Essays in Information Asymmetry, Information Acquisition, Corporate Governance, Capital Structure, and Financial Markets

by

Lei Gao

(Under the direction of Jeffry M. Netter)

Abstract

Information is a set of data or knowledge about a specific topic. Information has its economic value because it facilitates individuals to make strategic choices that yield higher expected utility than they would obtain in the absence of information. Most commonly in finance research, information asymmetries are studied in the context of agency problems, where the separation of ownership and controls brings in conflicts between the management and the shareholders. In financial markets, firms' public information, private information, and the asymmetry between them play a crucial role in security issuing decisions, corporate capital structure decisions, and investors investing decisions. My research investigates the interaction between information environment, corporate governance, corporate financing decisions, and investors' trading behavior.

The first essay of my dissertation examines pecking order theory and static trade off theory of capital structure with the natural experiment of SOX. SOX is the most important response to a series of high profile accounting scandals. It mandates better quality financial reports and more independent board. It could change firms' information environment and management career risk. I find that firms in general dropped leverage after SOX. Firms with larger information asymmetry ex ante dropped leverage more, and firms with more entrenched managers dropped leverage more. Managers have incentives to use leverage less than the optimal level, which is consistent with static trade-off theory and management entrenchment hypothesis.

The second essay directly examines the empirical association between information acquisition and investor trading. It is often assumed that investors will adjust their portfolio when there is new information. With the availability of internet search volume, we could measure how intensive the investor's information acquisition is. We find that doubling abnormal search intensity is associated with about a 9% increase in abnormal trading volume. The positive volume-search association holds for both buyer- and seller-initiated trades, and is greater i) for large trades than for small trades, ii) when search from local investors is more intensive, and iii) during earnings announcement period. These results are consistent with an increase in disagreement triggered by information acquisition.

Index words: Information Asymmetry, Information Acquisition, Agency Cost, Corporate Governance, Sarbanes-Oxley Act, Capital Structure, Financial Markets

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Dedication

To my wife Lily and daughter Annie, without your endless love and support this would never have been possible.

To my parents for investing their entire lives in ensuring the success of their children.

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Chapter 1

Introduction

Information is a set of data or knowledge about a specific topic. Information has its economic value because it facilitates individuals to make strategic choices that yield higher expected utility than they would obtain in the absence of information. Information asymmetry studies the decision in transactions that one party has more or better information than the other. Some transactions could go awry because of the imbalance in power. Examples are the adverse selection problem and the moral hazard problem. Adverse selection theory stems from Akerlof's "The Market for Lemons", and it predicts that "bad" results occur when buyers and sellers have different information set. Moral hazard refers to a situation that one party makes a decision, while the other party bears the risk. As a consequence, the party that makes decisions without taking corresponding risks may behave inappropriately.

Most commonly in finance research, information asymmetries are studied in the context of agency problems, where the separation of ownership and controls brings in conflicts between the management and the shareholders. In financial markets, firms' public information, private information, and the asymmetry between them play a crucial role in security issuing decisions, corporate capital structure decisions, and investors investing decisions. Corporate regulation laws designed for purposes might have some unintended consequences when they have universal requirements and change the firms' information environment.

My dissertation research investigates the interaction between information environment, corporate governance, corporate financing decisions, and investors' trading behavior.

Due to several high profile public firm accounting scandals in early 2000s, financial markets faced a big challenge of attracting investors. Because the information asymmetry between insiders and investors is threatening the viability of financial markets, the Sarbanes-Oxley Act (SOX) was passed to improve the financial reports' quality, and thus to gain investors' confidence. The passage of SOX provides a natural experiment to test the capital structure theories derived from the information asymmetry problems.

On the one hand, managers make financing decisions based on his perception of information asymmetry. On the other hand, investors try to become informed through information acquisition. Information goods are non-rivalrous and non-excludable. When there is new information released on a firm or the overall economic environment, the divergent understanding of the same information could lead to trade transactions. However, the relationship of between information acquisition, information intensity, and investors' trading behavior has not been empirically tested, partly due to the lack of a proxy for information acquisition or information intensity. My research aims to critically examine how information plays an important role in both corporate financing decisions and investor trading behaviors.

The first essay of my dissertation examines pecking order theory and static trade off theory of capital structure with the natural experiment of SOX. SOX is the most important response to a series of high profile accounting scandals (e.g. Enron and WorldCom). It mandates better quality financial reports and more independent board. Critics noted a "One-Size-Fits-All" policy might not be optimal. Empirically, it provides us a natural experiment to test theories of capital structure. And my study also contributes to the literatures of the unintended consequences of SOX.

I find that firms in general dropped leverage after SOX. Firms with larger information asymmetry ex ante dropped leverage more than firms with smaller information asymmetry, and firms with more entrenched managers dropped leverage more than firms with less entrenched managers. Managers have incentives to use leverage less than the optimal level, which is consistent with static trade-off theory and management entrenchment hypothesis.

The second essay directly examines the empirical association between information acquisition and investor trading. It is often assumed that investors will adjust their portfolio when there is new information. Investors choose to become informed through information acquisition and the cost of acquiring information is compensated by taking positions in risky assets and expecting positive abnormal returns. Information acquisition likely yields disagreement among investors and spurs trading. Despite the theoretical advancement, the association between information acquisition and trading activities has seldom been empirically tested due to the fact that the proxy for information acquisition is largely not observable.

How is information revealed and distributed? With the developing of technology, it is becoming easier for people to acquire information. For hundreds of years, people read newspapers to get information. When radio and TV were invented, people started to get more timely information. In the internet era, vast information is so easy to get that people call it "information explosion" era. Internet search engines provide good entrances to acquire information. If we could know what people search for and how intensive the searches are, we could learn the intensity of information acquisition. Out of all the web search engines, Google has around 70% market share. With the availability of internet search volume, we could measure how intensive the investor's information acquisition is. It is possible to examine the empirical association between information acquisition and daily abnormal trading activities.

We find that doubling abnormal search intensity is associated with about a 9% increase in abnormal trading volume. The positive volume-search association holds for both buyer- and seller-initiated trades, and is greater i) for large trades than for small trades, ii) when search from local investors is more intensive, and iii) during earnings announcement period. These results are consistent with an increase in disagreement triggered by information acquisition.

Chapter 2

Information Asymmetry, Management Entrenchment, and Capital Structure: Evidence from the Sarbanes-Oxley Act of 2002

2.1 Introduction

As a "one-size-fits-all" law, the Sarbanes-Oxley Act (SOX) of 2002 was designed to improve information transparency and investors' confidence in firms' financial reports. It has been praised widely by regulators and regarded as "the most far-reaching reform of American business practices since the time of Franklin D. Roosevelt"[1]. Academic researchers have found evidence of the benefits of SOX; these include corporate transparency improvements (Arping and Sautner (2010)) and positive abnormal returns for less compliant firms after the announcement of SOX (Chhaochharia and Grinstein (2007)). On the other hand, researchers have also identified some unintended consequences of SOX, such as its negative effect on firm value (Zhang (2007)), shifted supply and demand for directors (Linck, Netter, and Yang (2009)), changed compensation structure (Carter, Lynch, and Zechman (2009)), reduced investment (Kang, Liu and Qi (2010)), and smaller international companies' moving to stock exchanges in the United Kingdom rather than trading in the United States (Piotroski and Srinivasan (2008)).

In this paper, I examine the effects of SOX on capital structure, a subject that has not been studied in the literature. SOX can affect capital structure through its effect on corporate

[1] See *http://nytimes.com/*. Also see former Federal Reserve Chairman Alan Greenspan praised the Sarbanes-Oxley Act: "I am surprised that the Sarbanes-Oxley Act, so rapidly developed and enacted, has functioned as well as it has..." See *http://www.federalreserve.gov/boarddocs/speeches/2005/20050515/default.htm*. SEC Chairman Christopher Cox stated in 2007: "Sarbanes-Oxley helped restore trust in U.S. markets by increasing accountability, speeding up reporting, and making audits more independent." See *http://www.usatoday.com*.

information transparency. As stated by the pecking order theory, firms prefer internal funding over external funding and prefer debt funding over equity funding because of the adverse selection induced by information asymmetry. On the one hand, when information asymmetry is reduced, the disadvantage of equity financing relative to debt financing is also reduced, making firms more willing to use equity funding relative to debt financing. Thus, we should expect leverage to decrease a firm' information asymmetry is reduced. Since SOX requires public firms to release reliable financial reports and improve information transparency, we should expect a leverage reduction after the passage of SOX according to the pecking order theory. On the other hand, less information asymmetry lead to lower cost of debt and weaker debt covenants. Firms' leverage might increase post SOX.

SOX could also affect capital structure through its impact on the incentives of corporate managers. Trade-off theory, another major theory of capital structure, suggests that capital structure is determined by the trade-off between the costs and benefits based on a wide range of factors. On the one hand, management entrenchment theory suggests that managers are reluctant to issue debt because financial distress can lead to salary cuts, discipline, or even possible job losses (see Zwiebel (1996), Morellec (2004), and Berk, Stanton and Zechner (2010)). Since SOX was designed to regulate executives of public firms, especially those who are most responsible for the financial reports, such as CEOs and CFOs, SOX can increase the career risk of corporate executives (see Wang (2010), and Linck, Netter, and Yang (2009) among others). Job security is one of the most important determinants of human happiness (Clark and Oswald 1994; Di Tella, MacCulloch and Oswald 2001; Helliwell 2003);[2] when SOX adds to managers' career risk and upsets the balance of their trade-off, according to the hypotheses of management entrenchment theory, managers have sufficient motivation to

[2]Clark and Oswald (1994) report large well-being reductions from being unemployed. Similarly, Di Tella, MacCulloch, and Oswald (2001) find that a 1% increase in the unemployment rate decreases overall happiness 66% more than a 1% increase in the inflation rate. Furthermore, Helliwell (2003) finds that job loss is outranked only by divorce in its detrimental effect on happiness in the events he studies. Job loss even outranks the death of a spouse. This literature suggests that managers would treat the newly added career risk from SOX very seriously.

offset their career risk by reducing the leverage level. On the other hand, since SOX requires high quality financial reports, reports that require signature of both CEO and CFO and are authenticated by external auditors, firms who used to hide excessive debts could no longer hide as much. Firms need to unload debts to avoid financial distress. And firms with more entrenched managers may get rid of more debts even though the new debt level is not optimal.

The present study examines a large panel of over 7,000 U.S. corporations and finds that firms reduced their leverage by 8.6% (market leverage) or 2.4% (book leverage) on a univariate basis after SOX went into effect, which is effectively around 25% (market leverage) or 6% (book leverage) relative to the average leverage of the whole sample during the 8 years around SOX. At the industry level, 80% of industries reduced their book leverage and all the industries reduced their market leverage post SOX. The changes are both statistically and economically significant. The effects are robust in multivariate regressions. Firms reduced their market leverage by 4.5% (effectively around 15%) in a multivariate regression controlling for market-to-book and other factors.

To examine the explanation based on the pecking order theory, I look at the change in leverage across firms with different information asymmetry levels. Using the proxies of information asymmetry including analyst coverage (Chang, Dasgupta and Hilary (2006)), idiosyncratic volatility, and probability of informed trades (PIN, Easley, Kiefer and O'Hara (1997), and Adjusted PIN, Duarte and Young (2009)), I find that, consistent with the pecking order theory, firms with fewer analysts following them decreased leverage significantly more than firms with more analysts, and firms with higher idiosyncratic volatility reduced leverage significantly more than firms with lower idiosyncratic volatility. I also find that firms with a higher PIN (more information asymmetry) reduced leverage significantly more than firms with a lower PIN. Another unique information asymmetry proxy is information acquisition volatility (SVIVol), which is based on investor's ticker search behaviors on Google (See Da, Engelberg, and Gao (2011)).

I further examine whether trade-off theory also contributes to the reduced leverage. Specifically, I first examine whether firms with managers who are more sensitive to reputation or job loss dropped leverage significantly more than their counterparts. I use industry concentration of a firm as a proxy for managerial sensitivity to job loss; since it is harder for a manager who works in a highly concentrated industry to find a comparable job when being fired, he or she is naturally more sensitive to career risk. Consistent with the trade-off theory, I find that firms in highly concentrated industries reduced leverage by 25% more than their counterparts on a univariate basis. This result is robust in multivariate analyses. I also examine whether firms with managers who are more entrenched reduced leverage much more than their counterparts. I use institutional ownership, governance index, and entrenchment index as proxies for managerial entrenchment and find that firms with low institutional ownership, higher governance index (more entrenchment), and higher entrenchment index (more entrenchment) reduced leverage by at least 30% more than their counterparts.

As the first study to look at the impact of SOX on capital structure, my work contributes to both the capital structure literature and the SOX literature. My study tests both the information asymmetry and static trade-off theories on capital structure. It reveals that firms with higher information asymmetry ex ante reduced leverage more after the passage of SOX. My study investigates the interaction of industry concentration, institutional ownership, and internal corporate governance with capital structure. I find that executive preference and corporate governance could impact firms' observed capital structure significantly when firms face regulation shocks like SOX. My study suggests trade-off theory could explain the observed capital structure changes.

The rest of the present chapter is organized as follows. Section 2.2 presents a literature review and the development of the main hypotheses. Section 2.3 describes the sample data and empirical methods. Section 2.4 presents the results and analysis. Section 2.5 provides the conclusion and discussion.

2.2 Literature Review and Hypotheses Development

SOX was a consequence of a series of high profile accounting scandals, however, it is regarded as an extra burden for those firms who already complied the rules. When considering SOX as a regulation shock to test capital structure theories explaining observed capital structure changes, I focus on pecking order theory and trade-off theory.

Pecking order theory stems from Akerlof's (1970)'s "Lemon" theory - buyers will discount the price they are willing to pay when a seller has private information about the value of a good, due to adverse selection. Myers (1984) and Myers and Majluf (1984) extended the theory to include capital structure. In this paper, I use the terms pecking order theory and information asymmetry theory interchangeably because pecking order is implied by information asymmetry. According to pecking order theory, firms will prefer internal funding over external funding and debt financing over equity financing. The more information asymmetry associated with a firm, the less likely it will use equity financing relative to debt financing.

No doubt, SOX has increased financial report quality; and thus has improved information transparency. It is natural to assume that information asymmetry has been reduced since the passage of SOX. According to the original pecking order, this reduced information asymmetry should help to partially alleviate adverse selection and make firms more willing to use equity relative to debt to fund their projects. Therefore we should expect a leverage decrease as a result of SOX according to pecking order theory.

Figure 2.1 shows the market leverage and book leverage of U.S. firms over the 25 years from 1982 to 2006. There is no clear pattern of the capital structure of US public firms over this long period except that the market leverage is decreasing on average. There are several sharp short-term changes. The most recent one happened around year 2002, which coincides with the passage of the influencing law - SOX. This plummet is my interest of research.

Trade-off theory explains capital structure as a trade-off between the benefits and the costs of debt. Jensen and Meckling (1976) and Jensen (1986) regard debt as a monitoring tool to discipline managers and mitigate agency problems of free cash flow. Later the cost of debt in the trade-off was extended from the arguably small direct costs of bankruptcy to product and factor market interaction (e.g., Titman (1984), Maksimovic and Titman (1991), Jaggia and Takor (1994), Hart and Moore (1994)). More recently, Berk, Stanton and Zechner (2010) have modeled capital structure as the result of the trade-off between human capital costs and tax benefits.

According to the trade-off theory, because the corporate tax environment was not changed after the passage of SOX, the benefits of debt have remained the same. However, the career risk for CEOs and CFOs increased after the passage of SOX. Linck, Netter, and Yang (2009) report that average Director and Officer insurance premiums have increased by more than 150% in the post-SOX period compared to the pre-SOX period. The increased career risk might alter the managers' willingness to carry the burden of financial distress that usually accompanies executive turnover. Manager entrenchment based trade-off theory assumes that managers are entrenched and they do not necessarily have to maximize shareholders' value. According to this theory, managers face the trade-off between a relaxed and long tenure without discipline and job loss by hurting shareholder's value too much. When SOX adds more career risk (turnover, even imprison) to one side, managers will have sufficient motivation to alleviate the pressure by avoiding financial distress. On the one hand, management entrenchment theory suggests that managers are reluctant to issue debt because financial distress can lead to discipline, salary cuts, or even possible job losses (see Zwiebel (1996), Morellec (2004), and Berk, Stanton and Zechner (2010)). On the other hand, managers could also use debt to reduce the overt control threats (for example, mergers and acquisitions) or increase their own share value (e.g., Novaes (2003), Berger, Ofek and Yermack (1997)). Considering Karan and Sharifi (2006)'s finding that there were much considerably fewer mergers and acquisitions with public targets after 2001, when managers face less external threads, we should expect leverage decrease post SOX according to trade-off theory. Both the pecking order and trade-off theories lead to the same prediction about leverage changes after the passage of SOX. This is our first hypothesis:

H1. Firms reduced their leverage post SOX.

When SOX imposed information transparency requirements, those firms who used to suffer more information asymmetry would suffer less information asymmetry post-SOX. However, those firms which already had very transparent information would be impacted less. According to pecking order theory, firms with more information asymmetry ex-ante would reduce their leverage more than firms with less information asymmetry ex-ante when facing a "one-size-fits-all" shock like SOX.

There are several proxies for information asymmetry. In our case, analyst coverage is one of the best choices. Analyst coverage could reduce information asymmetry; Analysts typically begin their coverage of firms in order to generate trading in these stocks (Irvine(2003)). With increased awareness and improved liquidity, firms experience increases in institutional ownership and breadth of ownership. Institutional investors' proposals gain more support than individual investors', and market reaction varies too (Gillan and Starks (2000)). It is obvious that the more analyst coverage, the less information asymmetry. The same measure has been used as an information asymmetry proxy in finance research (See Chan, Menkveld and Yang (2008) , Zhang (2006), Chang, Dasgupta and Hilary (2006) among others). In fact, Chang, Dasgupta and Hilary (2006) show that analyst coverage affects security issuance. They find that firms covered by fewer analysts are less likely to issue equity as opposed to debt, the firms issue equity less frequently. And the accumulated effects are reflected as in firms' capital structure.

I also examine other information asymmetry measures in the robustness check. Probability of Informed Trading (PIN) is developed by Easley, Kiefer, O'Hara and Paperman (1996), and it has been shown that PIN is a determinant of asset returns (Easley, Hvidkjaer and O'Hara 2002). More recently, Easley, Hvidkjaer and O'Hara (2010)'s zero investment portfolios with high/low PIN stocks generate significant positive returns which could not be explained by factors like size, book-to-market ratio, momentum, or liquidity. Bharath, Pasquariello, and Wu (2009) use the PIN measure in testing the debt issuance and capital structure. Duarte and Young (2009) further split the PIN into the component of information asymmetry and the component of liquidity. In addition to the original PIN measure, I also used the component of information asymmetry of PIN for the empirical tests.

Google's stock ticker search is a direct measure of investor information acquisition behaviors. (See, Da, Engelberg, and Gao (2011) and Drake, Roulstone and Thornock (2011)). When firm information asymmetry is low and information is accurate, usually the search volume will shoot up and go back to normal level in a short period of time. However, when firm information asymmetry is high, information is vague and rumors fly, search volume will go up and down with long tails then back to normal level. So we could use search volume volatility to measure information asymmetry.[3]

With these six information asymmetry measures, we could test the following hypothesis:

H2. Firms with high information asymmetry reduced leverage more than firms with low information asymmetry after the passage of SOX.

Due to the fact that less information asymmetry leads to lower cost of debt and weaker debt covenants. The passage of SOX could facilitate the issuance of Debt compared to equity. Firms' leverage might increase post SOX. Here are two alternative hypotheses:

H1b. Firms increased their leverage post SOX.

