of the level of investor sentiment and the type of news releases. However, similar to the abnormal trading volume, these two measures of trading volume monotonically decrease with the level of investor sentiment.

Insert Figure 2-2 about here

Figure 2-2 displays the trading volume reactions to earnings announcements for large trades while Panel B of Table 2-3 presents the summary statistics. It can be seen that large trades do not exhibit as clear patterns over the sentiment index quartiles as small trades. For good news announcements, the difference in abnormal trading volume between quartile 1 and quartile 4 is only 22.50% (2.94 versus 2.40) for large trades while it is 120.74% for small trades, although the abnormal trading volume still decreases with investor sentiment. Further, the abnormal trading volume for negative earnings surprises exhibits no clear pattern. In particular, the abnormal trading volume in quartile 2 is higher than that in quartile 3 (2.00 versus 1.95). With regard to the earnings news type, good news announcements result in more intense trading volume reactions than bad news announcements. For each sentiment index quartile, the difference in the mean trading volume between these two news types is statistically significant at any conventional level. This result is similar to the one for small trades. Finally, Figure 2-2 shows that the buyer-initiated and seller-initiated abnormal trading volume measures display similar patterns to those for total abnormal trading volume.

As shown in Table 2-1, the investor sentiment index was much higher in years 2000 and 2001 than the rest of our sample period. The mean values are 1.27 in 2000 and 1.53 in 2001 while the sample mean value is 0.07. Furthermore, all earnings announcements made during these two years belong to sentiment index quartile 4. Thus, it is possible that the trading volume patterns shown in Figures 2-1 and 2-2 are partly driven by these announcements. To address this concern, we have partitioned firm-quarter observations in the 4th investor sentiment index quartile into two groups: 1) observations in years 2000 and 2001 and 2) observations in other years. Then, for each trade size class and each news type, we compare the mean values of these two groups. Although not tabulated in the paper, their mean values are not statistically different. Thus, we can rule out the possibility that observations in these two years drive our results.

Overall, the results in Figures 2-1 and 2-2 indicate that investor sentiment affects trading volume reactions by small traders and large traders differently. Specifically, the effect of investor sentiment is more pronounced among investors initiating small trades than investors initiating large trades. Further, positive earnings surprises increase the magnitude of abnormal trading volume more than negative earnings surprises for both small trades and large trades.

IV.2 Multivariate Regression Specification

The patterns of abnormal trading volume shown in the previous section generally suggest that earnings announcements increase trading activities, and that investor sentiment affects the magnitude of volume reactions. However, trading volume around earnings announcements is also influenced by earnings surprises and firm size. Thus, we use the following regression model to investigate the behavior of trading volume around earnings announcements:

$$Y_q = \beta_0 + \beta_1 SENT_q + \beta_2 FE_q^+ + \beta_3 FE_q^- + \beta_4 SENT_q \times FE_q^+ \quad (4)$$
$$+ \beta_5 SENT_q \times FE_q^- + \beta_6 Log(MVE_q) + \sum \gamma_t YearD_t + \varepsilon_q$$

where

Y_q = abnormal trading volume (alternatively: *AVOL_S* and *AVOL_L*) during the event period for firm-quarter q,

FE_q^+ = absolute value of forecast error (*FE*) if *FE* is zero or positive; 0 otherwise,

FE_q^- = absolute value of forecast error (*FE*) if *FE* is negative; 0 otherwise,

$SENT_q$ = investor sentiment index,

MVE_q = market value of equity, and

$YearD_t$ = indicator variable equal to 1 if the firm-quarter observation is from year t; 0 otherwise.

In Equation (4), the variable *SENT* captures the effect of investor sentiment on abnormal trading volume. A negative β_1 will indicate that as investor sentiment increases, investors place less weight on earning news and thereby react less intensely to earnings announcements. We include FE^+ and FE^- to examine the differential effects of positive and negative earnings surprises on trading volume reactions to earnings announcements. If $\beta_2 \neq \beta_3$, it will indicate that the abnormal trading volume is influenced not only by the magnitude of earnings surprise but also by its sign. We also include $SENT \times FE^+$ and $SENT \times FE^-$ in the regression model to control for the potential interaction effects of earnings surprises and investor sentiment on abnormal trading volume. In Equation (4), year dummy variables account for time fixed effects while the variable *Log(MVE)* controls for the effect of firm size on abnormal trading volume.

IV.3 Regression Results

Insert Table 2-4 about here

Table 2-4 presents the regression results. In the first two columns, the dependent variable is the abnormal daily trading volume for small trades during the event window (i.e., day 0 and day +1). In the next two columns, the dependent variable is the abnormal trading volume for large trades during the event window. Each measure of abnormal trading volume is the daily average during the event window minus the average over the benchmark period.

The coefficient on *SENT* is negative (-0.036) and significant (t-statistic = -4.20) for small trades. The coefficient estimate implies that the abnormal trading volume decreases by 0.023 as the sentiment index increases by one standard deviation. This reduction in abnormal trading volume represents 6.98% of the sample mean of 0.33 for small trades. For large trades, the coefficient on investor sentiment is negative (-0.123) but insignificant at the 5% level (t-statistic = -1.73). Thus, while prior studies suggest that the effect of investor sentiment on mispricing and price reactions is more pronounced in stocks predominantly held and traded by small (i.e., individual) investors (Statman et al. 2006; Lemmon and Portniaguian 2006; Mian and Sankaraguruswamy 2012), we provide direct evidence that investors initiating small trades are more susceptible to shifts in sentiment than investors initiating large trades.

We include FE^+ and FE^- in Equation (4) to investigate whether abnormal trading volume is affected not only by the magnitude of earnings surprise but also by the sign. For small trades, the coefficient on FE^+ is positive (0.044) and significant (t-statistic = 2.54). On the other hand, the coefficient on FE^- is negative (-0.048) and significant (t-statistic = -8.63) for bad news announcements. In addition, the difference in the regression coefficient (0.044 versus -0.048) is statistically significant (F-statistic = 38.04). These results imply that abnormal trading volume for small trades increases with the magnitude of earnings surprise when actual earnings meet or

beat analysts' expectations. On the other hand, when actual earnings fall below forecasts, the abnormal trading activities in small trades decrease with the magnitude of surprise. We interpret this finding as evidence that negative earnings surprises increase information asymmetry among investors (Brown et al. 2009), and that small traders, who have information disadvantages to large traders, refrain themselves from trading on earnings news. For large traders, the coefficients on FE^+ and FE^- are positive and significant. In addition, the magnitude of the coefficient is much greater for positive earnings surprises than negative earnings surprises (0.912 versus 0.131), and this difference is statistically significant (F-statistic = 38.17). Thus, the abnormal trading volume by large traders increases with the magnitude of earnings surprise. However, a positive earnings surprise increases the abnormal trading volume significantly more than a negative earnings surprise.

In our regression model, two interaction terms, $SENT \times FE^+$ and $SENT \times FE^-$, are included to examine whether investor sentiment modifies the effect of earnings surprises on trading volume reactions to earnings releases. The coefficients on these two terms are insignificant for both small trades and large trades, implying that investor sentiment and earnings surprises do not have a significant interaction effect on abnormal trading volume.

Finally, for small trades, the coefficient on firm size is negative (-0.028) and significant (t-statistic = -7.62), suggesting that trade responses to earnings news decrease with firm size. In contrast, the coefficient on firm size is positive (0.190) and significant (t-statistic = 6.73) for large trades, indicating that abnormal trading volume increases with firm size. These results are in a sharp contrast to findings in prior studies where firm size is used to control for the information environment.[11] They report that firm size is inversely associated with the magnitude

[11] Prior studies argue that larger firms have more analysts following (Bhushan 1989) and better disclose policies (Lang and Lundholm 1996) than smaller firms.

of price and volume reactions (e.g., Atiase 1985; Bamber 1986, 1987). However, our findings suggest that firm size may reflect the difference in trading behaviors between small and large traders as well as the cross-sectional differences in the shareholder composition.

V Additional Analyses

We conduct several sensitivity tests to ensure that our results are robust. These tests include estimating regressions using log-transformation of abnormal trading volume, using an alternative measure of earnings surprises, and classifying trades based on an alternative cut-off value. We also examine whether our results reported in the previous section are influenced by firm characteristics.

V.1 Log-Transformation of Abnormal Trading Volume

In estimating our regression model of Equation (4), we use the raw value of abnormal trading volume as the dependent variable for easier interpretations of regression coefficients. However, prior studies (e.g., Ajinkya and Jain, 1989; Bamber et al. 1997) report that the daily trading volume for individual securities is skewed to the right, and that the residuals of the regressions explaining trading volume reactions may exhibit significant departures from normality. To control for the potential skewness of our data, we rerun Equation (4) using the log-transformed value of abnormal trading volume for trade size class. As shown in Table 2-5, all regression coefficients have the same signs and maintain the similar significance levels to those reported in Table 2-4. Thus, our findings are robust to whether we use the raw values or the log-transformed values of trading volume in regressions.

Insert Table 2-5 about here

Our empirical results are also robust to using an alternative cut-off value for trade size classification. Although not tabulated, the use of 1,000 shares instead of 500 shares as the cut-off value yields similar results to those reported in Table 2-4.

V.2 Earnings Surprises based on Seasonal Random Walk Forecasts

As discussed earlier, we measure an earnings surprise as the actual EPS minus the mean of individual analysts' EPS forecasts, deflated by the stock price. However, prior studies suggest that different types of investors use different information sets when they make trading decisions. For example, Walther (1997) provides evidence that sophisticated investors (i.e., institutions) rely more on analysts' forecasts than forecasts from time-series model when they form earnings expectations. Bhattacharya (2001) and Battalio and Mendenhall (2005) show that investors initiating large trades respond to earnings surprises based on analysts' forecasts while investors initiating small trades respond to earnings surprises based on seasonal random walk (SRW) forecasts. Given the findings in these studies, there is a possibility that our measure of forecast errors may not be a proper proxy for earnings surprises for small trades. To address this issue, we have augmented our empirical analysis by using SRW forecasts instead of analysts' forecasts. Our alternative measure of earnings surprise is, thus, given by the actual EPS minus the SRW forecast, scaled by the stock price.

Insert Table 2-6 about here

Table 2-6 presents the regression results for small trades. The coefficient on *SENT* is negative (-0.037) and significant (t-statistic = -2.91). Further, the coefficient on FE^+ is positive (0.100) and significant (t-statistic = 8.79) while the coefficient on FE^- is negative (-0.037) and significant (t-statistic = -8.20). These results are similar to those reported in Table 2-4. Thus, the use of SRW forecasts does not alter our inferences for trading responses to earnings news by small traders.

V.3 Firm Characteristics and Investor Sentiment

Baker and Wurgler (2006) define investor sentiment as the propensity to speculate. Then, they argue that sentiment drives the relative demand for speculative investments and the effect of sentiment on mispricing varies cross-sectionally. They also provide evidence that speculative and difficult-to-arbitrage (i.e., small, young, high volatile, unprofitable, non-dividend paying, distressed, or with extreme growth potential) firms are more likely to be affected by shifts in investor sentiment than other firms. Furthermore, Mian and sankaraguruswamy (2012) document that the effect of investor sentiment on the earnings response coefficient (ERC) is more pronounced on these firms.

In this study, we hypothesize that small traders are more influenced by investor sentiment than large traders. To ensure that this differential effect of investor sentiment is not concentrated on the aforementioned speculative and difficult-to-arbitrage firms but it is observed in the cross-section of firms, we classify our observations using the methodology in Baker and Wurgler (2006). Specifically, we use six firm characteristic variables from COMPUSTAT and CRSP: 1) firm size, 2) firm age, 3) profitability, 4) dividends-to-equity ratio, 5) sales growth, and 6) distress. *Firm size* is the log of the market capitalization at the fiscal quarter end, measured by

price (Item 14) times shares outstanding (Item 61). *Firm age* is the number of months since a firm's first appearance in CRSP. *Profitability* is the return on equity, measured by income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), divided by book equity, where book equity is defined as shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). *Dividends* are measured as dividends per share (Item 26) times shares outstanding (Item 61), divided by book equity. *Sales growth* is the percentage change in net sales (Item 12). *Distress* is measured as the change in assets (Item 6) minus the change in retained earnings (Item 36), divided by assets. These definitions of variables are consistent with Baker and Wurgler (2006). The only exception is that we measure firm size at the quarter end while they measure it at the end of June.

Using each of the above six variables alternatively, we partition the sample into two sub-samples. A firm is classified as *speculative* or *non-speculative* based on whether a firm characteristic is above or below the sample median. Then, we estimate Equation (4) for each sub-sample. The results are shown in Table 2-7.

Insert Table 2-7 about here

Results in Panel A through Panel F show that, for small trades, our measure of investor sentiment (*SENT*) consistently attracts a negative and significant coefficient in both *speculative and non-speculative* sub-samples, after controlling for the sign and magnitude of earnings surprise and firm size. On the other hand, the coefficient on *SENT* is generally negative but insignificant for large trades. The only exception is firms with low growth potentials (Panel E) where the coefficient on *SENT* is significant at the 5% level (t-statistic = -2.16) for large trades.

These results suggest that the effect of investor sentiment on abnormal trading volume is more pronounced for small traders than large traders in both speculative and non-speculative sub-samples. Thus, our finding is not restricted to some segment of the cross-section. Instead, it is applicable to the cross-section of firms.

VI Conclusion

In this study, we investigate how different types of investors (i.e., small traders and large traders) respond to earnings releases under the influence of investor sentiment. We also extend prior research by conditioning on the sign and magnitude of earnings surprise, and by partitioning trades by trade size. In doing so, we provide new insights into trading volume reactions to earnings announcements.

We find that the magnitude of trading volume reactions is negatively associated with the level of investor sentiment for small traders. This result implies that small traders place more (less) weight on current information in making trading decisions when they have a pessimistic (optimistic) outlook. On the other hand, the relation between trading volume and the level of investor sentiment is marginally significant for large traders. Thus, we provide direct evidence that shifts in investor sentiment affects small traders more than large traders.

With regard to earnings surprises, we document that trading volume is related to both the sign and magnitude of earnings surprise. We further show that the sign and magnitude of earnings surprise affect different classes of investors differently. For small traders, their abnormal trading volume decreases (increases) with the magnitude of surprise when the actual earnings are lower than (equal to or higher than) analysts' median forecast. However, the abnormal trading volume is positively associated with the magnitude of surprise for large trades regardless of the sign of surprise. These results suggest that the usefulness of earnings news

differs across different investor classes. Further, our results are consistent with the notion that negative earnings surprises increase information asymmetry among investors, and that small traders, who are aware of their informational disadvantages, refrain themselves from trading on earnings news.

Finally, we find that the effect of firm size on trading volume differs for small trades and large trades. We show that the magnitude of trading volume is negatively (positively) related to firm size for small trades (large trades). This result raises a question about the validity of using firm size as a proxy for information environment. If small (large) traders concentrate their holdings and their trade activities in small (large) firms, then firm size will reflect the difference in trading behavior between these two investor classes and the cross-sectional differences in share holder composition. Our result is consistent with this notion.

In summary, our findings suggest that the impact of earnings news on trading decisions differs across different investor classes and at different levels of investor sentiment. Our results also reinforce the importance of considering both the direction and sign of earnings surprise in research on trading volume. We also suggest another role of firm size in event studies.

Bibliography

Ajinkya, Bipin and Prem Jain. 1989. The behavior of daily stock market trading volume. *Journal of Accounting and Economics* 11: 331-59.

Atiase, Rowland K. 1985. Predisclosure information, firm characteristics, and security price behavior around earnings announcements. *Journal of Accounting Research* 23: 21-36.

Atiase, Rowland K., and Linda S. Bamber. 1994. Trading volume reactions to annual accounting earnings announcements: The incremental role of predisclosure information asymmetry. *Journal of Accounting and Economics* 17: 309-329.

Baker, Malcolm, and Jeffrey Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61: 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21: 129-157.

Bamber, Linda S. 1986. The information content of annual earnings releases: A trading volume approach. *Journal of Accounting Research* 24: 40-56.

Bamber, Linda S. 1987. Unexpected earnings, firm size, and trading volume around quarterly earnings announcements. *The Accounting Reivew* 62: 510-532.

Bamber, Linda S., Orie E. Barron, and Thomas L. Stober. 1997. Trading volume and different aspects of disagreement coincident with earnings announcements. *The Accounting Review* 72: 575-597.

Bamber, Linda S., Orie E. Barron, and Douglas E. Stevens. 2011. Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and direction for future research. *Contemporary Accounting* Reseach 28: 431-471.

Barber, Brad M., Terrance Odean, and Ning Zhu. 2009. Do retain trades move markets? *Review of Financial Studies* 22: 151-186.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49: 307-343.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler. 2005. Comovement. *Journal of Financial Economics* 75: 283-317.

Barclay, Michael J., and Jerold B. Warner. 1993. Stealth trading and volatility. *Journal of Financial Economics* 34: 281-305.

Barron, Orie E., Richard A. Schneibkle, and Douglas E. Stevens. 2011. The firm size effect on trading volume reactions to earnings announcements: A re-examination and extension. Working Paper, Pennsylvania State University.

Battalio, Robert H., and Richard R. Mendenhall. 2005. Earnings expectations, investor trade size, and anomalous returns around earnings announcements. *Journal of Financial Economics* 77: 289-319.

Beaver, William H. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 6: 67-92.

Bhattacharya, Nilabhra. 2001. A model of investor sentiment. *The Accounting Review* 76: 221-244.

Bhushan, Ravi. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11: 255-274.

Brown, Gregory W., and Michael T. Cliff. 2005. Investor sentiment and asset valuation. *Journal of Business* 78: 405-440.

Brown, Stephen, Stephen A. Hillegeist, and Kin Lo. 2008. The effect of earnings surprises on information asymmetry. *Journal of Accounting and Economics* 47: 208-225.

Bushee, Brian J., and Theodore H. Goodman. 2007. Which institutional investors trade based on private information about earnings and returns? *Journal of Accounting Research* 45: 289-321.

Chakravarty, Sugato 2001. Stealth trading: Which traders' trades move stock price? *Journal of Financial Economics* 61: 289-307.

Cready, William M. 1988. Information value and investor wealth: The case of earnings announcements. *Journal of Accounting Research* 26: 1-27.

Conrad, Jennifer, Bradford Cornell, and Wayne R. Landsman. 2002. When is bad news really bad news? *Journal of Finance* 57: 2507-2532.

Conrad, Jennifer, Bradford Cornell, and Wayne R. Landsman. 2002. When is bad news really bad news? *Journal of Finance* 57: 2507-2532.

Daniel, Kent, David Hirshleifer, Avanidhar Subrahmanyam. 1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53: 1839-1885.

Hirshleifer, David. 2001. Investor psychology and asset pricing. *Journal of Finance* 56: 1533-1597.

Hirshleifer, David A., James N. Myers, Linda A. Myers, and Siew Hong Teoh. 2008. Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades. *The Accounting Review* 83: 1521-1550.

Hvidkjaer, Soeren. 2006. A trade-based analysis of momentum. *Review of Financial Studies* 19: 457-491.

Kaniel, Ron, and Shuming Liu, Gideon Saar, and Sheridan Titman. 2012. Investor psychology and asset pricing. *Journal of Finance* 67: 639-680.

Kim, Oliver, and Robert. E. Verrecchia. 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research* 29: 302-321.

Kim, Oliver, and Robert. E. Verrecchia. 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics* 17: 41-67.

Kumar, Alok, and Charles M.C. Lee. 2006. Retail investor sentiment and return comovements. *Journal of Finance* 61: 2451-2486.

Lang, Mark H., and Russell J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71: 467-492.

Lee, Charles M.C. 1992. Earnings news and small trades. *Journal of Accounting and Economics* 15: 265-302.

Lee, Charles M.C., and Mark J. Ready. 1991. Inferring trade direction from intraday data. *Journal of Finance* 46: 733-746.

Lee, Charles M.C., Andrei Shleifer, and Richard H. Thaler. 1991. Investor sentiment and the closed-end fund puzzle. *Journal of Finance* 46: 75-109.

Lemmon, Michael, and Evgenia Portniaguina.2006. Consumer confidence and asset prices: some empirical evidence. *Review of Financial Studies* 19: 1499-1529.

Lev, Baruch. 1988. Toward a theory of equitable and efficient accounting policy. *The Accounting Review* 53: 1-22.

Mian, G. Mujtaba, and Srinivasan Sankaraguruswamy. 2012. Investor sentiment and stock market response to earnings news. *The Accounting Review* 87: 1357-1384.

Shiller, Robert J. 2001. Irrational exuberance. Princeton University Press.

Shiller, Robert J., and John Pound. 1989. Survey evidence on diffusion of interest and information among investors. *Journal of Economic Behavior & Organization* 12: 1989, 47-66.

Skinner, Dougals J., and Richard G. Sloan. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7: 289-312.

Statman, Meir, Steven Thorely, and Keith Vorkink. 2006. Investor overconfidence and trading volume. *Review of Financial Studies* 19: 1531-1565.

The Conference Board. *The 2010 institutional investment report: trends in asset allocation and portfolio composition.* New York (2007).

Walther, Beverly R. 1997. Investor sophistication and market earnings expectations. *Journal of Accounting Research* 35: 157-179.

Figure 2-1: Mean Abnormal Trading Volume for Small Trades

The sample of 55,183 firm-quarter observations is partitioned into quartiles on the basis of investor sentiment. An observation is classified as 'good' news ('bad' news) if the actual EPS is higher than or equal to (lower than) the analysts' mean forecast. Quartile 1 (Quartile 4) includes the observations with the lowest (highest) level of sentiment. AVOL_S represents the mean abnormal trading volume for small trades while ABUY_S (ASELL_S) is the mean abnormal buyer-initiated (seller-initiated) trading volume. A small trade involves 500 shares or fewer.

Panel A. Good News

Panel B. Bad News

Figure 2-2: Mean Abnormal Trading Volume for Large Trades

The sample of 55,183 firm-quarter observations is partitioned into quartiles on the basis of investor sentiment. Quartile 1 (Quartile 4) includes the observations with the lowest (highest) level of sentiment. An observation is classified as 'good' news ('bad' news) if the actual EPS is higher than or equal to (lower than) the analysts' mean forecast. AVOL_L represents the mean abnormal trading volume for large trades while ABUY_L (ASELL_L) is the mean abnormal buyer-initiated (seller-initiated) trading volume. A large trade involves more than 500 shares.

Panel A. Good News

Panel B. Bad News

Table 2-1: Investor Sentiment Index and Sample Distributions

The sample period spans from 1990 to 2005. Columns 2 through 7 present the distribution of investor sentiment index. Each year, there are 12 monthly values of investor sentiment index. Column 7 (Column 8) shows the number of months in which the investor sentiment index is higher than (lower than or equal to) the sample median value of -0.06. Column 9 shows the number of firm-quarters observations.

	Investor Sentiment Index					# of Months with Index above the	# of Months with Index below the	# of Firm-Quarter
Year	Mean	Std. Dev.	Quartile 1	Median	Quartile 3	Sample Median	Sample Median	Observations
1990	-0.57	0.29	-0.83	-0.48	-0.34	0	12	2,327
1991	-0.51	0.33	-0.75	-0.36	-0.30	0	12	2,722
1992	-0.17	0.12	-0.26	-0.16	-0.10	2	10	3,072
1993	-0.24	0.15	-0.34	-0.26	-0.13	2	10	2,867
1994	-0.10	0.12	-0.24	-0.05	0.00	7	5	2,770
1995	-0.15	0.15	-0.23	-0.18	-0.05	3	9	2,924
1996	0.28	0.25	0.05	0.33	0.53	11	1	3,052
1997	0.37	0.21	0.18	0.35	0.57	12	0	3,266
1998	0.07	0.13	-0.03	0.11	0.17	9	3	3,486
1999	0.21	0.20	0.08	0.19	0.26	12	0	3,470
2000	1.27	0.43	0.92	1.30	1.57	12	0	3,371
2001	1.53	0.61	1.21	1.51	1.94	12	0	4,054
2002	0.16	0.49	-0.23	0.17	0.53	8	4	4,163
2003	-0.68	0.16	-0.80	-0.67	-0.58	0	12	4,425
2004	-0.21	0.19	-0.42	-0.12	-0.10	2	10	4,614
2005	-0.16	0.15	-0.30	-0.15	-0.04	3	8	4,600
Total	0.07	0.64	-0.31	-0.06	0.24	96	96	55,183

Table 2-2: Summary Statistics

The sample includes 55,183 firm-quarter observations during the period 1990-2005. *FE* is the forecast error, measured as 100 times the actual EPS minus the mean of analysts' forecasts, deflated by the stock price. FE^+ is equal to |*FE*| if it is zero or positive; zero, otherwise. FE^- is equal to |*FE*| if it is negative; zero, otherwise. *VOL* is the daily trading volume, measured as $1{,}000 \times \frac{\text{Number of Shares Traded}}{\text{Number of Shares Outstanding}}$. *VOL_S* (*VOL_L*) is the daily trading volume for small (large) trades during the benchmark period (i.e., from day -50 and day -11), where a small (large) trade involves 500 shares or fewer (more than 500 shares). *AVOL_S* (*AVOL_L*) is the daily turnover for small (large) trades during the event window (i.e., day 0 and day +1). *MVE* is the market value of equity.

	Mean	Std. Dev.	Quartile 1	Median	Quartile 3
FE	-0.10	0.69	-0.11	0.01	0.09
|FE|	0.31	0.63	0.03	0.10	0.30
FE^+	0.19	0.29	0.03	0.08	0.22
FE^-	0.45	0.85	0.04	0.14	0.44
VOL	3.70	2.80	1.78	3.03	4.84
VOL_S	0.70	0.81	0.20	0.37	0.88
VOL_L	2.98	2.34	1.40	2.41	3.89
AVOL	2.65	5.10	-0.16	0.92	3.60
AVOL_S	0.33	0.69	-0.00	0.08	0.35
AVOL_L	2.32	4.68	-0.20	0.76	3.15
MVE (in $BB's)	4.25	8.40	0.45	1.29	3.88

Table 2-3: Abnormal Trading Volume around Earnings Announcements

This table reports the mean values of abnormal trading volume (in percent) during the sample period 1990-2005. The abnormal trading volume is measured as the average daily turnover during the event window (i.e., days 0 and +1 relative to the earnings announcement date) minus the average daily turnover during the benchmark period (from day -50 to day -11). *AVOL_S* (*AVOL_L*) is the abnormal trading volume for small (large) trades, where a small (large) trade involves 500 shares or fewer (more than 500 shares). Quartile 1 (Quartile 4) includes firm-quarter observations with the lowest (highest) level of investor sentiment. An observation is classified as 'good news' ('bad news') if the actual EPS is higher than or equal to (lower than) the median of analysts' forecasts. |*FE*| is the absolute value of forecast error where the forecast error is measure as the actual EPS minus the mean of analysts' forecasts, deflated by the stock price. * and ** indicate the significance at the 5% and 1% levels, respectively.

Panel A: Small Trades

		Good News			Bad New			t-stat. for mean difference	
	Quartile	|FE|	AVOL_S	N	|FE|	AVOL_S	N	|FE|	AVOL_S
Sentiment Index	1	0.19	0.51	7,893	0.44	0.31	6,122	21.28**	15.70**
	2	0.19	0.46	7,377	0.44	0.26	6,864	23.76**	15.27**
	3	0.18	0.37	7,071	0.44	0.23	6,663	24.52**	13.45**
	4	0.19	0.23	7,535	0.47	0.15	5,658	22.86**	10.36**
	Total	0.19	0.40	29,876	0.45	0.24	25,307	46.21**	27.17**
F-stat. for mean differences (All quartiles)		7.09	812.73**		4.18	303.80**			
t-stat. for mean difference (4 versus 1)		1.66	24.62**		1.92	15.77**			

Table 2-3 (Continued)

Panel B: Large Trades

		Good News			Bad New			t-stat. for mean difference	
	Quartile	|FE|	AVOL_L	N	|FE|	AVOL_L	N	|FE|	AVOL_S
Sentiment Index	1	0.19	2.94	7,893	0.44	2.24	5,671	21.28**	8.56**
	2	0.19	2.47	7,377	0.44	1.95	6,114	23.76**	6.72**
	3	0.18	2.42	7,071	0.44	2.00	6,155	24.52**	5.43**
	4	0.19	2.40	7,535	0.47	1.97	5,368	22.86**	5.20**
	Total	0.19	2.56	29,876	0.45	2.04	25,307	46.21**	13.22**
F-stat. for mean differences (All quartiles)		7.09	64.95**		4.18	15.34**			
t-stat. for mean difference (4 versus 1)		1.66	6.96**		1.92	3.09**			

Table 2-4: Forecast Errors, Investor Sentiment, and Trading Volume Reactions

This table reports regression results using 55,183 firm-quarter observations during the sample period 1990-2005. The dependent variable (alternatively: *AVOL_S* or *AVOL_L*) is the abnormal trading volume, measured as the average daily turnover during the event window (days 0 and +1 relative to the earnings announcement date) minus the average daily turnover during the benchmark period (from day -50 to day -11). *AVOL_S* (*AVOL_L*) is the abnormal trading volume for small (large) trades, where a small (large) trade involves 500 shares or fewer (more than 500 shares). *FE* is the forecast error, measured as the actual EPS minus the mean of analysts' forecasts, deflated by the stock price. FE^+ is equal to |*FE*| if *FE* is zero or positive; zero, otherwise. FE^- is equal to |*FE*| if *FE* is negative; zero, otherwise. *SENT* is the level of investor sentiment. *MVE* is the market value of equity. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. * and ** indicate the significance at the 5% and 1% levels, respectively.

	Small Trades		Large Trades	
Constant	0.480	(14.05)**	1.099	(4.37)**
SENT	-0.036	(-4.20)**	-0.124	(-1.70)
FE^+	0.044	(2.53)*	0.920	(6.55)**
FE^-	-0.048	(-8.64)**	0.133	(2.78)**
$SENT \times FE^+$	0.015	(0.88)	-0.200	(-1.21)
$SENT \times FE^-$	0.001	(0.14)	-0.061	(-0.86)
Log(MVE)	-0.028	(-7.62)**	0.193	(6.69)**
Year Dummies	Included		Included	
Adjusted R^2	18.48%		2.84%	
F-stat. for $\beta_{EE+} = \beta_{EE-}$:	33.04**		38.17**	

Table 2-5: Forecast Errors, Investor Sentiment, and Trading Volume Reactions: Using Log-Transformation

This table reports regression results using 55,183 firm-quarter observations during the sample period 1990-2005. The dependent variable for each trade size group is the log of (1 + abnormal trading volume), where the abnormal trading volume is measured as the average daily turnover during the event window (days 0 and +1 relative to the earnings announcement date) minus the average daily turnover during the benchmark period (from day -50 to day -11). *AVOL_S* (*AVOL_L*) is the abnormal trading volume for small (large) trades, where a small (large) trade involves 500 shares or fewer (more than 500 shares). *FE* is the forecast error, measured as the actual EPS minus the mean of analystforecasts, deflated by the stock price. FE^+ is equal to |*FE*| if *FE* is zero or positive; zero, otherwise. FE^- is equal to |*FE*| if *FE* is negative; zero, otherwise. *SENT* is the level of investor sentiment. *MVE* is the market value of equity. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. * and ** indicate the significance at the 5% and 1% levels, respectively.

	Small Trades		Large Trades	
Constant	0.241	(9.42)**	1.086	(4.39)**
SENT	-0.036	(-4.20)**	-0.123	(-1.73)
FE^+	0.044	(2.54)*	0.912	(6.63)**
FE^-	-0.048	(-8.63)**	0.131	(2.78)**
$SENT \times FE^+$	0.015	(0.89)	-0.197	(-1.22)
$SENT \times FE^-$	0.001	(0.14)	-0.060	(-0.86)
Log(MVE)	-0.027	(-7.62)**	0.190	(6.73)**
Year Dummies	Included		Included	
Adjusted R^2	18.48%		2.6%	

Table 2-6: Seasonal Random Walk Earnings Surprise and Trading Volume Reactions

This table reports regression results using 55,183 firm-quarter observations during the sample period 1990-2005. The dependent variable (*AVOL_S*) is the abnormal trading volume for small trades, measured as the average daily turnover during the event window (days 0 and +1 relative to the earnings announcement date) minus the average daily turnover during the benchmark period (from day -50 to day -11). A small trade involves 500 shares or fewer. *FE* is the forecast error, measured as the actual EPS minus the seasonal random walk forecast, deflated by the stock price. FE^+ is equal to |*FE*| if *FE* is zero or positive; zero, otherwise. FE^- is equal to |*FE*| if *FE* is negative; zero, otherwise. *SENT* is the level of investor sentiment. *MVE* is the market value of equity. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. * and ** indicate the significance at the 5% and 1% levels, respectively.

	Small Trades	
Constant	0.626	(15.22)**
SENT	-0.029	(-2.91)**
FE^+	0.100	(8.79)**
FE^-	-0.037	(-8.20)**
SENT×FE^+	-0.014	(-0.98)
SENT×FE^-	-0.006	(-1.39)
Log(MVE)	-0.044	(-10.28)**
Year Dummies	Included	
Adjusted R^2	20.83%	

Table 2-7: Firm Characteristics and Effect of Investor Sentiment on Abnormal Trading Volume

This table reports regression results for the sample period 1990-2005. The dependent variable (alternatively: *AVOL_S* or *AVOL_L*) is the abnormal trading volume, measured as the average daily turnover during the event window (days 0 and +1 relative to the earnings announcement date) minus the average daily turnover during the benchmark period (from day -50 to day -11). *AVOL_S* (*AVOL_L*) is the abnormal trading volume for small (large) trades, where a small (large) trade involves 500 shares or fewer (more than 500 shares). *FE* is the forecast error, measured as the actual EPS minus the mean of analysts' forecasts, deflated by the stock price. FE^+ is equal to |*FE*| if *FE* is zero or positive; zero, otherwise. FE^- is equal to |*FE*| if *FE* is negative; zero, otherwise. *SENT* is the level of investor sentiment. *MVE* is the market value of equity. Firm *size* is the log of the market capitalization at the fiscal quarter end, measured by price (Item 14) times shares outstanding (Item 61). *Firm age* is the number of months since a firm's first appearance in CRSP. *Profitability* is the return on equity, measured by income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), divided by book equity, where book equity is defined as shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). *Dividends* is measured as dividends per share (Item 26) times shares outstanding (Item 61), divided by book equity. *Sales growth* is the percentage change in net sales (Item 12). *Distress* is measured as the change in assets (Item 6) minus the change in retained earnings (Item 36), divided by assets. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. T-stat. is the test statistic for the difference in regression coefficients between the two sub-samples. * and ** indicate the significance at the 5% and 1% levels, respectively.

Panel A: Firm size

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	Small		Large		Small		Large	
Constant	0.013	(0.25)	1.118	(16.35)**	-0.927	(-2.74)**	4.995	(9.11)**
SENT	-0.042	(-2.96)**	-0.028	(-2.75)**	-0.064	(-0.60)	-0.200	(-1.92)
FE^+	0.094	(4.76)**	-0.023	(-0.75)	1.168	(7.72)**	0.623	(2.25)*
FE^-	-0.024	(-4.45)**	-0.055	(-2.85)**	0.171	(3.85)**	0.409	(2.17)*
$SENT \times FE^+$	0.007	(0.34)	0.041	(1.27)	-0.134	(-0.75)	-0.387	(-1.05)
$SENT \times FE^-$	0.004	(0.74)	0.005	(0.32)	0.001	(0.01)	-0.309	(-1.38)
Log(MVE)	0.051	(6.76)**	-0.105	(-13.80)**	0.465	(9.56)**	-0.223	(-3.76)**
Year Dummies	Included		Included		Included		Included	
N	27,329		27,854		27,329		27,854	
Adjusted R^2	15.02%		24.02%		1.87%		4.18%	

Table 2-7 (Continued)

Panel B: Firm age

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	Young		Mature		Young		Mature	
Constant	0.339	(6.60)**	0.326	(9.53)**	0.235	(0.62)	-0.638	(-2.34)*
SENT	-0.036	(-2.94)**	-0.039	(-3.28)**	-0.083	(-0.74)	-0.188	(-2.01)*
FE^+	-0.006	(-0.28)	0.111	(4.29)**	0.359	(2.34)**	1.688	(6.79)**
FE^-	-0.061	(-8.56)**	-0.022	(-2.49)*	0.017	(0.30)	0.368	(4.20)**
$SENT \times FE^+$	0.055	(2.50)*	-0.035	(-1.29)	-0.001	(-0.00)	-0.395	(-1.31)
$SENT \times FE^-$	0.015	(2.32)*	-0.012	(-1.28)	-0.041	(-0.57)	0.019	(0.14)
Log(MVE)	-0.005	(-0.74)	-0.043	(-9.05)**	0.351	(7.42)**	0.160	(4.43)**
Year Dummies	Included		Included		Included		Included	
N	27,243		27,940		27,243		27,940	
Adjusted R^2	15.58%		22.54%		2.59%		4.03%	

Panel C: Profitability

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	Low		High		Low		High	
Constant	0.429	(9.66)**	0.689	(13.00)**	0.606	(1.67)	2.033	(5.63)**
SENT	-0.038	(-2.71)**	-0.046	(-3.31)**	-0.123	(-1.03)	-0.145	(-1.23)
FE^+	0.049	(2.29)*	0.071	(2.12)*	1.080	(6.09)**	0.639	(2.72)**
FE^-	-0.046	(-7.08)**	-0.048	(-3.92)**	0.096	(1.63)	0.185	(1.81)
$SENT \times FE^+$	0.020	(0.83)	-0.027	(-0.86)	-0.093	(-0.37)	-0.218	(-0.77)
$SENT \times FE^-$	0.000	(0.03)	-0.011	(-0.61)	-0.122	(-2.07)*	-0.085	(-0.33)
Log(MVE)	-0.023	(-4.96)**	-0.048	(-9.25)**	0.242	(6.08)**	0.105	(2.73)**
Year Dummies	Included		Included		Included		Included	
N	22,910		23,243		22,910		23.243	
Adjusted R^2	16.00%		23.07%		2.78%		3.42%	

Table 2-7 (Continued)

Panel D: Dividends

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	Low		High		Low		High	
Constant	0.099	(1.99)*	0.508	(10.84)**	-1.929	(-5.09)**	0.446	(1.44)
SENT	-0.034	(-2.24)*	-0.042	(-3.69)**	-0.139	(-1.10)	-0.132	(-1.44)
FE^{+}	0.027	(1.07)	0.034	(1.37)	0.831	(4.26)**	0.655	(3.45)**
FE^{-}	-0.061	(-7.68)**	-0.022	(-2.32)*	0.043	(0.66)	0.256	(3.18)**
$SENT \times FE^{+}$	0.024	(0.95)	0.016	(0.63)	-0.140	(-0.58)	-0.302	(-1.42)
$SENT \times FE^{-}$	0.012	(1.54)	-0.012	(-0.96)	-0.073	(-0.83)	0.045	(0.27)
Log(MVE)	0.004	(0.48)	-0.037	(-8.58)**	0.555	(9.49)**	0.165	(5.22)**
Year Dummies	Included		Included		Included		Included	
N	23,457		23,748		23,457		23,748	
Adjusted R^2	17.31%		20.31%		3.96%		2.44%	

Panel E: Sales growth

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	Low		High		Low		High	
Constant	0.248	(7.57)**	0.248	(7.77)**	-0.792	(-2.97)**	-0.484	(-1.96)
SENT	-0.040	(-3.19)**	-0.040	(-3.02)**	-0.234	(-2.16)*	-0.035	(-0.31)
FE^{+}	0.070	(3.35)**	0.032	(1.13)	1.446	(7.96)**	0.435	(2.33)*
FE^{-}	-0.038	(-5.21)**	-0.058	(-7.29)**	0.182	(2.92)**	0.099	(1.38)
$SENT \times FE^{+}$	0.029	(1.19)	0.009	(0.36)	-0.053	(-0.24)	-0.141	(-0.56)
$SENT \times FE^{-}$	-0.003	(-0.46)	0.004	(0.51)	0.003	(0.03)	-0.203	(-2.04)*
Log(MVE)	-0.030	(-6.70)**	-0.028	(-6.28)**	0.195	(5.65)**	0.218	(6.09)**
Year Dummies	Included		Included		Included		Included	
N	26,559		26,654		26,559		26,654	
Adjusted R^2	18.38%		19.26%		3.78%		2.70%	

Table 2-7 (Continued)

Panel F: Distress

	Small Trades (AVOL_S)				Large Trades (AVOL_L)			
	High		Low		High		Low	
Constant	0.409	(9.15)**	0.570	(12.80)**	1.034	(3.00)**	1.190	(3.89)**
SENT	-0.028	(-2.20)*	-0.043	(-3.22)**	-0.086	(-0.77)	-0.167	(-1.56)
FE^+	0.051	(2.05)*	0.039	(1.69)	0.700	(3.66)**	1.230	(6.40)**
FE^-	-0.046	(-6.53)**	-0.052	(-6.38)**	0.074	(1.20)	0.171	(2.53)*
$SENT \times FE^+$	0.019	(0.75)	0.020	(0.80)	-0.144	(-0.68)	-0.069	(-0.26)
$SENT \times FE^-$	0.006	(0.82)	-0.007	(-0.89)	-0.097	(-0.99)	-0.089	(-0.81)
Log(MVE)	-0.020	(-4.56)**	-0.037	(-8.05)**	0.217	(5.99)**	0.181	(5.35)**
Year Dummies	Included		Included		Included		Included	
N	26,062		26,181		26,062		26,181	
Adjusted R^2	17.16%		20.68%		2.44%		3.95%	

Chapter 3

When Are Investors Momentum or Contrarian Traders?

I Introduction

In this paper, we investigate when investors use contrarian trading strategies (i.e., buying past losers and selling past winners) and when they use momentum trading strategies (i.e., buying past winners and selling past losers) based on stock returns in the last five years. In doing so, we differentiate between the trading behavior of two different classes of investors: small traders (i.e., traders initiating small trades) and large traders (i.e., traders initiating large trades).

It has been well documented in the extant literature that trading strategies based on past stock returns can generate abnormal returns. De Bondt and Thaler (1985, 1987), for example, document that stock prices overreact to information and that contrarian strategies generate significant positive returns three years after portfolio formation. Jegadeesh (1991) and Jegadeesh and Titman (1993) find that momentum strategies based on past year's stock returns significantly outperform contrarian strategies. Thus, these studies suggest that there is short-term return momentum based on past year's returns and long-term return reversal based on returns over years -5 to -2.

More recently, other studies (Grinblatt et al., 1995; Odean, 1998b; Nofdinger and Sias, 1999; Grinblatt and Keloharju, 2000, 2001; Froot et al., 2001; Hvidkjaer, 2006) show that different classes of investors use different trading strategies. These studies document evidence that small (i.e., individual) investors are more likely to buy stocks that performed poorly in the previous year, whereas large (i.e., institutional) investors are

more likely to buy stocks that performed well in the previous year. Thus, they suggest that in a relatively short horizon, small investors use contrarian trading strategies and large investors use momentum strategies. We extend these studies by examining whether trading activities by these two classes of investors depend on past returns over longer time horizons (i.e., years -5 to -2). Such an extension allows us to examine whether past returns over longer horizons affect trading and whether these returns affect small and large traders differently.

Prior studies suggest that investors use contrarian trading strategies due to various reasons. Shefrin and Statmen (1985) suggest that investors tend to sell winners too early and hold on to losers too long. This tendency, known as the disposition effect, is consistent with the prospect theory by Kahneman and Tversky (1979) in that investors become risk averse when they have gains, but become risk seeking when they incur losses. The tendency of buying past losers and selling past winners can be also observed when investors have mean-reversion beliefs (Odean, 1998) or when investors sell stocks with large positive returns to rebalance their portfolios (Chordia et al., 2007; Griffin et al., 2007).

Momentum trading is used when investors believe that stock prices will continue to trend. Kyle (1986) show that when stock prices fail to incorporate private information fully and immediately, past winners (losers) will continue to generate positive (negative) returns. The incentive to buy past winners and sell past losers could also be stronger at year-end due to tax avoidance loss selling or window dressing motives. For individual investors, selling losing stocks before year-end allows them to save tax payments as realized capital loss is deductible for tax purpose (Constantinides, 1984). Evidence on the

existence of tax avoidance loss selling is provided by various studies (Reinganum, 1983; Keim, 1989; Sias and Starks, 1997; Dyl, 1977; Lakonishok and Smidt, 1986; and Ritter 1988). Sias and Starks (1997) document that institutional investors also have incentives to sell losers at year end to window-dress their portfolio performance.

To investigate the trading by small and large traders based on past stock returns, we use the intraday transaction data from the Institute for the Study of Security Markets (ISSM) database and the New York Stock Exchange Trade and Quote (TAQ) database to construct monthly trading volume variables. The use of intraday transaction data allows us to classify trades into small trades and large trades based on trade size and to examine how past stock returns in different intervals affect small and large traders' trading differently. In doing so, we partition each 5-year period into 3 intervals: interval 1 includes the previous year (months -12 to -1)[12], interval 2 includes month -36 to -13 (i.e, years -3 to -2); and interval 3 includes months -60 to -37 (i.e., years -5 to -4). Interval 1 is denoted as the short horizon, and interval 2 and 3 are denoted as long term horizons (i.e., years -5 to -2). In our empirical analysis, we also control for a number of firm characteristics. Chordia, et al. (2007) argue that regressions of trading volume on past stock returns could lead to misleading results if other determinants of trading are not properly controlled for.

Using the monthly net-buy (i.e., buy minus sell) volume for small and large traders over 1992 to 2005, we find that small traders tend to buy more of stocks which are losers in the past year, and more of stocks which are winners in years -5 to -2. Large

[12] Our results are not affected in any meaningful way if we partition interval 1 into month-1, and months -12 to -2.

traders are more likely to buy the past year's winners than losers and they also buy long-term past losers, though these effects on large traders are not significant. By partitioning the sample into three subsamples (December, January, and February to November) based on the month in which trading takes places, we also find that both small and large traders exhibit significantly strong sell preference for the past year's losing stocks in December, consistent with small traders' tax loss selling incentive and large traders' window dressing motive. Finally, we find that some firm characteristics affect the trading by small and large traders differently. Small traders prefer small firms and firms with high stock prices, while large traders tend to buy more of large firms and low priced stocks.

This study makes two important contributions to the literature. First, we extend prior studies to show that small traders' trading on long-term past returns is not consistent with the long-term reversals. Second, while prior studies (e.g., Sias and Starks, 2007) show that both small and large traders use momentum trading strategies at year-ends due to the tax avoidance loss selling and window dressing motives, the analysis is based on a small set of firms and covers a quite short period. Our study examines past returns in the last 5 years and covers a much large sample of firms.

The remaining part of the paper is structured as follows: section II reviews the related literature and sets up the main empirical questions, section III discusses data sources and variable construction, section IV presents main empirical results, section V conducts a number of robustness checks, and section VI concludes.