H2b. Firms with high information asymmetry reduced leverage less than firms with low information asymmetry after the passage of SOX.

SOX was designed to regulate public firms' executives, especially those who are most responsible for the financial reports - CEOs and CFOs. SOX can increase the career risk of corporate executives (e.g., Wang (2010), Linck, Netter, and Yang (2009)). Management entrenchment theory suggests that managers face a personal trade-off, they are reluctant to use debt because financial distress can lead to discipline, salary cuts, or even possible job losses (see Zwiebel (1996), Morellec (2004), and Berk, Stanton and Zechner (2010)). Because job security is one of the most important determinants of human happiness, when

[3]This also implies that firms with lower search volume index volatility have higher mean search volume index, because Google Insight sets the maximum search index to be 100 and scales the rest.

SOX adds to managers' career risk and upsets the balance of their trade-off, according to the hypotheses of management entrenchment theory, managers have sufficient motivation to offset their career risk by reducing the leverage level.

Garvey and Hanka (1999) find that state antitakeover laws lead to reductions in firms' leverage, which is consistent with increased corporate slack. The threat of hostile takeover motivates managers to take on debt they would otherwise avoid. Graham, Harvey, and Puri (2008) document a strong relation between CEO risk aversion and corporate characteristics such as growth or merger activity. They also find a negative relation between CEO risk aversion and leverage (although not statistically significant). SOX was designed to improve transparency by improving the accuracy and reliability of corporate financial reports. To some degree, the improved transparency should be helpful in merger and acquisition transactions. However, potential targets face enhanced scrutiny with regard to their compliance with SOX requirements for financial reporting and internal controls. Some practitioners worried about staying in compliance with SOX rules. It is quite likely that the law has discouraged some mergers and acquisitions, as acquirers are reluctant to buy companies that have accounting issues. [4] Other evidence that managers became slack and/or entrenched is that firms added more provisions to protect executives' jobs.

Motivated by recent corporate governance literature, I measure a firm's vulnerability to empire-building using the corporate entrenchment index of Bebchuk, Cohen, and Ferrell (2009) and governance index of Gompers, Ishii, and Metrick (2003). Gompers, Ishii, and Metrick (2003) governance index includes 24 provisions, and Bebchuk, Cohen, and Ferrell (2009) entrenchment index includes 6 provisions of the 24 provisions. Four provisions directly limit the power of a majority of shareholders, provisions including staggered boards, limits to shareholder bylaw amendments, supermajority requirements for mergers, and supermajority requirements for charter amendments. The other two provisions reduce the likelihood of a hostile takeover (poison pills and golden parachutes). The higher the score is, the more

[4] "it's time to revise Sarbanes-Oxley", Editorial, *Chief Executive*, Jan / Feb, 2005

entrenched the managers are likely to be. When managers are more entrenched, they have more power to further drop leverage than peers if they deem financial distress as extra pressure on them. Due to this, we have the following hypotheses.

H3. Firms with worse governance measures (more entrenched) reduced leverage much more than firms with better governance measures (less entrenched) post SOX.

It has been noted that product market competition should have explanatory power in capital structure. Industrial economists started to pay attention to the effects of capital structure on product-market behavior in the mid-1980's. Financial economists started to study the role of product competition in assessing the choice of capital structure a little bit later (Maksimovic (1988), Kovenock and Phillips (1995)). Bradley, Jarrell and Kim (1984) find that debt ratios differ significantly across industries. Titman (1984) finds that customers avoid purchasing a firm's products if they think that the firm might go out of business, especially if the products are unique; consequently, firms that produce unique products might avoid using debt. In fact, production and financing decisions can be intertwined (see Brander and Lewis (1986)). Titman and Wessels (1988) find that firms with more unique or specialized products, as measured by R&D/sales and selling expenses/sales ratios, tend to be less levered. Harris and Raviv (1991) point out that the nature of products or competition in the product/input market is a determinant of capital structure. The product market environment or nature of competition varies across industries in a way that affects optimal debt policy.

Nalebuff and Stiglitz (1983) regard the important role played by competition as one of the dominant characteristics of modern capitalist economics. Shleifer and Vishny (1997) emphasize the importance of corporate governance, but they agree that product market competition is probably the most powerful force toward economic efficiency in the world. More recently, Giroud and Mueller (2010) have found that executives working in highly concentrated industries tend to be slack compared to executives in non-concentrated industries after the exogenous shock of anti-takeover business combination laws. They find that input costs, wages, and overhead costs all increase after the passage of the law in highly concentrated industries. If managers in highly concentrated industries are slack, they must be more sensitive to the career risk increase post SOX.

To better understand why industry concentration is a good measure for competition, let's look at the problem from the managers' point of view. There are fewer companies in concentrated industries; thus, it will be harder for the fired managers to find a comparable job with their industry specific expertise. So even without competition monitoring stories, we could also say that managers in concentrated industries are more sensitive to possible job loss, and they are more sensitive to financial distress. And this is why we could use a concentration index from the views of the literature of managerial goal and agency cost instead of competition.

With big block of stocks, institutional owners do not only have strong motivations to keep a close eye on managers' investment decisions and financing policies, but also have the power and resource to impact managers' decisions (e.g., Gillan and Starks (2000) and Smith (1996)). When firms have more institutional ownership, it is likely that the manager is less entrenched. Management entrenchment theory forecasts that if managers need to alleviate financial distress threat on their carrier, firms with smaller institutional ownership will drop their leverage more than their counterparts.

In consideration of these points, here is our last hypothesis:

H4. Firms in highly concentrated industries, with strong market power, and with less institutional ownership reduced leverage more than firms in non-concentrated industries post SOX.

2.3 Data

2.3.1 Sample Selection

I obtain the accounting data of U.S. firms from Compustat. I exclude all observations for which the book assets or sales are missing, and exclude regulated utility firms (SIC 4900 -

4999) and finance industries (SIC 6000-6999). The final sample contains 7,363 firms from 1999 to 2006. The analyst coverage data is from I/B/E/S as the number of analysts covering a sample firm.

To test hypothesis 2, I obtain PIN data from Soren Hvidkjaer's website and adjusted PIN data from Lance Young. The data on PIN covers only the period between 1983 and 2001 and the adjusted PIN data is from 1983 to 2004. I assume that the order of information asymmetry will not change much in a short period and extend the data of 2001 to other years from 2002 to 2006 in my analysis. The PIN data have been used in several corporate finance researches including Bharath, Pasquariello, and Wu (2009).

I obtain stock tickers weekly search volume Index (SVI) data from Google Insight (*http://www.google.com/insights/search/*). Since Google does not provide SVI data prior to January 2004, I used 2004 to 2006 data to calculate SVIVol and expand the data to earlier years. As a robustness check, I use 2005 year data alone to sort firms by the information asymmetry proxy of SVIVol; my results are very similar. I also test the information asymmetry order across years of 2004, 2005, and 2006, and the results are consistent. I download stocks in Russell 3000 index. Google does not report search volume data when search volume is too low. Many small-cap stocks have too low search volume, which is below a minimum threshold to be included in Google Insight. The Russell 3000 index covers 90 percent of total U.S. equity market capitalizations. I manually go through all Russell 3000 tickers and exclude 243 "noisy" tickers with generic meaning such as "A", "B", "CAT", "DNA", and "GPS".

2.3.2 Definition of variables and summary statistics

My measures of leverage are the market leverage and book leverage.[5] I calculate market leverage as book debt divided by the summation of total assets minus book equity plus market

[5]Following Harford, Klasa, and Walcott (2009), I focus on market leverage instead of book leverage because almost all theoretical predictions related to leverage are made with respect to market leverage. Further, most recent related works, such as Flannery and Rangan (2006), Leary and Roberts(2005), Welch(2004), and Hovakimian, Opler, and Titman (2001) focus on market

equity). Book debt is total assets minus book equity, and book equity is total assets minus summation of total liabilities and preferred stock, plus deferred taxes and convertible debt. Market equity is common shares outstanding times stock price. I also show main results with book leverage. With data from Compustat, market leverage is calculated as: [Data6 - book equity] / [Data6 - [Data6 - [data181 + data10] + data35 + data79] + [Data25×data199]], Book leverage is calculated as book debt divided by total assets. With data from Compustat, Book leverage is calculated as: Book Debt/Data6.

Analysts: analyst coverage, defined as the number of analysts who cover a specific firm. The number is counted from I/B/E/S database. Analyst Forecast Dispersion and Analyst Forecast Errors are also widely used as information asymmetry measure. I use them as robustness check for analyst coverage.

Information Opacity: a moving sum of absolute values of accruals measure of the precision of public accounting, and they are associated with earnings management and financial opacity. The opacity is positive correlated with information asymmetry. To distinguish normal and discretionary accruals, I use the modified Jones Model (see Dechow, Sloan, and Sweeney (1995), and Hutton, Marcus, and Tehranian (2009)). I estimate accruals using firms in Fama and French (1997) 48 industries for each fiscal year between 1996 to 2006 with Equation (2.1):

$$\frac{TA_{jt}}{Assets_{jt-1}} = \alpha_0 \frac{1}{Asset_{jt-1}} + \beta_1 \frac{\Delta Sales_{jt}}{Assets_{jt-1}} + \beta_2 \frac{PPE_{jt}}{Assets_{jt-1}} + \epsilon_{jt} \tag{2.1}$$

Discretionary annual accruals are then calculated with Equation (2.2) using estimates from Equation (2.1):

$$DAcc_{jt} = \frac{TA_{jt}}{Assets_{jt-1}} - \hat{\alpha}_0 \frac{1}{Asset_{jt-1}} - \hat{\beta}_1 \frac{\Delta Sales_{jt} - \Delta Receivables_{jt}}{Assets_{jt-1}} - \hat{\beta}_2 \frac{PPE_{jt}}{Assets_{jt-1}} \tag{2.2}$$

where TA_{jt} is total accrual for firm j in year t; $Asset_{jt-1}$ is the deflator, total asset in previous year; $\Delta Sales_{jt}$ is the sales change; $\Delta Receivables_{jt}$ is the changes in Receivables; PPE_{jt} is

leverage. My results generally hold when using book leverage except several information asymmetry interaction terms.

net property, plant, and equipment. My final measure of information opacity is the three-year moving sum of the absolute value of annual discretionary accruals. IVOL: idiosyncratic volatility. I used daily stock return and basic CAPM model to estimate the idiosyncratic volatility. When doing robustness check, I tried Fama-French 3 factor model and raw return standard deviation and the results are similar. PIN: probability of informed trade. The PIN measure is derived from a trading model that represents informed and uninformed order arrivals as a combined Poisson process (see Easley, Hvidkjaer and O'Hara (2002)). The PIN is defined as equation (2.3)

$$PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s} \tag{2.3}$$

where α is the probability of an information event, μ represents the order arrival of informed traders, $\alpha\mu$ is the arrival rate for informed traders, and ϵ_b and ϵ_s correspond to the order arrival of uninformed traders. Duarte and Young (2009) further filtered out the information asymmetry component from PIN, I used this adjusted PIN (adjPIN) to do robustness check.

SVIVol: Search volume index volatility: I download Google stock ticker search volume index from Google Insight application. Then I calculate the standard deviation of the search volume index.

Herfindahl-Hirschman index (HHI): a market concentration measure well-grounded in industrial organization theory (see Tirole (1988)). I calculate the index based on Fama and French (1997) 48 industry classification. Markets in which the HHI is between 1000 and 1800 basis points are considered to be moderately concentrated and those in which the HHI is in excess of 1800 points are considered to be concentrated. Transactions that increase the HHI by more than 100 points in concentrated markets presumptively raise antitrust concerns under the Horizontal Merger Guidelines issued by the U.S. Department of Justice and the Federal Trade Commission. HHI (Low) and HHI (High) are dummy variables that equal one if the HHI lies below and above 1000 points respectively. HHI is defined as the sum of squared market shares,

$$HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2 \tag{2.4}$$

where s_{ijt} is the market share of firm i in industry j in year t. Market shares are computed from Compustat. (Data12)

PWR: profitability of a firm, a proxy for product market power. It is defined as earnings divided by sales. Usually firms that are more profitable with per capita sale have stronger market power. I use this variable as a proxy for product market power. The higher the number is, the stronger the firm is in the product market competition. (Data13/data12)

INST_hld: institutional ownership. It is the percentage of stocks held by all 13F-filling institutional investors. I use 1 minus INST_hld as the retails investors' holding in some regressions.

GX: Governance Index. Gompers, Ishii, and Metrick (2003) develop governance index. It includes 24 provisions, for example, staggered boards, supermajority requirements for mergers, supermajority requirements for charter amendments, poison pills and golden parachutes. The value range is from 0 to 24. Based on Gompers et. al.(2003)'s arguments, the higher the index, the worse the firm governance is.

EX: Entrenchment Index. Bebchuk, Cohen, and Ferrell (2009) develop entrenchment index which includes 6 provisions of the 24 provisions in GX. Four provisions directly limit the power of a majority of shareholders, provisions including staggered boards, limits to shareholder bylaw amendments, supermajority requirements for mergers, and supermajority requirements for charter amendments. The other two provisions reduce the likelihood of a hostile takeover (poison pills and golden parachutes). The range of EX is from 0 to 6. Similar to GX, the higher the score is, the more entrenched the managers are likely to be.

I describe the other commonly used control variables in my models later in the paper. These variables regularly appear as characteristics affecting capital structure choice in the literature (e.g., Rajan and Zingales (1995), Hovakimian, Opler, and Titman (2001), Flannery and Rangan (2006), Kayhan and Titman (2007)). The calculation of these variables with corresponding Compustat variables are listed in the parenthesis following the descriptions.

R&D, SE: R&D/sales and selling expenses/sales ratios. Titman and Wessels (1988) find that firms with more unique or specialized products, as measured by R&D/sales and selling expenses/sales ratios, tend to be less levered. (Data46/data12 and Data181/data12 respectively) MB: market-to-book is regarded as an indicator of investment opportunities and risk. It is well believed that high market-to-book firms might have a lower debt capacity. ([Data6 - [Data6 - [data181 + data10] + data35 + data79] + [Data25 $\times$ data199]]/data6)

PPE: defined as net property, plant, and equipment / total sales. It is a proxy for asset tangibility. (Data8/data6)

EBTID: defined as earnings before interest, tax, and depreciation / total asset. It is a proxy for firm profitability. Note that PWR is earnings divided by sales. Compared to EBTID, PWR presents the market power. High PWR firms have room to price their products. (Data13/data6)

SIZE: defined as natural logarithm of net sales (log(data12)). As robustness check, I also tried total assets and market value, and my results still hold.

Fama and French (1997) industry dummies: As in Kayhan and Titman (2007) and Harford, Klasa, and Walcott (2009), to control for other firm characteristics and contemporaneous industry shocks that could be common to firms in a particular industry I include industry dummies in the model. These dummy variables correspond to the 48 industries classified by Fama and French (1997).

The descriptive statistics are presented in Table 2.1. The two main measures of leverage are reported in the first two rows. The next variable is the event dummy variable: SOX. Since there are fewer observations post SOX, the mean of SOX is 0.39. Information asymmetry measures (Analysts, Information Opacity, Idiosyncratic Volatility, PIN, Adjusted PIN, and SVIVol) are listed afterwards. I created dummy variables for each information asymmetry measures, the variable names are ended with "_d" in Table 2.1. Industry concentration measure (HHI), product market power measure (PWR), and institutional ownership (INST_hld) are the proxies to external pressures on managers. Notice that there are extreme value problems with PWR variable, so I use rank variable in the multivariate analysis. GX and EX are internal governance measures. MB, PPE, EBITD, R&D, DR&D, SE, and SIZE are common control variables that impact capital structure.

Table 2.2 tabulates the long term trends of firms' capital structure in the United States. This table reports the main result - leverage drop post-SOX. For both market leverage and book leverage, the first column reports the 4-year period averages from 1982 to 2006; the second column reports the change scales from last 4-year period; the third column report the statistical significance. Different research has chosen either 2002 (see Linck, Netter, and Yang (2009)) or 2003 (see Kang, Liu, and Qi (2010)) as the year of SOX in effect. The leverage decrease is much more significant if I choose year 2003 as the year of SOX in effect.[6] The plummet after the passage of SOX is obvious in both setups. Considering the moderate adjustment speed of capital structure, I choose year 2003 in my study.

Table 2.3 shows the leverage changes around SOX for 40 industries. 8 industries are dropped from Fama and French (1997) 48 industries. The table is sorted by book leverage median changes. All the industries face a drop of market leverage. 32 out of 40 industries face a drop of book leverage. The exceptions of Defense, Shipping containers, Shipbuilding, Railroad Equipment, Beer & Liquor, Business Supplies, Business Services, and Pharmaceutical Product. The exceptions may be related to the IRAQ war of 2003. The war provided a demand shock for a few industries, and the firms in these industries issued debts to grow. It seems that because cost of debt is lower than cost of equity, when there are "obvious" positive net present values projects, firms choose Debt to finance.

[6]The real effect date of SOX was July 30th, 2002. See *http://www.gpo.gov/fdsys/pkg/PLAW-107publ204/content-detail.html*. However, it also makes sense to argue that it takes months for the managers to understand the law and take actions to respond to it.

2.3.3 Empirical Methodology

Information Asymmetry and capital structure

I use the Differences-in-differences research method to check the effects. Using the following model, I examine the impact of the passage of SOX on firms' capital structure for firms with different level of information asymmetry.

$$\begin{aligned} y_{it} = \quad & \alpha_i + \alpha_t + \beta_1 SOX_t + \beta_2 Proxy_{it} + \beta_3 (Proxy_{it} \times SOX_t) \\ & + \gamma' X_{it} + \epsilon_{it} \end{aligned} \tag{2.5}$$

where y is the dependent variable of interest, market leverage for each firm. SOX is a dummy variable that equals to 1 for year 2003 and thereafter; 0 otherwise. Proxy variable is a proxy for information asymmetry. For example, Analysts, the number of analysts coverage for each firm. reflects the primary effects of the passage of SOX on firms' capital structure. reflects the primary of effects of information asymmetry on firms' capital structure. is the coefficient for the interaction term of information asymmetry proxy and SOX dummy variable, and it reflects the different effects of SOX on firms leverage changes with different number of analyst coverage. The same tests are used for firm information opacity (three-year moving sum of absolute value of discretional accrual), idiosyncratic volatility, PIN, adjusted PIN, and SVIVol.

I employ information asymmetry proxy - PIN in this model. I first use PIN of 2001 as a measure of firms' information asymmetry. I also create a dummy variable to check the different effects of the passage of SOX on firms' capital structure. The dummy variable PIN_d equals 1 if the PIN of 2001 is above median, 0 otherwise. I then expand the value to other years. As a robustness check, I set dummy variable PIN_d equal to 1 if the PIN is above median, 0 otherwise for each year between 1999 and 2004, the result still holds. With continuous adjusted PIN variable, I test the subsample for year 1999 to 2004. The results hold in all the specifications. I take a similar approach for SVIVol when data is missing, the results are robust.

Internal Governance and External Pressure effects

I examine whether the passage of SOX Act of 2002 has a different effect on capital structure across the levels of industry concentration, market power, and institutional ownerships. I use the same model in equation (5) to test the effects. Governance Index, Entrenchment Index, product market power, and institutional ownership are firm level data, and HHI is the only one industry level measure in my study.