II Empirical Questions and Related Literature

In this section, we discuss the determinants of trading volume, focusing on what motivates investors to undertake contrarian or momentum trading strategies based on past stock returns.

II.1 Cross-Sectional Determinants of Trading Volume

In contrarian trading, investors buy (sell) past losers (winners). The possible motivations for contrarian trading strategies include the disposition effect, mean-reversion belief and portfolio rebalancing. The disposition effect, proposed by Shefrin and Statman (1985), refer to the phenomenon that investors tend to sell winners too early and hold losers too long. This effect is motivated by the prospect theory of Kahneman and Tversky (1979) which argues that investors have an S-shaped utility function, concave in the domain of gains and convex in the domain of losses. Thus, investors become risk averse when they have gains and risk seeking when they incur losses. Contrarian trading could also arise if investors hold mean-reversion beliefs and expect past losers (winners) to perform well (poorly) in the future. Griffin et al. (2007) and Chordia et al. (2007) suggest that selling past winners can also be due to portfolio rebalancing needs.

In momentum trading, investors believe that poorly performing stocks will continue to perform poorly and strong performers will remain strong. One rationale for this strategy is that current stock prices and returns contain information about future prices and returns. Kyle (1986) argues that a subset of investors have private information and this information is incorporated into prices gradually over time. This slow incorporation of private information into stock prices causes price under-reactions. Thus,

poor performers will continue to perform poorly and strong performers will continue to perform well.[13] Momentum trading can also arise due to behavioral factors. Positive past returns will increase investors' confidence or catch their attention more easily. This induces more trading and net-buy (Gervais and Odean, 2001; Odean, 1999; Barber and Odean, 2008). On the contrary, stocks with negative returns reduce investors' confidence and their trading.

Momentum trading may also be stronger at the end of the year due to either tax avoidance loss selling or window dressing. Constantinides (1984) argues that capital gains taxes make it optimal for investors to sell past losers before the end of the year so as to save tax payments. Keim (1983) documents that large abnormal returns in small firms are mainly concentrated in January, especially in the first week of January, consistent with the tax avoidance loss selling explanation. Reinganum (1983), Keim (1989), and Sias and Starks (1997) provide evidence on the tax avoidance loss selling by analyzing stock returns around year ends. Dyl (1977), and Laknishok and Smidt (1986) show that trading volume for past losers (winner) is much higher (lower) in December than the rest of the year. Ritter (1988) provides evidence that past losers have a lower average buy-to-sell ratio in December than past winners. For institutional investors, momentum trading could also be stronger at year-ends due to the window dressing motive. Sias and Starks (1997) suggest that fund managers may buy past winners and sell past losers before the year-end such that they can make their performance attractive to investors.

[13] Sources of momentum profits could be due to risk, under-reaction to information, covariance of industry returns, among others. See Conrad and Kaul (1988), Moskowitz and Grinblatt (1999), and Grundy and Martin (2001).

The extant literature provides evidence that future stock returns are predictable based on past stock returns. Jegadeesh (1991), and Jegadeesh and Titman (1993) find that stocks which perform well or poorly in the past three to twelve months tend to continue the momentum in the subsequent months. De Bondt and Thaler (1985, 1987) document that long term losers tend to outperform long term winners, and such long term return reversals cannot be simply explained by the year-end effect, risk factors, or size effect. Hong and Stein (1999) argue that the predictability of future returns is driven by initial under-reaction and eventual over-reaction to information by investors. Hong, et al. (2000) provide evidence that momentum profits are higher for firms with low analyst coverage, consistent with the argument that investors are more likely to under-react to information in low coverage firms.

In addition to past stock returns, trading volume is also affected by various other firm characteristics which proxy for information asymmetry, opinion divergence, and estimation uncertainty. Trading will be more intensive when there is higher information asymmetry, more divergence of opinion, or greater estimation uncertainty because there will be more room for belief revision (Chordia et al, 2007). Firm level characteristics (such as stock prices) can also proxy for behavioral trading incentives such as stock visibility and investor attention.

II.2 Small and Large Traders

Studies on the effect of past stock returns on trading usually differentiate between small and large traders. Grinblatt et al. (1995), Nofdinger and Sias (1999), Grinblatt and

Keloharju (2000, 2001), and Froot et al. (2001) show that small traders are generally contrarian traders, while large traders are momentum traders when they choose trading strategies based on stock returns in the previous year. We extend these studies by examining the effect of past returns at longer horizons. Furthermore, unlike some prior studies which rely on proprietary trading data (e.g., Grinblatt and Keloharju, 2000, 2001; and Froot et al., 2001), we use the transactions data from the Institute for the Study of Security Markets (ISSM) and the Trade and Quote (TAQ) databases such that our sample covers a larger number of listed firms and includes all transactions made by investors. The use of transaction level data also allows us to partition transactions into two types based on trade size (i.e., small trades and large trades) and to examine whether past returns at longer horizons affect these two classes of traders differently

III Data

III.1 Data Sources

Our sample includes firms listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) from 1992 to 2005. We obtain intraday transaction data from the ISSM database for 1992 and the NYSE's Trade and Quote (TAQ) database for the period 1993-2005. We also use stock price and return data from the Center for Research in Security Price (CRSP), financial data from COMPUSTAT, and analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S). To mitigate the concern of outliers, we winsorize all variables at the top and bottom 1% levels.

III.2 Trading Volume Variables

We use intraday transaction data to construct monthly trading volume variables for small and larger traders. Following the prior studies (e.g., Chan and Lakonishok 1993; Easley and O'Hara, 1987), we use 500 shares as the cutoff value for small and large trades. Hence a trade is classified as a small trade if the size is 500 shares or less, and as a large trade otherwise. For each firm and each trading day, the daily trading volume for trade size group k=S,L is computed as:

$$DVOL\_k = 1000 \times \frac{Number\ of\ Shares\ Traded\ \_k}{Number\ of\ Shares\ Outanding}. \quad (1)$$

Then, we calculate the monthly trading volume for each size group k, VOL_k, by averaging the daily volume over the month. In addition to the aggregate trading volume for small and large trades, we construct the net-buy volume measures (i.e., order imbalance) for small and large trades. Using the method in Lee and Ready (1991), we first classify each trade as a buyer-initiated or seller-initiated trade. Then we sum all buyer- and seller-initiated trades for each trader class to obtain the daily buyer- and seller-initiated shares. Then, the daily net-buy volume for trade size group k=S,L is defined as:

$$DBUY\_k \quad (2)$$
$$= 1000 \times \frac{Buyer\ Initiated\ Shares\ \_k - Seller\ Initiated\ Shares\ \_k}{Number\ of\ Shares\ Outanding}.$$

The monthly net-buy volume BUY_k for size group k is the average daily net-buy volume in the month. As a robustness check, we also construct the corresponding trading

volume variables by using 1000 shares as the threshold. The use of this alternative cut-off value, however, does not alter out results in any meaningful way.

A possible concern for using trading volume variables in a panel study is that there are seasonal variations and time trend in trading volume. To address this concern, we adjust our trading volume variables using the adjustment procedure in Gallant et al. (1991) and Chordia et al. (2007). This adjustment procedure removes the seasonal variations and time trend in trading volume variables, while maintaining the means and variances of the original variables.

More specifically, we make adjustments of each trading volume variable for each firm using a two-stage procedure. In the first stage, we regress the trading volume variable W on a set of adjustment factors X, and obtain the least square residual, $\hat{\varepsilon}$,

$$W = X'B + \varepsilon.$$

The adjustment factors include a dummy variable for each month, time variable t, and t^2. In the second stage, we use the logged value of squared residuals as the dependent variable, and regress on the same set of adjustment factors:

$$\ln(\hat{\varepsilon}^2) = X'\Pi + \eta.$$

Finally, the adjusted trading volume variable is obtained using the linear transformation:

$$AdjW = a + b * \left[\frac{\hat{\varepsilon}}{\exp\,(X'\Pi)}\right],$$

where a and b are chosen such that the means and variances of W and AdjW are the same. The adjustment process ensures that the original and adjusted variables have the same

units of measurement, which makes the interpretation of empirical results easier. After the adjustment, the monthly aggregate trading volume $VOL\_\_k$, and monthly net buy volume $BUY\_\_k$ become $AdjVOL\_\_k$, and $AdjBUY\_\_k$, respectively.

III.3 Past Stock Returns

We partition each 5-year period into 3 intervals and compute the cumulative returns over each interval: $ret_{-12:-1}$ for months -12 to -1 (interval 1); $ret_{-36:-13}$ for months -36 to -13 (interval 2); and $ret_{-60:-37}$ for months -60 to -37 (interval 2). Returns over interval 1 is denoted as short-term past returns, while returns over intervals 2 and 3 are denoted as long-term past returns. Because the effect of positive past returns on trading activities differs from that of negative past returns (Grinblatt and Keloharju, 2001; Chordia et al., 2006), we use $ret^{+}_{t_1:t_2}$ and $ret^{-}_{t_1:t_2}$ for each time interval $(t_1: t_2)$. $ret^{+}_{t_1:t_2}$ is equal to $ret_{t_1:t_2}$ if $ret_{t_1:t_2}$ is positive; zero otherwise. Similarly, $ret^{-}_{t_1:t_2}$ is equal to the absolute value of $ret_{t_1:t_2}$ if $ret_{t_1:t_2}$ is negative; zero otherwise. For easy interpretation of regression coefficients, we use the absolute value of past stock returns.

III.4 Control Variables

In the regression analysis, we include a number of control variables which are shown to be important predictors of trading activities in Chordia et al. (2007). These control variables include proxies for liquidity trading (firm size, firm age, logged price, and market to book ratio), proxies for information asymmetry and opinion divergence

(leverage, logged number of analysts, and analyst forecast dispersion), and proxies for estimation uncertainty (beta, earnings changes, and earnings volatility).

The control variables are constructed using financial data from COMPUSTAT, stock price data from CRSP, and analyst forecast data from I/B/E/S. Ln(MVE) is the logged value of market capitalization at the end of the prior month. Firm Age is the number of months since the firm's first appearance in the CRSP database. Ln(Price) is the logged value of stock price at the end of the previous month. MTB is the ratio of price (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as the logged value of 1 plus the number of analysts following in the previous month; Dispersion is defined as the standard deviation of analyst forecasts during the month. ΔEarnings is the change in earnings, defined as the difference between current earnings and earnings in the same quarter of the prior year, deflated by the stock price. Earnings volatility, σ(Earnings), is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Following Chordia et al (2007), we adjust Ln(MVE), Ln(Price), and Ln(# Analysts) for seasonality and time trends using the same procedure as the one used for trading volume variables.

Due to the estimation noise in firm beta, we compute portfolio beta following Fama and French (1992) and Chordia et al. (2007). For each firm, we first assign each firm to one of the 10 size-based portfolios. Then within each size portfolio, we assign the firm to one of the 10 pre-ranking beta portfolios where the pre-ranking beta of each firm is computed using the monthly stock returns data from the last 36 months. Therefore, we

have 100 size and pre-ranking beta portfolios at each year-end. For each portfolio, we compute the monthly value-weighted returns and estimate the beta by regressing the month returns on the market returns. Finally, we assign each portfolio beta to firms.

III.5 Empirical Methodology

Our regression model augments the Chordia et al. (2007) cross sectional trading volume regression with additional past stock return variables, and differentiates between small and large traders to allow us to examine systematically how past stock returns at various time horizons affect trading by different classes of investors. The advantage of this regression model is that it controls for a large number of firm level characteristics which may confound the relation between past stock returns and trading volume, while prior studies on trading volume usually do not control for these firm level factors. More specifically, the regression equation takes the following form:

$$AdjW = \alpha + \beta_1 * ret^{+}_{-12:-1} + \beta_2 * ret^{-}_{-12:-1} + \beta_3 * ret^{+}_{-36:-13} + \beta_4 * ret^{-}_{-36:-13} + \beta_5 * ret^{+}_{-60:-37} + \beta_6 * ret^{-}_{-60:-37} + X'\Lambda + \varepsilon,$$

where $AdjW$ is the adjusted trading volume, X is the vector of control variables. The return variables $ret^{+}_{t_1:t_2}$ and $ret^{-}_{t_1:t_2}$ are defined as above. To capture the time variation in trading volume, we include year-month fixed effects in all regressions. Our main interest is the coefficient estimates of β_1 through β_6, which capture the impacts of past stock returns on trading responses by small or large traders. A positive coefficient indicates that trading volume increases with the magnitude of past stock returns, while a negative coefficient implies that trading volume decreases with the magnitude of past returns. In

our empirical analysis, we compare the regression coefficients on positive and negative past returns in the same time interval. For example, if $\beta_1 > \beta_2$ in the regression with the net-buy volume as the dependent variable, we interpret it as the evidence that investors are more likely to buy last year's winners than losers, and hence they are momentum traders on last year's stock returns; if $\beta_1 < \beta_2$, investors are considered as contrarian traders on last year's stock returns because they tend to buy more of losing stocks.

IV Empirical Results

IV.1 Summary Statistics

Table 3-1 presents the summary statistics of all variables used in the empirical analysis. During the sample period, the monthly adjusted trading volume is 3.52 (or 0.352% of total shares outstanding) for all traders, with 0.579 representing 16.4% of the total trading volume from small traders and 2.942 representing 83.6% of the total trading volume from large traders. The monthly adjusted net-buy volume is 0.203 (0.02% of all shares outstanding) for all traders, with 0.037 representing 18.2% of the total net-buy volume from small traders and 0.167 representing 82.7% of the total net-buy volume from large traders. The trading volume variables exhibit slight right skewness as shown by larger means than medians. The mean and median stock return in the last year are 15% and 11.7%, respectively. In the long-term, stock returns in years -3 to -2 has the mean (median) value of 30.5% (22.1%), while the mean (median) return in years -5 to -3 is 31.8% (23.4%).

Insert Table 3-1 about here

For firm level characteristics, our sample firms have the mean size (measured by logged market capitalization) of 13.88 (which corresponds to $1,066 million), and the mean age of 347 months (almost 29 years). The average market-to-book and leverage ratios in our sample are 1.675 and 26.2% respectively. In addition, the average number of analysts is 3.8. Finally, the average earnings change is almost zero, and the average earnings volatility is 0.146.

Table 3-2 provides the correlation matrix of our explanatory variables. To save space, we present the correlations of past stock returns variables and control variables separately. Stock returns in the past year are negatively and significantly correlated with past returns over months -36 to -13, and over months -60 to -37, consistent with short-term return momentum, and long-term return reversals. The correlations among control variables are also largely consistent with expectations. For example, large firms tend to be mature firms, and they also have higher prices, more analysts, smaller forecast dispersion, and smaller earnings volatility.

Insert Table 3-2 about here

IV.2 Aggregate Trading Volume

In Table 3-3, we first present the regression results for the monthly aggregate trading volume. In columns 2 and 3, the dependent variable is the adjusted trading volume for small traders, AdjVOL_S. Our main interest is the coefficients on past returns, i.e., β_1 through β_6. For positive past returns, the regression coefficients are always positive, indicating that trading activities increase with the magnitude of past

returns. Furthermore, these coefficients decrease with the time horizon. For example, the coefficient on $ret^{+}_{-12:-1}$ is 0.29 (t-statistic = 11.94), whereas the coefficients on $ret^{+}_{-36:-13}$ and $ret^{+}_{-60:-37}$ are 0.081 (t-statistic = 5.31) and 0.012 (t-statistic = 0.87), respectively. For negative past returns, the regression coefficient on $ret^{-}_{-12:-1}$ is positive and significant at 0.516 with t-statistic 10.99, while the regression coefficients are negative for negative returns at longer horizons.

At the bottom of Table 3, we present the p-value of testing coefficient equality between positive and negative returns for each interval. For short horizons, the regression coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.29 (t-statistic = 11.94) and 0.516 (t-statistic = 10.99), respectively, and these two values are significantly different (p-value = 0.000). These values imply that, if negative (positive) past returns increase by one standard deviation (0.352), trading activities will increase by 0.182 (0.102). These increases amount to 47.5% and 26.6% of the median daily trading volume of 0.383 for small traders. Thus, negative returns in the previous year increase trading activities of small traders more than positive returns. For longer horizons, positive returns increase small traders' trading more than negative returns. For example, coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are 0.081 (t-statistic = 5.31) and -0.061 (t-statistic = -1.45), respectively, and these two values are significantly different (p-value 0.000).

Columns 4 and 5 present the results for large traders. For positive past returns, the regression coefficients are always positive, indicating that trading increases with the magnitude of returns. In addition, the coefficients decrease with time horizon, similar to those for small traders. For example, the coefficient on $ret^{+}_{-12:-1}$ is 1.043 (t-statistic = 11.46), whereas the coefficients on $ret^{+}_{-36:-13}$ and $ret^{+}_{-60:-37}$ are 0.231 (t-statistic = 4.34)

and 0.143 (t-statistic = 2.76), respectively. For negative past returns, the regression coefficients are also positive for all horizons, suggesting that large traders trade more actively on stocks with larger negative returns.

The p-values for testing coefficient equality at the bottom of the table indicate that negative returns increase trading more than positive returns at all horizons for large traders. For example, the regression coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 1.043 (t-statistic = 11.46) and 2.37 (t-statistic = 10.47), respectively, and these two values are significantly different (p-value = 0.000). These values imply that, if negative (positive) past year's returns increase by one standard deviation (0.352), trading activities will increase by 0.834 (0.367). These increases amount to 37.5% and 16.5% of the median daily trading volume of 2.226 for large traders.

Insert Table 3-3 about here

The regression coefficients on control variables are generally significant and have expected signs. For both small and large investors, trading activities increase with beta, the market-to-book ratio, the number of analysts following, the dispersion of analysts' forecasts, and the change in earnings, and decrease with firm age. These results are consistent with the ones in Chordia et al. (2007). We also find that small (large) investors' trading activities decrease (increase) with firm size. This finding is not consistent with the view that firm size is a proxy for information asymmetry. Instead, it may suggest that shares of small firms are predominantly held by retail investors and that the relative importance of their trading activities increases as firm size decreases.

IV.3 Net-Buy Volume

Table 3-4 presents the regression results in which the net-buy volume measures are used as dependent variables. The explanatory variables are the same as the ones used in the aggregate volume regressions in the previous section.[14]

Insert Table 3-4 about here

In columns 2 and 3, the dependent variable is the adjusted net-buy volume for small traders, AdjBUY_S. Our main interest is the coefficients on past returns, i.e., β_1 through β_6. For positive past returns, the regression coefficients are always positive, indicating that the net-buy volume increases with the magnitude of past returns. Furthermore, these coefficients decrease with the time horizon. For example, the coefficient on $ret^{+}_{-12:-1}$ is 0.015 (t-statistic = 6.49), whereas the coefficients on $ret^{+}_{-36:-13}$ and $ret^{+}_{-60:-37}$ are 0.012 (t-statistic = 7.88) and 0.001 (t-statistic = 0.96), respectively. For negative past returns, the regression coefficient on $ret^{-}_{-12:-1}$ is positive and significant (0.042 with t-statistic = 7.71), while the regression coefficients are negative and significant for longer horizon returns.

In Table 3-4, we also present the results of testing coefficient equality between positive and negative returns for each time interval. For the short horizon, the regression coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.015 (t-statistic = 6.49) and 0.042 (t-statistic = 7.71), respectively, and these two values are significantly different (p-value = 0.000). These values imply that, if past year's negative (positive) return increases by one

[14] Chordia, et al. (2007) argue that factors affecting aggregate trading volume should also affect net-buy volume (or order imbalance).

standard deviation (0.352), the net-buy will increase by 0.015 (0.005). This increase amounts to 75% (25%) of the median daily net buy volume of 0.02 for small traders. Thus, we present evidence that small traders are contrarian traders on the past year's returns, consistent with prior studies. For longer horizons, coefficients on positive returns are significantly larger than those on negative returns. For example, coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are 0.012 (t-statistic = 7.88) and -0.028 (t-statistic = -6.33), respectively, and these two values are significantly different (p-value = 0.000). These values imply that, if positive (negative) returns over year -3 to -2 increase by one standard deviation (0.562), net buy will increase by 0.007 (-0.016). These changes amount to 35% (-80%) of the median daily net buy volume of 0.02 for small traders. Thus, these results are consistent with the view that small traders are momentum traders on long horizon past returns.

Columns 4 and 5 of Table 3-4 present the results for large traders' net-buy volume. For positive returns, the coefficients are positive and significant only on past year's returns with value 0.091 (t-statistic = 3.45). The coefficients on long-term positive returns are insignificantly different from zero. On the other hand, the coefficients on negative returns are all insignificantly different from zero. The p-values at the bottom of the table suggest that large traders are momentum traders on the past year's returns and contrarian traders on long-term past returns, though the effects are not statistically significant. For example, coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.091 (t-statistic = 3.45) and 0.039 (t-statistic = 0.62), respectively, and these two values are not significantly different (p-value = 0.429). However, these values imply that, if positive (negative) past year's returns increase by one standard deviation (0.352), net buy will increase by 0.032 (0.014).

This increase amounts to 29.4% (12.8%) of the median daily net buy volume of 0.109 for large traders. For longer horizons, coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are -0.012 (t-statistic = -0.69) and 0.077 (t-statistic = 1.25), respectively, and these two values are not significantly different (p-value = 0.151). These values imply that, if negative (positive) returns over years -3 to -2 increase by one standard deviation (0.562), net buy will increase by 0.043 (-0.007). This change amounts to 39.4% (-6.4%) of the median daily net buy volume of 0.109 for large traders. Thus, we find (weak) evidence that large traders are momentum traders based on past year's returns, and contrarian traders based on returns over year -5 to -2.

The results in Table 3-4 also indicate that certain firm characteristics have differential impacts on small and large traders' net-buy behavior. First, the coefficients on firm size are -0.004 (t-statistic = -5.67) and 0.058 (t-statistic = 5.38) for small and large traders, respectively, suggesting that small traders prefer small firms, while large traders prefer large firms. This finding is not consistent with the view that firm size serves as a proxy for information asymmetry, but instead it is consistent with the argument that investor composition affects trading as ownership of small firms is more likely to be concentred in retail investors. Second, the coefficients on logged price are 0.02 (t-statistic = 11.70) and -0.04 (t-statistic = -2.16) for small and large traders respectively, implying small (large) traders tend to buy more of high (low) priced stocks. Also, the regression results suggest that small investors' trading is more likely to be subject to stock visibility and attention as high priced stocks can easily catch their attention.

IV.4 Seasonality

The results in Table 3-4 show that small investors tend to use contrarian trading strategies based on previous year's returns but momentum strategies based on longer horizon returns; while large traders tend to use momentum trading strategies on the past year's returns but contrarian trading strategies on longer horizon returns. Prior studies (e.g., Constantinides, 1984; Sias and Starks, 1997) suggest that investors may have more incentives to sell past losers at year end due to tax avoidance loss selling or window dressing motives. To examine this possibility, we split the sample into three sub-samples based on the month of trading: December, January, and the rest of the year (February-November), and perform the regression analysis for each sub-sample separately.

Insert Table 3-5 about here

Table 3-5 presents the regression results for these three sub-samples. Panel A presents the regression results for small traders. We find that trading strategies based on the past year's returns depends crucially on the month of trading. When trading takes places in December (first two columns), the coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.03 (t-statistic = 6.20) and -0.032 (t-statistic = -2.84), respectively, and these two values are significantly different (p-value = 0.000). This result implies that, if the past year's negative (positive) return increases by one standard deviation (0.352), net-buy will increase by -0.011 (0.011) in December. This increase amounts to -55% (55%) of the median daily net-buy volume of 0.02 for small traders. These results suggest that small traders tend to buy more of the past year's winners than losers in December, which is consistent with the tax loss selling incentive at year-end. In contrast, the coefficients on

$ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.009 (t-statistic = 1.70) and 0.067 (t-statistic = 5.80), respectively, in January; and are 0.015 (t-statistic = 6.01) and 0.046 (t-statistic = 8.25), respectively, in February to November. These differences are both significant at a 0.000 confidence level. Hence for the rest of the year, small traders clearly tend to buy more of past year's losers than winners.

As per the effects of long-term returns on trading activities, we find that while small traders tend to buy more of winning stocks in interval 2 (months -36 to -13), this effect is stronger in December. The coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are 0.015 (t-statistic = 5.76) and -0.045 (t-statistic = -5.20), respectively, in December. And these two values are significantly different (p-value = 0.000). These values imply that if the positive (negative) return increases by one standard deviation (0.562), net-buy will increase by 0.008 (-0.08) in December. In contrast, the coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are 0.012 (t-statistic = 4.05) and -0.014 (t-statistic = -1.62), respectively, in January; and 0.012 (t-statistic = 7.43) and -0.028 (t-statistic = -6.17), respectively, in February to November. These values imply a net buy differential of 0.026 (0.012 - (-0.014)) in January, and 0.04 (0.012 - (-0.028)) in February to November, if both positive and negative returns increase by one standard deviation (0.562). Thus small traders exhibit a stronger tendency to sell stocks which are losers in years -3 to -2 at year-ends, consistent with the tax avoidance loss selling incentive.

Panel B of Table 3-5 presents the regression results for large traders. For returns in the previous year, the coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.11 (t-statistic = 2.12) and -0.347 (t-statistic = -2.58), respectively, in December, and the difference is highly significant (p-value = 0.000). These values imply that, if the past year's positive

(negative) return increases by one standard deviation (0.352), net-buy will increase by 0.039 (-0.122) in December. This increase amounts to 35.8% (-111.9%) of the median daily net-buy volume of 0.109 for large traders. In contrast, the coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.018 (t-statistic = 0.31) and 0.008 (t-statistic = 0.07), respectively, in January; and are 0.096 (t-statistic = 3.51) and 0.076 (t-statistic = 1.14), respectively, in February to November; and the differences are insignificant at any confidence level. These results suggest while large traders tend to buy more of the past year's winners, this effect is mainly concentrated in December. Hence window dressing in December plays an important role in large traders' trading strategies based on the previous year's returns.

For longer horizons returns, there is no systematic evidence showing that large traders are more likely to sell past losers in December. For example, the coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are -0.006 (t-statistic = -0.24) and -0.062 (t-statistic = -0.62) in December, respectively, and these two values are not significantly different (p-value = 0.557).

V Robustness Checks

The results in the previous section show that small traders are contrarian traders on the past year's returns, but they are momentum traders on long term returns, while large traders use momentum trading strategies based on the past year's returns. Furthermore, we find that both small and large traders tend to sell the previous year's losing stocks in December. In this section, we perform a number of robustness checks to ensure that our results are not sensitive to outliers, alternative measures and specifications.

V.1 Logged Trading Volume

Because trading volume is skewed to the right (e.g., Chae, 2005), there is a concern that our results may be driven by large values of trading volume. Even after we winsorize all variables at the top and bottom 1% levels, the mean values of trading volume variables are greater than their median values, as shown in Table 1. To ensure that our results are not driven by large values of trading volume, we first log-transform the trading volume variables and then obtain the adjusted measures of these log-transformed variables.

In Table 3-6, we present the regression results where each dependent variable is log-transformed. As shown in Panel A, the effects of past returns on trading activities are similar to those reported in Table 3. That is, small traders tend to trade more on stocks with negative returns during the previous year, and more on stocks with positive returns over years -5 to -2. For large traders, their trading increases with the magnitude of past returns at all time horizons, and the effect is stronger for negative returns.

Insert Table 3-6 about here

Panel B presents the results for adjusted logged monthly net buy volume. We also find that small traders are contrarian traders based on returns in the previous year and momentum traders based on longer horizon past returns. The coefficients on $ret^{+}_{-12:-1}$ and $ret^{-}_{-12:-1}$ are 0.15 (t-statistic = 6.50) and 0.42 (t-statistic = 7.73), respectively, and the difference is highly significant (p-value 0.000). For long-term past returns, the coefficients on $ret^{+}_{-36:-13}$ and $ret^{-}_{-36:-13}$ are 0.012 (t-statistic = 7.87) and -0.028 (t-

statistic = -6.32), respectively, and these two values are also significantly different (p-value 0.000). In contrast, large traders are more willing to sell past year's losers as evidenced by the larger coefficient on $ret^{+}_{-12:-1}$ than $ret^{-}_{-12:-1}$, and buy long-term losing stocks, though the differences in coefficients are insignificant. Overall, the results with logged volume variables are similar to those in Table 3 and 4, hence the skewness of trading volume is not a concern or driving force for our baseline results.

V.2 Alternative Trade Size

In our empirical analysis, we use 500 shares as the cutoff value to differentiate between trades made by small and large traders. Another commonly used threshold value is 1000 shares. We have partitioned trades into small and large trades using this alternative threshold value and repeated the empirical analysis. However, the use of this alternative threshold value does not affect our results in meaningful ways (results not reported).

V.3 Weekly Regressions

Throughout the paper, we carry out our empirical analysis using monthly trading volume measures. We repeat the analysis using weekly regressions. The explanatory variables are similar to those in the monthly analysis. For example, past stock returns are defined on three intervals: weeks -52 to -1, weeks -156 to -53, and weeks -260 to -157. As we use weekly trading variables, the sample size is roughly four times that in monthly

analysis. However, the patterns documented in earlier sections still hold even when we use weekly trading volume measures. More specifically, small traders are more likely to sell winners based on returns over the last 52 weeks, but are more likely to buy winning stocks based on long-term past returns. For large traders, they are more likely to buy the previous year's winners.

VI Conclusions

In this paper, we investigate how stock returns in the past five years affect trading by different types of investors (i.e., small and large traders). We also extend prior studies by controlling for the effect of various firm characteristics. By doing so, we provide additional insights on the trading behavior of different types of investors.

We find that small traders trade more actively on stocks which performed poorly in the past year, and stocks which performed well over years -5 to -2. For large traders, their trading response is stronger on negative returns than positive returns for all time intervals.

With respect to buy and sell behaviors of different types of investors, we document that small traders tend to be contrarian traders on the past year's returns, but momentum traders on long-term past returns. In contrast, large traders tend to buy more of stocks which are winners in the most recent year, but they buy more of losers based on returns over years -5 to -2. Thus we provide evidence that small and large traders use different trading strategies when they trade based on long-term past stock returns. Furthermore, we find small and large traders are more likely to sell past year's losing

stocks in December, consistent with the tax avoidance loss selling or window dressing motives.

Finally, we find that some firm characteristics affect trading by small and large traders differently. Small traders tend to buy more of small firms and high priced firms, while large traders tend to buy more of large firms and low priced firms. Our findings suggest that these firm characteristics are important in explaining small and large traders' trading activities.

In summary, our study suggests that trading strategies by small and larger traders depend on the time interval of past stock returns and on the month in which trading takes places. We also find that certain firm characteristics have differential impacts on trading by different types of investors.

Bibliography

Barber, Brad M., and Terrance Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55, 773-806.

Barber, Brad M., and Terrance Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785-818.

Barberis, N., M. Huang, and T. Santos. 2001. "Prospect theory and asset prices." *Quarterly Journal of Economics* 116, 1-53.

Bessembinder, H. "Trade execution costs and market quality after decimalization." *Journal of Financial and Quantitative Analysis*, 38 (2003), 747-777.

Bushee, B., D. Matsumoto, and G. Miller. "Managerial and investor responses to disclosure regulation: The case of Regulation FD and conference calls." *The Accounting Review*, 79 (2004), 617-643.

Chakravarty, Sugato. "Stealth trading: Which traders' trades move stock price?" *Journal of Financial Economics*, 61 (2001), 289-307.

Chan, L. K. C. and J. Lakonishok. 1993. "Institutional trades and intraday stock price behavior". *Journal of Financial Economics* 33, 173-199.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subramanyam. 2007. The cross section of expected trading activity. *Review of Financial Studies* 20, 709-741.

Conrad, Jennifer, and Gautam Kaul. 1998. An anatomy of trading strategy. *Review of Financial Studies* 11, 489-519.

Constantinides, George M. 1984. Optimal stock trading with personal taxes. *Journal of Financial Economics* 13, 65-89.

De Bondt, Werner F.M., and Richard Thaler. 1985. Deoes the stock market overreact? *Journal of Finance* 40, 793-805.

De Bondt, Werner F.M., and Richard Thaler. 1987. Further evidence on investor overreaction and stock market seasonality. *Journal of Finance* 42, 557-581.

Dyl, Edward A. 1977. Capital gains taxation and year-end stock market behavior. *Journal of Finance* 32, 165-175.

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

Fama, Eugene F., and Kenneth R. French. 1992. The cross section of expected stock returns. *Journal of Finance* 47, 427-465.

Frazzini, F. 2006. "The disposition effect and underreaction to news." *Journal of Finance* 61, 2017-2046.

Froot, Kenneth A., Paul G. J. O'Connell, and Mark Seasholes. 2001. The portfolio flows of international investors. *Journal of Financial Economics* 59, 151-193.

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

Gervais, Simon, and Terrance Odean. 2001. Learning to be overconfident. *Review of Financial Studies* 14, 1-27.

Griffin, John M., Federico Nardari, and Rene M. Stulz. 2007. Do investors trade more when stocks have performed well? Evidence from 46 countries. *Review of Financial Studies* 20, 905-951.

Grinblatt, M., and Bing Han. 2005. "Prospect theory, mental accounting, and momentum." *Journal of Financial Economics* 78, 311-339.

Grinblatt, M., and M. Keloharju. 2001. "What makes investors trade?" *Journal of Finance* 56, 589-616.

Grinblatt, M., and T. Moskowitz. 2004. Predicting stock price movements from the pattern of past returns: the role of consistency and tax-loss selling. *Journal of Financial Economics* 71, 541-579.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review* 85, 1088-1105.

Grundy, B., and S. Martin. 2001. "Understanding the nature of risks and source of rewards to momentum investing." *Review of Financial Studies* 14, 29-78.

Heflin, F., K. Subramanyam, and Y. Zhang. "Regulation FD and the financial reporting environment: Early evidence." *The Accounting Review*, 78 (2003), 1-37.

Hvidkjaer, Soeren. 2006. A trade-based analysis of momentum. *Review of Financial Studies* 19, 457-491.

Jegadeesh, N. 1990. "Evidence of predictable behavior of security returns." *Journal of Finance* 45, 881-898.

Jegadeesh, N., and S. Titman. 1993. "Returns to buying winners and selling losers: implication for stock market efficiency." *Journal of Finance* 48, 65-91.

Kahneman, D., and A. Tversky. 1979. "Prospect theory: an analysis of decision under risk." *Econometrica* 47, 263-291.

Karpoff, Jonathan M. 1987. The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis* 22, 109-126.

Kaul, Gautam, and M. Nimalendran. 1990. Price reversals: bid-ask errors or market overreaction? *Journal of Financial Economics* 28, 67-93.

Keim, Donald B. 1989. Trading patterns, bid-ask spreads, and estimated security returns: the case of common stocks at calendar turning points. *Journal of Finance* 25, 75-97.

Kumar, Alok, and Charles M.C. Lee. 2006. Retail investor sentiment and return comovements. *Journal of Finance* 61: 2451-2486.

Kyle, Albert S. 1985. Continuous auctions and insider trading. *Econometrica* 53, 1315-1335.

Lakonishok, Josef, and Seymour Smidt. 1986. Volume for winners and losers: taxation and other motives for stock trading. *Journal of Finance* 41, 951-974.

Lee, C. and M. Ready. 1991. "Inferring trade direction from intraday data". *Journal of Finance* 46, 733-746.

Lee, Charles M.C., Andrei Shleifer, and Richard H. Thaler. 1991. Investor sentiment and the closed-end fund puzzle. *Journal of Finance* 46: 75-109.

Lee, M. C., and B. Swaminathan. 2000. "Price momentum and trading volume. *Journal of Finance* 55, 2017-2069.

Lo, Andrew W., and A. Craig MacKinlay. 1990. When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-205.

Odean, Terrance. 1998. Are investor reluctant to realize their losses? *Journal of Finance* 53, 1775-1798.

Odean, Terrance. 1998b. Volume, volatility, price, and profit when all traders are above average. *Journal of Finance* 53, 1887-1934.

Odean. 1999. Do investors trade too much? *American Economic Review* 89, 1279-1298.

Reinganum, Marc R. 1983. The anomalous stock market behavior of small firms in January: empirical tests for tax-loss selling effects. *Journal of Financial Economics* 12, 89-104.

Roll, Richard. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39, 1127-1139.

Schwert, William. 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1155.

Shefrin, H., and M. Statman. 1985. "The disposition to sell winners too early and ride losers too long: theory and evidence." *Journal of Finance* 40, 777-790.

Shleifer, A., and R. Vishny. 1997. "The limits to arbitrage." *Journal of Finance* 52, 35-55.

Sias, Richard W., and Laura T. Starks. 1997. Institutions and individuals at the turn-of-the-year. *Journal of Finance* 52, 1543-1562.

Statman, Meir, Steven Thorely, and Keith Vorkink. 2006. Investor overconfidence and trading volume. *Review of Financial Studies* 19: 1531-1565.

Ritter, Jay R. 1988. The buying and selling behavior of individual investors at the turn of the year. *Journal of Finance* 43, 701-717.

Thaler, R. 1980. "Toward a positive theory of consumer choice." *Journal of Economic Behavior and Organization* 1, 39-60.

Weber, M., and C. Camerer. 1998. "The disposition effect in securities trading: an experimental analysis." *Journal of Economic Behavior and Organization* 33, 167-184.

Table 3-1: Summary Statistics

This table presents the summary statistics of main variables. AdjVOL_S (AdjVOL_L) is the adjusted measure of monthly trading volume for small (large) trades, where a small (large) trade involves 500 shares or fewer (more than 500 shares). AdjBUY_S (AdjBUY_L) is the adjusted measure of order imbalance for small (large) trades. $ret_{t_1:t_2}$ is the cumulative return from month t_1 to month t_2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the market-to-book ratio. Leverage is the leverage ratio. # Analyst is the number of analysts following. Dispersion is the standard deviation of analyst forecasts. ΔEarnings is the change in earnings. σ(Earnings) is the volatility of earnings.

	Mean	SD	1st Quartile	Median	3rd Quartile
Volume variables					
AdjVOL	3.520	3.483	1.468	2.729	4.660
AdjVOL_S	0.579	0.769	0.150	0.383	0.849
AdjVOL_L	2.942	3.147	1.137	2.226	3.908
AdjBUY	0.203	1.094	-0.193	0.138	0.556
AdjBUY_S	0.037	0.099	-0.016	0.020	0.073
AdjBUY_L	0.167	1.077	-0.206	0.109	0.505
Past Return Variables					
$\text{ret}_{-12:-1}$	0.150	0.352	-0.072	0.117	0.324
$\text{ret}_{-36:-13}$	0.305	0.562	-0.058	0.221	0.556
$\text{ret}_{-60:-37}$	0.318	0.575	-0.059	0.234	0.581
Other Variables					
Ln(MVE)	13.881	1.584	12.777	13.882	15.024
Beta	0.975	0.282	0.776	0.953	1.127
Ln(Price)	3.219	0.688	2.857	3.297	3.688
Firm Age	346.865	220.247	167.000	313.000	431.000
MTB	1.675	0.915	1.125	1.375	1.870
Leverage	0.262	0.170	0.135	0.256	0.367
Ln(# Analysts)	1.336	0.595	0.854	1.241	1.733
Dispersion	0.071	0.105	0.014	0.035	0.080
ΔEarnings	-0.000	0.012	-0.001	0.001	0.003
σ(Earnings)	0.146	0.165	0.046	0.088	0.179

Table 3-2: Correlation of Explanatory Variables

This table presents correlation matrix of explanatory variables. ret_-1 is the cumulative stock returns over the last month, $r_{\_t1:t2}$ denote the cumulative returns over month t1 to month t2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the ratio of prices (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as ln(1+number of analysts); Dispersion is the standard deviation of analyst forecasts in the month. ΔEarnings are the difference between current earnings and earnings in the same quarter in prior year, deflated by price. σ(Earnings) is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Following Chordia, et al, (2007), firm size Ln(MVE), Ln(Price) and Ln(# Analyst) are also adjusted for seasonality and time trends. * and ** indicate the significance at the 5% and 1% levels, respectively.

	$ret_{-12:-1}$	$ret_{-36:-13}$	$ret_{-60:-37}$
$ret_{-12:-1}$	1		
$ret_{-36:-13}$	-0.065**	1	
$ret_{-60:-37}$	-0.015**	-0.090**	1

	Ln(MVE)	Beta	Ln(Price)	Firm Age	MTB	Leverage	Ln(# Analysts)	Dispersion	ΔEarnings
Ln(MVE)	1								
Beta	-0.114**	1							
Ln(Price)	0.700**	-0.154**	1						
Firm Age	0.328**	-0.157**	0.255**	1					
MTB	0.263**	-0.042**	0.185**	0.022**	1				
Leverage	-0.000	-0.071**	-0.075**	0.050**	-0.238**	1			
Ln(# Analysts)	0.411**	0.000	0.234**	0.100**	0.125**	0.000	1		

Dispersion	-0.015**	-0.053**	0.022**	0.097**	-0.127**	0.119**	-0.018**	1	
ΔEarnings	0.124**	-0.020**	0.172**	0.013**	0.035**	-0.013**	0.032**	-0.031**	1
σ(Earnings)	-0.047**	-0.043**	-0.016**	0.090**	-0.209**	0.190**	-0.044**	0.563**	-0.056**

Table 3-3: Monthly Regression of Volumes on Past Stock Returns

This table presents the regression results of monthly trading volumes using 103,051 observations over 1992-2005. The dependent variables are adjusted trading volumes of small traders (AdjVOL_S), and large traders (AdjVOL_L), where we use 500 shares as the cutoff value for small and large trades. $r_{\_t1:t2}$ denote the cumulative returns over month t1 to month t2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the ratio of prices (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as ln(1+number of analysts); Dispersion is the standard deviation of analyst forecasts in the month. ΔEarnings are the difference between current earnings and earnings in the same quarter in prior year, deflated by price. σ(Earnings) is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ** and * denote 1% and 5% significant levels, respectively.

	AdjVOL_S		AdjVOL_L	
Constant	0.997	(9.08)**	-1.357	(-2.78)**
$ret^{+}_{-12:-1}$	0.290	(11.94)**	1.043	(11.46)**
$ret^{-}_{-12:-1}$	0.516	(10.99)**	2.370	(10.47)**
$ret^{+}_{-36:-13}$	0.081	(5.31)**	0.231	(4.34)**
$ret^{-}_{-36:-13}$	-0.061	(-1.45)	0.465	(2.39)*
$ret^{+}_{-60:-37}$	0.012	(0.87)	0.143	(2.76)**
$ret^{-}_{-60:-37}$	-0.099	(-2.55)*	0.859	(4.83)**
Ln(MVE)	-0.100	(-13.26)**	0.220	(6.54)**
Beta	0.190	(5.05)**	1.635	(11.11)**
Ln(Price)	0.351	(18.39)**	-0.027	(-0.38)
Ln(Firm Age)	-0.118	(-7.63)**	-0.388	(-5.36)**
MTB	0.030	(2.94)**	0.116	(2.24)*
Leverage	0.117	(2.06)*	0.184	(0.81)
Ln(# Analysts)	0.083	(8.08)**	0.686	(14.47)**
Dispersion	0.219	(3.70)**	1.119	(4.74)**
ΔEarnings	1.062	(2.81)**	6.897	(3.46)**
σ(Earnings)	-0.065	(-1.17)	0.493	(1.78)
Year-Month Dummies	YES		YES	
Adjusted R^2	0.199		0.103	
Test p-values				
$ret^{+}_{-12:-1} = ret^{-}_{-12:-1}$	0.000		0.000	
$ret^{+}_{-36:-13} = ret^{-}_{-36:-13}$	0.001		0.243	
$ret^{+}_{-60:-37} = ret^{-}_{-60:-37}$	0.005		0.000	

Table 3-4: Monthly Regression of Net Buy Volumes on Past Stock Returns

This table presents the regression results of monthly net buy volumes using 103,051 observations over 1992-2005. The dependent variables are net buy volumes of small traders (AdjBUY_S), net buy volume of large traders (AdjBUY_L), where we use 500 shares as the cutoff value for small and large trades. $r_{\_t1:t2}$ denote the cumulative returns over month t1 to month t2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the ratio of prices (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as ln(1+number of analysts); Dispersion is the standard deviation of analyst forecasts in the month. ΔEarnings are the difference between current earnings and earnings in the same quarter in prior year, deflated by price. σ(Earnings) is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Time fixed effects are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ** and * denote 1% and 5% significant levels, respectively.

	AdjBUY_S		AdjBUY_L	
Constant	0.070	(6.84)**	-0.758	(-4.82)**
$ret^{+}_{-12:-1}$	0.015	(6.49)**	0.091	(3.45)**
$ret^{-}_{-12:-1}$	0.042	(7.71)**	0.039	(0.62)
$ret^{+}_{-36:-13}$	0.012	(7.88)**	-0.012	(-0.69)
$ret^{-}_{-36:-13}$	-0.028	(-6.33)**	0.077	(1.25)
$ret^{+}_{-60:-37}$	0.001	(0.96)	-0.011	(-0.71)
$ret^{-}_{-60:-37}$	-0.018	(-4.10)**	0.030	(0.54)
Ln(MVE)	-0.004	(-5.67)**	0.058	(5.38)**
Beta	0.013	(3.99)**	0.130	(3.48)**
Ln(Price)	0.020	(11.70)**	-0.040	(-2.16)*
Ln(Firm Age)	-0.014	(-9.86)**	0.005	(0.31)
MTB	0.003	(3.55)**	-0.005	(-0.44)
Leverage	0.015	(2.73)**	-0.061	(-0.88)
Ln(# Analysts)	0.006	(5.51)**	0.070	(5.84)**
Dispersion	0.008	(1.29)	0.044	(0.66)
ΔEarnings	0.273	(5.55)**	0.186	(0.36)
σ(Earnings)	0.004	(0.59)	0.037	(0.54)
Year-Month Dummies	YES		YES	
Adjusted R^2	0.089		0.017	
Test p-values				
$ret^{+}_{-12:-1} = ret^{-}_{-12:-1}$	0.000		0.429	
$ret^{+}_{-36:-13} = ret^{-}_{-36:-13}$	0.000		0.151	
$ret^{+}_{-60:-37} = ret^{-}_{-60:-37}$	0.000		0.432	

Table 3-5: Monthly Regression of Net Buy Volume on Past Stock Returns: Seasonality

This table presents the regression results of net buy volumes using 103,051 observations over 1992-2005. The dependent variables are adjusted logged net buy volume of small trades (AdjLBUY_S) in Panel A, and adjusted logged net buy volume of large trades (AdjLBUY_L) in Panel B, where we use 500 shares as the cutoff value for small and large trades. $r_{t1:t2}$ denote the cumulative returns over month t1 to month t2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the ratio of prices (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as ln(1+number of analysts); Dispersion is the standard deviation of analyst forecasts in the month. ΔEarnings are the difference between current earnings and earnings in the same quarter in prior year, deflated by price. σ(Earnings) is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Following Chordia, et al, (2007), firm size Ln(MVE), Ln(Price) and Ln(# Analyst) are also adjusted for seasonality and time trends. Time fixed effects are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ** and * denote 1% and 5% significant levels, respectively.