I use HHI as an example to show how to test my hypothesis 3a and 3b. HHI is calculated based market shares. For the dummy variable HHI_d, I use the U.S. Department of Justice criteria , which are HHI_d equals to 1 when HHI is more than 1000 points and equals to 0 otherwise; For firms with a given HHI, the total effect is $\beta_1 + (\beta_2 + \beta_3)HHI$. If managers of the firms in concentrated industries are more sensitive to career riskiness shocks, we should observe that the firms respond to exogenous SOX shock differently. $\beta_1 + \beta_3 HHI$ is the difference created by the passage of SOX. β_1 should reflect the primary effect of SOX. The effects of any given HHI is the difference of $(\beta_2 + \beta_3)HHI$ and $\beta_2 HHI$. When HHI is close to 1, managers are the most likely to be slack (see Giroud and Mueller (2010)), and it is unlikely to find another comparable position once the managers lose their jobs; they will reduce leverage the most. So β_3 is expected to be significantly negative.

As a robustness check for market competition, firms that are more profitable with per capita sale have stronger market power and more competitive in product market. I use PWR variable. In a similar test as to HHI, I find that firms with stronger product market power reduced leverage more than firms with weak product market power.

The forecast of first-order effects on capital structure is provided in the second column of Table 2.6.

Table 2.4 shows the correlation between market leverage, book leverage, and other variables. The upper right corners of the correlation tables (above the diagonal) are Pearson correlations, and the lower left corners (below the diagonal) are Spearman correlations. Panel a of Table 2.4 shows the correlation between market leverage, book leverage, and information asymmetry measures, and other control variables. Note that market leverage is positively (negatively) correlated with information asymmetry measures when information asymmetry measure is proxy for large (small) information asymmetry. This is consistent with Bharath, Pasquariello and Wu (2009)'s findings. Panel b of Table 2.4 shows the correlation between market leverage, book leverage, corporate governance quality measures, and other control variables. Consistent with intuition, leverage is positively correlated to HHI and PWR, which implies that firms that face smaller product market competition (in highly concentrated industries) and firms with bigger product market power use higher leverage on average.

2.4 Results and Discussions

2.4.1 Univariate Results

I first look at if leverage changed generally after SOX. The full sample univariate results are in Table 2.2, industry specific results are in Table 2.3, and leverage changes across different information asymmetry firms and industry concentrations are reported in Table 2.5. Firm reduced their leverage post SOX by 860 basis points (from 0.346 to 0.260) from Table 2.2 post SOX. After the passage of SOX, the leverage of firms with higher information asymmetry dropped 1260 basis points (or 26%) to 0.362 from 0.48. However the leverage of firms with lower information asymmetry only dropped 550 basis points (or 15%) from 0.318 to 0.373. The results are shown in panel a of Table 2.5. The pattern is consistently found in all the other information asymmetry measures.

After merging with management entrenchment measures, we could extend my test on firms with different entrenchment levels. For example, the leverage changes for high concentrated industries and non concentrated industries. Consistent with intuition, non concentrated industries have lower leverage (0.279) than high concentrated industries (0.433). However, It could also shows high concentrated industries reduced their leverages (0.055) more than non concentrated industries (0.047). All the results are both statistically and economically significant.

As an extra test to show information asymmetry changes, I tested the PIN and adjusted PIN changes after the passage of SOX. In unreported results, I find that firms' information asymmetry measured by PIN dropped by 14% (from 0.165 to 0.141) after the passage of SOX. Also analyst forecast dispersions decreased by 15% (from 0.16 to 0.13) post SOX.

2.4.2 Main Regression Results

Our main regression results are in Tables 2.6, 2.7, 2.8 and 2.9. All the variables based on ratios are winsorized at 1% and 99% level and then normalized to be standard normal distribution.

Table 2.6 shows the results of the two regression models with market leverage and book leverage. Hypothesis column shows the expected sign for the variable of interest. Column 1 is the pooled OLS result with two-way clustered standard errors. The SOX dummy variable coefficient is -0.079, which means that firms leverage dropped by 7.9% on average after controlling for other factors that may also impact capital structure. Column 2 is the panel data regression controlled for firm fixed effects, the results shows that firms' leverage on average dropped 4.4%. The book leverage results are similar. All other control variables coefficients (Market to Book, PPE, EBITD, R&D, SE, and SIZE) are consistent with other empirical research. These results are consistent with Hypothesis 1.

Table 2.7 shows the regression results for market leverage. The first regression is for Analysts variable, which is the number of analyst coverage. Analyst_d is set to 1 when the number of analyst coverage is above the median in the year, and 0 otherwise. Firms with less analyst coverage reduced leveraged 240 basis points ($t = -8.13$) more than their counterparts. And their leverage is 370 basis points more than their counterparts in general. Regressions with the other two Analyst forecast variables, Analyst Dispersion and Analyst forecast error, lead to very similar results.

The group of firms with high information opacity, as proxied by three-year moving sum of the absolute value of adjusted accruals based on modified Jones model, dropped 110 basis points ($t = -3.64$) more than firms with low information opacity. In the third regression, for firms with high idiosyncratic volatility dropped 120 basis points ($t = -4.49$) more than their counterparts. And firms with high idiosyncratic volatility use 280 basis points leverage more than firms with low idiosyncratic volatility.

The fourth and fifth columns of regression results are for PIN and adjusted PIN. For firms within high PIN group, which means they are facing more information asymmetry, they dropped 200 basis points more than their counterparts. When we use the more precise information asymmetry measure of the adjusted PIN, we observe that the high information asymmetry firms reduce leverage by 240 basis points more than their counterparts. It should also be noticed that the high PIN (adjusted PIN) group has 190 (210) basis points higher than low PIN (adjusted PIN) group, which is consistent with information asymmetry theory.

The last column shows result with SVIVol measure. The group of firms with high SVIVol (low information asymmetry), dropped 100 basis points ($t = 2.51$) less than firms with low SVIVol. And the group of firms with high SVIVol (low information asymmetry) uses 450 basis points leverage less than firms with low SVIVol (high information asymmetry).

All other control variables coefficients (Market to Book, PPE, EBITD, R&D, SE, and SIZE) are consistent with those documented in the literature. To summarize, the results in Table 2.7 lend strong support to hypothesis 2.

Table 2.8 shows the regression results for firms with different level of governance index. I find that firms with higher governance index reduced leverage more than firms with lower entrenchment index. Unreported results also shows entrenchment indexes increased significantly post SOX. Regression results in column (1) shows that firms with higher governance index dropped 180 basis points ($t = -4.63$) more than firms with lower governance index. As a robustness check, column (2) shows that for each additional provision added in the governance index, firms reduced leverage by 30 basis point ($t = -3.88$). Column (3) shows that firms with higher entrenchment index reduced leverage by 170 basis points ($t = -4.36$) more than firms with lower entrenchment index, which is expected, because EX and GX are highly correlated in Table 2.4 panel b. Column (4) shows that for each additional provision added, firms further dropped leverage by 50 basis points ($t = -3.46$). All these result are consistent with hypothesis 3a.

Table 2.9 reports the results from panel regressions of industry concentration index (HHI), product market power, and institutional (or retail) ownership. In Column (1) and Column (2), I show the different leverage adjustment levels for firms in industries with different level of concentration. HHI in column (1) is standardized, so when HHI increase by one standard deviation, firms reduced 70 basis points more post SOX. From column (2), we can see that firms in concentrated or highly concentrated industries reduced their leverage by 130 basis points more than firms in non-concentrated industries. I also notice that the coefficient on HHI_d dummy is positive and significant (0.010 with t=3.20), which shows that firms in highly concentrated industries can use higher leverage. This is consistent with the (conventional) interpretation that firms in concentrated industries make more profits and are able to use higher leverage.

Column (3) and column (4) shows the different SOX impact on firms with different level of product market power. Due to the fact that the product market power (earnings divided by sales) is a ratio and have many negative numbers, I used rank of the number in column (3) as a robustness check for column (4) results. However, the economic explanation relies on column (4). Column (4) shows that firms with big product power dropped 110 basis points ($t = -3.98$) more than firms with small product power post SOX.

Column (5) and column (6) shows the different SOX impact on firms with different level of institutional ownership. To avoid confusion, I used one minus institutional ownership in the regression of column (5). And INST_d equals 1 when institutional ownership is less than median and 0 otherwise. Column (6) shows that firms with low institutional ownership dropped leverage by 160 basis points ($t = -5.55$) more than firms with high institutional ownership. We can also see the effects in column (5), one standard deviation of institutional ownership brings in 130 basis points ($t = -8.92$) variation in firms leverage change post SOX.

The regression results show that managers in concentrated industries will tend to reduce financial distress more. The reason might be that they were facing spiking career risk and less threat from external threat of mergers and acquisitions at the same time. Consistent with the existing literatures, I find that firms with stronger market power, proxied by earnings divided by sales, are more levered than firms that are relatively weak. Firms with stronger market power reduced leverage much more than firms that are relatively weak post SOX. The fact that these firms that have chosen higher leverage may be a reason that the same firms want to reduce financial distress after SOX. Considering that SOX is not designed to depress investments or discourage debt usage and that debt actually acts as a monitoring tool to control management entrenchment (see Jensen and Meckling (1976), and Jensen (1986)), the shift of observed capital structure is totally one of the unintended consequences (check some others in studies such as Linck, Netter, and Yang (2009)).

Even in the same industry, firms that are stronger in product market have different optimal level of debt compared to firms that are weaker in product market. If a firm can benefit from an advantageous position in fixing prices, maybe a monopolistic position, and the firm should have bigger debt capacity. Sullivan (1974) finds that economically powerful firms might be able to avoid the discipline of the capital markets with regard to financial structure that would be applied to less powerful firms. He argues that the managers in economically powerful firms might "exploit monopoly elements in its output market" and "use less than optimum debt" to produce superior profits and the reduced risk associated with a conservative capital structure. This combination of high profitability with reduced fixed interest costs and profit variability strengthens the control of the current management. Considering that job loss is one of the most painful things in one's life, when facing increased career risk, the managers in more economically powerful firms have more room to and are willing to reduce financial distress with the advantages from product markets.

Considering that job loss is one of the most painful determents to a human being's happiness (see Di Tella, MacCulloch, and Oswald (2001) and Helliwell (2003)), it is reasonable to assume that managers want to maximize her job tenure, which is threatened by two events: financial distress and a takeover. In this setting, the manager's optimal debt minimizes the probability that she loses her job in a takeover or in financial distress. When external threats weaken, managers have more room to reduce leverage under the optimal level where the marginal cost of tax is equal to the marginal benefits. The motivation to use less debt becomes even stronger when managers face increased career riskiness. In an unreported table, data shows firms' entrenchment index, which is a measure of their vulnerability to empire building, increased after SOX.

2.4.3 Other theory and factors to explain capital structure

The third capital structure theory, market timing theory, implied by Myers (1984) and developed by Baker and Wurgler (2002) and Welch (2004) among others, has gained much attention recently. However, this theory can not propose a testable hypothesis based on human cost. The idea is that managers look at current conditions in both debt and equity markets; if they need funding, they choose whichever market looks more favorable. As a result, the firm's current capital structure depends on the market conditions that existed when it sought funding in the past. In order to determine whether market timing theory is applicable to explain the leverage shift after SOX, I analyze the observed aggregate leverage shift, overall capital market condition, and Federal Reserve debt rates. From Figure 2.3 and Figure 2.4, we can see marketing timing overall forecast is not consistent with our results.

Tax environment changes, especially personal taxes changes, have been widely ignored in capital structure studies (exceptions include Miller (1977), and Graham (1999)). I notice tax changes during my study period and I ignore the effects in my current version study because of the following reasons (see Figure 2.2). First, the personal tax changes is universal for my sample, it is unlikely to bring in systematic diversified capital structure changes across firms with different levels of information asymmetry and management entrenchment. Second, the cost of equity might drop as the consequence of tax breaks. However, equity is still a financing means “of last resort”. Third, the effect of tax changes might be low. By Graham (1999), the 1997 capital gain tax break (reducing the top rate from 28% to 20% for assets held 18 months, later changed to 12 months, and further reducing to 18% in 2000) only caused the debt ratio to drop from 20.8% to 20.7% by 10 basis points.

As robustness check, I studied banking industry’s leverage changes around SOX period. Due to the fact that there have been already similar regulation terms as found in SOX for banking industry since late 1980s, the impact of SOX on bank’s capital structure should be minimal compare to other industries. The results are in Table 2.11. Banking industry are much less impacted in both the univariate and multivariate analysis. I have also checked private firms leverage changes in the same period and observed very different patterns. Private firms’ leverage increased post-SOX. Private firms’ book leverage increased from 73.2% to 79.2% Post SOX. The results are in Table 2.10 panel a. Private firms data is from Sageworks. Table 2.10 panel b. presents the comparison of capital structure changes post SOX between U.S. pubic firms and U.K. firms. U.S. and U.K. financial markets are the most developed financial markets in the world. SOX is enforced in U.S. but not in U.K., we observe different patterns in the capital structure changes in these two markets. U.K. firms leverage is quite flat (or increased slightly) post SOX compared to pre SOX period.

I also run all regressions controlling for survivorship bias and check all the regression with book leverage. My results generally hold when using book leverage except several information asymmetry interaction terms. After controlling for survivorship bias, the decrease effects for both market leverage and market leverage become stronger.

In addition, I also checked the mechanism of the leverage changes. It seems that firms changed leverage by retired debts, especially short-term debts. This result is consistent with literatures finding that firms reduced investment post-SOX.

2.5 Conclusion and Discussions

Using the passage of the Sarbanes-Oxley Act of 2002 (SOX) as a regulation shock, I examine if this law impacted firms' capital structure and if it had different effects on 1) firms that have different levels of information asymmetry, and 2) firms whose managers have different levels of sensitivity to regulation shocks.

Consistent with information asymmetry theory, I find firms with higher low analyst coverage, higher absolute accrual measures, higher idiosyncratic volatility, PIN, higher adjusted PIN, and low SVIVol reduced their leverage significantly more than their counterparts. As a law designed to improve information transparency and rebuild investors' confidence, SOX has been useful for improving information environment for those firms that used to have high information asymmetry. Firms with higher information asymmetry ex-ante reduced their leverage much more than their counterparts.

Although I cannot definitively rule out the possibility that the information asymmetry proxies may capture other effects, they draw a consistent picture that firms with higher information asymmetry use higher leverage, and that firms with higher information asymmetry ex-ante reduced leverage more than firms with lower information asymmetry ex-ante. Investors require compensation for the information asymmetry risk they bears when investing in equity. The higher the information asymmetry is, the less the firms are willing to use equity compared to debt. When SOX mandated higher quality of financial reports and more transparency, firms with higher information asymmetry ex-ante reduced leverage more than their counterparts, which implies that firms with higher information asymmetry ex-ante are willing to use more equity post-SOX and that the information asymmetry has been reduced more.

Similarly, Static trade-off theory is also supported by my tests. Ceteris paribus, higher debt levels usually imply a higher probability of bankruptcy or financial distress. Financial distress could decrease managers' compensation below contracts. If the firm cannot make interest payments at the contracted wage level, then managers usually are willing to take a temporary pay cut to ensure full payment of the debt. When the firm's financial health improves, managers' compensations return to their contracted level. If the reduced compensation can no longer help to pay interest, then it will cause bankruptcy and managers will lose their jobs; so managers will have to find a position with the labor market rate. Since SOX has made the careers of managers riskier, especially CEOs and CFOs, who are the most responsible for capital structure choices, on the one hand, managers need to be compensated. On the other hand, managers have their own motivation to reduce their career risk by reducing leverage to avoid financial distress and/or by adding more provisions to alleviate the riskiness of turnover.

The asymmetric responses to the same regulation shock are consistent with management entrenchment theory based on trade off of the human costs and benefits of debt. Managers of firms in highly concentrated industries, with stronger product market power, lower institutional ownership, higher governance index and higher entrenchment index reduced their leverage more than their counterparts. All industries dropped leverage post SOX with only a few exceptions, for example, defense industry and shipping containers industry. IRAQ war of 2003 might have provided many new orders and investment opportunities, and thus the whole industry borrowed to grow and took advantage of the obvious investment opportunities. In consideration of this, we may say the cautiousness of the firms which dropped leverage and the foregoing investment opportunities at the same time might have contributed to more economic loss than compliance cost alone estimated by some economists. Some managers might also have shifted their focus from business to compliance with the rules imposed by SOX and thus have made less effort in regard to investment. This kind of "indirect compliance cost" should remind us to pay careful attention to "one-size-fits-all" regulation policies.

2.6 References

Akerlof, G., 1970, The Market For Lemons, *Quarterly Journal of Economics* 84, 488-500.

Arping, S., and Z. Sautner, 2010, The Effect of Corporate Governance Regulation On Transparency: Evidence From The Sarbanes-Oxley Act of 2002, Working Paper.

Baker, M., and J. Wurgler, 2002, Market Timing and Capital Structure, *Journal of Finance*, 1-32.

Bebchuk, L., A. Cohen, and A. Ferrell, 2009, What Matters In Corporate Governance?, *Review of Financial Studies* 22, 783.

Berger, P., E. Ofek, and D. Yermack, 1997, Managerial Entrenchment and Capital Structure Decisions, *Journal of Finance* 52, 1411-1438.

Berk, J., R. Stanton, and J. Zechner, 2010, Human Capital, Bankruptcy, and Capital Structure, *Journal of Finance* 65, 891-926.

Bharath, S. T., P. Pasquariello, and G. Wu, 2009, Does Asymmetric Information Drive Capital Structure Decisions?, *Review of Financial Studies* 22, 3211.

Bradley, M., G. Jarrell, and E. Kim, 1984, On The Existence of an Optimal Capital Structure: Theory and Evidence, *Journal of Finance* 39, 857-878.

Brander, J., and T. Lewis, 1986, Oligopoly and Financial Structure: The Limited Liability Effect, *The American Economic Review* 76, 956-970.

Carter, M., L. Lynch, and S. Zechman, 2009, Changes In Bonus Contracts In The Post-Sarbanes-Oxley Era, *Review of Accounting Studies* 14, 480-506.

Chan, K., A. Menkveld, and Z. Yang, 2008, Information Asymmetry and Asset Prices: Evidence From The China Foreign Share Discount, *Journal of Finance* 63, 159-196.

Chang, X., S. Dasgupta, and G. Hilary, 2006, Analyst Coverage and Financing Decisions, *Journal of Finance* 61, 3009-3048.

Chhaochharia, V., and Y. Grinstein, 2007, Corporate Governance and Firm Value: The Impact of The 2002 Governance Rules, *Journal of Finance* 62, 1789-1825.

Clark, A., and A. Oswald, 1994, Unhappiness and Unemployment, *The Economic Journal* 104, 648-659.

Da, Z., Engelberg, J. , and P. Gao, 2011, In Search of Attentions, *Journal of Finance* Forthcoming.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney, 1995, Detecting Earnings Management, *Accounting Review*, 193-225.

Di Tella, R., R. Macculloch, and A. Oswald, 2001, Preferences Over Inflation and Unemployment: Evidence From Surveys of Happiness, *American Economic Review*, 335-341.

Drake, M., D. Roulstone, and J. Thornock, 2011, Investor Information Demand: Evidence From Google Searches Around Earnings Announcements(Working Paper, The Ohio State University).

Duarte, J., and L. Young, 2009, Why Is PIN Priced?, *Journal of Financial Economics* 91, 119-138.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2002, Is Information Risk A Determinant of Asset Returns?, *Journal of Finance* 57, 2185-2221.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2010, Factoring Information Into Returns, *Journal of Financial and Quantitative Analysis* 45, 293-309.

Easley, D., N. Kiefer, and M. O'Hara, 1997, One Day In The Life of A Very Common Stock, *Review of Financial Studies* 10, 805.

Easley, D., N. Kiefer, M. O'Hara, and J. Paperman, 1996, Liquidity, Information, and Infrequently Traded Stocks, *Journal of Finance* 51, 1405-1436.

Fama, E., and K. French, 1997, Industry Costs of Equity, *Journal of Financial Economics* 43, 153-193.

Flannery, M., and K. Rangan, 2006, Partial Adjustment Toward Target Capital Structures, *Journal of Financial Economics* 79, 469-506.

Garvey, G., and G. Hanka, 1999, Capital Structure and Corporate Control: The Effect of Antitakeover Statutes On Firm Leverage, *Journal of Finance* 54, 519-546.

Gillan, S., and L. Starks, 2000, Corporate Governance Proposals and Shareholder Activism: The Role of Institutional Investors, *Journal of Financial Economics* 57, 275-305.

Giroud, X., and H. Mueller, 2010, Does Corporate Governance Matter In Competitive Industries?, *Journal of Financial Economics*.

Gompers, P., M. Ishii, and A. Metrick, 2003, Corporate Governance and Equity Returns, *The Quarterly Journal of Economics* 118, 107-155.

Graham, J., C. Harvey, and M. Puri, 2008, Managerial Attitudes and Corporate Actions, Working Paper.

Graham, J. R., 1999, Do Personal Taxes Affect Corporate Financing Decisions?, *Journal of Public Economics* 73, 147-186.

Graham, J. R., and L. F. Mills, 2008, Using Tax Return Data To Simulate Corporate Marginal Tax Rates, *Journal of Accounting and Economics* 46, 366-388.

Harford, J., S. Klasa, and N. Walcott, 2009, Do Firms Have Leverage Targets? Evidence From Acquisitions, *Journal of Financial Economics* 93, 1-14.

Harris, M., and A. Raviv, 1991, The Theory of Capital Structure, *Journal of Finance* 46, 297-355.

Helliwell, J., 2003, How's Life? Combining Individual and National Variables To Explain Subjective Well-Being, *Economic Modeling* 20, 331-360.

Hovakimian, A., T. Opler, and S. Titman, 2001, The Debt-Equity Choice, *Journal of Financial and Quantitative Analysis* 36, 1-24.

Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009, Opaque Financial Reports, R2, and Crash Risk, *Journal of Financial Economics* 94, 67-86.

Irvine, P., 2003, The Incremental Impact of Analyst Initiation of Coverage, *Journal of Corporate Finance* 9, 431-451.

Jensen, M., 1986, Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers, *The American Economic Review* 76, 323-329.

Jensen, M., and W. Meckling, 1976, Theory of The Firm: Managerial Behavior, Agency Costs and Ownership Structure, *Journal of Financial Economics* 3, 305-360.

Kang, Q., Q. Liu, and R. Qi, 2010, The Sarbanes-Oxley Act and Corporate Investment: A Structural Assessment, *Journal of Financial Economics*.

Karan, V., and M. Sharifi, 2006, Will SOX Kill The Deal?, *Journal of Corporate Accounting & Finance* 17, 37-44.

Kayhan, A., and S. Titman, 2007, Firms' Histories and Their Capital Structures, *Journal of Financial Economics* 83, 1-32.

Kovenock, D., and G. Phillips, 1995, Capital Structure and Product-Market Rivalry: How Do We Reconcile Theory and Evidence?, *The American Economic Review*, 403-408.

Leary, M., and M. Roberts, 2005, Do Firms Rebalance Their Capital Structures?, *Journal of Finance* 60, 2575-2619.

Linck, J., J. Netter, and T. Yang, 2009, The Effects and Unintended Consequences of The Sarbanes-Oxley Act On The Supply and Demand For Directors, *Review of Financial Studies* 22, 3287.

Maksimovic, V., 1988, Capital Structure In Repeated Oligopolies, *The RAND Journal of Economics* 19, 389-407.

Miller, M. H., 1977, Debt and Taxes, *Journal of Finance*, 261-275.

Morellec, E., 2004, Can Managerial Discretion Explain Observed Leverage Ratios?, *Review of Financial Studies* 17, 257.

Myers, S., 1984, The Capital Structure Puzzle, *Journal of Finance* 39, 575-592.

Myers, S., and N. Majluf, 1984, Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have, *Journal of Financial Economics* 13, 187-221.

Nalebuff, B., and J. Stiglitz, 1983, Information, Competition, and Markets, *The American Economic Review* 73, 278-283.

Novaes, W., 2003. Capital Structure Choice When Managers Are In Control: Entrenchment Versus Efficiency, *Journal of Business* 76, 49-81.

Piotroski, J., and S. Srinivasan, 2008, Regulation and Bonding: The Sarbanes Oxley Act and The Flow of International Listings, *Journal of Accounting Research* 46, 383-425.

Rajan, R., and L. Zingales, 1995, What Do We Know About Capital Structure? Some Evidence From International Data, *Journal of Finance* 50, 1421-1460.

Shleifer, A., and R. Vishny, 1997, A Survey of Corporate Governance, *Journal of Finance* 52, 737-783.

Smith, M. P., 1996, Shareholder Activism By Institutional Investors: Evidence From Calpers, *Journal of Finance*, 227-252.

Sullivan, T., 1974, Market Power, Profitability and Financial Leverage, *Journal of Finance* 29, 1407-1414.

Tirole, J., 1988, The Theory of Industrial Organization(The MIT Press).

Titman, S., 1984, The Effect of Capital Structure On A Firm's Liquidation Decision, *Journal of Financial Economics* 13, 137-151.

Titman, S., and R. Wessels, 1988, The Determinants of Capital Structure Choice, *Journal of Finance* 43, 1-19.

WANG, X., 2010, Increased Disclosure Requirements and Corporate Governance Decisions: Evidence From Chief Financial Officers In The Pre-And Post-Sarbanes Oxley Periods, *Journal of Accounting Research.*

Welch, I., 2004, Capital Structure and Stock Returns, *Journal of Political Economy* 112, 106-131.

Zhang, I., 2007, Economic Consequences of The Sarbanes-Oxley Act of 2002, *Journal of Accounting and Economics* 44, 74-115.

Zhang, X. F., 2006, Information Uncertainty and Stock Returns, *Journal of Finance* 61, 105-137.

Zwiebel, J., 1996, Dynamic Capital Structure Under Managerial Entrenchment, *The American Economic Review* 86, 1197-1215.

Table 2.1: Descriptive Statistics

Table 2.1 shows the descriptive statistics of variables of interests. Leverage is market leverage defined as Book debt / (total assets − book equity + market equity), calculated as [Data6 − book equity] / [Data6 − [Data6 − [data181 + data10] + data35 + data79] + [Data25 × data199]] . Leverage(b) is book leverage defined as Book debt / total assets, calculated as Book Debt / Data6. Analysts, Opacity, IVOL PIN, AdjPIN, and SVIVol are firm information asymmetry measures. Analysts is the number of analysts who cover the specific firm. Information Opacity is the moving sum of previous three-year's absolute value of discretional accruals based on Jones' model. And IVOL is the idiosyncratic volatility of the stock. PIN is uninformed market participants' perceived probability of the informed trades. AdjPIN is the information asymmetry portion of PIN. SVIVol is the information acquisition volatility measure. HHI is the Herfindahl-Hirschman index, a product market concentration index well-grounded in industrial organization theory (See Tirole(1998)), and it is used as a measure that proxy for the difficulty that managers could find a comparable job if fired. PWR is defined as the earnings divided by sales (Data13 / Data12), a proxy for firms' market power. INST_hld, GX, and EX are corporate governance measures. INST_hld is the percentage of stocks held by all 13F-filling institutional investors. GX is the governance index. EX is the entrenchment index. MB, PPE, EBITD, R&D, DR&D, SE, and SIZE are classical capital structure control variables. MB is market to book ratio. PPE is net property, plant, and equipment / total sales. It is a proxy for asset tangibility. EBITD is defined as earnings before interest, tax, and depreciation / total asset. It is a proxy for firm profitability. R&D is R&D / sales and DR&D is a dummy variable that equals one if there is a value for R&D, 0 otherwise. SE is selling expenses/sales ratio. SIZE is the natural log of sales. The variables with "_d" are dummy variables for the repressors High and Low levels.

Variables	Mean	S.D.	Min	25%	Median	75%	Max
Leverage	0.31	0.24	0.01	0.11	0.26	0.47	0.93
Leverage(b)	0.42	0.23	0.04	0.23	0.41	0.59	0.95
SOX	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Analysts	7.83	7.63	1.00	2.00	5.00	10.00	67.00
Analysts_d	0.46	0.50	0.00	0.00	0.00	1.00	1.00
Opacity	0.19	0.14	0.00	0.08	0.14	0.24	1.09
Opacity_d	0.50	0.50	0.00	0.00	0.00	1.00	1.00
IVOL	0.04	0.03	0.01	0.03	0.04	0.06	0.14
IVOL_d	0.51	0.50	0.00	0.00	1.00	1.00	1.00
PIN	0.20	0.11	0.03	0.12	0.17	0.24	1.00
PIN_d	0.49	0.50	0.00	0.00	0.00	1.00	1.00
AdjPIN	0.16	0.08	0.00	0.10	0.14	0.19	0.85
AdjPIN_d	0.49	0.50	0.00	0.00	0.00	1.00	1.00
SVIVol	8.92	8.78	0.00	2.16	7.07	12.24	46.04
SVIVol_d	0.51	0.50	0.00	0.00	1.00	1.00	1.00
HHI	0.14	0.13	0.02	0.06	0.09	0.17	1.00
HHI_d	0.45	0.50	0.00	0.00	0.00	1.00	1.00
PWR	−0.59	3.39	−27.19	0.00	0.09	0.16	0.64
PWR_d	0.50	0.50	0.00	0.00	0.50	1.00	1.00
INST_hld	0.42	0.30	0.00	0.14	0.39	0.67	1.00
INST_d	0.50	0.50	0.00	0.00	1.00	1.00	1.00
GX	8.93	2.65	1.00	7.00	9.00	11.00	18.00
GX_d	0.55	0.50	0.00	0.00	1.00	1.00	1.00
EX	2.30	1.30	0.00	1.00	2.00	3.00	6.00
EX_d	0.46	0.50	0.00	0.00	0.00	1.00	1.00
MB	2.22	2.18	0.49	1.05	1.48	2.43	14.23
PPE	0.25	0.22	0.00	0.07	0.17	0.35	0.90
EBITD	0.03	0.25	−1.16	−0.01	0.10	0.16	0.39
R&D	0.35	1.58	0.00	0.00	0.01	0.11	12.98
DR&D	0.32	0.47	0.00	0.00	0.00	1.00	1.00
SE	0.92	1.95	0.08	0.26	0.44	0.78	15.74
SIZE	5.12	2.32	−1.08	3.59	5.12	6.71	10.50

Table 2.2: Long-run capital structure Changes

Table 2.2 shows five-year average capital structure of public firms in the United States from 1982 to 2006. The data excludes utility (SIC code 4900–4999) and financial industry (SIC code 6000–6999). Market leverage is calculated as "Book debt / (total assets − book equity + market equity)", where book debt is "Total assets − book equity", book equity is "Total assets − [total liabilities + preferred stock] + deferred taxes + conv. Debt", market equity is "Common shares outstanding × price". Book leverage is calculated as "Book debt / total assets". All the values are from Compustat. Market leverage = [Data6 − book equity] / [Data6 − [Data6 − [data181 + data10] + data35 + data79] + [Data25 × data199]], and Book Leverage = Book Debt / Data6. Different research has chosen either 2002 (see, e.g. Linck, Netter, and Yang (2008)) or 2003 (see e.g. Kang, Liu, and Qi (2010)) as the year of SOX in effect. Considering the moderate speed to adjust toward target leverage, I choose 2003 as the year of SOX in effect in my study. My result is robust when choosing 2002 or 2004 as the split point.

Panel a. Treat 2003 as the year of SOX in effect

Period	*Market Leverage*	*Changes*	*Tstat*	*Book Leverage*	*Changes*	*Tstat*
1983−1986	0.351			0.444		
1987−1990	0.385	0.034	12.88	0.465	0.021	8.54
1991−1994	0.331	−0.054	−20.78	0.443	−0.022	−8.94
1995−1998	0.305	−0.026	−10.97	0.437	−0.006	−2.66
1999−2002	0.346	0.043	17.58	0.429	−0.008	−3.55
2003−2006	0.26	−0.087	−33.64	0.405	−0.024	−9.61

Panel b. Treat 2002 as the year of SOX in effect

Period	Market Leverage	Changes	Tstat	Book Leverage	Changes	Tstat
1982−1985	0.366			0.446		
1986−1989	0.367	0.001	0.23	0.459	0.013	5.29
1990−1993	0.353	−0.014	−5.12	0.45	−0.009	−3.65
1994−1997	0.301	−0.052	−21.28	0.436	−0.014	−5.91
1998−2001	0.34	0.039	16.51	0.434	−0.002	−0.79
2002−2005	0.293	−0.048	−18.36	0.412	−0.022	−8.97

Table 2.3: Capital Structure changes by industry around the passage of SOX

Table 2.3 shows firms' capital structure changes from preSOX period to postSOX period by industry. The first 6 columns of numbers are median market leverage, book leverage, and leverage changes. The second 6 column of numbers are mean market leverage, book leverage, and mean leverage changes. The last three columns are the number of observations in each industry and the changes of the numbers. The Rows are sorted by industry median leverage changes. The industry classification is based on Fama and French (1997) 48 industries. Financial industries and utility industries are dropped. Firm's book leverage dropped post SOX in 32 of 40 industries (or 80% industries). Firms' market leverage dropped post SOX in all 40 industries.

Code	*Industry*	*Market leverage(mean)*			*Book leverage(mean)*			*Market leverage(med)*			*Book leverage(med)*			*Obs.*		
		Pre	*Post*	*Diff*	*Pre*	*Post*	*Diff*	*PreSOX*	*Post*	*Diff*	*Pre*	*Post*	*Diff*	*Pre*	*Post*	*Diff*
28	*Mining*	0.318	0.090	−0.228	0.381	0.233	−0.148	0.351	0.132	−0.219	0.395	0.254	−0.142	112	139	27
16	*Textiles*	0.687	0.466	−0.221	0.578	0.463	−0.115	0.650	0.496	−0.154	0.572	0.448	−0.124	99	56	−43
1	*Agriculture*	0.491	0.298	−0.194	0.558	0.456	−0.102	0.504	0.344	−0.160	0.544	0.441	−0.103	81	65	−16
23	*Automobiles and Trucks*	0.567	0.394	−0.173	0.624	0.539	−0.085	0.536	0.439	−0.097	0.591	0.539	−0.052	295	238	−57
27	*Precious Metals*	0.234	0.100	−0.134	0.288	0.212	−0.076	0.294	0.126	−0.168	0.305	0.253	−0.052	162	179	17
17	*Construction Materials*	0.451	0.325	−0.127	0.515	0.439	−0.076	0.459	0.317	−0.142	0.496	0.431	−0.066	395	277	−118
11	*Healthcare*	0.395	0.232	−0.163	0.492	0.420	−0.073	0.414	0.270	−0.144	0.478	0.417	−0.061	326	300	−26
9	*Consumer Goods*	0.385	0.282	−0.103	0.515	0.444	−0.071	0.417	0.333	−0.083	0.515	0.468	−0.047	336	245	−91
12	*Medical Equipment*	0.140	0.091	−0.048	0.309	0.238	−0.071	0.209	0.135	−0.074	0.344	0.279	−0.065	760	687	−73
10	*Apparel*	0.351	0.229	−0.122	0.415	0.350	−0.065	0.409	0.283	−0.125	0.440	0.381	−0.059	328	272	−56
19	*Steel Works Etc*	0.559	0.368	−0.191	0.545	0.484	−0.061	0.562	0.395	−0.167	0.546	0.500	−0.046	339	244	−95
6	*Recreation*	0.383	0.250	−0.134	0.450	0.389	−0.061	0.409	0.310	−0.098	0.442	0.415	−0.026	211	146	−65
30	*Petroleum and Natural Gas*	0.360	0.261	−0.099	0.468	0.410	−0.058	0.376	0.274	−0.102	0.448	0.411	−0.037	785	784	−1
3	*Candy & Soda*	0.458	0.408	−0.051	0.569	0.520	−0.050	0.438	0.382	−0.056	0.558	0.512	−0.045	55	49	−6
8	*Printing and Publishing*	0.318	0.290	−0.028	0.528	0.480	−0.049	0.351	0.320	−0.031	0.531	0.502	−0.029	176	151	−25
43	*Restaurants, Hotels, Motels*	0.465	0.304	−0.160	0.486	0.437	−0.049	0.482	0.334	−0.148	0.500	0.465	−0.036	425	315	−110
41	*Wholesale*	0.532	0.400	−0.132	0.583	0.535	−0.048	0.527	0.417	−0.110	0.562	0.526	−0.036	870	626	−244
7	*Entertainment*	0.514	0.330	−0.183	0.568	0.520	−0.048	0.472	0.352	−0.120	0.541	0.511	−0.030	313	245	−68
42	*Retail*	0.410	0.307	−0.104	0.509	0.466	−0.043	0.436	0.356	−0.080	0.508	0.483	−0.025	1201	921	−280
15	*Rubber and Plastic Products*	0.566	0.389	−0.178	0.581	0.540	−0.041	0.541	0.423	−0.118	0.568	0.529	−0.038	205	123	−82
20	*Fabricated Products*	0.568	0.426	−0.142	0.542	0.504	−0.037	0.556	0.432	−0.124	0.528	0.473	−0.055	88	47	−41
21	*Machinery*	0.345	0.255	−0.090	0.449	0.420	−0.029	0.381	0.299	−0.082	0.461	0.434	−0.028	728	570	−158
24	*Aircraft*	0.444	0.379	−0.065	0.572	0.549	−0.023	0.460	0.377	−0.083	0.557	0.532	−0.026	76	74	−2
2	*Food Products*	0.372	0.313	−0.059	0.532	0.514	−0.018	0.403	0.332	−0.071	0.521	0.487	−0.034	344	261	−83
36	*Electronic Equipment*	0.157	0.143	−0.014	0.263	0.247	−0.016	0.237	0.192	−0.045	0.320	0.301	−0.018	1485	1325	−160
18	*Construction*	0.597	0.439	−0.158	0.596	0.580	−0.015	0.576	0.450	−0.126	0.580	0.563	−0.017	281	214	−67
14	*Chemicals*	0.450	0.354	−0.096	0.554	0.543	−0.011	0.451	0.361	−0.089	0.520	0.516	−0.004	382	369	−13
5	*Tobacco Products*	0.402	0.312	−0.090	0.625	0.616	−0.009	0.390	0.299	−0.091	0.584	0.683	0.099	22	30	8
33	*Personal Services*	0.487	0.326	−0.161	0.506	0.500	−0.007	0.479	0.370	−0.109	0.513	0.521	0.007	241	199	−42
22	*Electrical Equipment*	0.316	0.247	−0.069	0.410	0.405	−0.005	0.343	0.285	−0.058	0.419	0.412	−0.007	307	283	−24
29	*Coal*	0.593	0.385	−0.208	0.689	0.685	−0.004	0.528	0.387	−0.141	0.584	0.668	0.084	17	44	27
37	*Measuring & Control Equipment*	0.155	0.144	−0.011	0.251	0.249	−0.002	0.201	0.173	−0.028	0.293	0.300	0.007	499	458	−41
35	*Computers*	0.198	0.168	−0.030	0.329	0.334	0.005	0.255	0.212	−0.043	0.375	0.379	0.003	1140	796	−344
13	*Pharmaceutical Products*	0.075	0.082	0.006	0.234	0.241	0.007	0.135	0.114	−0.020	0.297	0.294	−0.003	1305	1367	62
25	*Shipbuilding, Railroad Equipment*	0.425	0.319	−0.106	0.504	0.515	0.010	0.430	0.324	−0.106	0.500	0.493	−0.008	38	41	3
34	*Business Services*	0.193	0.173	−0.019	0.323	0.354	0.031	0.266	0.225	−0.042	0.371	0.390	0.019	3520	2434	−1086
38	*Business Supplies*	0.493	0.467	−0.026	0.555	0.590	0.035	0.503	0.477	−0.025	0.545	0.575	0.030	298	215	−83
4	*Beer & Liquor*	0.331	0.278	−0.052	0.418	0.476	0.058	0.355	0.309	−0.046	0.443	0.471	0.028	95	74	−21
26	*Defense*	0.392	0.344	−0.048	0.454	0.543	0.089	0.376	0.317	−0.059	0.495	0.486	−0.008	28	42	14
39	*Shipping Containers*	0.561	0.514	−0.046	0.605	0.700	0.096	0.558	0.542	−0.017	0.616	0.691	0.075	67	53	−14
	Total	0.297	0.213	−0.084	0.417	0.386	−0.031	0.346	0.260	−0.086	0.429	0.405	−0.024	18435	14958	−3477

Table 2.4: Correlation Table

Table 2.4 shows Pearson (above the diagonal) and Spearman (below the diagonal) correlations among variable of interests. Leverage is market leverage defined as Book debt / (total assets−book equity + market equity), calculated as [Data6 − book equity] / [Data6 − [Data6 − [data181 + data10] + data35 + data79] + [Data25 × data199]] . Leverage(b) is book leverage defined as Book debt / total assets, calculated as Book Debt/Data6. Analysts, Opacity, IVOL PIN, AdjPIN, and SVIVol are firm information asymmetry measures. Analysts is the number of analysts who cover the specific firm. Information Opacity is the moving sum of previous three-year's absolute value of discretional accruals based on Jones' model. And IVOL is the idiosyncratic volatility of the stock. PIN is uninformed market participants' perceived probability of the informed trades. AdjPIN is the information asymmetry portion of PIN. SVIVol is the information acquisition volatility measure. HHI is the Herfindahl-Hirschman index, a product market concentration index well-grounded in industrial organization theory (See Tirole(1998)), and it is used as a measure that proxy for the difficulty that managers could find a comparable job if fired. PWR is defined as the earnings divided by sales (Data13/Data12), a proxy for firms' market power. INST_hld, GX, and EX are corporate governance measures. INST_hld is the percentage of stocks held by all 13F-filling institutional investors. GX is the governance index. EX is the entrenchment index. MB, PPE, EBITD, R&D, DR&D, SE, and SIZE are classical capital structure control variables. MB is market to book ratio. PPE is net property, plant, and equipment / total sales. It is a proxy for asset tangibility. EBITD is defined as earnings before interest, tax, and depreciation / total asset. It is a proxy for firm profitability. R&D is R&D/sales and DR&D is a dummy variable that equals one if there is a value for R&D, 0 otherwise. SE is selling expenses/sales ratio. SIZE is the natural log of sales. The variables with "_d" are dummy variables for the repressors High and Low levels.