Panel A: Small Traders (AdjBUY_S)						
	December		January		February-November	
Constant	0.080	(5.35)**	0.074	(4.81)**	0.069	(6.72)**
$ret^{+}_{-12:-1}$	0.030	(6.20)**	0.009	(1.70)	0.015	(6.01)**
$ret^{-}_{-12:-1}$	-0.032	(-2.84)**	0.067	(5.80)**	0.046	(8.25)**
$ret^{+}_{-36:-13}$	0.015	(5.76)**	0.012	(4.05)**	0.012	(7.43)**
$ret^{-}_{-36:-13}$	-0.045	(-5.20)**	-0.014	(-1.62)	-0.028	(-6.17)**
$ret^{+}_{-60:-37}$	0.004	(1.30)	-0.002	(-0.69)	0.001	(0.96)
$ret^{-}_{-60:-37}$	0.001	(0.06)	-0.025	(-2.68)**	-0.019	(-4.32)**
Ln(MVE)	-0.003	(-2.79)**	-0.005	(-4.17)**	-0.004	(-5.80)**
Beta	0.017	(3.37)**	0.003	(0.49)	0.014	(4.11)**
Ln(Price)	0.015	(5.88)**	0.021	(7.58)**	0.020	(11.86)**
Ln(Firm Age)	-0.015	(-7.99)**	-0.015	(-7.12)**	-0.014	(-9.63)**
MTB	0.002	(1.48)	0.005	(3.28)**	0.003	(3.54)**
Leverage	0.011	(1.60)	0.018	(2.24)*	0.015	(2.72)**
Ln(# Analysts)	0.005	(2.46)*	0.010	(4.62)**	0.005	(5.15)**
Dispersion	-0.001	(-0.12)	0.025	(1.81)	0.008	(1.18)
ΔEarnings	0.408	(4.43)**	0.047	(0.55)	0.279	(5.17)**
σ(Earnings)	0.012	(1.23)	-0.001	(-0.09)	0.003	(0.50)
Observations	8847		8116		86123	

Adjusted R^2	0.119	0.085	0.087
Test p-values			
$\text{ret}^{+}_{-12:-1} = \text{ret}^{-}_{-12:-1}$	0.000	0.000	0.000
$\text{ret}^{+}_{-36:-13} = \text{ret}^{-}_{-36:-13}$	0.000	0.001	0.000
$\text{ret}^{+}_{-60:-37} = \text{ret}^{-}_{-60:-37}$	0.709	0.009	0.000

Panel B: Large Traders (AdjBUY_L)						
	December		January		February-November	
Constant	-0.704	(-3.15)**	-0.655	(-2.27)*	-0.771	(-4.54)**
$\text{ret}^{+}_{-12:-1}$	0.110	(2.12)*	0.018	(0.31)	0.096	(3.51)**
$\text{ret}^{-}_{-12:-1}$	-0.347	(-2.58)**	0.008	(0.07)	0.076	(1.14)
$\text{ret}^{+}_{-36:-13}$	-0.006	(-0.24)	0.026	(0.79)	-0.016	(-0.89)
$\text{ret}^{-}_{-36:-13}$	-0.062	(-0.62)	0.184	(1.63)	0.079	(1.22)
$\text{ret}^{+}_{-60:-37}$	-0.028	(-1.02)	-0.040	(-1.30)	-0.007	(-0.40)
$\text{ret}^{-}_{-60:-37}$	-0.005	(-0.06)	-0.131	(-1.27)	0.049	(0.83)
Ln(MVE)	0.059	(3.95)**	0.031	(1.71)	0.060	(5.10)**
Beta	0.141	(2.54)*	0.174	(2.41)*	0.125	(3.22)**
Ln(Price)	-0.065	(-2.12)*	0.001	(0.02)	-0.041	(-2.09)*
Ln(Firm Age)	-0.006	(-0.23)	0.013	(0.50)	0.005	(0.31)
MTB	0.010	(0.64)	0.010	(0.62)	-0.008	(-0.63)
Leverage	-0.002	(-0.03)	-0.040	(-0.34)	-0.069	(-0.90)
Ln(# Analysts)	0.094	(4.53)**	0.078	(3.51)**	0.066	(5.02)**
Dispersion	0.057	(0.42)	0.069	(0.50)	0.041	(0.59)
ΔEarnings	-0.746	(-0.69)	0.855	(0.62)	0.188	(0.35)
σ(Earnings)	0.051	(0.54)	0.040	(0.25)	0.035	(0.51)
Observations	8847		8116		86123	
Adjusted R2	0.017		0.018		0.016	
Test p-values						
$\text{ret}^{+}_{-12:-1} = \text{ret}^{-}_{-12:-1}$	0.001		0.941		0.775	
$\text{ret}^{+}_{-36:-13} = \text{ret}^{-}_{-36:-13}$	0.557		0.155		0.141	
$\text{ret}^{+}_{-60:-37} = \text{ret}^{-}_{-60:-37}$	0.767		0.346		0.319	

Table 3-6: Monthly Regression of Logged Volumes on Past Stock Returns

This table presents the regression results of monthly logged trading and net buy volumes using 103,051 observations over 1992-2005. The dependent variables are adjusted logged trading volumes of small traders (AdjLVOL_S), adjusted logged trading volume of large traders (AdjLVOL_L) in Panel A, and adjusted logged net buy volume of small trades (AdjLBUY_S) and adjusted logged net buy volume of large trades (AdjLBUY_L), where we use 500 shares as the cutoff value for small and large trades. $r_{\_t1:t2}$ denote the cumulative returns over month t1 to month t2. Ln(MVE) is the logged value of market capitalization at the end of prior month. Firm Age is the number of months since a firm's first appearance in the CRSP. Ln(Price) is the logged value of stock price in the prior month. MTB is the ratio of prices (Item 199) times shares outstanding (Item 25) plus book assets (Item 6) minus book equity (Item 60) to the book value of assets. Leverage is the ratio of debt in current liability (Item 34) plus long term debt (Item 9) to total assets (Item 6). Ln(# Analysts) is defined as ln(1+number of analysts); Dispersion is the standard deviation of analyst forecasts in the month. ΔEarnings are the difference between current earnings and earnings in the same quarter in prior year, deflated by price. σ(Earnings) is computed as the standard deviation of quarterly earnings in the most recent eight quarters. Following Chordia, et al, (2007), firm size Ln(MVE), Ln(Price) and Ln(# Analyst) are also adjusted for seasonality and time trends. Time fixed effects are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ** and * denote 1% and 5% significant levels, respectively.

Panel A: Logged Aggregate Volume				
	AdjLVOL_S		AdjLVOL_L	
Constant	0.998	(9.11)**	-1.726	(-3.74)**
$ret^{+}_{-12:-1}$	0.290	(11.97)**	1.030	(11.87)**
$ret^{-}_{-12:-1}$	0.516	(11.00)**	2.386	(11.24)**
$ret^{+}_{-36:-13}$	0.081	(5.31)**	0.224	(4.46)**
$ret^{-}_{-36:-13}$	-0.062	(-1.49)	0.512	(2.78)**
$ret^{+}_{-60:-37}$	0.012	(0.87)	0.143	(2.96)**
$ret^{-}_{-60:-37}$	-0.100	(-2.56)*	0.901	(5.38)**
Ln(MVE)	-0.100	(-13.30)**	0.238	(7.59)**
Beta	0.190	(5.07)**	1.632	(11.55)**
Ln(Price)	0.350	(18.41)**	-0.039	(-0.58)
Ln(Firm Age)	-0.118	(-7.63)**	-0.373	(-5.49)**
MTB	0.030	(2.94)**	0.115	(2.33)*
Leverage	0.116	(2.05)*	0.211	(0.98)
Ln(# Analysts)	0.083	(8.11)**	0.689	(15.04)**
Dispersion	0.219	(3.71)**	1.095	(4.91)**
ΔEarnings	1.059	(2.81)**	6.397	(3.39)**
σ(Earnings)	-0.064	(-1.16)	0.520	(1.95)
Year-Month Dummies	YES		YES	

Adjusted R^2	0.199	0.116
Test p-values		
$\text{ret}^{+}_{-12:-1} = \text{ret}^{-}_{-12:-1}$	0.000	0.000
$\text{ret}^{+}_{-36:-13} = \text{ret}^{-}_{-36:-13}$	0.001	0.128
$\text{ret}^{+}_{-60:-37} = \text{ret}^{-}_{-60:-37}$	0.005	0.000

Panel B: Logged Net Buy Volume				
	AdjLBUY_S		AdjLBUY_L	
Constant	0.069	(6.82)**	-0.833	(-6.94)**
$\text{ret}^{+}_{-12:-1}$	0.015	(6.50)**	0.096	(3.97)**
$\text{ret}^{-}_{-12:-1}$	0.042	(7.73)**	0.081	(1.40)
$\text{ret}^{+}_{-36:-13}$	0.012	(7.87)**	-0.013	(-0.89)
$\text{ret}^{-}_{-36:-13}$	-0.028	(-6.32)**	0.063	(1.28)
$\text{ret}^{+}_{-60:-37}$	0.001	(0.96)	-0.009	(-0.58)
$\text{ret}^{-}_{-60:-37}$	-0.018	(-4.11)**	0.012	(0.25)
Ln(MVE)	-0.004	(-5.65)**	0.073	(8.12)**
Beta	0.013	(4.00)**	0.100	(2.67)**
Ln(Price)	0.020	(11.68)**	-0.051	(-2.75)**
Ln(Firm Age)	-0.014	(-9.85)**	-0.019	(-1.21)
MTB	0.003	(3.56)**	0.003	(0.26)
Leverage	0.015	(2.72)**	-0.013	(-0.20)
Ln(# Analysts)	0.006	(5.51)**	0.075	(6.84)**
Dispersion	0.008	(1.28)	0.029	(0.39)
ΔEarnings	0.272	(5.53)**	-0.062	(-0.11)
σ(Earnings)	0.004	(0.60)	0.072	(1.11)
Year-Month Dummies	YES		YES	
Adjusted R^2	0.089		0.021	
Test p-values				
$\text{ret}^{+}_{-12:-1} = \text{ret}^{-}_{-12:-1}$	0.000		0.806	
$\text{ret}^{+}_{-36:-13} = \text{ret}^{-}_{-36:-13}$	0.000		0.123	
$\text{ret}^{+}_{-60:-37} = \text{ret}^{-}_{-60:-37}$	0.000		0.662	

Chapter 4

Financial Statement Comparability, Corporate Cash Holdings and Investment

I Introduction

In this study, we examine how financial statement comparability[15] affects the sensitivity of corporate investment to cash (i.e., the investment-cash sensitivity). Firms' financial statements are considered comparable if they report similar accounting numbers when they experience the same economic events (De Franco, et al., 2011; Francis, et al., 2014). Recent studies (De Franco, et al., 2011; Kim, et al., 2012) find that financial statement comparability reduces information asymmetry, and results in lower cost of external capital. This paper investigates the real economic consequences of financial statement comparability by examining its effect on the investment-cash sensitivity.

Our study is motivated by and contributes to two literatures. The corporate finance literature documents that corporate investment is sensitive to and constrained by the availability of internal funds (such as cash or cash flow) due to costly external finance. With financial market imperfection, firms may not be able to obtain funds from outside or outside funds are too costly even though they possess positive net present value projects (e.g., Jaffee and Russell, 1976; Stiglitz and Weiss, 1981; Myers and Majluf, 1984; Holmstrom and Tirole, 1997). Consequently, corporate investment depends crucially on the availability of internal funds, especially for firms which face more obstacles to obtain external finance (i.e., financially constrained firms). Empirical

[15] In this paper, we use financial statement comparability, financial reporting comparability, and accounting comparability interchangeably.

evidence on the relation between investment and internal funds is documented by various studies which focus on either cash holdings (e.g., Opler, et al., 1999; Love, 2003; Denis and Sibilkov, 2010; Duchin, et al., 2010) or cash flow (e.g., Fazzari, et al., 1988; Hoshi, et al., 1991; Gilchrist and Himmelberg, 1995; McLean, et al., 2012). The sensitivity of investment to cash implies investment inefficiency as growth opportunities must be forgone when cash short firms find it too costly to obtain external finance. This study examines whether comparability reduces the investment-cash sensitivity and hence improves investment efficiency.

A second literature shows that high quality accounting information alleviates information asymmetry, and reduces the cost of raising capital from outside. Easley and O'Hara (2004) and O'Hara (2003) argue that high quality information reduces the required compensation from uninformed investors as they are less likely to trade with informed traders. As one important aspect of high quality accounting, financial statement comparability facilitates information analysis and processing, and allows more information of higher precision to be extracted from financial statements (De Franco, et al., 2011). More and better information decreases the information advantage of privately informed traders, and also enables investors to more accurately assess the reporting firm's future cash flows. Thus the required rate of return demanded by investors declines when comparability improves. Recent empirical evidence confirms that financial statement comparability lowers information asymmetry (De Franco, et al., 2011), and results in lower cost of external capital (e.g., Fang, et al., 2012; Kim, et al., 2012).

We build on these prior studies to examine the effects of financial statement comparability on the investment-cash sensitivity. More specifically, if financial statement

comparability reduces information asymmetry (De Franco, et al., 2011) and high comparability firms incur lower cost of external capital (Kim, et al., 2012), then these firms should be more able to invest regardless of internal cash positions. In other words, the sensitivity of investment to corporate cash holdings decreases with financial statement comparability. Furthermore, we conjecture that if financial statement comparability reduces the cost of external capital and hence the investment-cash sensitivity, this effect should be stronger for financially constrained firms as these firms are more likely to face the burden of costly external finance.

To investigate the effect of comparability, we use a reduced form investment regression with cash and financial statement comparability measures. Following the methodology of De Franco, et al. (2011), we construct measures of financial statement comparability by computing the difference in imputed earnings between firms when they are assumed to experience the same stock returns (as proxy for economic events).

Using investment regressions with cash and comparability over the period of 1990 to 2010, we find that investment is highly sensitive to cash holdings for low comparability firms, but this sensitivity disappears for firms in the top quartile of comparability. After partitioning the sample firms into constrained and unconstrained groups based on the median values of firm financing constraint variables such as firm size, payout ratio, and bond ratings, and industry proxies of external financial dependence, we find that the sensitivity of investment to cash and the mitigating role of comparability exist only in constrained firms, but not in unconstrained firms. We perform a number of robustness analyses to ensure that our findings are not subject to various concerns. First, to address the endogeneity issue of comparability, we show that it is not a widespread

practice for firms to make large changes in comparability from year to year. In addition, alternative regression specifications such as a two-stage least square method yield similar results. Second, we repeat our analysis using several alternative comparability measures. Third, we show that our results are not affected if we add additional controls to address the noisiness of the Q variable (defined as the market value of equity plus book assets minus book equity divided by book assets). Fourth, we show that financial statement comparability does not simply pick up the effect of firm size by including firm size (logged assets) and its interaction with cash in the regression.

Given that financial statement comparability alleviates investment-cash sensitivity, it is natural to ask why (financially constrained) firms do not improve their comparability to reduce cost of external capital such that their investment is less sensitive to the availability of internal funds. There are several possibilities that firms cannot or do not intend to improve comparability. These possibilities include: constrained firms may actually have lower cost of external capital; they may be in a highly competitive industry and more comparable financial statements will lead to possible leakage of proprietary information to competitors; and they have lower earnings quality. We evaluate these possibilities and find that the most plausible explanation is that firms with low comparability also have low earnings quality, and they choose low comparability such that it is harder for investors to uncover their earnings management activities. Furthermore, including earnings quality proxies in the regression does not affect our findings that comparability reduces the sensitivity of investment to cash. Thus comparability does not simply pick up the effect of earnings quality even though there is a significantly positive relation between comparability and earnings quality.

Financial statement comparability has been emphasized by both the accounting standard setters and securities market regulators as being essential for efficient capital allocation of investors. The Financial Accounting Standard Board (FASB) states that "information about a reporting entity is more useful if it can be compared with similar information about other entities and with similar information about the same entity for another period or another date" (FASB 2000). In its Concept Release (2000), the Securities and Exchange Commission (SEC) claims that: "the efficiency of capital allocation of investors would be reduced without consistent, comparable, relevant and reliable information regarding the financial condition and operating performance of potential investments." This study provides additional insights by showing that financial statement comparability also improves the capital allocation efficiency of firms.

The remaining part of the paper is organized as follows: section II reviews the related literature; section III discusses sample construction and our empirical strategy; section IV presents the main results of comparability, cash holdings and investment; section V discusses why some firms do not improve comparability; section VI conducts analysis on operating performance and firm value; and section VII concludes.

II Literature Review

II.1 Literature on Cash Holdings and Investment

When external finance is costly due to capital market imperfections, internal funds such as cash enable firms to undertake investment opportunities. Denis and Sibilkov (2010) find that corporate investment is positively and significantly related to

cash holdings, especially for financially constrained firms. Duchin, et al. (2010) focus on the recent financial crisis, and show that firms with larger pre-crisis cash holdings experience smaller drops in investment after the onset of crisis, especially for financially constrained firms. Love (2003) conjectures that financial development facilitates external financing and documents that the sensitivity of investment to cash holding is lower in countries with better financial development.

We use cash instead of cash flow to examine the real effect of comparability such that our results are not subject to the well-known debate as to whether cash flow proxies for financial position or growth opportunities. Fazzari, et al. (1998) document that investment is sensitive to cash flow and interpret this finding as evidence that cash flow reflects corporate financial positions. Several studies (e.g., Kaplan and Zingales, 1997; Alti, 2003) argue that the investment-cash flow sensitivity documented in Fazarri, et al. (1998) arises because cash flow captures unobserved growth opportunities when Q is noisy, and show that investment-cash flow sensitivity may be higher for financially unconstrained firms. Using an alternative specification or sample, studies such as Gilchrist and Himmelberg (1995) and McLean, et al. (2012) provide evidence which is consistent with Fazzari, et al. (1998).

II.2 Financial Reporting Quality, the Cost of Capital and Investment

Better financial reporting reduces information asymmetry, and firms with higher financial reporting quality can obtain external capital at lower costs. Easley and O'Hara (2004) and O'Hara (2003) show that more public information reduces the cost of capital

as uninformed traders require a lower level of compensation for possibly trading with informed traders with private information. Lambert et al. (2007) also show that high quality accounting information reduces cost of capital by lowering the assessed covariance of a firm's cash flow with other firms' cash flows. Empirical evidence on the relation between accounting information quality and the cost of capital has traditionally focused on the effect of earnings quality. For example, Francis, et al. (2004) examine the relation between several earnings attributes and cost of capital, and find that the accrual quality proxy from the Dechow and Dichev (2002) model has strongest effects. Francis, et al. (2005) find that higher accounting quality is associated with lower cost of debt and equity capital.[16] Bharath, et al. (2008) document that firms with poorer accounting quality rely more on private credit, and pay higher prices on loans. Bhattacharya, et al. (2012) provide evidence that earnings quality has not only a direct effect on the cost of equity, but also an indirect effect through information asymmetry and beta. Recent studies by De Franco et al. (2011) and Kim et al. (2012) provide evidence that comparability facilitates information analysis and processing and reduces information asymmetry, and the cost of capital is lower for high comparability firms.

The real economic consequences of financial reporting quality are also investigated by several studies. Biddle and Hilary (2006), for example, show that higher financial reporting quality results in lower investment-cash flow sensitivity in a cross country setting. Biddle et al. (2009) and Chen et al. (2011) document that high reporting quality is associated with less deviation from the expected level of investment and hence lower levels of under- and over-investment. This paper differs from prior studies on

[16] However, Core, et al. (2008) argue that the method used by Francis, et al. (2005) is not appropriate, and show that accruals quality is not a priced risk factor.

financial reporting quality and investment in two important aspects: first, we consider the role of financial statement comparability in alleviating the investment-cash sensitivity, while prior studies focus generally on proxies related to earnings quality; second, we examine the role of cash holdings in corporate investment, after controlling for investment opportunities.

III Data and Empirical Strategy

In this section, we first describe the sample selection and the construction of main regression variables; and then discuss the empirical methodology.

III.1 Sample

Annual data on publicly traded firms over 1990 to 2010 are obtained from Compustat. We exclude firms in financial industries (SIC code from 6000 to 6999) and utilities industries (SIC code from 4900 to 4999), and firms with negative sales, assets or cash. Following Almeida, et al. (2004) and Duchin, et al. (2010), we delete firms with asset or sales growth above 100% because these firms may undergo mergers and acquisitions or restructuring.

The dependent variable, corporate investment, is defined as the sum of capital expenditure (Item 128) and R&D (Item 46), divided by lagged total assets (Item 6). Corporate cash holdings (denoted as NCash) are measured as cash and marketable securities (Item 1) divided by total assets. Our main control variables are Tobin' Q and

cash flow. Following prior studies (e.g., Baker, et al., 2003; McLean, et al., 2012), we defined Tobin's Q as the market value of equity (Item 199 times Item 25) plus book assets (Item 6) minus book equity (Item 60) and deferred taxes (Item 74), divided by the book value of assets;[17] Cash Flow is defined as operating income (Item 18) plus depreciation (Item 14), divided by assets. We augment the empirical analysis by using an alternative measure of cash flow, defined as cash flow from operating activities (Item 308) divided by assets. However, the use of this alternative measure does not affect our results in a meaningful way. To mitigate the effect of outliers, we winsorize all financial variables at the top and bottom 1% level.

III.2 Comparability Measures

De Franco, et al. (2011) develop measures of financial statement comparability based on the argument that two firms (in the same industry) have comparable financial statements if they report similar accounting earnings when they experience the same set of economic events. Following their methodology, the financial statement comparability between two firms: firm *i* (the firm in consideration) and firm *j* (any other firm in the same industry as firm *i*) is constructed using the following procedure. First, for each firm *k=i,j*, a relation between stock returns (as the proxy for economic events) and accounting earnings is estimated using the last 16 quarters of data:

$$Earnings_{k,t} = \alpha_k + \beta_k * Return_{k,t} + \varepsilon_{k,t}. \quad (1)$$

[17] Using alternative definition of Q without deferred taxes yields similar results.

The estimated coefficients $\hat{\beta}_i$ and $\hat{\beta}_j$ captures how underlying economic events are mapped to accounting earnings in firm *i and j*. Second, the estimated coefficients $\hat{\beta}_i$ and $\hat{\beta}_j$ are used to predict accounting earnings given firm *i*'s stock returns:

$$E(Earnings)_{ii,t} = \hat{\alpha}_i + \hat{\beta}_i * Return_{i,t},$$

$$E(Earnings)_{ij,t} = \hat{\alpha}_j + \hat{\beta}_j * Return_{i,t}. \quad (2)$$

Note that in equation (2), the stock return is from firm *i*. Thus, equation (2) predicts what earnings numbers will be reported by firm *i* and *j*, given that both firms experience the same set of economic events (i.e., firm *i*'s economic events). Finally, the comparability or closeness of financial statements between firm *i* and *j* is computed as:

$$Comparability_{ij,t} = -\frac{1}{16}\sum_{t-15}^{t}\left|E(Earnings)_{ii,t} - E(Earnings)_{ij,t}\right|. \quad (3)$$

This variable captures how much firm *j*'s predicted earnings differ from that of firm *i*, and is computed for all firms *j* which are in the same industry as firm *i*. A minus sign is included such that the possible range of values for the comparability variable is from minus infinity to zero, and larger values (i.e., less negative values) indicate higher financial statement comparability.