Panel a. Pearson/ Spearman correlations among leverage, information asymmetry measures, and other regression variables

	Leverage	*Lev. (b)*	*SOX*	*PIN_d*	*AdjPIN_d*	*Analysts*	*Opaycity*	*IVOL_d*	*SVIVold*	*MB*	*PPE*	*EBITD*	*R&D*	*DR&D*	*SE*	*SIZE*
Leverage		0.720	−0.139	0.198	0.232	−0.257	−0.004	0.096	−0.066	−0.798	0.127	−0.507	−0.219	0.120	0.328	0.075
Leverage(b)	0.714		−0.099	−0.003	0.003	0.003	−0.045	−0.021	−0.065	−0.214	0.053	−0.188	−0.066	0.019	0.395	0.320
SOX	−0.149	−0.096		−0.022	−0.010	0.009	0.025	0.094	0.003	0.118	−0.083	−0.049	0.004	−0.003	−0.013	0.066
PIN_d	0.215	0	−0.022		0.707	−0.568	0.110	0.227	0.005	−0.299	0.007	−0.210	−0.152	0.130	−0.09	−0.527
AdjPIN_d	0.247	0.009	−0.010	0.707		−0.590	0.127	0.205	0.028	−0.339	−0.001	−0.223	−0.152	0.147	−0.082	−0.540
Analysts	−0.269	−0.033	−0.001	−0.471	−0.504		−0.107	−0.162	0.020	0.374	0.117	0.257	0.091	−0.070	0.168	0.646
Opacity	0.001	−0.048	0.025	0.110	0.127	−0.092		0.207	0.014	−0.034	−0.220	−0.124	−0.016	0.039	−0.134	−0.171
IVOL_d	0.141	−0.020	0.094	0.227	0.205	−0.124	0.207		0.044	−0.157	−0.084	−0.301	0.016	0.042	−0.007	−0.253
SVIVol_d	−0.063	−0.066	0.003	0.005	0.028	0.019	0.014	0.044		0.042	0.042	0.057	−0.082	0.071	−0.033	−0.078
MB	−0.604	−0.205	0.004	−0.189	−0.229	0.283	0.019	−0.05	0.039		−0.136	0.582	0.246	−0.149	−0.156	0.164
PPE	0.117	0.036	−0.07	0.013	0.003	0.155	−0.191	−0.068	0.066	−0.134		0.164	−0.249	0.112	0.217	−0.031
EBITD	−0.356	−0.135	−0.030	−0.177	−0.188	0.205	−0.121	−0.284	0.067	0.284	0.128		−0.037	−0.018	−0.249	0.124
R&D	−0.086	−0.033	−0.005	−0.004	−0.002	−0.024	0.058	0.095	−0.027	0.205	−0.064	−0.478		−0.657	0.117	0.058
DR&D	0.122	0.026	−0.003	0.130	0.147	−0.070	0.039	0.042	0.071	−0.131	0.187	0.007	−0.071		0.101	−0.161
SE	0.130	0.167	−0.001	0.018	−0.002	0.041	0.001	0.073	−0.026	0.002	0.195	−0.374	0.492	0.114		0.002
SIZE	0.070	0.310	0.062	−0.494	−0.497	0.592	−0.179	−0.272	−0.076	0.029	−0.075	0.228	−0.207	−0.143	−0.251	

Panel b. Pearson/ Spearman correlations among leverage, corporate governance measures, and other regression variables

	Leverage	*Lev.(b)*	*HHI*	*HHI_d*	*INST_d*	*INST_hld*	*GX*	*EX*	*MB*	*PPE*	*EBITD*	*R&D*	*DR&D*	*SE*	*SIZE*
Leverage		0.791	0.307	0.273	−0.027	−0.063	0.202	0.158	-0.744	0.239	-0.253	-0.377	0.198	0.329	0.32
Leverage(b)	0.761		0.312	0.262	0.013	-0.051	0.218	0.134	-0.236	0.221	0.026	-0.302	0.115	0.356	0.471
HHI	0.195	0.215		0.864	0.059	0.045	0.125	0.072	-0.145	0.118	0.097	-0.404	0.098	-0.111	0.259
HHI_d	0.237	0.256	0.601		0.065	0.063	0.11	0.065	-0.146	0.126	0.067	-0.394	0.121	-0.092	0.216
INST_d	-0.057	0.006	0.036	0.065		0.589	0.104	0.121	0.055	0.03	0.153	-0.038	0.021	-0.005	0.204
INST_Hld	-0.001	-0.002	0.004	0.015	0.063		0.085	0.149	0.05	-0.046	0.102	-0.039	0	0.007	0.156
GX	0.172	0.206	0.091	0.113	0.102	0.016		0.762	-0.08	0.112	0.067	-0.075	-0.005	0.085	0.242
EX	0.135	0.127	0.033	0.065	0.122	0.026	0.755		-0.104	0.09	0.024	-0.06	-0.004	0.053	0.088
MB	-0.552	-0.218	-0.125	-0.181	-0.014	-0.011	-0.086	-0.111		-0.123	0.477	0.249	-0.184	-0.195	-0.002
PPE	0.206	0.171	0.027	0.043	0.019	-0.014	0.083	0.081	-0.14		0.296	-0.365	0.096	0.076	0.213
EBITD	-0.138	0.066	0.097	0.116	0.199	0.011	0.074	0.036	0.204	0.22		-0.251	0.046	-0.302	0.301
R&D	-0.136	-0.154	-0.1	-0.133	-0.067	-0.007	-0.052	-0.018	0.084	-0.095	-0.435		-0.64	0.193	-0.283
DR&D	0.186	0.112	0.038	0.121	0.021	-0.007	-0.006	-0.003	-0.144	0.156	0.086	-0.104		0.049	0.044
SE	0.055	0.028	-0.094	-0.117	-0.049	-0.009	-0.012	0.012	-0.015	0.039	-0.407	0.794	-0.004		0.06
SIZE	0.274	0.439	0.203	0.214	0.242	0.021	0.217	0.068	-0.053	0.152	0.432	-0.349	0.049	-0.273	

Table 2.5: Leverage before and after the SOX Act

Table 2.5 shows average capital structure and leverage changes of public firms in the United States from before SOX to after SOX. The sample period is from 1999 to 2006. The data excludes utility (SIC code 4900–4999) and financial industry (SIC code 6000-6999). Market leverage is calculated as "Book debt / (total assets − book equity + market equity)", where book debt is "Total assets − book equity", book equity is "Total assets − [total liabilities + preferred stock] + deferred taxes + conv. Debt", market equity is "Common shares outstanding × price". All the values are from Compustat. I choose 2003 as the year that split the sample period in this table. My results still hold if choosing 2002 as the year to split. Under the H-L and Pre-Post values are the t-stat for the two groups, the differences are all both statistically and economically significant. Under the mean values are the numbers of observations.

Panel a. Firms with different level of Information Asymmetry

Leverage	PIN(H)	PIN(L)	Combined	L-H
Pre-SOX	0.488	0.373	0.429	−0.115
	2664	2813	5477	−17.562
Post-SOX	0.362	0.318	0.339	−0.044
	1224	1224	2557	−5.352
Combined	0.449	0.356	0.4	−0.093
	3888	4146	8034	−17.633
Post-Pre	−0.126	−0.055	−0.09	
	−14.512	−7.675	−15.717	

Panel b. Firms within industries of different Competition

Leverage	HHI (L)	HHI(H)	Combined	L-H
Pre-SOX	0.279	0.433	0.346	−0.155
	10330	7989	18319	−41.749
Post-SOX	0.218	0.317	0.26	−0.099
	7846	7057	14903	−30.351
Combined	0.253	0.379	0.31	−0.127
	18176	15046	33222	−49.417
Post-Pre	−0.06	−0.116	−0.086	
	−18.101	−29.942	−30.695	

Table 2.6: Regressions of Leverage on SOX Dummy and control variables

Table 2.6 presents the regression results of market leverage and book leverage changes on a SOX dummy variable and control variables. Results are presented for regressions with two−way clustered standard errors by firm and year and regressions with firm fixed effects and standard errors clustered by firm. Market leverage is defined as "Book debt / (total assets−book equity + market equity)", calculated as [Data6 − book equity] / [Data6 − [Data6 − [data181 + data10] + data35 + data79] + [Data25 × data199]]. book leverage is defined as Book debt / total assets, calculated as Book Debt/Data6. MB, PPE, EBITD, R&D, DR&D, SE, and SIZE are classical capital structure control variables. MB is market to book ratio. PPE is net property, plant, and equipment / total sales. It is a proxy for asset tangibility. EBITD is defined as earnings before interest, tax, and depreciation / total asset. It is a proxy for firm profitability. R&D is R&D/sales and DR&D is a dummy variable that equals one if there is a value for R&D, 0 otherwise. SE is selling expenses/sales ratio. SIZE is the natural log of sales. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

		Market Leverage		Book Leverage	
	Hypothesis	(1)	(2)	(3)	(4)
SOX	−	−0.079***	−0.045***	−0.038***	−0.006***
		(−6.84)	(−31.47)	(−3.84)	(−4.09)
MB		−0.111***	−0.060***	−0.029***	0.000
		(−12.62)	(−67.05)	(−9.91)	(−0.07)
PPE		0.025***	0.041***	0.022***	0.054***
		(8.37)	(18.06)	(6.78)	(23.26)
EBITD		−0.049***	−0.059***	−0.055***	−0.054***
		(−12.11)	(−44.92)	(−11.19)	(−40.61)
R&D		−0.032***	−0.019***	−0.043***	−0.032***
		(−8.60)	(−13.42)	(−10.39)	(−21.24)
DR&D		0.064***	0.005	0.046***	−0.002
		(9.51)	(1.14)	(8.70)	(−0.50)
SE		0.031***	0.027***	0.048***	0.039***
		(6.69)	(20.76)	(11.28)	(29.15)
SIZE		0.062***	0.072***	0.097***	0.078***
		(18.97)	(21.55)	(28.33)	(22.68)
Constant		0.326***	0.332***	0.428***	0.431***
		(46.48)	(201.32)	(44.25)	(253.38)
Industry Dummy		Yes	Yes	Yes	Yes
Firm Fixed Effects			Yes		Yes
Observations		32,584	32,584	32,584	32,584
R-squared		0.38	0.38	0.22	0.22

Table 2.7: Regression of Market leverage on different information asymmetry measures

Table 2.7 presents the regression results of market leverage on SOX, information asymmetry measures and control variables. Results are presented for regressions with firm fixed effects. Analysts, Opacity, IVOL PIN, AdjPIN, and SVIVol are firm information asymmetry measures. Analysts is the number of analyst coverage. Opacity is the moving sum of previous three−year's absolute value of discretional accruals based on Jones' model. IVOL is the idiosyncratic volatility of the stock. PIN is uninformed market participants' perceived probability of the informed trades. AdjPIN is the information asymmetry portion of PIN. SVIVol is the Search volume Index Volatility. The variables with "_d" are dummy variables for the repressors High and Low levels. Tstats are in the parenthesis. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)
	Hypothesis	Mkl	Mkl	Mkl	Mkl	Mkl	Mkl
SOX	−	−0.029***	−0.051***	−0.040***	−0.045***	−0.045***	−0.062***
		(−13.79)	(−22.70)	(−18.25)	(−13.18)	(−13.02)	(−23.61)
Analysts_d × SOX	+	0.024***					
		(8.13)					
Analysts_d		−0.037***					
		(−13.79)					
Opacity_d × SOX	−		−0.011***				
			(−3.64)				
Opacity_d			0.004*				
			(1.70)				
IVOL_d × SOX	−			−0.012***			
				(−4.39)			
IVOL_d				0.028***			
				(12.52)			
PIN_d × SOX	−				−0.020***		
					(−2.80)		
PIN_d					0.019***		
					(7.69)		
AdjPIN_d × SOX	−					−0.024***	
						(−2.92)	
AdjPIN_d						0.021***	
						(7.87)	
SVIVol_d × SOX	+						0.010**
							(2.51)
SVIVol_d							−0.045***
							(−4.29)
MB		−0.050***	−0.071***	−0.059***	−0.093***	−0.092***	−0.053***
		(−49.48)	(−50.01)	(−66.37)	(−31.84)	(−31.51)	(−38.43)
PPE		0.042***	0.039***	0.041***	0.036***	0.036***	0.039***
		(13.70)	(12.94)	(18.04)	(7.43)	(7.45)	(10.25)
EBITD		−0.069***	−0.068***	−0.061***	−0.095***	−0.095***	−0.060***
		(−38.11)	(−35.22)	(−45.59)	(−25.87)	(−25.87)	(−22.59)
R&D		−0.024***	−0.025***	−0.020***	−0.018***	−0.018***	−0.032***
		(−12.24)	(−11.48)	(−13.57)	(−4.09)	(−4.11)	(−12.39)
DR&D		0.00	0.01	0.01	(0.01)	(0.01)	0.01
		(0.72)	(1.44)	(1.26)	(−0.62)	(−0.63)	(1.33)
SE		0.029***	0.030***	0.028***	0.039***	0.040***	0.037***
		(15.66)	(16.13)	(21.30)	(10.81)	(10.99)	(15.89)
SIZE		0.057***	0.062***	0.076***	0.128***	0.128***	0.048***
		(11.18)	(12.33)	(22.47)	(14.88)	(14.84)	(8.22)
Constant		0.279***	0.337***	0.312***	0.335***	0.336***	0.325***
		(99.35)	(136.82)	(145.15)	(54.02)	(54.38)	(52.14)
Firm Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Observations		20142.00	21480.00	32584.00	7972.00	7972.00	11629.00
R-squared		0.29	0.28	0.26	0.27	0.27	0.29

Table 2.8: Regressions of Leverage Changes on Different governance index

Table 2.8 presents the regression results of market leverage on SOX, management entrenchment measures (proxies) and control variables. Results are presented for regressions with firm fixed effects. GX, and EX are corporate governance measures. GX is the governance index. EX is the entrenchment index. The variables with "*_d*" are dummy variables for the repressors High and Low levels. Tstats are in the parenthesis. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

		(1)	(2)	(3)	(4)
	Hypothesis	Mkl	Mkl	Mkl	Mkl
SOX	−	−0.037***	−0.022***	−0.040***	−0.035***
		(−12.42)	(−3.26)	(−14.30)	(−8.84)
GX_d × SOX	−	−0.018***			
		(−4.63)			
GX_d		0.004			
		(0.84)			
GX × SOX	−		−0.003***		
			(−3.88)		
GX			0.000		
			(−0.21)		
EX_d × SOX	−			−0.017***	
				(−4.36)	
EX_d				0.008*	
				(1.71)	
EX × SOX	−				−0.005***
					(−3.46)
EX					0.00
					(−0.10)
MB		−0.064***	−0.064***	−0.063***	−0.063***
		(−29.61)	(−29.62)	(−29.40)	(−29.46)
PPE		0.049***	0.050***	0.050***	0.050***
		(10.66)	(10.69)	(10.82)	(10.78)
EBITD		−0.092***	−0.093***	−0.093***	−0.093***
		(−22.89)	(−22.97)	(−22.94)	(−22.94)
R&D		−0.058***	−0.058***	−0.058***	−0.058***
		(−11.30)	(−11.30)	(−11.34)	(−11.32)
DR&D		0.01	0.01	0.01	0.01
		(1.21)	(1.22)	(1.23)	(1.21)
SE		0.052***	0.052***	0.052***	0.052***
		(12.52)	(12.48)	(12.57)	(12.57)
SIZE		0.066***	0.066***	0.066***	0.066***
		(8.42)	(8.42)	(8.48)	(8.50)
Constant		0.292***	0.297***	0.291***	0.295***
		(44.86)	(22.86)	(45.37)	(37.29)
Firm Fixed Effects		Yes	Yes	Yes	Yes
Observations		8514	8514	8514	8514
R-squared		0.30	0.30	0.30	0.30

Table 2.9: Regressions of Market leverage on different external governance measures

Table 2.9 presents the regression results of market leverage on SOX, management entrenchment measures (proxies) and control variables. Results are presented for regressions with firm fixed effects. HHI is the Herfindahl−Hirschmanindex, a product market concentration index, and it is used as a measure that proxy for the difficulty that managers could find a comparable job if fired. PWR is defined as earning divided by sales, and it is a proxy for firms' product market power because usually firms that are more profitable with per capita sale have stronger market power. $INST\_hld$ is institutional ownership, the percentage of stocks held by all 13F−filling institutional investors. PVT_hld is 1 minus $INST\_hld$. The variables with "$\_d$" are dummy variables for the regressors High and Low levels. Tstats are in the parenthesis. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)
	Hypothesis	Mkl	Mkl	Mkl	Mkl	Mkl	Mkl
SOX	−	−0.045***	−0.038***	−0.033***	−0.044***	−0.041***	−0.044***
		(−31.63)	(−20.30)	(−11.90)	(−22.72)	(−24.26)	(−22.43)
HHI × *SOX*	−	−0.007***					
		(−5.39)					
HHI		0.013***					
		(5.48)					
HHI_d × *SOX*	−		−0.013***				
			(−4.73)				
HHI_d			0.010***				
			(3.20)				
PWRr × *SOX*	−			−0.037***			
				(−7.62)			
PWRr				−0.066***			
				(−10.78)			
PWR_d × *SOX*	−				−0.011***		
					(−3.98)		
PWR_d					−0.027***		
					(−10.68)		
PVT_hld × *SOX*	−					−0.013***	
						(−8.92)	
PVT_hld						0.045***	
						(21.83)	
PVT_d × *SOX*	−						−0.016***
							(−5.55)
PVT_d							0.042***
							(14.90)
MB		−0.060***	−0.060***	−0.056***	−0.057***	−0.055***	−0.053***
		(−66.80)	(−66.52)	(−61.22)	(−61.94)	(−54.28)	(−52.14)
PPE		0.041***	0.041***	0.039***	0.039***	0.032***	0.034***
		(18.14)	(18.06)	(15.89)	(15.96)	(11.54)	(18.23)
EBITD		−0.059***	−0.059***	−0.045***	−0.050***	−0.055***	−0.055***
		(−45.06)	(−45.11)	(−27.78)	(−34.19)	(−32.75)	(−32.05)
R&D		−0.019***	−0.019***	−0.017***	−0.018***	−0.021***	−0.022***
		(−13.41)	(−13.37)	(−11.11)	(−11.97)	(−11.79)	(−12.50)
DR&D		0.005	0.005	0.005	0.005	−0.003	−0.002
		(1.02)	(1.00)	(1.09)	(1.08)	(−0.60)	(−0.41)
SE		0.027***	0.027***	0.025***	0.025***	0.031***	0.029***
		(20.71)	(20.64)	(17.89)	(18.54)	(18.82)	(17.62)
SIZE		0.072***	0.072***	0.076***	0.068***	0.074***	0.056***
		(21.55)	(21.50)	(20.27)	(18.43)	(16.41)	(12.72)
Constant		0.333***	0.328***	0.367***	0.347***	0.304***	0.292***
		(201.53)	(152.00)	(102.72)	(159.53)	(157.11)	(121.05)
Firm Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Observations		32584	32584	32584	32584	22965	22965
R-squared		0.30	0.30	0.26	0.26	0.29	0.27

Table 2.10: Control Groups capital structure changes around the passage of SOX

Table 2.10 panel a. presents capital structure changes from pre SOX period to post SOX period for private firms in U.S. Due to the availability of Data, the pre SOX period is defined as 2000 to 2002, and post SOX period is from 2003 to 2006. Different from public firms, private firms leverage increased post SOX. Panel b. presents the comparison of capital structure changes post SOX between U.S. pubic firms and U.K. firms. U.S. and U.K. financial markets are the most developed financial markets in the world. SOX is enforced in U.S. but not in U.K., we observe different patterns in the capital structure changes in these two markets.

Panel a. U.S. Private firms capital structure changes

Industry	Pre SOX	Post Sox
11 - Agriculture, Forestry, Fishing, and Hunting (private)	0.650	0.694
21 - Mining (private)	0.628	0.687
22 - Utilities (private)	0.634	0.667
23 - Construction (private)	0.739	0.870
31, 32, 33 - Manufacturing (private)	0.700	0.802
42 - Wholesale Trade (private)	0.777	0.772
44, 45 - Retail Trade (private)	0.745	0.826
48, 49 - Transportation and Warehousing (private)	0.831	0.791
51 - Information (private)	0.759	0.847
52 - Finance and Insurance (private)	0.790	0.821
53 - Real Estate and Rental and Leasing (private)	0.745	0.872
54 - Professional, Scientific, and Technical Services (private)	0.720	0.788
55 - Management of Companies and Enterprises (private)	0.698	0.687
56 - Administrative and Support and Waste Management and Remediation Services (private)	0.789	0.804
61 - Educational Services (private)	0.607	0.723
62 - Health Care and Social Assistance (private)	0.757	0.805
71 - Arts, Entertainment, and Recreation (private)	0.671	0.700
72 - Accommodation and Food Services (private)	0.747	0.801
81 - Other Services (except Public Administration) (private)	0.660	0.754
All industries	0.732	0.792

Panel b. U.S. and U.K. firms capital structure changes

	Pre-SOX	Post-SOX
U.S. Book Leverage	0.239	0.197
Obs.(average)	2906	2728
U.K. Book Leverage	0.447	0.452
Obs.(average)	502	688

Table 2.11: U.S. Control Groups capital structure changes

Table 2.11 presents capital structure changes from pre SOX period to post SOX period for banking industry in U.S. Since there were similar regulation terms in banking industry since late 1980s, the impacts of SOX on banking industry is much less compared to other industries.

Panel a. Banking industry Leverage Changes post SOX

Period	*Market Leverage*	*Changes*	*Tstat*	*Book Leverage*	*Changes*	*Tstat*
1999-2002	0.857			0.889		
2003-2006	0.815	-0.042	-13.44	0.884	-0.005	-1.98

Panel b. Regressions of Leverage on SOX Dummy and control variables					
		Market Leverage		Book Leverage	
	Hypothesis	(1)	(2)	(3)	(4)
SOX	-	-0.076***	-0.048***	-0.029***	-0.007***
		(-6.17)	(-40.28)	(-2.83)	(-5.66)
Bank × SOX	+	0.034***	0.012***	0.018*	0.001
		(3.44)	(3.92)	(1.80)	(0.17)
Bank		0.438***	0.041	0.441***	0.043
		(67.76)	(1.62)	(39.94)	(1.61)
MB		-0.107***	-0.054***	-0.037***	-0.003***
		(-18.54)	(-78.32)	(-15.96)	(-3.92)
EBITD		-0.029***	-0.047***	-0.034***	-0.042***
		(-7.38)	(-48.21)	(-7.25)	(-40.94)
SIZE		0.059***	0.054***	0.089***	0.064***
		(20.75)	(20.64)	(35.51)	(22.82)
Constant		0.370***	0.404***	0.428***	0.474***
		(47.58)	(110.42)	(43.89)	(122.32)
Firm Fixed Effects			Yes		Yes
Observations		42,979	42,979	42,979	42,979
R-squared		0.58	0.38	0.45	0.15

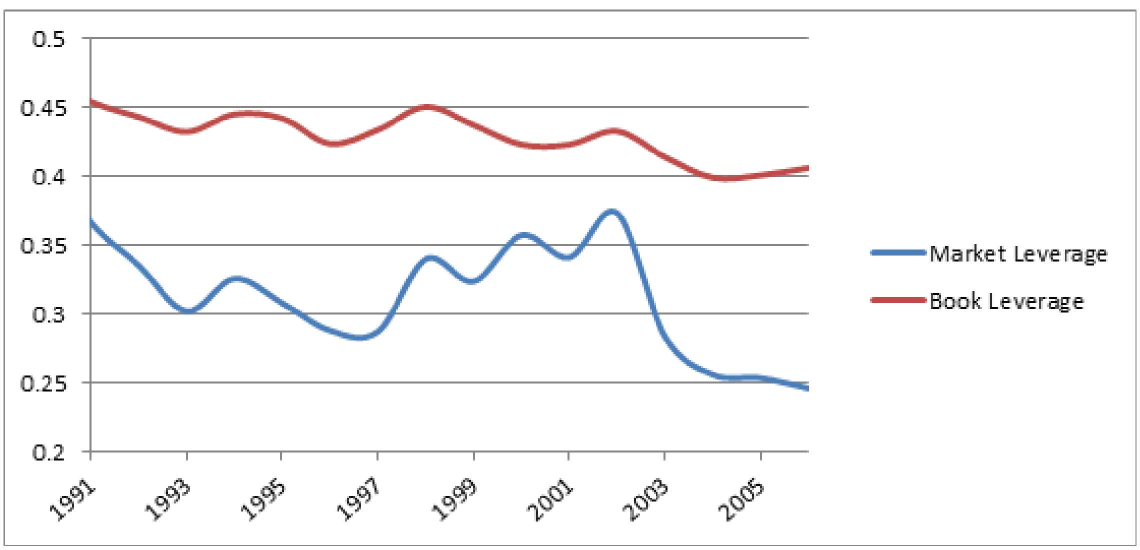

Figure 2.1: U.S. public firms' capital structure from 1982 to 2006

This figure shows the 25 years of U.S. firms capital structure trend measured both by market leverage and book leverage. There is no clear pattern that US public firms were following on their capital structure over the long period, though the market leverage is decreasing on average. However, we could still observe several sharp changes. The most recent one happened around year 2002, which coincides with the passage of the influencing law - SOX. This plummet is my interest of research. The data is from Compustat.

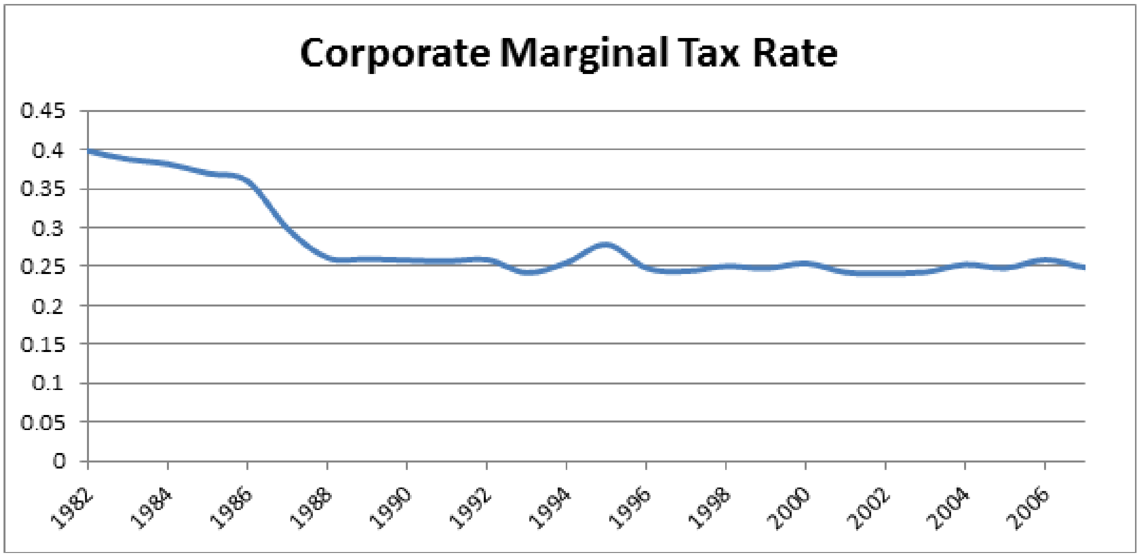

Figure 2.2: U.S. public firms' Marginal Taxes from 1982 to 2006

This figure shows the 25 years of U.S. firms' marginal tax rates. Firms' marginal tax rates did not change much in the 10 years centered at the passage of SOX. For the calculation of the marginal tax rates, please refer to Graham and Mills (2008).

Figure 2.3: Dow Jones Industrial Average between 1997 and 2006

This figure shows the Dow Jones Industry Average index between 1997 and 2006. The Dow Jones Industrial Average between 1998 and 2005 is a "v" shape. However, the index is higher before the passage of SOX than after the passage of SOX most of the time. If market timing is the dominant determinant in capital structure, managers would use more equity before the passage of SOX than after the passage of SOX, which implies that the leverage should be higher after the passage of SOX. At the same time, we could not make forecasts on the leverage adjustments' difference between firms with high information asymmetry, firms in concentrated industries, firms with strong product power and their counterparts if we solely rely on market timing theory.

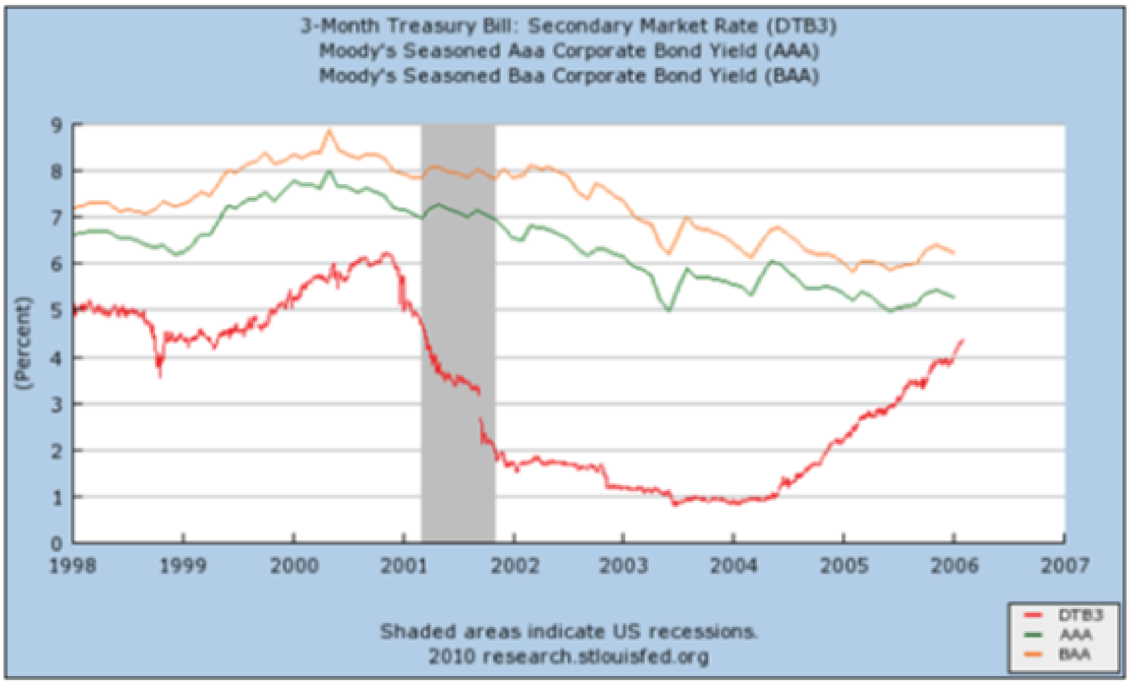

Figure 2.4: 3-Month T-Bill, AAA bond, and BAA bond yield between 1998 and 2006

This figure shows the interest rate for 3-month T-Bill, AAA bond, and BAA bond between 1998 and 2006. The interest rate after SOX is even lower than before SOX. The yield of the 3-month Treasury bill, AAA bond, and BAA bond all dropped after SOX. There is no evidence showing that the cost of debt shot up after the passage of SOX. So we should expect firms to use more debt due to the decrease of the cost of debt if market timing is the dominator determinant in choosing leverage. Thus, if market timing is the dominant power in the capital structure decisions, the capital structure around the passage of SOX should follow a different pattern than the observed capital structure. The data is from Federal Reserve St. Louis website.

Chapter 3

Information Acquisition and Investor Trading: Daily Analysis

3.1 Introduction

How does information acquisition affect investors' trading? Dating back to Grossman and Stiglitz (1980), researchers have been deeply interested in the economics of information acquisition and investors' trading behaviors (Karpoff (1986); Holthausen and Verrecchia (1990); Kim and Verrecchia (1991; 1994; 1997); Verrecchia (2001)). One general conclusion is that investors choose to become informed through information acquisition and the cost of acquiring information is compensated by taking positions in risky assets and expecting positive abnormal returns. Another proposition is that information acquisition likely triggers disagreement among investors and spurs trading (Kim and Verrecchia (1997)). Despite the theoretical advancement, we know little about the empirical associations between investors' trading activities and information acquisition.[1] In addition, it is not clear how accounting information and disclosure environment affect these associations. One major obstacle for empirical inquires is that investors' information acquisition process has been largely unobservable.

In this study, we examine the effect of information acquisition on investors' trading activities by focusing on investors' stock ticker search recorded by Google. Google's stock ticker search is likely a direct measure of the observable search for firm-specific information by a subset of less sophisticated investors (Da, Engelberg and Gao (2011)). We also expect it to proxy for the unobservable information acquisition of more sophisticated investors through

[1]Prior accounting research in this area has focused on trading volume and earnings signals around the earnings announcement period (See the recent review by Bamber, Barron, and Stevens (2011)).

their proprietary channels. The reason is twofold. First, abnormal change in observable ticker search on the Internet is likely triggered by firm-, industry-, or macro-level news, and sophisticated investors have the incentive to acquire information relating to it. Second, the intensity of their proprietary information acquisition is likely positively correlated with the observable Internet search.[2]

Our empirical analyses build primarily on the intuition of the Kim and Verrecchia (1997) model, which establishes the impact of information acquisition prior to and during a news event on investor trading. Their model suggests that individual investors' information acquisition triggers idiosyncratic information and induces a change in the demand of shares independent of price reactions. Empirically, we predict a positive contemporaneous association between daily abnormal trading volume (and the number of trades) and abnormal ticker search after controlling for the absolute price change (i.e., a positive search-volume association). In addition, because large and small traders are likely to focus on different signals of firm value (e.g., Bhattacharya (2001); Mikhail, Walther, and Willis (2007); Ayers, Li, and Yeung (2011)), we expect ticker search to induce asymmetric participation among different types of investors and predict a positive association between intra-day abnormal volatility of trade size (i.e., our proxy for asymmetric participation) and abnormal ticker search.

We test these empirical predictions using daily ticker search data for Standard and Poor 500 firms provided by Google and intra-day trading data provided by the New York Stock Exchange's Trade and Quote (TAQ) database for all trades executed from 2005 through 2007. We find a positive contemporaneous association between abnormal dollar trading volume (or abnormal number of trades) and abnormal ticker search after controlling for daily absolute price change. This association is economically significant, as doubling abnormal ticker search

[2]Consistent with this expectation, Drake, Roulstone and Thornock (2011) find that greater Google ticker search during pre-earnings announcement period reduces volume reactions during the earnings announcement period. Their evidence suggests that Google search before earnings announcements represents sophisticated information acquisition,which substitutes for the information content of subsequent earnings announcements. Of course, we do not completely rule out the possibility that sophisticated investors also use Google to acquire information.

is associated with about a 9% increase in abnormal trading volume. We also find a much smaller impact of abnormal ticker search during the prior trading day on abnormal trading activities, equivalent to about one-third of the contemporaneous association. This association likely reflects the impact on current day trading of after-hours search on the prior trading day.

Consistent with theory, we find that the positive association between abnormal ticker search and abnormal volume of large trades is more pronounced than that between abnormal ticker search and abnormal volume of small trades. Because large traders are likely to be more sophisticated and have the time and resources to analyze signals of firm value than small traders do (e.g., Easley and O'Hara (1987); Lee (1992)), they are more likely to produce more precise idiosyncratic information per unit of search (Internet or proprietary channel search), which induces more pronounced trading. This evidence is also consistent with the presumption that Google ticker search proxies for information acquisition of both small and large investors.

As predicted, we also find that the intra-day abnormal volatility of trade size is positively associated with current and lagged abnormal ticker search, consistent with a greater degree of asymmetric participation among different types of investors as ticker search increases. In addition to our non-directional trading results, we find that both abnormal buying volume and selling volume (and abnormal number of buyer- or seller-initiated orders) increase with abnormal ticker search, consistent with the notion that individual investors' information acquisition results in more idiosyncratic opinions.

We further test whether the impact of accounting information on the trading activities associated with information acquisition is consistent with the more refined predictions of the Kim and Verrecchia (1997) model. Specifically, their model suggests that trading volume (independent of price change) increases with both the magnitude and the precision of investors' idiosyncratic information. We therefore propose and test the following empirical predictions.

First, we predict that the positive association between abnormal ticker search and abnormal trading volume is more pronounced for firms with large magnitude of accruals. On one hand, accruals are associated with earnings management and financial opacity that may deter investors from trading, as the precision of public accounting signals is generally low (Dechow, Sloan, and Sweeney (1995); Hutton, Marcus, and Tehranian (2009)). On the other hand, opacity leads to greater expected benefits through information acquisition (i.e., obtaining signals more precise than public signals). Therefore, for firms with large magnitude of accruals, information acquisition helps investors to better understand firms' financials and generate valuable trading information (e.g., Sloan (1996)). Therefore, we predict a stronger volume-search association for firms with large accruals.