To compute the comparability of firm *i*'s financial statement with its industry peers, we aggregate the comparability variable in (3) over all or subset of peer firms which are in the same industry as firm *i*. For example, the median comparability of firm *i* with its industry peers is defined as:

$$Comparability\_Median_{i,t} = Median_{\forall j}\left(Comparability_{ij,t}\right). \quad (4)$$

Following De Franco, et al. (2011), we construct three firm-year measures of financial statement comparability for a firm *i*: Comparability_Median (the median of comparability values with all peer firms), Comparabilility_10 (the average of comparability values of 10 peer firms with highest comparability to firm *i*), and Comparability_4 (the average of comparability values of 4 peer firms with highest comparability to firm *i*)[18].

In our empirical analysis, we use decile values of all three comparability measures (denoted as Comp_Median, Comp_10, and Comp_4) instead of their raw values due to several considerations. First, the use of decile values mitigates the effect of outliers; second, decile values make the interpretation of regression coefficients easier, because coefficient estimates on deciles of comparability measures imply how the dependent variable will change if firms improve their financial statement comparability by just one decile when other things are fixed; third, even if financial statement comparability measures are estimated with noises, as long as such noises do not make firms switch to other deciles, the use of deciles will reduce the effect of estimation noise (Cetorelli and Gambera, 2001).

III.3 Empirical Strategy

[18] We do not use the average of a firm's comparability values with all of its industry peer firms, because the comparability variable developed in (3) has a maximum value of zero, but no minimum values. Thus the average comparability measure can be easily affected by a few large negative values. In other words, the average comparability measure is easily affected by those industry peer firms which are least comparable to firm *i*.

The empirical model is the reduced form investment regression as in prior studies (e.g., Denis and Sibilkov, 2010; Duchin, et al., 2010), and is augmented by including financial statement comparability and its interaction with cash:

$$Investment_{i,t} = \alpha + \beta_1 * Cash_{i,t-1} + \beta_2 * Comparability_{i,t-1} + \beta_3 * Cash_{i,t-1} \times Comparability_{i,t-1} + \beta_4 * Q_{i,t-1} + \beta_5 * Cash\ Flow_{i,t-1} + \Sigma f_i + \Sigma year_t + \varepsilon_{i,t}. \quad (5)$$

In the above regression specification, Cash, Q, and Cash Flow denote corporate (residual) cash holdings (to be discussed below), Tobin's Q, and cash flow respectively. Firm and year dummies f_i and $year_t$ are included in the regression to control for firm and macroeconomic factors which affect investment. Our focus is on the coefficient estimates of β_1 and β_3. Investment is sensitive to the availability of cash reserves due to costly external finance, and we expect β_1 >0. Financial statement comparability alleviates information asymmetry and reduces costs of external capital, and firms with more comparable financial reporting should be more able to invest irrespective of the availability of cash. Thus investment will be less sensitive to cash when financial statement comparability is high, and we expect β_3<0.

The Cash variable in equation (5) is the corporate residual (or excess) cash, instead of the normal cash to asset ratio (i.e., NCash). Including normal cash in the investment-cash regression (5) may raise the concern that both investment and cash holdings are endogenous to unobserved investment opportunities. Thus a positive coefficient estimate on β_1 may not imply that investment is sensitive to cash holdings, but rather indicate that cash holdings respond to unobserved investment opportunities as

actual investment does. Furthermore, Almeida, et al. (2004) show that firms tend to save cash out of cash flow, especially when they are financially constrained. This implies that coefficients on normal cash may also include the effect of cash flow. To obtain the residual cash, we employ the empirical strategy as in Opler, et al. (1999), and Durchin, et al., (2010) to first regress the cash to asset ratio (i.e., NCash) on a set of variables which include proxies for investment opportunities:

$$NCash_{i,t} = \alpha + \delta_1 * Size_{i,t} + \delta_2 * Q_{i,t} + \delta_3 * Cash\ Flow_{i,t} + \delta_4 * Net\ Working\ capital_{i,t} + \delta_5 * Industry\ CF\ Volatility_{j,t} + \Sigma year_t + \varepsilon_{i,t}. \quad (6)$$

Here $NCash$ denotes the ratio of cash-to-total assets, Q and $Cash\ Flow$ capture the effect of investment opportunities and the cash flow sensitivity of cash. The residual from the regression is denoted as Cash and used as the cash holding variable in the main regression (5). Throughout the paper, we use NCash to denote normal or original cash to asset ratio, and Cash to denote residual or excess cash.

III.4 Summary Statistics

Table 4-1 presents summary statistics of variables used in our empirical analysis. The original Comparability_Median measure has a mean value of -2.582 and median value of -1.77. The original Comparability_10 and Comparability_4 measures have mean (median) values at -0.92 and -0.64 (-0.41 and -0.26) respectively. These results suggest that there are large negative values for all comparability measures, and it is appropriate to

use decile values of all comparability measures instead of original values in regression analysis. In addition, the Comparability_Median measure has larger negative mean and median values than both Comparability_10 and Comparability_4, because the latter two measures include only peer firms which are more comparable in financial reporting. For all the following analysis, we use the deciles of all three comparability measures, unless otherwise specified.

Insert Table 4-1 about here

The sample firms have an average investment-to-assets ratio of 11.6%, with the capital expenditure-to-assets ratio of about 6.3%. The mean (median) value of NCash (the cash-to-asset ratio) is 16.4% (9.1%), while the (residual or excess) Cash has a mean value close to zero.

IV Results on Comparability, Cash Holdings and Investment

In this section, we provide empirical evidence on the effect of financial statement comparability on the sensitivity of corporate investment to cash holdings. We first show that financial statement comparability reduces the investment-cash sensitivity, and this effect is stronger for financially constrained firms. Next, we provide various evidences to confirm that our main results are not driven by the endogeneity of comparability. Finally, we show that the results are robust to alternative measures of comparability, and to including additional control variables.

IV.1 Baseline Results

Table 4-2 presents main regression results based on specification (5), with the investment ratio (capital expenditure plus R&D, divided lagged total assets) as the dependent variable. In all columns, we use the excess cash after regressing cash on a set of variables as in equation (6), and decile values of comparability measures. To save space, we do not report the results for the cash holdings regression (6), which are consistent with prior studies (e.g., Opler, et al., 1999), that is, cash holdings increase in Q, cash flow and industry cash flow volatility, but decrease in firm size and net working capital.

Insert Table 4-2 about here

Column (1) uses Comp_Median as the measure of financial statement comparability. As expected, the coefficient estimate on Cash is positive (0.047) and significant at the 1% confidence level (t-statistic = 3.47), confirming that investment is sensitive to the availability of cash. Our main interest is the coefficient on the interaction term Cash × Comp_Median. This coefficient is negative (-0.007) and significant (t-statistic = -3.70). The coefficient on Cash (0.047) implies that for firms with lowest financial statement comparability, the investment ratio will increase by 0.7% if residual cash holdings increase by one standard deviation (14.1% as shown in Table 4-1), and the coefficient on Cash × Comp_Median suggests that when a firm's financial statement comparability is in the seventh decile, this sensitivity is eliminated. Correspondingly, investment by firms in the top quartile of financial statement comparability is not

constrained by cash holdings. This finding confirms that higher financial statement comparability mitigates the importance of cash holdings to corporate investment.

Results in the remaining columns when we use alternative measures of comparability show similar patterns, with positive and significant coefficients on Cash, and negative and significant coefficients on the Cash and comparability measure interaction terms. Note that our results cannot be explained by the argument that cash picks up the effect of cash flow because we use residual cash instead of normal cash. Additional regression analysis adding the interaction of cash flow and comparability yields similar results.

For control variables, we find that investment is highly responsive to investment opportunities as proxied by Q (coefficient 0.018 and t-statistic = 18.81). The coefficients on cash flow are negative (-0.015) and marginally significant at a 10% confidence level in columns (1) and (3). This finding is consistent with Duchin, et al. (2010), but opposite to other studies.

IV.2 Financing Constraints

To show that the mitigating effect of comparability on investment-cash sensitivity is mainly concentrated in financially constrained firms because these firms are more likely to face the burden of costly external finance, we partition firms into constrained and unconstrained groups. As there is no single best proxy for financing constraints, we employ three different proxies commonly used in the literature: firm size, payout ratio, and bond rating. Large firms have higher institutional ownership, more analyst following,

lower information asymmetry and costs of capital, and their investment is less likely to be constrained by cash. Constrained firms are less likely to pay dividends to investors (Fazzari, et al., 1988). Firms without bond ratings are less likely to obtain funds from outside (e.g., Denis and Sibilkov, 2010)

Firm size is measured by logged total assets. The payout ratio is defined as cash dividends divided by net income. Bond rating is a dummy variable which takes value 1 if a firm is assigned a credit rating by the S&P, and 0 otherwise (Denis and Sibilkov, 2010; Duchin et al., 2010). Sample firms are sorted into constrained (unconstrained) groups if their assets or payout ratios are below (above) sample medians, or if they do not have (have) bond rating.

Insert Table 4-3 about here

Table 4-3 presents the results when we perform regression analysis for constrained and unconstrained groups separately. For each constraint variable, the first column (i.e., columns with odd numbers) presents the results for constrained firms, and the second column (i.e., columns with even numbers) presents the results for unconstrained firms. In columns (1) and (2), the coefficients on the variable Cash are 0.059 (t-statistic = 3.54) and 0.007 (t-statistic = 0.32) for small and large firms, respectively. The p-value for testing coefficient equality at the bottom of the table indicates that the two values are significantly different (p-value = 0.035). These values imply that if cash increases by one standard deviation (0.141), investment will increase by 0.86% for small firms with the lowest comparability and 0.14% for large firms with the lowest comparability. Thus our results confirm prior studies that cash is more

important to investment for constrained small firms. Turning to the interaction term, the coefficients on Cash×Comp_Median are -0.008 (t-statistic = -3.00) and -0.004 (t-statistic = -1.23) for small and large firms, respectively. The p-value for testing coefficient equality at the bottom of the table indicates that the difference is insignificant (p-value = 0.147). Since Comp_Median is the decile of comparability, the coefficient on Cash × Comp_Median implies the reduction of investment-cash sensitivity if comparability is improved by one decile. These values suggest that when small firms improve their comparability to the eighth decile, the dependence of investment on cash is eliminated. Hence small firms with highest comparability can invest regardless of their internal cash positions because it is easier to obtain external finance.

Similar results are found when we use payout ratio and bond rating to partition firms in column (3) through (6). The importance of cash to investment and the mitigating role of comparability are observed only in constrained firms, but not in unconstrained firms.

IV.3 External Financial Dependence

One possible problem associated with using firm-level financing constraint proxies is that these variables may be affected by corporate decisions and activities. To provide further support to our findings, we use two industry-level proxies of financing dependence to see whether the effect of financial statement comparability varies across industries.

Both proxies of industrial dependence on external finance are proposed by Rajan and Zingales (1998), and widely used in prior studies (e.g., Rajan and Zingales, 1998; Denis and Sibilkov, 2010; Duchin, et al., 2010). The external financial dependence variable is constructed as investment (capital expenditure plus R&D) minus cash flow,[19] divided by investment. The external equity dependence variable is the difference between equity issuance (Item 108) and equity repurchase (Item 115), divided by investment[20]. For both external dependence variables, we first compute the firm level median over the past ten years, and then obtain the industrial median over all firms in the same two-digit SIC industry. Firms are sorted into constrained or unconstrained groups based on whether they are in an industry with above or below median external dependences.

The regression results (not reported) are similar to those in Table 4-3: investment is highly sensitive to the availability of cash in industries which depend heavily on external finance, and this dependence is significantly lower for firms with higher financial statement comparability. These patterns are not found for firms in industries which do not depend much on external finance.

IV.4 Endogeneity of Financial Statement Comparability

In prior analysis, we interpret negative coefficients on the interaction terms of cash and comparability as evidence supporting the argument that investment is less

[19] To be consistent, we use the sum of income before extraordinary items and depreciation as cash flow. Our results are not affected if we use the cash flow as defined in Rajan and Zingales (1998).

[20] We normalize the two dependence variables with the sum of capital expenditure and R&D to be consistent with our definition of investment, our results will still hold if we use capital expenditure as in Rajan and Zingales (1998).

dependent on cash as comparability improves. An alternative explanation might be that firms improve their accounting comparability when they expect to have more investment opportunities but no enough cash in the future, and hence comparability may be a response to future investment opportunities and cash positions. We conduct two sets of analysis to address this issue. First, we show that large changes in comparability are not common for sample firms. Second, we employ a number of alternative regression specifications and measures.

Insert Figure 4-1 about here

Firms usually do not make large changes to financial statement comparability from year to year. Figure 4-1 presents the distribution of changes in comparability deciles for our sample firms. The range of values for comparability changes is from -9 to 9. Figure 4-1a shows that about 40% of the firm-years do not have changes in Comp_Median across deciles, and about 76% of the firm years have changes in Comp_Median between -1 and 1. The percentage of firm years with absolute changes equal to or more than 4 is smaller than 5%. In addition, the distribution of comparability change is symmetric around zero, and there is an equal probability that firms increase or reduce their comparability. Similar patterns are also found for Comp_10 and Comp_4 in Figure 4-1b and 4-1c respectively.

Next, we adopt alternative regression specifications and alternative measures of financial statement comparability to show that our main results are not affected. First, we use a two-stage least squares approach where financial reporting comparability measures are first regressed on investment opportunities and cash positions. The residuals from the

first stage regression are used in the second stage regression of equation (5). The residual comparability measures remove the portion of comparability which is driven by investment opportunities and cash positions. Second, we use comparability measures which are lagged two years, such that we consider only the impact of pre-change comparability if firms change their reporting style based on new investment opportunities and cash positions in the most recent year. Corresponding results in Table 4-4 show that our results are robust to reverse causality. For example, in column (1), the coefficients on Cash and Cash×Comp_Median are 0.075 (t-statistic = 5.52) and -0.011 (t-statistic = -6.11), respectively. These values imply that investment will increase by 1.05% for firms with lowest comparability if cash increases by one standard deviation (0.141), and such sensitivity of investment to cash is eliminated if a firm improves its comparability to the seventh decile. Results in other columns are similar with smaller coefficient magnitude.

Insert Table 4-4 about here

Some caveats should be made before we move on. First, our analysis indicates that it is not a widespread phenomenon that firms make large changes to financial statement comparability when they face investment opportunities and cash shortage, but it is possible that some firms will make large changes in comparability. Second, we consider changes in comparability compared to the previous year, and do not rule out the possibility that firms may improve their financial statement comparability in the long term, and such improvement benefits firms.

IV.5 Alternative Measures of Comparability

When constructing the comparability measures, we first regress quarterly earnings on contemporaneous stock returns in equation (1). Due to the forward looking property of stock prices, stock returns usually lead firm performance and accounting earnings, and current earnings may not fully reflect the information contained in current returns. To address this issue, we modify equation (1) by including lagged stock returns:

$$Earnings_{k,t} = \alpha_k + \beta_k * Return_{k,t} + \beta_{k,-1} * Return_{k,t-1} + \varepsilon_{k,t}. \quad (1')$$

Correspondingly, equation (2) is modified when we compute predicted earnings for firm *i* and *j* based on firm *i*'s stock returns:

$$E(Earnings)_{ik,t} = \hat{\alpha}_k + \hat{\beta}_k * Return_{i,t} + \hat{\beta}_{k,-1} * Return_{i,t-1}, k = i, j. \quad (2')$$

We denote the comparability measures computed after including lagged returns in equation (1') as Comparability2_Median and the corresponding deciles as Comp2_Median, etc.

The regression results using this alternative set of comparability measures are presented in Table 4-5. Not surprisingly, our baseline findings are robust to the use of these alternative measures. For example, in column (1), the coefficients on Cash and Cash × Comp2_Median are 0.045 (t-statistic = 3.35) and -0.007 (t-statistic = -3.63), respectively. These values imply that investment will increase by 0.6% for firms with lowest comparability if cash increases by one standard deviation (0.141), and such sensitivity of investment to cash is eliminated if a firm improves its comparability to the seventh decile.

A second possible issue associated with out comparability measures is that all measures are based on 2-digit SIC industries. This could be problematic as we may compare financial reporting, for example, between a meat packing firm with Coca-Cola when both belong to the same 2-digit SIC industry. Alternatively, we consider only peer firms in the same 4-digit SIC industry when we compute the comparability measures for a firm. The main findings are not affected in any significant way if we use comparability measures based on 4-digit SIC industries.

Insert Table 4-5 about here

An additional concern with the comparability measure is that these measures may reflect underlying firm fundamentals instead of financial statement comparability. For example, growth firms may exhibit similar relation between stock prices and operating performance. While it is hard to disentangle economic similarity from financial statement comparability (De Franco, et al., 2011; Kim, et al., 2012), we construct some additional comparability measures to address this concern. More specifically, we split firms in each industry into quartiles based on their size (assets), market-to-book ratio, or return on assets (ROA). To compute the financial statement comparability for any firm, we consider only other firms in the same size, market to book or ROA quartile as peer firms. Our results are not affected in any significant way if we use these firm fundamentals controlled comparability measures.

Finally, we have also constructed accruals based comparability measures following Francis et al. (2013). The accruals based comparability measures compute

differences in total accruals or abnormal accruals[21] between firms, and firms with smaller absolute differences in total or abnormal accruals are considered as having higher comparability. However, the use of these accruals based comparability measures does not affect our results in any meaningful way.

IV.6 Other Robustness Checks

In our empirical analysis, we focus on cash to examine the effect of comparability on investment. The main advantage of focusing on cash instead of cash flow is that the interpretation of main results is not subject to the usual criticism that cash flow may proxy for unobserved investment opportunities due to the noisiness of Q (e.g., Kaplan and Zingales, 1997; Alti, 2003). However, our results may still be affected if the Q variable does not adequately capture unobserved growth opportunities.

To ensure that our results are not sensitive to the above concerns, we perform several robustness analyses. First, we include the lagged sale growth rate as an additional control variable which may capture part of unobserved growth opportunities not captured by the Q variable (Denis and Sibilkov, 2010). Second, we include the lagged sales-to-capital ratio in the regression, following Fazzari et al. (1988). Hayashi (1982) show that the observed average Q is the same as the marginal Q when firms are in perfectly competitive markets and have a constant return to scale in both production and installation cost functions. When firms have the market power, the marginal Q and the

[21] We use both the Jones (1991) model and the Dechow and Dichev (2002) model to compute total and abnormal accruals, and results are similar.

average Q differ by a function of sales-to-capital ratio. The inclusion of sales-to-capital ratio is thus intended to capture this difference when perfect competition does not hold.

Insert Table 4-6 about here

Table 4-6 presents the regression results after we include both the lagged sales-capital ratio and the sales growth as additional controls. Including these additional proxies of growth opportunities does not affect the main results on cash and the interaction of cash and comparability, that is, we still find that investment is sensitive to cash and this sensitivity decreases in comparability. For example, in column (1), the coefficients on Cash and Cash×Comp_Median are 0.063 (t-statistic = 4.70) and -0.007 (t-statistic = -3.85), respectively. These values imply that investment will increase by 0.9% for firms with lowest comparability if cash increases by one standard deviation (0.141), and such sensitivity of investment to cash is eliminated if a firm improves its comparability to the ninth decile. In addition, we find that both the lagged sales-capital ratio and the sales growth rate have positive and significant coefficients, confirming that these variables contain additional information about growth opportunities not captured by the Q variable.

Another possible concern is that large firms have higher comparability than small firms (Table 4-7 below), and comparability may simply pick up the effect of firm size on the investment-cash sensitivity. To address this issue, we include firm size (logged assets) and its interaction with cash in the regression, and the regression results show that the investment-cash sensitivity is indeed lower in large firms. However, we still find a

significant effect of comparability on the investment-cash sensitivity. Hence comparability does not simply reflect the effect of firm size.

V Why Don't Constrained Firms Improve Their Comparability?

Though our results show that financial statement comparability alleviates the corporate investment-cash sensitivity, especially for financially constrained firms, constrained firms usually have lower comparability than unconstrained firms. For example, the mean value of Comp_Median is 4.72 for small firms, and 6.26 for large firms. It is natural to ask why constrained firms do not improve comparability such that they can reduce cost of external capital and investment-cash sensitivity, and what are the possible obstacles which prevent constrained firms from improving comparability.

We consider several possible explanations for the above question. One possibility is that the three financing constraint variables do not classify constrained and unconstrained firms correctly, and constrained firms actually have lower costs of external capital than unconstrained firms. A second possibility is that constrained firms are more likely to be in competitive industries, and higher financial statement comparability may lead to leakage of some proprietary information to competitors. Third, financial statement comparability is one aspect of financial reporting, and firms may not want to or be able to choose higher levels of comparability due to other financial reporting decisions. For example, Peterson, et al. (2012) show that there is a positive relation between accruals quality and comparability.

To examine these possibilities, we compare certain firm and industry characteristics between constrained and unconstrained firms. The classification of constrained and unconstrained firms is based on the three firm-level constraint variables. We first show that constrained firms do have lower average comparability, and then compare average costs of capital, proxies of industry competition, and earnings quality proxies between constrained and unconstrained firms.

Insert Table 4-7 about Here

The comparison results are reported in Table 4-7. For each constraint variable, asterisks in the second column indicate the significance of mean equality tests between constrained and unconstrained firms. The first three rows confirm that constrained firms have significantly lower average comparability than unconstrained firms. For example, the average values of comparability measures range from 4.71 to 4.93 for small firms, and are all above 6 for large firms.

To compare cost of capital between constrained and unconstrained firms, we use two variables: Interest Cost is defined as interest expenses divided by the sum of long-term and short-term debt; Cost of Equity is computed using the Easton (2004) method[22] (details in the Appendix). Both cost of capital variables are higher for constrained firms, and the differences are significant. For example, the mean interest costs are 0.13 and 0.09 for small and large firms, and the difference is significant at 1% confidence level. It is therefore unlikely that we misclassify constrained and unconstrained firms such that constrained firms have lower costs of capital.

[22] The choice of this implied cost of equity is based on the findings by Botosan and Plumlee (2005) that this proxy of cost of capital is consistent with firm specific risk measures.

Industry competition is proxied by four firm sales concentration ratio (Concen4, defined as the fraction of top 4 firms' sales in industry total sales), and the Herfindahl-Hirschman (HH) index. The results do not consistently support the conjecture that constrained firms are in less concentrated industries. To examine the relation between comparability and earnings quality in constrained and unconstrained firms, we employ two proxies: the absolute value of abnormal accruals Ab (DA), and the standard deviation of abnormal accruals in the last five years SD_DA, where abnormal accruals are computed using the Dechow and Dichev (2002) model[23]. Results in the last two rows indicate that constrained firms have consistently higher absolute abnormal accruals and SD_DA. For example, SD_DA are 0.053 and 0.033 in small and large firms, and the difference is significant at 1% confidence level.

[Inert Table 4-8 about Here]

To provide further evidence that lower accruals quality may impede some firms to improve comparability, we compute the average values of Ab (DA) and SD_DA by comparability deciles, and the results are presented in Table 4-8. For both accruals quality variables and all comparability measures, accruals quality increases monotonically with corporate financial reporting comparability. For example, the first column of Panel A indicates that firms in the first decile (D1) of comparability have average absolute abnormal accruals 0.053, and this value declines to 0.024 for firms in the last decile (D10) of comparability. The p-values at the bottom of the table show that the differences between D1 and D10 are all significant. Hence some constrained firms

[23] Using the Jones (1991) model or modified Jones Model to compute abnormal accruals yields similar results.

fail to improve their comparability because of low accruals quality. This is consistent with the argument and finding in Peterson, et al. (2012) that firms may choose low financial statement comparability to conceal their earnings management activities.