Second, we predict that the positive association between abnormal ticker search and abnormal trading volume is stronger during earnings-announcement period than during non-earnings announcement period. At earnings announcements, investors receive much greater amount of firm-specific news than during non-earnings announcement period. Greater amount of firm-specific news likely increases the idiosyncrasy of investors' information set per unit of their search (Barron, Byard, and Kim (2002); Barron, Harris, and Stanford (2005)). We therefore predict a stronger positive search-volume association during earnings-announcement period.

Third, we expect that the positive association between abnormal ticker search by local investors and abnormal trading volume is more pronounced than the positive association between abnormal ticker search by distant investors and abnormal trading volume. Local investors have information advantages over distant investors because of direct observation of a firm's operations or possible face-to-face meetings with a firm's managers, directors, employees, suppliers and customers (Coval and Moskowitz (2001)). As a result, these signals help investors better understand the accounting signals reported by the firm (Ayers, Ramalingegowda, and Yeung (2011)). Thus, local information advantages allow local investors to produce more precise idiosyncratic information than distant investors. We therefore predict stronger positive search-volume association for local search than for distant search.

Consistent with these predictions, we find that the association between daily abnormal trading volume (abnormal number of trades) and abnormal ticker search is stronger for firms with large accruals, during earnings announcement period, and when local investors' information acquisition is more intense.

Finally, in the supplemental analysis, we further demonstrate that when ticker search is relatively more intense, directional daily abnormal trading volume (as proxied by buy-sell order imbalance) is more positively associated with future stock returns. Consistent with the rational expectation framework, this evidence indicates that trading activities triggered by information acquisition likely represent informed trading.[3]

Our study makes several important contributions to the literature on investors' trading. First, we are the first study to provide direct empirical evidence on how daily and intra-day measures of trading activities (outside earnings announcement period) are associated with a proxy for information acquisition. Our results support Kim and Verrecchia's (1997) theory as a general characterization of the impact of information acquisition on investors' trading. While existing theories mainly concern trading volume around anticipated earnings announcements (e.g., Kim and Verrecchia (1991; 1994; 1997)), we document empirical evidence suggesting that the intuition of the existing theories can be generalized to all periods.

Second, we provide empirical evidence on how accounting information and firm information environment affects the volume-search association. We find that the search-volume association is stronger for firms with large accruals than for firms with small accruals, during earnings announcement period than during non-earnings announcement period, and

[3]Our results are unlikely to be explained by a reverse causality (i.e., volume triggers search) for several reasons. First, because investors cannot observe number of trades nor intra-day abnormal volatility of trade size, it is unlikely that abnormal ticker search is driven by these abnormal trading measures. Second, the association between abnormal trading activities and lagged abnormal ticker search cannot be attributed to a reverse causality. Third, it is difficult to explain the observed systematic cross-sectional variations in the search-volume association based on the reverse causality argument.

for information acquisition by local investors than by distant investors. These results provide strong support for the theory that trading volume associated with idiosyncratic information increases with both the magnitude and the precision of idiosyncratic information (Kim and Verrecchia (1997)). This support is important because, as pointed out by Bamber, Barron, and Stevens (2011), researchers draw inferences based on the properties of trading volume after controlling for price change as a measure of disagreement.

Our study also adds to the growing empirical work that examines investors' information gathering activities (Da et al. (2011); Drake, Roulstone and Thornock (2011)). One debatable issue is the nature of the search. While Da et al. (2011) argue that greater ticker search reflects increased attention of unsophisticated investors, Drake et al.'s (2011) findings suggest that Internet search before earnings announcements represents sophisticated information acquisition. Our results are more consistent with ticker search reflecting the general information acquisition activities of different types of investors.

The rest of the paper proceeds as follows. Section 2 discusses our theoretical framework and develops hypotheses. Section 3 discusses our data and research methods. Section 4 presents empirical results. Section 5 summarizes and concludes.

3.2 Literature, Theoretical Framework and Hypotheses

3.2.1 Theoretical Framework

Since Grossman and Stiglitz (1980), researchers have been grappling with the question of how information is impounded into prices through trading. In a rational expectations framework, non-liquidity investors trade off the cost of being informed through information acquisition against expected returns from taking positions in the risky assets. One important result is that, to cover information acquisition costs, investors' informed trading is necessarily masked by liquidity trades, and prices do not fully reflect the informed traders' idiosyncratic information (i.e., idiosyncratic information should be independent from price movements).

Kim and Verrecchia (1991; 1994; 1997) extend this intuition to the context of earnings announcements. In the more recent Kim and Verrecchia (1997) model, informed investors trade at earnings announcements due to two reasons. First, they trade during the news period to settle their prior bets, which is (negatively) associated with contemporaneous stock returns (i.e., they sell on good news and buy on bad news), causing a positive contemporaneous association between absolute stock return and trading volume. Second, during the news period investors generate and bet on their idiosyncratic information about firm value. However, this type of trades should be unassociated with contemporaneous stock returns, because their trading becomes unprofitable if prices otherwise reveal their information.

Our hypotheses build on the intuition of Kim and Verrecchia (1997). More specifically, they suggest that trading volume can be expressed as an aggregation of the absolute changes in demand for shares across individual Investor i's:

$$\Delta Demand_{it} = r_i[s_i\epsilon_i + (\rho_i - \rho)(-1 \times Ret_t) + (s_i - s)TerminalRet), \tag{3.1}$$

where $\Delta Demand_{it}$ is the change in Investors i's demand for shares during Period t; r_i is Investor i's level of risk tolerance; ϵ_i is the idiosyncratic information generated by Investor i during Period t; s_i is Investor i's precision of idiosyncratic information; s is the average precision of idiosyncratic information across all investors; ρ_i is the precision of Investor i's prior belief; ρ is the average precision of prior belief across all investors; Ret_t is stock return during Period t; and $TerminalRet$ is the liquidating return to investors.

Our main interest in Equation (3.1) is the insight that trading volume is associated with investors' idiosyncratic information ($s_i\epsilon_i$) independent of price changes (Ret_t). Trading volume (i.e., $|\Delta Demand_{it}|$) is greater when investors generate large idiosyncratic information (large $|\epsilon_i|$) and, holding its magnitude constant, when idiosyncratic information is more precise (i.e., large s_i).

Trading volume is also associated with Period t stock returns (i.e., the term $(\rho_i - \rho)(-1 \times Ret_t)$). As we have discussed earlier, the intuition is that when Investor i has private information (i.e., $\rho_i > \rho$) before the news period, she should have taken a position before the news period and trades in the opposite direction to the price change during the news period ($-1 \times Ret_t$). We control for price change in our analyses to focus on the effect of information acquisition during the news period t.

The last term in Equation (3.1), $(s_i - s)TerminalRet$, is related to the ultimate resolution of uncertainty in the model. We treat this term as white noise in our empirical analyses as the probability of an actual ultimate liquidation is not empirically determinable during the current period.

Equation (3.1) also suggests that, holding everything else constant, trading volume (i.e., aggregate absolute value of change in demand $|\Delta Demand_{it}|$) is higher when investors' risk tolerance (r_i) is greater. This is intuitive because less risk-averse investors are more willing to bet more than more risk-averse investors given the exact same information.

3.2.2 Empirical Predictions And Hypotheses

While Kim and Verrecchia's (1997) model is developed in the context of anticipated earnings announcements, the intuition of the model should be generalizable to continuous trading settings in which investors continuously receive signals of firm value. For example, besides firm-specific earnings signals, investors receive macro- and industry-level value relevant information on daily basis. These signals likely trigger idiosyncratic information and spur trading. Thus, the main theoretical result illustrated in Equation (3.1) should be applicable to other types of news events that contain signals of firm value and induce investors to acquire idiosyncratic information (i.e., continuous trading settings).

We argue that Google stock ticker search is a good measure of information acquisition of all information-based, non-liquidity traders. It is straightforward to see that Google ticker search is a direct measure of the observable search for firm-specific information by a subset of less sophisticated investors. We expect Google ticker search to also proxy for the unobservable information acquisition of more sophisticated investors for two reasons. First, abnormal Google ticker search is likely to be triggered by firm-, industry-, or macro-level news, and sophisticated investors should have the incentive to acquire information to help interpret the news.[4] Second, even if sophisticated investors are more likely to rely on proprietary channels for information, we expect that the intensity of their information acquisition through proprietary channels should be positively correlated with the observable Internet search intensity. If Google search is orthogonal to sophisticated investors' information acquisition through proprietary channels, however, we would not observe any association between abnormal Google search and trades of large, sophisticated investors.

Empirically, we predict a positive contemporaneous association between abnormal daily trading volume and abnormal ticker search after controlling for the absolute price change (i.e., term $(\rho_i - \rho)(-1 \times Ret_t)$ in Equation (3.1)) and propose the following hypothesis:

H1: Daily abnormal dollar trading volume (or abnormal number of trades) is positively associated with contemporaneous abnormal ticker search after controlling for absolute price change.

We further predict that the positive association between abnormal ticker search and abnormal trading volume of large trades is more pronounced than the positive association between abnormal ticker search and abnormal trading volume of small trades. Large traders are likely to be wealthier and more sophisticated investors who have and are able to spend the resources to yield more precise and sophisticated idiosyncratic information through proprietary research (e.g., having access to in-depth analyst reports). In contrast, small traders who rely on online search are less likely to have the time and specialty to form precise idiosyncratic information (Easley and O'Hara (1987); Lee (1992); Ali, Klasa, and Li (2008)). This reasoning suggests that the precision of idiosyncratic information (i.e., si in Equation (3.1)) is greater for large traders than for small traders. This is also consistent with prior evidence that large investors trade on more sophisticated information signals than small investors

[4]Prior studies (i.e., Gao et al. (2011) and Drake et al. (2011)) show that firm-specific news (e.g., dividend announcements, management earnings forecasts, etc.) only explain less than 5% of the variation in ticker search intensity, suggesting that industry-wide news and market-wide news trigger abnormal ticker search. For instance, investors may acquire firm-specific information when employment data are released.

do. For instance, while small investors trade on random-walk based earnings signals, large trades are more associated with analysts-based earnings signals (Bhattacharya (2001); Battalio and Mendenhall (2005); Ayers, Li, and Yeung(2011)). In addition, large traders respond to more sophisticated signals in analysts' reports while small investors appear to fail to do so (Malmendier and Shanthikumar (2007); Mikhail, Walther, and Willis (2007)).[5] We therefore propose the following hypothesis:

H2: The positive association between abnormal ticker search and daily abnormal trading volume (or abnormal number of trades) for large trades is more pronounced than that for small trades.

Similar to the logic behind hypothesis H2, we predict that information acquisition increases asymmetric participation across different types of investors (i.e., large and small traders). To the extent that each investor clientele trades with certain size range, when more investor types participate in trading, the variance of trade size should increase. We use the intra-day abnormal volatility of trade size as a measure of asymmetric participation across different types of investors and make the following prediction:

H3: Intra-day abnormal volatility of trade size is positively associated with contemporaneous abnormal ticker search.

Kim and Verrecchia's (1997) model also allows us to test the effects of accounting information and general information environment on the search-volume association. First, we predict that earnings management and related financial opacity affects the volume-search associations. Relative to the cash flows component in earnings, accruals are more likely to contain managerial discretion because they are heavily influenced by managers' subjective estimates of uncertain future events and thus are susceptible to manipulation (Dechow, Sloan, and Sweeney (1995)). In addition, accruals management also reflects general financial reporting opacity (Hutton, Marcus, and Tehranian (2009)). Thus, large accruals may

[5]We note that large traders may have the incentives to split their large order into smaller trades. Thus, it is noisier to infer the true identity of the traders conditional on small trades (e.g., smaller than five thousand dollars). On the other hand, large trades (e.g., half million dollars per trade) are unlikely to reflect retail trading.

discourage trading as the precision of public signals is low on average. On the other hand, opacity leads to greater expected benefits from information acquisition because it is less costly to obtain relatively more precise signals (greater s_i in Equation (3.1)). For instance, investors may obtain information to understand the nature of accruals and make better investment decisions (Sloan (1996)). Therefore, for firms with large magnitude of accruals, information acquisition helps investors better understand firms' financials and generate valuable trading information. We thus predict that the positive association between abnormal ticker search and abnormal trading volume is stronger for firms with large accruals and propose the following hypothesis:

H4: The positive association between abnormal ticker search and daily abnormal trading volume (or abnormal number of trades) is more pronounced when the magnitude of accruals is large.

Next, we predict that the positive association between abnormal ticker search and abnormal trading volume is stronger during earnings-announcement period than during non-earnings announcement period. At earnings announcements, investors receive much greater amount of firm-specific news than during non-earnings announcement period. Greater amount of firm-specific news potentially has two effects on investors' information set. First, it increases the magnitude of idiosyncratic information (ϵ_i) since information search helps investors develop greater idiosyncratic interpretations on public information (Barron et al. (2002; 2005).) Second, greater amount of firm-specific news increases the precision of idiosyncratic information (s_i) simply because there are a greater number of signals during earnings announcements. We therefore predict that the positive association between abnormal ticker search and trading volume is stronger during earnings-announcement period than during non-earnings announcement period and propose the following hypothesis:

H5: The positive association between abnormal ticker search and daily abnormal trading volume (abnormal number of trades) is more pronounced during earnings announcement period than during non-earnings announcement period.

We predict that the positive association between abnormal trading volume and abnormal ticker search by local investors is stronger than that by distant investors. Local investors have information advantages over distant investors because of direct observation of firms' operations or possible face-to-face meetings with managers, directors, employees, suppliers, customers, etc. In addition, local media also provides easier access to information. This information advantage allows local investors to understand the firm's fundamentals beyond financial reports (Ayers et al. (2011)) and produce more precise idiosyncratic information than distant investors (i.e., greater s_i in Equation (3.1)). We predict a stronger positive search-volume association when local search is more intense and propose the following hypothesis:

H6: The positive association between abnormal ticker search and daily abnormal trading volume (or abnormal number of trades) is more pronounced when local search is more intense.

3.3 Data and Research Design

3.3.1 Sample

We obtain ticker search data, namely, individual stock daily Search Volume Index (SVI), from Google Insight (*http://www.google.com/insights/search/*), which provides data on search term volume and related regional search dating back to January 2004. Daily SVIs for individual stocks are provided by Google Insight at monthly intervals. Values of daily SVIs for each stock during a month are available only on a relative scale ranging from 0 to 100, as the actual number of daily search is scaled by the maximum daily search during this month. To maintain comparability across calendar months, we further standardize SVIs across months using monthly SVIs from Google Insight using the following formula:

$$SVI = SVI_{dofm} \times SVI_m/100, \tag{3.2}$$

where SVIdofm is provided by Google Insight (calculated as daily SVI scaled by the maximum SVI during the month multiplied by 100) and SVIm is monthly SVI scaled by the maximum SVI during our sample period.

Because SVI represents relative ticker search intensity, our empirical analyses rely on relative changes in SVIs, which is defined as the difference in the natural log of SVI for the current trading day and the natural log of average SVI for the prior ten trading days ($\Delta logSVI$). Because daily SVIs are relatively incomplete for year 2004, our sample period starts in January 2005 and ends in December 2007.[6]

We focus on stocks in the S&P 500 index for two reasons. First, SVIs allowed to be downloaded from Google are limited per user per day. To make data collection and cleaning task more manageable, we focus on daily SVIs (available at monthly intervals) of S&P 500 stocks, which requires 18,000 downloads for our three-year sample period (i.e., 12 months $\times$ 500 firms $\times$ 3 years). Second and more importantly, many mid- and small-cap stocks have zero daily SVIs because their daily search volume is below a minimum threshold to be included in Google Insight. In these cases, measures of changes in SVI are less meaningful. The S&P 500 index includes 500 largest companies in leading industries of the U.S. economy and covers about 75% of U.S. equities. We exclude 48 firms without daily SVI available from Google Insight.

We also manually go through all S&P 500 tickers and exclude 52 "noisy" tickers with generic meanings (e.g., "A", "B", and "CAT") from our sample. These tickers are associated with high search intensity but are not necessarily associated with information of listed stocks. As a robustness check, we also include noisy tickers in our analyses, and our inferences continue to hold.

Our trading volume data is from the TAQ database, which allows us to divide trades into size-based categories to test hypotheses. In addition, we rely on the TAQ database to infer buyer-initiated or seller-initiated trading volumes based on the Lee and Ready (1991) and Lee (1992) algorithm. We lose 24 firms that we do not have intra-day data from TAQ. Thus,

[6]While we exclude searches occurring on weekends and holidays from our main analyses, as a robustness check, we incorporate weekend and holiday searches in the trading day immediately following it (i.e., averaging ticker search of the weekend/holiday period and the trading day following it) and find similar results. We exclude weekend and holiday search because their values are on average only about 80% of search during normal trading days.

we have 376 unique firms in our final sample that includes daily trading data for these firms during the 2005-2007 sample period.

3.3.2 Model Specification and Variable Definition

We rely on the following regression model to test hypotheses H1, H2, and H3, which is primarily motivated by the theoretical model illustrated in Equation (3.1):

$$\begin{aligned}\Delta logDV_d \texttt{ or } \Delta logNT_d = \alpha_0 &+ \alpha_1 \Delta logSVI_d + \alpha_2 |Ret_d| + \alpha_3 \Delta logSVI_{d-1} + \alpha_4 Size_{im-1} \\ &+ \alpha_5 Held_pct_{q-1} + \alpha_6 RetVol_{q-1} + \alpha_7 Vol5D_d + \alpha_8 \Delta Turnover_{m-1} \\ &+ \alpha_9 BM_{m-1} + \alpha_{10} Ret_{m-1} + \alpha_{11} DRet1dUp_d + \alpha_{12} DRet5dUp_d \\ &+ \Sigma DWeekDay + \epsilon_{1d}.\end{aligned} \tag{3.3}$$

In this model, the first dependent variable, the change in log dollar trading volume ($\Delta logDV$), is our measure of daily abnormal trading volume, defined as the difference between the natural log of volume (DV) in million U.S. dollars on Day d and the log of average daily dollar volume during the prior ten trading days. We focus on the change in log of trading volume to be consistent with $\Delta logSVI$. A distinct advantage of using a double-log functional form is the ease of interpreting the coefficients. For instance, α_1 indicates the percentage increase in abnormal trading volume per a 100% increase in abnormal ticker search.

Similarly, our second measure of trading activities, daily abnormal number of trades ($\Delta logNT$), is defined as the difference between the natural log of daily number of trades (NT) on Day d and the log of average number of trades during the prior ten trading days. Our hypothesis H1 predicts $\alpha_1 > 0$ in regressions of $\Delta logDV$ and $\Delta logNT$.

To test hypothesis H2, we create stratified measures of daily abnormal trading volume at different trade size categories: $\Delta logDV0\_5$ (below \$5,000), $\Delta logDV5\_25$ (between \$5,000 and \$25,000), $\Delta logDV25\_50$ (between \$25,000 and \$50,000), $\Delta logDV50\_100$ (between \$50,000 and \$100,000), $\Delta logDV100\_200$ (between \$100,000 and \$200,000), $\Delta logDV200\_500$ (between

\$200,000 and \$500,000), and $\Delta logDV500$ (above \$500,000). [7] For instance, $\Delta logDV0\_5$ is defined as the natural log of total volume for all trades with dollar value below \$5000 minus the log of average daily volume for this trade size category during the prior ten trading days. Similarly, we also create stratified measure of daily abnormal number of trades ($\Delta logNT$) at different trade size categories. We predict that α_1 is greater in large trade regressions than in small trade regressions.