If there is a close relation between accruals quality and comparability, it might the concerned that our main results are due to omitted accrual quality variables. Table 4-9 provides the regression results when we include the standard deviation of abnormal accruals SD_DA and its interactions with cash[24]. The results show that comparability has consistently significant effect on investment-cash sensitivity, but not accruals quality proxies.

Insert Table 4-9 about here

VI. Additional Analyses

This section examines the effect of financial statement comparability on the value of cash. In addition, we consider the effect of comparability on other corporate investment and spending variables.

VI.1 Comparability and the Value of Cash

First, we examine whether financial statement comparability affects the value of cash. The empirical model extends that in Faulkender and Wang (2006), Dittmar and

[24] Including Ab (DA) in the regressions yields similar results.

Mahrt-Smith (2007), and Denis and Sibilkov (2010) by including comparability measures and their interactions with cash and earnings change:

$$r_{i,t} - R_{i,t}^{B} = \gamma_0 + \gamma_1 \frac{\Delta C_{i,t}}{M_{i,t-1}} + \gamma_2 \frac{\Delta E_{i,t}}{M_{i,t-1}} + \gamma_3 \frac{Inv_{i,t}}{M_{i,t-1}} + \gamma_4 \frac{\Delta RD_{i,t}}{M_{i,t-1}} + \gamma_5 \frac{\Delta I_{i,t}}{M_{i,t-1}} + \gamma_6 \frac{\Delta D_{i,t}}{M_{i,t-1}}$$
$$+ \gamma_7 \frac{C_{i,t}}{M_{i,t-1}} + \gamma_8 L_{i,t} + \gamma_9 \frac{NF_{i,t}}{M_{i,t-1}} + \gamma_{10} \frac{\Delta C_{i,t}}{M_{i,t-1}} \times \frac{C_{i,t}}{M_{i,t-1}} + \gamma_{11} L_{i,t} \times \frac{\Delta C_{i,t}}{M_{i,t-1}}$$
$$+ \gamma_{12} Comparability_{i,t-1} + \gamma_{13} \frac{\Delta C_{i,t}}{M_{i,t-1}} \times Comparability_{i,t-1}$$
$$+ \gamma_{14} \frac{\Delta E_{i,t}}{M_{i,t-1}} \times Comparability_{i,t-1} + \epsilon_{i,t,}$$

where $r_{i,t}$ is firm i's stock return in fiscal year t, $R_{i,t}^{B}$ is firms i's benchmark stock return based on Fama and French (1992)'s 25 size and book-to-market (BM) portfolios[25]. C is cash plus marketable securities, E is the earnings before extraordinary items plus interest expenses, deferred tax credit, and investment tax credit, Inv is the sum of capital expenditure and R&D, I is interest expense, D is common dividends paid, L is leverage ratio, and NF is total equity issuance minus repurchases plus debt issuance minus debt redemption. All explanatory variables are deflated by the lagged market value of equity $M_{i,t-1}$ except the leverage ratio $L_{i,t}$ and comparability measures.

Insert Table 4-10 about here

The focus here is on the coefficient estimates of γ_{13} and γ_{14}. The coefficient γ_{13} captures how the valuation of an additional dollar of cash depends on financial statement comparability. Firms with higher comparability have lower costs of external finance, and

[25] The benchmark portfolios at the end of June in year t are computed using the market capitalization at the end of June in year t, and book value of equity in the last fiscal year ending in year t-1 divided by the market value of equity at the end of December in year t-1. There are totally 25 size-BM portfolios.

internal funds are less important to these firms, and the value of an additional dollar of cash will be lower. Thus we expect γ_{13}<0.

In addition, γ_{14} measures how financial statement comparability enhances the value of earnings increase. More comparable financial statements facilitate investors' analysis and processing of information, and they are more able to assess the quality of reported earnings. Furthermore, Peterson, et al. (2012) and evidences from the previous section suggest that firms with high comparability are less likely to engage in earnings management activities. Consequentially, investors will put higher valuation on earnings increases reported by comparable firms, and we expect a positive coefficient on γ_{14}.

Table 4-10 presents the regression results. The coefficients on ΔC are positive and greater than one in all columns. These values imply that one dollar of additional cash increases firm value by \$1.10-1.26[26] in firms with lowest comparability. The coefficients on ΔC and comparability interaction variables (i.e., γ_{13}) are all negative and have values between -0.024 (column 2) to -0.057 (column 1). These values imply that for firms with highest comparability, an additional dollar of cash increases firm value by only \$0.69-0.86.

Finally, earnings increase enhances firm value, and this effect is stronger for firms with higher comparability. In column (1), an additional dollar of earnings increases firm value by \$0.38 for firms with lowest comparability, but by \$1.62 for firms with highest comparability. This large difference suggests that one dollar of additional earnings is greatly discounted for firms with low comparability, but is accompanied by a value

[26] These values are computed for firms with mean values of lagged cash and leverage ratio. For example, in column (1), it is computed as 1.660-0.937*0.165-1.150*0.211=1.26.

premium for firms with high comparability. Control variables in the table have expected signs and are significant at conventional confidence levels. For example, an additional dollar of cash is less valuable when a firm has already large holdings of cash, or larger amount of debt.

VI.2 Other Investment Variables

For the empirical analysis so far, we use the investment ratio (capital expenditure plus R&D, divided by lagged total assets) as the dependent variable. Table 4-11 presents regression results for other corporate spending variables. In column (1) and (2), we examine capital expenditures and R&D separately. As expected, both capital expenditures and R&D depend critically on cash, and financial statement comparability is able to mitigate this dependence. In the remaining columns, we consider other corporate spending variables: changes in inventory in column (3), and two other measures of corporate investment: changes in non-cash assets in column (4), and the sum of changes in property, plant and equipment (PPE), changes in inventory, and R&D in column (5). We find that the coefficient estimates on the interaction term Cash×Comp_Median are all negative, and significant in column (5).

Insert Table 4-11 about here

VII Conclusions

This paper examines how financial statement comparability affects corporate investment. Based on the analytical literature on accounting information and the cost of capital and recent empirical studies on financial statement comparability, we conjecture that as more comparable financial reporting reduces costs of raising funds from outside, investment will be less constrained by the availability of internal funds (cash) for high comparability firms. Furthermore, we expect this effect to be stronger for financially constrained firms because such firms are more likely to face obstacles when they obtain external finance to undertake investment.

Using data on public firms over 1990 to 2010, we find that investment-cash sensitivity is significantly lower for firms with higher financial statement comparability. Using both firm-level and industry-level proxies of financing constraints, we find that financial statement comparability has stronger effects on the investment-cash sensitivity in financially constrained firms.

To address the concern that firms may change their financial statement comparability based on future investment opportunities and cash positions, we first show that large changes in financial statement comparability are not widespread for our sample firms. Next we employ various alternative regression specifications. For example, we consider a two stage least squares approach where residual comparability values are used in the investment-cash regression. Results from the two stage approach and other regression specifications confirm that our results are not mainly driven by the endogeneity of financial statement comparability.

Based on our findings, it is natural to ask why financially constrained firms do not improve their comparability to reduce the dependence of investment on cash. The comparison between constrained and unconstrained firms suggest that financial reporting comparability is closely related to earnings quality, and firms may be entrenched in their earnings management activities such that it is hard to improve comparability. Finally, we find that cash is less valuable in high comparability firms, consistent with the finding that comparability reduces the importance of cash to investment.

In summary, we provide empirical evidence that financial statement comparability alleviates the sensitivity of investment to cash. Various studies have shown that investment is sensitive to the availability of cash due to costly external finance. Our results imply that one way to alleviate the costly external finance is to improve the comparability of financial reporting with industry peers. In addition, the analysis here also shows that financial reporting matters for corporate financing and real decisions.

Appendix 4-A: Definition of Variables

Comparability Variables	
Comparability_Median	The median of comparability scores of all industry peer firms
Comparability_10	The average of comparability scores of 10 industry peer firms with closest comparability to a firm
Comparability_4	The average of comparability scores of 4 industry peer firms with closest comparability to a firm
Comp_Median	Deciles of Comparability_Median
Comp_10	Deciles of Comparability_10
Comp_4	Deciles of Comparability_4
Investment Variables	
Investment	Capital expenditure (Item 128) plus R&D (Item 46) divided by lagged total assets (Item 6)
Capital Expenditure	Capital expenditure (Item 128) divided by lagged assets
R&D	R&D expenditure (Item 46) divided by lagged assets
ΔInventory	Changes in inventory (Item 3) divided by lagged assets
ΔNAssets	Changes in net assets (assets minus cash) divided by lagged assets
Investment 2	Changes in property, plant and equipment (Item 8), plus changes in SG&A plus R&D, divided by lagged assets
Other Firm Variables	
NCash	Cash and marketable securities (Item 1) divided by total assets (Item 6)
Cash	The residuals from the cash regression
Ln(Assets)	Logged value of total assets (Item 6)
Q	Price at fiscal year end (Item 199) times share outstanding (Item 25) plus assets minus book equity (Item 60) and deferred taxes (Item 74) divided by assets
Cash Flow	Income before extraordinary item (Item 18) plus depreciation (Item 14) divided by assets
Net Working Capital	Working capital (Item 179) minus cash divided by assets
Leverage	Long term debt (Item 9) plus debt in current liabilities (Item 34) divided by assets
SD_Cash Flow	Standard deviation of cash flow in the last five years
Ab (DA)	Absolute abnormal accruals, where abnormal accruals are estimated using Dechow and Dichev (2002) model for each

	industry-year
SD_DA	Standard deviation of abnormal accruals in the last five years, where abnormal accruals are estimated using Dechow and Dichev (2002) model for each industry-year
Payout Ratio	The ratio of cash dividends to net income
Bond Rating	A dummy variable which takes value 1 if a firm has been assigned a credit rating by S&P, and 0 otherwise
Interest Cost	Interest expense (Item 15) divided by total debt (Item 9 plus Item 34)
Cost of Equity	Implied cost of equity capital estimated using the Easton (2004) method
Industry Variables	
External Dependence	Investment (capital expenditure plus R&D) minus cash flow divided by investment, computed as the median over last ten years for all firms in the same industry
Equity Dependence	Difference between equity issuance (Item 108) and equity repurchase (Item 115), divided by investment (capital expenditure plus R&D), computed as the median over last ten years for all firms in the same industry
Concen4	Four firm concentration ratio by sales for each 2 digit SIC industry
HH Index	Herfindahl-Hirschman index computed using sales for each 2 digit SIC industry
Cash Flow Volatility	Standard deviation of cash flow in the last ten years

Appendix 4-B: Estimation of Abnormal Accruals

The abnormal accruals are estimated using the Dechow and Dichev (2002) model and the Jones (1991) model. For the Dechow and Dichev (2002) model:

$$\frac{\Delta WC_{i,t}}{AvgAssets_{i,t}} = \alpha_0 \frac{1}{AvgAssets_{i,t}} + \alpha_1 \frac{CFO_{i,t-1}}{AvgAssets_{i,t}} + \alpha_2 \frac{CFO_{i,t}}{AvgAssets_{i,t}} + \alpha_3 \frac{CFO_{i,t+1}}{AvgAssets_{i,t}} + \varepsilon_{i,t}.$$

In the above model, $\Delta WC = \Delta AR + \Delta Inventory - \Delta AP - \Delta TP + \Delta OtherAssets(net)$. Using the Compustat item numbers, the changes in working capital is the negative of the sum of item 302, 303, 304, 305 and 307.

For the Jones (1991) model, total accruals (defined as the difference between net income and cash flow (item 123 minus 308) is regressed on a set of variables using the following specification:

$$\frac{TA_{i,t}}{Assets_{i,t-1}} = \alpha_0 \frac{1}{Assets_{i,t-1}} + \alpha_1 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \alpha_2 \frac{PPE_{i,t}}{Assets_{i,t-1}} + \varepsilon_{i,t.}$$

For both models, estimation is performed for all industry-years with at least ten observations. Based on the residuals from the models, we construct four accruals quality variables: the standard deviation of abnormal accruals in the last five years, and the absolute abnormal accruals from both models.

Appendix 4-C: Cost of Capital Variables

Interest Cost is total interest expense divided by total debt. The implied cost of equity capital is based on Easton (2004):

$$Cost\ of\ Equity_{i,t} = \sqrt{\frac{EPS_{i,t+2} - EPS_{i,t+1}}{P_{i,t}}},$$

where $EPS_{i,t+2}$ and $EPS_{i,t+1}$ are firm *i*'s mean earnings per share forecasts for year t+2 and t+1; and $P_{i,t}$ is the stock price. Earnings forecast information is obtained from the Institutional Broker's Estimate System (IBES) database. The stock price is measured at the end of June in year t+1 following Fama and French (1992).

Bibliography

Almeida, Heitor, Merillo Campello, and Michael S. Weisbach. 2004. The cash flow sensitivity of cash. *Journal of Finance* 59, 1777-1804.

Alti, Aydogan. 2003. How sensitive is investment to cash flow when financing is frictionless? *Journal of Finance* 58, 707-722.

Baker, Malcolm, Jeremy Stein, and Jeffrey Wurgler. 2003. When does the market matter? Stock prices and the investment of equity dependent firms. *Quarterly Journal of Economics* 118, 969-1005.

Bates, Thomas W., Kathleen M. Kahle, and Rene M. Stulz. 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64, 1985-2021.

Bharath, Sreedhar T., Jayanthi Sunder, and Shyam V. Sunder. 2008. Accounting quality and debt contracting. *The Accounting Review* 83, 1-28.

Biddle, Gary C., and Gilles Hilary. 2006. Accounting quality and firm-level capital investment. *The Accounting Review* 81, 963-982.

Biddle, Gary C., Gilles Hilary, and Rodrigo S. Verdi. 2009. How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics* 48, 112-131.

Botosan, Christine A. 1997. Disclosure level and the cost of equity capital. *The Accounting Review* 72, 323-349.

Botosan, Christine A., and Marlene A. Plumlee. 2005. Assessing alternative proxies for the expected risk premium. *The Accounting Review* 80, 21-53.

Brochet, Francois, Alan D. Jagolinzer, and Edward J. Riedl. 2012. Mandatory IFRS adoption and financial statement comparability. *Contemporary Accounting Research* forthcoming.

Cetorelli, Nicola, and Michele Gambera. 2001. Banking market structure, financial dependence, and growth: International evidence form industry data. *Journal of finance* 56, 617-648.

Chen, Ciao-Wei, Daniel W. Collins, Todd D. Kravet, and Richard Mergenthaler Jr. 2012. Financial statement comparability and the efficiency of acquisition decisions. SSRN paper.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler. 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. *Quarterly Journal of Economics*, 969-1005.

Bates, Thomas W., Kathleen M. Kahle, and Rene Stulz. 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64, 1985-2021.

Bhattacharya, Utpal, Hazem Daouk, and Michael Welker. 2003. The world price of earnings opacity. *The Accounting Review* 78, 641-678.

Bhattacharya, Nilabhra, Frank Ecker, Per M. Olsson, and Katherine Schipper. 2012. Direct and mediated associations among earnings quality, information asymmetry and the cost of equity. *The Accounting review* 87, 449-482.

Chen, Feng, Ole-Kristian Hope, Qingyuan Li, and Xin Wang. 2011. Financial reporting quality and investment efficiency of private firms in emerging markets. *The Accounting Review* 86, 1255-1288.

Core, John E., Wayne R. Guay, and Rodrigo Verdi. 2008. Is accruals quality a priced risk stock? *Journal of Accounting and Economics* 46, 2-22.

De Franco, Gus, S. P. Kothari, and Rodrigo S. Verdi. 2011. The benefits of financial statement comparability. *Journal of Accounting Research* 49, 895-931.

Dechow, Patricia M., and Ilia D. Dichev. 2002. The quality of accruals and earnings: The rolw of accruals estimation errors. *The Accounting Review* 77, 35-59.

Denis, David J., and valeriy Sibilkov. 2010. Financial constraints, investment, and the value of cash holdings. *Review of Financial Studies* 23, 247-269.

Dittmar, Amy, and Jan Mahrt-Smith. 2007. Corporate governance and the value of cash holdings. *Journal of Finance* 83, 599-634.

Dittmar, Amy, Jan Mahrt-Smith, and Henri Servaes. 2003. International corporate governance and corporate cash holdings. *Journal of Financial and Quantitative Analysis* 38, 111-133.

Duchin, Ran, Oguzhan, and Berk Sensoy. 2010. Costly external finance, corporate investment, and the subprime mortgage crisis. *Journal of Financial Economics* 97, 418-435.

Easley, David, and Maureen O'Hara. 2004. Information and the cost of equity. *Journal of Finance* 59, 1553-1583.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara. 2002. Is information risk a determinant of asset returns? *Journal of Finance* 57, 2185-2221.

Easton, Peter D., 2004. PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review* 79, 73-95.

Fama, Eugene F., and Kenneth French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 427-465.

Fang, Vivian W., Mark G. Maffet, and Bohui Zhang. 2012. The effect of foreign institutional investment on financial reporting comparability. SSRN paper.

Fang. Xiaohua, Yutao Li, Baohua Xin, and Wenjun Zhang. 2012. Accounting comparability and bank loan contracting. SSRN paper.

Faulkender, Michael, and Rong Wang, 2006. Corporate financial policy and the value of cash. *Journal of Finance* 61, 1957-1989.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen. 1988. Financing constraints and corporate investment. *Brookings Paper on Economic Activity* 1, 141-206.

Financial Accounting Standards Board (FASB). 1980. Statement of Financial Accounting Concepts No. 2: Qualitative Characteristics of Accounting Information.

Financial Accounting Standards Board (FASB). 2010. Statement of Financial Accounting Concepts No. 8: Conceptual Framework for Financial Reporting.

Francis, Jennifer, Ryan LaFond, Per M. Olsson, and Katherine Schipper. 2004. Cost of equity and earnings attributes. *The Accounting Review* 79, 967-1010.

Francis, Jennifer, Ryan LaFond, Per M. Olsson, and Katherine Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39, 295-327.

Francis, Jere R., Matt Pinnuck, and Olena Watanabe. 2014. Auditor style and financial statement comparability. *The Accounting Review* forthcoming.

Fresard, Laurent. 2010. Financial strength and product market behavior: The real effects of corporate cash holdings. *Journal of Finance* 65, 1097-1122.

Gilchrist, Simon, and Charles P. Himmelberg. 1995. Evidence on the role of cash flow for investment. *Journal of Monetary Economics* 36, 541-572.

Greenwald, Bruce, Joseph E. Stiglitz, and Andrew Weiss. 1984. Information imperfections in the capital market and macroeconomic fluctuations. *American Economics Review* 74, 194-199.

Gunny, Katherine A. 2011. The relation between earnings management using real activities manipulation and firm performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research* 27, 855-888.

Harford, Jarrad. 1969. Corporate cash reserves and acquisitions. *Journal of Finance* 54, 1969-1997.

Hayashi, Fumio. 1982. Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica* 50, 213-224.

Holmstrom, Bergt, and Jean Tirole. 1997. Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics* 112, 663-691.

Hoshi, Takeo, Anil Kashyap, and David Schatfstein. 1991. Corporate structure, liquidity, and investment: Evidence from Japanese industrial groups. *Quarterly Journal of Economics* 106, 33-60.

Hubbard, R. Glenn. 1998. Capital market imperfections and investment. *Journal of Economic Literature* 36, 193-225.

Jaffee, Dwight M., and Thomas Russell. 1976. Imperfect information, uncertainty, and credit rationing. *Quarterly Journal of Economics* 90, 651-666.

Jones, Jennifer. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29, 193-228.

Kaplan, Stephen N., and Luigi Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112, 169-215.

Kaplan, Stephen N., and Luigi Zingales. 2000. Investment-cash flow sensitivities are not valid measures of financing constraints. *Quarterly Journal of Economics* 115, 707-712.

Keynes, John M. 1936. The General Theory of Employment, Interest and Money. Harcourt Brace, London.

Kim, Seil, Pepa Kraft, and Stephen G. Ryan. 2012. Financial statement comparability and credit risk. New York University working paper.

Lambert, Richard, Christian Leuz, and Robert E. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45, 385-420.

Love, Inessa. 2003. Financial development and financing constraints: international evidence from the structural investment model. *Review of Financial Studies* 16, 765-791.

Masulis, Ronald W., Cong Wang, and Fei Xie. 2012. Globalizing the boardroom – The effects of foreign directors on corporate governance and firm performance. *Journal of Accounting and Economics* 53, 527-554.

McLean, R. David, Tianyu Zhang, and Mengxin Zhao. 2012. Why does the law matter? Investor protection and its effects on investment, finance and growth. *Journal of Finance* 67, 313-350.

Modigliani, Franco, and Merton Miller. 1958. The cost of capital, corporation finance and the theory of investment. *American Economic Review* 48, 261-297.

Myers, Stewart C., and Nicholas S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13, 187-221.

O'Hara, Maureen . 2003. Presidential address: liquidity and price discovery. *Journal of Finance* 58, 1335-1354.

Opler, Tim, Lee Pinkowitz, Rene Stulz, and Rohan Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52, 3-46.

Peterson, Kyle, Roy Schmardebeck, and T. Jeffrey Wilks. 2012. Accounting comparability and earnings attributes. SSRN

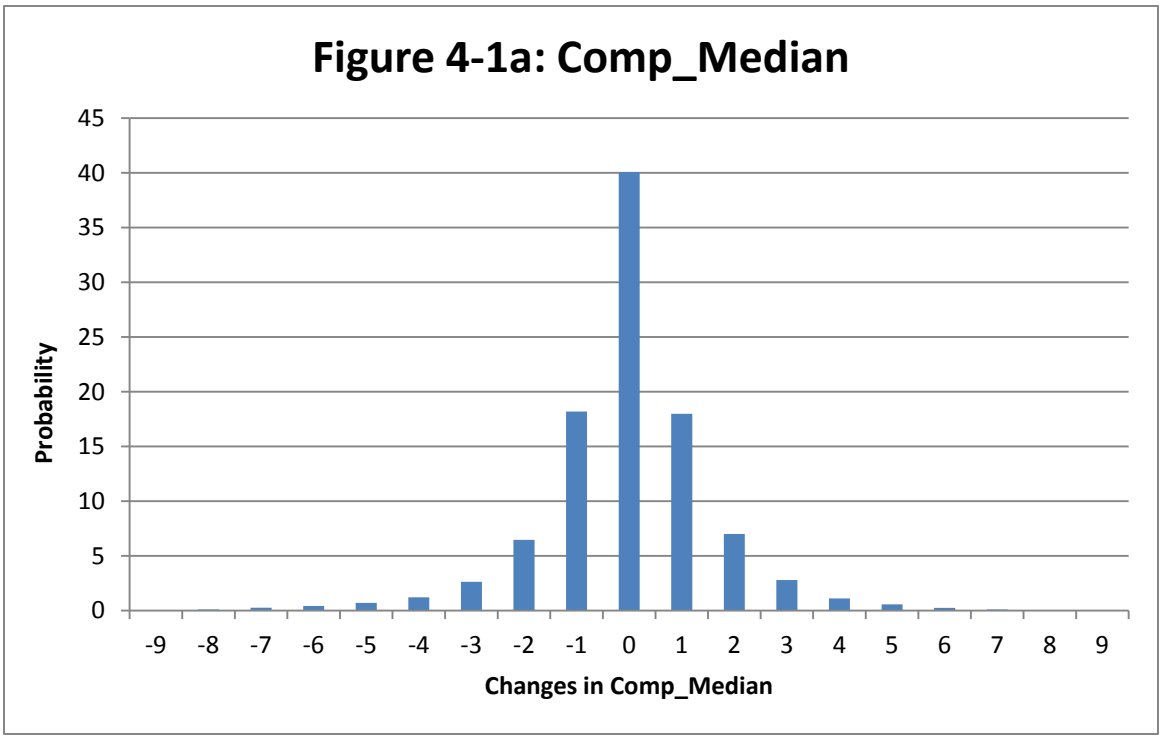
Rajan, Raghuram G., and Luigi Zingales. 1998. Financial dependence and growth. *American Economic Review* 88, 559-586.

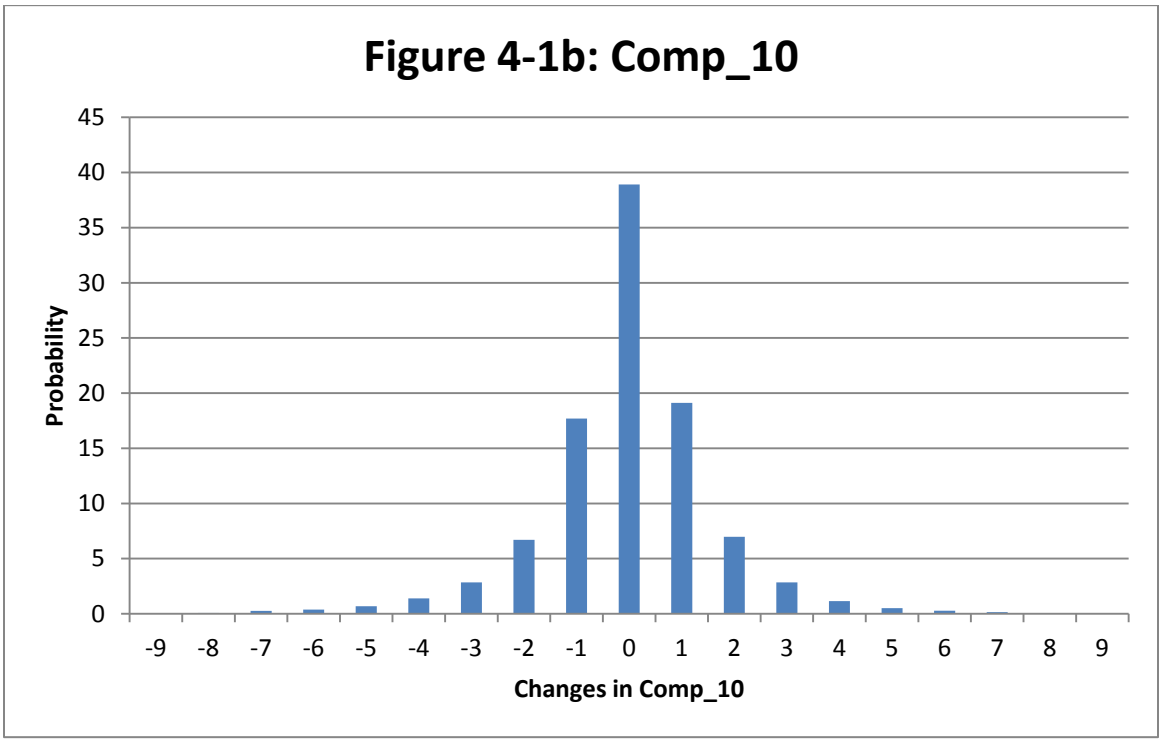
Securities and Exchange Commission (SEC). 2000. SEC Concept Release: International Accounting Standards. Available at http://www.sec.gov/rules/concept/34-42430.htm

Stiglitz, Joseph, and Andrew Weiss. 1981. Credit rationing in markets with imperfect information. *American Economic Review* 71, 393-410.

Whited, Toni M., and Guojun Wu. 2006. Financial constraints risk. *Review of Financial Studies* 19, 531-559.

Figure 4-1: Distribution of Changes in Comparability Measures





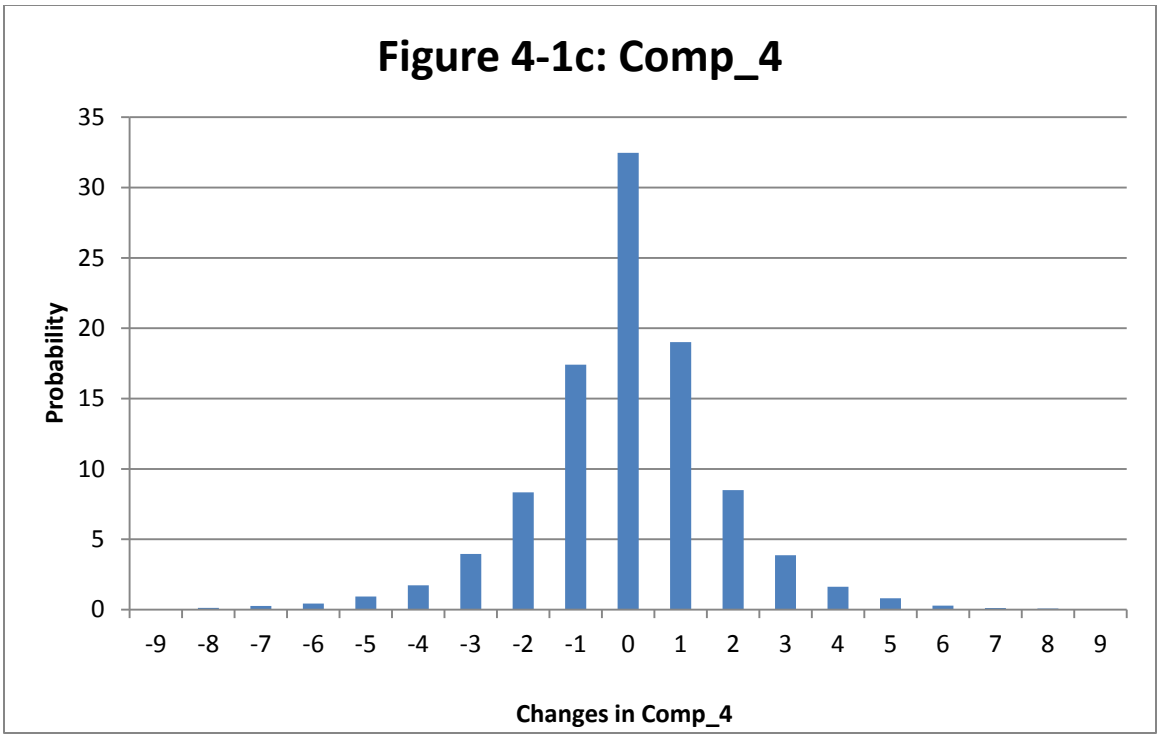


Figure 4-1c: Comp_4
Probability
35
30
25
20
15
10
5
0
-9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9
Changes in Comp_4

Table 4-1: Summary Statistics

This table presents summary statistics of variables used in the paper. All variables are as defined in the Appendix.

	Mean	SD	Q1	Median	Q3
Comparability					
Comparability_Median	-2.582	2.616	-2.840	-1.770	-1.220
Comparability_10	-0.915	1.657	-0.940	-0.410	-0.200
Comparability_4	-0.642	1.338	-0.610	-0.260	-0.130
Investment Variables					
Investment	0.116	0.109	0.043	0.085	0.152
Capital Expenditure	0.063	0.070	0.021	0.041	0.078
R&D	0.050	0.085	0.000	0.009	0.070
ΔInventory	0.008	0.044	-0.005	0.000	0.018
ΔNAssets	0.060	0.196	-0.040	0.035	0.133
Investment 2	0.103	0.145	0.022	0.079	0.162
Other Firm Variables					
Ncash	0.164	0.183	0.026	0.091	0.242
Cash	0.000	0.141	-0.091	-0.023	0.066
Q	1.823	1.236	1.077	1.432	2.099
Cash Flow	0.051	0.157	0.031	0.083	0.128
Ln(Assets)	5.662	2.059	4.115	5.566	7.129
Net Working Capital	0.096	0.171	-0.016	0.084	0.207
SD_Cash Flow	0.073	0.092	0.022	0.041	0.084
Ab (DA)	0.040	0.040	0.012	0.027	0.053
SD_DA	0.044	0.035	0.020	0.034	0.059
Interest Cost	0.107	0.177	0.056	0.076	0.101
Cost of Equity	0.117	0.074	0.070	0.097	0.140
Industry Variables					
External Dependence	0.168	0.645	-0.173	0.281	0.444
Equity Dependence	0.065	0.183	0.008	0.039	0.070
Concen4	0.401	0.135	0.313	0.372	0.467
HH Index	0.072	0.070	0.040	0.051	0.080
Cash Flow Volatility	0.068	0.028	0.044	0.065	0.088

Table 4-2: Regressions of Corporate Investment on Cash Holdings and Financial Statement Comparability

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability. The dependent variable is the ratio of investment (capital expenditures plus R&D) to lagged total assets. Comp_Median, Comp_10, Comp_4 are deciles of the corresponding comparability measures. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)
Constant	0.066***	0.068***	0.068***
	(8.13)	(8.54)	(8.46)
Cash	0.047***	0.042***	0.039***
	(3.47)	(3.08)	(2.91)
Comp_Median	0.000		
	(0.80)		
Cash×Comp_Median	-0.007***		
	(-3.70)		
Comp_10		-0.000	
		(-0.99)	
Cash×Comp_10		-0.005***	
		(-2.74)	
Comp_4			-0.000
			(-0.62)
Cash×Comp_4			-0.005**
			(-2.52)
Q	0.018***	0.018***	0.018***
	(18.81)	(18.77)	(18.77)
Cash Flow	-0.015*	-0.013	-0.014*
	(-1.86)	(-1.61)	(-1.67)
Observations	31466	31466	31466
Adjusted R^2	0.664	0.664	0.664

Table 4-3: Regressions of Investment on Cash Holdings and Financial Statement Comparability: Financing Constraints

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability based on whether a firm is financially constrained or not. The dependent variable is the ratio of investment (capital expenditures plus R&D) to lagged total assets. Comp_Median is the deciles of the corresponding comparability measure. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)	(4)	(5)	(6)
Financing Constraints Variables	Ln(Assets)		Payout Ratio		Bond Rating	
	Small	Large	Low	High	No	Yes
Constant	0.073***	0.055***	0.069***	0.026***	0.077***	0.044***
	(6.14)	(5.21)	(5.04)	(3.35)	(7.28)	(8.13)
Cash	0.059***	0.007	0.055***	-0.014	0.050***	0.027
	(3.54)	(0.32)	(2.88)	(-0.69)	(3.20)	(1.01)
Comp_Median	-0.000	0.001	-0.000	0.000	-0.000	0.001
	(-0.59)	(1.54)	(-0.19)	(1.05)	(-0.18)	(1.54)
Cash×Comp_Median	-0.008***	-0.004	-0.008**	-0.001	-0.008***	-0.000
	(-3.00)	(-1.23)	(-2.41)	(-0.50)	(-3.46)	(-0.10)
Q	0.017***	0.018***	0.020***	0.009***	0.017***	0.019***
	(13.42)	(12.71)	(13.41)	(6.81)	(15.46)	(9.99)
Cash Flow	-0.038***	0.069***	-0.022**	0.217***	-0.029***	0.064***
	(-4.00)	(5.69)	(-2.23)	(8.26)	(-3.23)	(3.56)
Observations	15697	15696	14306	14306	21174	10292
Adjusted R^2	0.667	0.694	0.647	0.664	0.664	0.704
Cash: C=U vs C>U	0.035		0.007		0.237	
Cash×Comparability: C=U vs C<U	0.147		0.058		0.051	

Table 4-4: Regressions of Corporate Investment on Cash Holdings and Financial Statement Comparability: Check for Endogeneity of Comparability

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability. Column (1)-(3) use the two stage least squares method where comparability measures are residuals from the first stage regressions; column (4)-(6) use the lagged comparability measures. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)	(4)	(5)	(6)
	2 Stage Least Squares			Lagged Comparability		
Constant	0.072***	0.070***	0.069***	0.072***	0.075***	0.074***
	(8.88)	(8.52)	(8.49)	(8.53)	(8.99)	(8.85)
Cash	0.075***	0.035**	0.032**	0.029*	0.036**	0.038**
	(5.52)	(2.51)	(2.36)	(1.90)	(2.38)	(2.57)
Comp_Median	-0.001***			-0.001**		
	(-2.67)			(-2.35)		
Cash×Comp_Median	-0.011***			-0.004**		
	(-6.11)			(-2.04)		
Comp_10		-0.000			-0.001***	
		(-1.18)			(-3.96)	
Cash×Comp_10		-0.005**			-0.005**	
		(-2.34)			(-2.26)	
Comp_4			-0.000			-0.001***
			(-1.13)			(-3.62)
Cash×Comp_4			-0.004**			-0.005**
			(-2.13)			(-2.50)
Q	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(18.41)	(18.15)	(18.19)	(16.69)	(16.66)	(16.67)
Cash Flow	-0.007	-0.009	-0.009	0.000	-0.000	-0.000
	(-0.84)	(-1.13)	(-1.15)	(0.02)	(-0.04)	(-0.03)
Observations	31095	31095	31095	25928	25928	25928
Adjusted R^2	0.663	0.661	0.661	0.671	0.672	0.672

Table 4-5: Regressions of Corporate Investment on Cash Holdings and Financial Statement Comparability: Alternative Measures of Comparability

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability using alternative measures of comparability. The dependent variable is the ratio of investment (capital expenditures plus R&D) to lagged total assets. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)
Constant	0.065***	0.066***	0.065***
	(8.01)	(8.19)	(8.12)
Cash	0.045***	0.043***	0.040***
	(3.35)	(3.18)	(3.01)
Comp2_Median	0.000		
	(0.62)		
Cash×Comp2_Median	-0.007***		
	(-3.63)		
Comp2_10		-0.000	
		(-0.09)	
Cash×Comp2_10		-0.006***	
		(-2.92)	
Comp2_4			0.000
			(0.31)
Cash×Comp2_4			-0.005***
			(-2.72)
Q	0.018***	0.018***	0.018***
	(18.78)	(18.74)	(18.74)
Cash Flow	-0.015*	-0.014*	-0.015*
	(-1.84)	(-1.73)	(-1.78)
Observations	31206	31206	31206
Adjusted R^2	0.667	0.666	0.666

Table 4-6: Regressions of Corporate Investment on Cash Holdings and Financial Statement Comparability: Additional Controls

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability using additional controls and alternative measures of Q. The dependent variable is the ratio of investment (capital expenditures plus R&D) to lagged total assets. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)
Constant	0.031***	0.033***	0.033***
	(3.72)	(4.02)	(4.01)
Cash	0.063***	0.058***	0.054***
	(4.70)	(4.33)	(4.12)
Comp_Median	0.001**		
	(2.47)		
Cash*Comp_Median	-0.007***		
	(-3.85)		
Comp_10		0.000	
		(1.04)	
Cash*Comp_10		-0.006***	
		(-2.92)	
Comp_4			0.000
			(1.28)
Cash*Comp_4			-0.005***
			(-2.62)
Q	0.016***	0.016***	0.016***
	(17.13)	(17.07)	(17.06)
Cash Flow	-0.021***	-0.019**	-0.020**
	(-2.67)	(-2.44)	(-2.45)
Sales-Capital	0.035***	0.035***	0.035***
	(12.33)	(12.31)	(12.34)

Sales Growth	0.005**	0.005**	0.005**
	(1.98)	(2.02)	(2.03)
Observations	30822	30822	30822
Adjusted R^2	0.664	0.664	0.664

Table 4-7: Comparison between Constrained and Unconstrained Firms

This table presents the comparison between financially constrained and unconstrained firms on comparability measures, cost of capital, industry concentration and accruals quality. All variables are defined as in the Appendix. Asterisk ***, ** and * denote significance at 1%, 5% and 10% confidence level, for mean equality tests between constrained and unconstrained firms.

	Firm Size		Payout Ratio		Bond Rating	
	Small	Large	Low	High	No	Yes
Comp_Median	4.714	6.259***	4.412	6.694***	5.259	5.946***
Comp_10	4.925	6.004***	4.611	6.371***	5.403	5.590***
Comp_4	4.887	6.014***	4.581	6.375***	5.380	5.595***
Interest Cost	0.130	0.090***	0.122	0.091***	0.120	0.087***
Cost of Equity	0.148	0.107***	0.139	0.099***	0.125	0.107***
Concen4	0.401	0.402	0.400	0.408***	0.400	0.404***
HH Index	0.073	0.071	0.073	0.073	0.072	0.073**
Ab (DA)	0.047	0.029***	0.046	0.031***	0.043	0.032***
SD_DA	0.053	0.033***	0.052	0.034***	0.049	0.032***

Table 4-8: Mean Absolute Abnormal Accruals and Standard Deviation of Abnormal Accruals by Deciles of Comparability Measures

This table presents mean values of absolute abnormal accruals Ab (DA) and standard deviation of abnormal accruals SD_DA by deciles of comparability measures. All variables are defined in the Appendix. The last row presents p-values for mean equality tests between the first decile D1 and last decile D10.

Panel A: Ab (DA)			
	Comp_Median	Comp_10	Comp_4
D1	0.053	0.046	0.047
2	0.050	0.048	0.048
3	0.043	0.043	0.043
4	0.040	0.040	0.041
5	0.041	0.041	0.041
6	0.038	0.039	0.038
7	0.039	0.037	0.037
8	0.037	0.036	0.036
9	0.031	0.035	0.034
D10	0.024	0.033	0.032
D1=D10	0.000	0.000	0.000

Panel B: SD_DA			
	Comp_Median	Comp_10	Comp_4
D1	0.059	0.050	0.051
2	0.057	0.050	0.051
3	0.049	0.049	0.049
4	0.049	0.048	0.046
5	0.047	0.046	0.047
6	0.044	0.044	0.044
7	0.040	0.042	0.043
8	0.037	0.040	0.040
9	0.032	0.037	0.037
D10	0.025	0.035	0.034
D1=D10	0.000	0.000	0.000

Table 4-9: Regressions of Corporate Investment on Cash Holdings and Financial Statement Comparability: Controlling for Accruals Quality

This table presents the results of regressions of corporate investment ratio on cash holdings and financial statement comparability after controlling for accruals quality. The dependent variable is the ratio of investment (capital expenditures plus R&D) to lagged total assets. Comp_Median, Comp_10, Coparability_4 are deciles of the corresponding comparability measures. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)
Constant	0.088***	0.089***	0.089***
	(4.01)	(4.17)	(4.19)
Cash	0.058**	0.051**	0.045*
	(2.24)	(2.13)	(1.90)
Comp_Median	0.000		
	(0.49)		
Cash×Comp_Median	-0.009**		
	(-2.57)		
Comp_10		-0.000	
		(-0.17)	
Cash×Comp_10		-0.006*	
		(-1.96)	
Comp_4			0.000
			(0.01)
Cash×Comp_4			-0.005*
			(-1.69)
SD_DA	0.016***	0.016***	0.016***
	(11.01)	(10.96)	(10.95)
Cash×SD_DA	-0.026**	-0.025*	-0.025*
	(-1.99)	(-1.91)	(-1.95)
Q	0.101***	0.099***	0.100***
	(3.82)	(3.77)	(3.78)

Cash Flow	0.097 (0.53)	0.108 (0.59)	0.115 (0.63)
Observations	12831	12831	12831
Adjusted R^2	0.671	0.671	0.671

Table 4-10: Regression of Abnormal Stock Returns on Comparability, Cash Changes, Investment and Earnings Change

This table presents the results of regressions of abnormal stock returns on cash changes, investment, earnings change and financial statement comparability. The dependent variable is the abnormal stock returns over the fiscal year. Comp_Median, Comp_10, and Comp_4 are deciles of the corresponding comparability measure. C is cash plus marketable securities, E is the earnings before extraordinary items plus interest expenses, deferred tax credit, and investment tax credit, NA is net assets (total assets minus cash), Inv is investment, I is interest expense, RD is R&D, D is common dividends paid, L is leverage ratio, NF is total equity issuance minus repurchases plus debt issuance minus debt redemption. All explanatory variables are deflated by the lagged market value of equity $M_{i,t-1}$ except the leverage ratio $L_{i,t}$ and comparability measures. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1)	(2)	(3)
Constant	-0.113***	-0.099***	-0.099***
	(-9.80)	(-8.92)	(-8.85)
Comp_Median	0.009***		
	(7.87)		
ΔC×Comp_Median	-0.057***		
	(-3.48)		
ΔE×Comp_Median	0.124***		
	(10.77)		
Comp_10		0.007***	
		(6.44)	
ΔC×Comp_10		-0.024	
		(-1.44)	
ΔE×Comp_10		0.130***	
		(10.72)	
Comp_4			0.007***
			(6.39)
ΔC×Comp_4			-0.029*
			(-1.73)
ΔE×Comp_4			0.130***

			(10.39)
ΔC	1.660***	1.475***	1.502***
	(11.98)	(10.93)	(11.25)
Inv	0.255***	0.226***	0.228***
	(7.00)	(6.23)	(6.27)
ΔE	0.380***	0.369***	0.374***
	(7.45)	(7.36)	(7.36)
ΔRD	1.433***	1.608***	1.603***
	(6.00)	(6.71)	(6.69)
ΔI	-1.174***	-1.145***	-1.127***
	(-3.69)	(-3.61)	(-3.55)
D	112.919***	117.030***	116.860***
	(5.00)	(5.20)	(5.20)
C	0.212***	0.196***	0.195***
	(7.92)	(7.55)	(7.51)
L	-0.054***	-0.048**	-0.049**
	(-2.82)	(-2.46)	(-2.49)
NF	0.067**	0.066**	0.065*
	(2.02)	(1.99)	(1.96)
ΔC×C	-0.937***	-0.872***	-0.880***
	(-5.60)	(-5.37)	(-5.42)
ΔC×L	-1.150***	-1.115***	-1.127***
	(-5.03)	(-4.81)	(-4.86)
Observations	21821	21821	21821
Adjusted R^2	0.130	0.129	0.129

Table 4-11: Regressions of Investment on Cash Holdings and Comparability: Components of Investment and Other Corporate Spending Variables

This table presents the results of regressions of other investment variables on cash holdings and financial statement comparability. Comp_Median is deciles of the corresponding comparability measure. Cash is the residuals from the cash regression. All other variables are as described in the Appendix. Firm and year dummies are included in all regressions. Values in parentheses are t-statistics which are based on heteroskedasticity robust standard errors clustered by firms. ***, **, * denote significance at 1%, 5% and 10% confidence level.

	(1) Capital Expenditure	(2) R&D	(3) ΔInventory	(4) ΔNAssets	(5) Investment 2
Constant	0.022***	0.043***	-0.006	-0.083***	0.009
	(5.87)	(6.24)	(-1.16)	(-3.75)	(0.93)
Cash	0.016**	0.026**	0.030***	0.349***	0.154***
	(2.29)	(2.53)	(5.37)	(12.46)	(7.92)
Comp_Median	0.001***	-0.001***	-0.000	0.001	0.001**
	(3.20)	(-3.44)	(-0.76)	(1.30)	(2.43)
Cash×Comp_Median	-0.002**	-0.004***	-0.001	-0.002	-0.010***
	(-2.12)	(-3.12)	(-0.92)	(-0.43)	(-3.58)
Q	0.010***	0.007***	0.005***	0.048***	0.028***
	(17.19)	(10.29)	(13.64)	(22.90)	(21.60)
Cash Flow	0.040***	-0.052***	0.029***	0.193***	0.060***
	(10.75)	(-8.60)	(9.05)	(12.99)	(5.20)
Observations	31373	31420	31003	31296	30956
Adjusted R^2	0.591	0.849	0.091	0.201	0.376