We include a number of control variables in regression Equation (3.3). The most important control variable is $|Ret_d|$, defined as the absolute value of the contemporaneous daily stock return. Based on Kim and Verrecchia (1997), we expect a positive coefficient on $|Ret_d|$ ($\alpha_2 > 0$).

$\Delta logSVI_{id-1}$ is a measure of abnormal ticker search for the previous trading day. We include lagged abnormal ticker search to control for any lingering effect from information acquisition during the prior day. While we expect rational investors to trade on their idiosyncratic information swiftly, this variable could capture the impact of investors' information acquisition during after-hours of the prior trading day.

We include both firm size ($Size_{m-1}$) and institutional ownership ($Held\_pct_{q-1}$) to control for a firm's information environment. $Size_{m-1}$ is defined as the log of the market value of equity at the beginning of the month. Bamber (1986; 1987) suggests that firm size can proxy for a firm's disclosure environment. Large firms have better disclosure practice in general, leading to less disagreement among investors and therefore less trading volume. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F filing institutional shareholders at the end of the

[7] Because trading data reflect the active side of a trade, measuring trading volume within small and large trade size categories effectively captures trades initiated by large and small traders. Generally there are three types of orders: market orders, limit orders, and standing orders. A market order demands immediate execution and reflects active side of the trade, while limit orders and standing orders reflect the passive side of the trade. After the opening trade, a trade occurs only when a market order arrives. With few exceptions, both the size and direction of a trade in TAQ data reflect the market order, or the active side of the trade (e.g., Lee (1992)). For example, if a market order is filled by several smaller limit orders, the transaction is recorded as a single transaction at the size of the market order. Thus, measuring trading volume within small and large trade-size categories captures trades initiated by large and small traders.

previous quarter. We control for this variable because it captures the proportion of relatively more sophisticated traders (Ali et al. (2008)), which in turn affects a firm's information environment and/or volume of liquidity trading.

We also control for $RetVol_{q-1}$, $Vol5d_d$, and $\Delta Turnover_{m-1}$ to capture liquidity trading. $RetVol_{q-1}$ is return volatility defined as the daily individual stock return standard deviation during the prior quarter, and Vol5dd is defined as standard deviation of stock returns during the prior five trading days. $\Delta Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month.

We control for value- and momentum-related trading behaviors by including BM_{m-1}, Ret_{m-1}, $DRet1dUp_d$ and $DRet5dUp_d$, where BM_{m-1} is book to market value of equity ratio at the beginning of the month, Ret_{m-1} is defined as stock return during the prior month, and $DRet1dUp_d(DRet5dUp_d)$ is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. Finally, we include Monday through Thursday dummy variables (DWeekDay).

To test hypothesis H3 (i.e., asymmetric participation), we create a variable $\Delta logStdTS$, defined as the difference between the natural log of intra-day standard deviation of trade size (in thousands of dollars) and the natural log of average intra-day standard deviation of trade size over the prior ten trading days. We then replace abnormal trading volume measures in Equation (3.3) with $\Delta logStdTS$. Our hypothesis H3 predicts $\alpha_1 > 0$ in regressions of $\Delta logStdTS$.

To test hypothesis H4, we create an interaction variable ($\Delta logSVI \times |Accruals|$) and estimate the following regression model that slightly modifies Equation (3.3):

$$\begin{aligned}\Delta logDV_d \texttt{ or } \Delta logNT_d = \beta_0 + \beta_1 \Delta logSVI_d + \beta_2 \Delta logSVI_d \times |Accruals| + \beta_3 |Accruals| \\ + \Sigma Controls + \epsilon_{2d}\end{aligned} \tag{3.4}$$

where $|Accruals|$ is the tercile rank of the average absolute value of abnormal accruals (Hutton et al. (2009)), estimated as the residuals of the modified Jones' model (Dechow et al. (1995)). Hypothesis H4 predicts $\beta_2 > 0$.

We create an interaction variable ($\Delta logSVI \times EA$) and estimate the following regression model to test hypothesis H5:

$$\begin{aligned}\Delta logDV_d \texttt{ or } \Delta logNT_d = \rho_0 + \rho_1 \Delta logSVI_d + \rho_2 \Delta logSVI_d \times EA_d + \rho_3 EA_d \\ + \Sigma Controls + \epsilon_{3d}\end{aligned} \tag{3.5}$$

where EA is an indicator variable that equals one if a given trading day is within the (-5, +5) trading day window centered on a Compustat earning announcement date. Hypothesis H5 predicts $\rho_2 > 0$. Finally, to test hypotheses H6, we create an interaction variable, $\Delta logSVI \times HiLocal$, and estimate the following regression model:

$$\begin{aligned}\Delta logDV_d \texttt{ or } \Delta logNT_d = \lambda_0 + \lambda_1 \Delta logSVI_d + \lambda_2 \Delta logSVI_d \times HiLocal_d + \lambda_3 HiLocal_d \\ + \Sigma Controls + \epsilon_{4d}\end{aligned} \tag{3.6}$$

where $HiLocal$ is an indicator variable that equals one if local ticker search is above the sample median in a given year and zero otherwise. A local ticker search is initiated by an investor from the state where a firm's headquarter is located. Hypothesis H6 predicts $\lambda_2 > 0$.

3.4 Results

3.4.1 Descriptive Statistics

Table 3.1 presents descriptive statistics of key variables of interest. As discussed earlier, the value of SVI ranges from 0 to 100, representing the minimum and maximum search intensity for a particular firm during our sample period. The mean value of $\Delta logSVI$ is 0.03 while the median is 0.01, indicating that on average there is little change in abnormal ticker search over our sample period. On average, the daily trading volume of our sample is $200 million dollars. The mean value of abnormal trading volume $\Delta logDV$ for all trades is -0.05, and the median value is -0.07. As trade size increases, both the mean and median values of $\Delta logDV$ decrease. On average, the daily number of trades is 11.64 thousand. The distribution of $\Delta logNT$ (stratified $\Delta logNT$ within each trade size category) is similar to that of $\Delta logDV$ (stratified $\Delta logDV$ within each trade size category). We also observe that the average intraday volatility in trade size ($StdTS$) is 2.01 thousand dollars. Since we focus on S&P 500 firms, we observe that firms in our sample have large market values, high institutional ownership, low stock return volatilities, and low book-to-market ratios.

Table 3.2 presents Pearson and Spearman correlations among our key variables. Panel A shows the correlations between abnormal ticker search ($\Delta logSVI$) and abnormal total trading volume ($\Delta logDV$) and abnormal trading volumes within various trade size categories (from $\Delta logDV0\_5$ to $\Delta logDV500$). Consistent with our prediction of a positive search-volume association, we find that $\Delta logSVI$ is positively correlated with $\Delta logDV$ for all trades and $\Delta logDV$s for various trade size categories.

Interestingly, we find that both the Pearson and Spearman correlations are higher for small trades (e.g., $\Delta logDV0\_5$, $\Delta logDV5\_25$, and $\Delta logDV25\_50$) than for large trades ($\Delta logDV200\_500$ and $\Delta logDV500$). Consistent with our expectation, these results indicate that Google ticker search is more likely to capture the actual information acquisition of small traders (i.e., better explain small trades than large trades). Also note that the observed patterns do not contradict our prediction because correlation coefficients indicate explanatory power instead of volume per unit of search. On the other hand, the differences in the magnitude are not as large as one might expect, consistent with Google ticker search being a reasonable proxy for large traders' information acquisition. Even if large traders primarily rely on proprietary channels, their information acquisition efforts through proprietary channels are likely positively correlated with internet ticker search activities. Consistent with the dollar trading volume measures, correlations presented in Panel B regarding the number of traders ($\Delta logNT$) show similar patterns.

Panel C shows the correlations between abnormal trading volume (and abnormal number of trades) and control variables in our regression models. Except the correlations with $|Retd|$, most of the correlations among control variables are small in magnitude, indicating that multicollinearity should not be a concern. In addition, the signs and magnitudes of Pearson and Spearman correlations are consistent, indicating that our empirical results are unlikely to be influenced by outliers.

3.4.2 Main Results

Table 3.3 presents results of estimating regression Equation (3.3) where the dependent variable is abnormal dollar trading volume ($\Delta logDV$) or abnormal number of trades ($\Delta logNT$). To rule out the possibility that our results are sensitive to model specifications, we estimate the following three alternative specifications: i) two-way clustered standard errors by firm and month in Models (1) and (2), ii) Fama-MacBeth regression with Newey-West adjusted standard errors in Models (3) and (4), and iii) firm- and month-fixed effects in Models (5) and (6).

We find that the estimated coefficients on $\Delta logSVI$ are positive and significant in Models (1) and (2). Specifically, the estimated coefficient is 0.097 ($t = 10.01$) when $\Delta logDV$ is the dependent variable and 0.080 ($t = 9.46$) when $\Delta logNT$ is the dependent variable. The magnitudes of the estimated coefficients on $\Delta logSVI$ using the Fama-MacBeth method in Models (3) and (4) are slightly lower, but those obtained in the fixed effects in Models (5) and (6) are similar in magnitude. These results support hypothesis H1 that abnormal trading volume (or the number of trades) is positively associated with abnormal ticker search after controlling for the absolute price change.

Because both abnormal ticker search and abnormal volume metrics are constructed as the change in log, the estimated coefficients on $\Delta logSVI$ are easily interpreted. For example, a coefficient of 0.097 in Model (1) indicates that a 100% increase in abnormal ticker search is associated with a 9.7% increase in abnormal dollar trading volume. Across all specifications, doubling abnormal ticker search is associated with about a 6% to 10% increase in abnormal trading activities.

We also find that the estimated coefficients on $\Delta logSVI_{d-1}$(lagged one trading day) are significant in all models ($t \geq 5.55$) and their magnitudes are about one-third of those on contemporaneous $\Delta logSVI$. These results suggest that information acquisition on the prior trading day affects the trading of current period, possibly due to investor ticker search during after-hours of the prior trading day. Further (non-tabulated) results show that $\Delta logSVI_d - 2$ (lagged two trading days) is not positively associated with trading measures in Equation (3.3).

Estimated coefficients on $|Retd|$ are positive and significant in all model specifications, consistent with prior empirical findings and support the prediction of the Kim and Verrecchia (1997) model. Coefficients on $Size_{m-1}$ are positive and significant. In addition, we find mostly insignificant coefficients for institutional ownership ($Held\_pct_{q-1}$). Estimated coefficients on $RetVol_{q-1}$, $Vol5d_d$ and $\Delta Turnover_{m-1}$, our controls for liquidity trading, are significantly negative. An explanation is that we subtract trading volume of prior period (as a proxy for liquidity trading) to derive abnormal trading volume. Estimated coefficients on BM_{m-1} and Ret_{m-1} are significantly positive in some models, providing modest support for the presence of trading related to value and momentum strategies.

Panels A and B of Table 3.4 present results of regression Equation (3.3) for different trade size categories. Hypothesis H2 predicts that the positive search-volume association is stronger for large trades than for small trades. For brevity, we only report results with two-way clustered standard errors by firm and month. Results using Fama-MacBeth and firm- and month-fixed effects specifications are similar. In regressions of abnormal dollar trading volume (Panel A), we find that the estimated coefficient on $\Delta logSVI$ is positive and significant in each trade size category. Further, the estimated coefficient on $\Delta logSVI$ increases monotonically from 0.078 ($t = 8.26$) for trade size below $5,000 to 0.148 ($t = 9.30$) for trade size larger than $500,000. In regressions of abnormal number of trades (Panel B), the estimated coefficient on $\Delta logSVI$ also increases from 0.077 ($t = 8.20$) for trade size below \$5,000 to 0.143 ($t = 10.25$) for trade size larger than \$500,000. These results support hypothesis H2 that the positive association between abnormal trading volume and abnormal ticker search is more pronounced for large trades than for small trades.

Table 3.5 reports regression results when we use intra-day abnormal volatility of trade size ($\Delta logStdTS$) as the dependent variable. Consistent with hypothesis H3, we find significantly positive coefficients on $\Delta logSVI$ in all model specifications. For instance, the estimated coefficient on $\Delta logSVI$ in Model (1) is 0.044 ($t = 4.03$). We also find that the estimated coefficients on lagged $\Delta logSVI$ are relatively large and significant. These results indicate that information acquisition triggers asymmetric participation among different types of traders. Non-tabulated results further show that $\Delta logSVI_{d-2}$ (lagged two trading days) is not positively associated with $\Delta logStdTS$ in Equation (3.3).

We report results for testing H4 in Columns (1) and (2) of Table 3.6. For brevity, we only report results with two-way clustered standard errors by firm and month. Results using Fama-MacBeth and firm- and month-fixed effects specifications are similar. Consistent with lower signal precision for firms with large accruals, the coefficients on $|Accruals|$ are significantly negative (t $\leq$ -3.32) On the other hand, we find the coefficients on $\Delta logSVI \times |Accruals|$ are positive and significant (t $\geq$ 3.05), supporting hypothesis H4 that the positive association between ticker search and trading volume is stronger when firms have large magnitude of accruals. Thus, acquiring financial information is more valuable for firms with relatively poor financial reporting.

Columns (3) and (4) of Table 3.6 report results testing Hypothesis H5 which predicts stronger search-volume association during earnings announcement period than non-earnings announcement period. Consistent with Hypothesis H4, we find that the coefficients on $\Delta logSVI \times EA$ are positive and significant (t $\geq$ 4.07), indicating that abnormal dollar volume and abnormal number of trades associated with abnormal ticker search are more pronounced during earnings announcement period.

We report results for testing hypotheses H6 in Columns (5) and (6) of Table 3.6. We find that the estimated coefficients on $\Delta logSVI \times HiLocal$ are positive and significant (t $\geq$ 2.25) This evidence supports Hypothesis H6 that when local search is more intense, the positive association between abnormal trading volume (and number of trades) and abnormal ticker search is stronger, because local investors are more likely to produce precise idiosyncratic information.

To summarize, we find positive contemporaneous associations between abnormal trading volume and abnormal ticker search after controlling for price changes. In our sample, doubling abnormal ticker search is associated with about a 9% increase in abnormal trading volume. We also find a much smaller impact of ticker search during the prior trading day on trading activities, equivalent to about one-third of the contemporaneous association. We further find that the positive search-volume association is more pronounced for large trades than for small trades. In addition, the intra-day abnormal volatility of trade size, a proxy for asymmetric participation among different types of investors, is positively associated with current and lagged abnormal ticker search. Finally, the search-volume association is stronger for firms with large magnitude of accruals than for those with small magnitude of accruals, during earnings announcement period than during non-earnings announcement period, and for information acquisition by local investors than by distant investors. These results indicate that accounting information significantly affects investors' trading activities.

3.4.3 Directional Trading Volume

To corroborate our results on non-directional trading volume, we also examine the effect of abnormal ticker search on directional buy and sell orders separately (i.e., buyer- or seller-initiated trades). If ticker search results in investors' idiosyncratic information, we expect increases in both buy and sell volumes because investors disagree on whether the prevailing prices are too high or too low in comparison with their own beliefs.

We classify trades into buyer-initiated or seller-initiated orders using the Lee and Ready (1991) and Lee (1992) algorithm. While the number of shares bought equals the number of shares sold in a transaction, the Lee (1992) algorithm identifies the likelihood that a transaction is buyer-initiated or seller-initiated. This algorithm largely depends on which investor demands liquidity more urgently. [8] Specifically, we compare traded prices with quotes that are at least five seconds earlier. If the traded price is above the mid-point of the bid-ask spread, we define the trade as a buy. If the traded price is below the mid-point of the bid-ask spread, we define the trade as a sell. We do not classify a trade if the traded price occurs at the mid-point of the bid-ask spread. For any given trading day, we add up all buys and all sells separately. To be consistent with the definition of $\Delta logDV$, our abnormal buy (sell) volume ($\Delta logBuyDV or \Delta logSellDV$) is defined as the natural log of dollar value of buys (sells) minus natural log of average buys (sells) during the prior ten trading days.

We re-run regression Equations (3.3), (3.4), (3.5) and (3.6) by separately using abnormal buy volume or abnormal sell volume as the dependent variable. Hypothesis H1 predicts positive coefficients on $\Delta logSVI$ in regression Equation (3.3) for both abnormal buy volume and abnormal sell volume. To examine the effect of large trades on directional volume (i.e., hypothesis H2), we create an interaction variable $\Delta logSVI \times Large$, where Large is a dummy variable equal to one if the average trade size of the trading day is above the average daily trade size of prior month. Hypothesis H2 predicts positive coefficients on this interaction variable in both abnormal buy and abnormal sell regressions. Hypotheses H3, H4 and H5 predict positive coefficients on $\Delta logSVI \times |Accruals|$, $\Delta logSVI \times EA$, and $\Delta logSVI \times HiLocal$ in Equations (3.4), (3.5) and (3.6), respectively.

[8] Recall that after the opening trade, a trade occurs only when a market order arrives. If a market order to buy is filled by a limit order to sell, the trade is classified as a buyer-initiated trade. If a market order to sell is filled by a limit order to buy, the trade is classified as a seller-initiated trade. Sometimes, the size of a market order and the size of a limit order are not equal. If one large market order to buy (sell) is filled by several small limit orders to sell (buy) (and possibly partially filled by the specialist), the trade is classified as one large buyer- (seller-) initiated trade. If several small market orders to buy (sell) are filled by one large limit order to sell (buy) (and possibly partially filled by the specialist), the trades are classified as several buyer- (seller-) initiated trades (Lee (1992)).

Table 3.7 reports regression results. Panel A shows results when abnormal buy volume and sell volume are the dependent variables, while Panel B shows the results when abnormal numbers of buy orders and sell orders are the dependent variables. When abnormal buy volume is the dependent variable ($\Delta logBuyDV$), we find a significantly positive coefficient on $\Delta logSVI$ in Column (1) (0.100, t = 9.53), indicating that doubling abnormal ticker search is associated with about a 10% increase in abnormal buy orders. Consistent with our hypotheses, we find significantly positive estimated coefficients on $\Delta logSVI \times Large$ in Column (2) (0.061, t = 3.71), on $\Delta logSVI \times |Accruals|$ in Column (3) (0.032. t = 2.62), on $\Delta logSVI \times EA$ in Column (4) (0.114, t = 2.68), and on $\Delta logSVI \times HiLocal$ in Column (5) (0.061, t = 3.71).

When abnormal sell volume is the dependent variable ($\Delta logBuyDV$), we find a significantly positive coefficient on $\Delta logSVI$ in Column (6) (0.096, t = 8.37), indicating that doubling abnormal ticker search is associated with about a 10% increase in abnormal sell orders. Consistent with our predictions, we find significantly positive estimated coefficients on $\Delta logSVI\times$ Large in Column (7) (0.054, t = 3.93), on $\Delta logSVI \times |Accruals|$ in Column (8) (0.040, t = 2.59), on $\Delta logSVI \times EA$ in Column (9) (0.187, t = 3.29), and on $\Delta logSVI \times HiLocal$ in Column (10) (0.092, t = 3.95).

Panel B of Table 3.7 shows the results when abnormal number of buy orders ($\Delta logBuyN$) and abnormal number of sell orders ($\Delta logSellN$) are the dependent variables. Results are similar to those reported in Panel A. Overall, results based on directional trades in Table 3.7 are consistent with our prediction of increases in both buy and sell volumes resulting from information acquisition. In addition, we document similar magnitudes between the search-buy association and search-sell association, consistent with increases in investor's idiosyncratic opinions associated with information acquisition.

3.4.4 Predicting Future Stock Returns

Chordia and Subrahmanyam (2004) hypothesize that because relatively informed large traders may optimally choose to split their orders over multiple trading days, trades predict future buy-sell imbalance and hence future stock returns. Consistent with this conjecture, they find evidence that directional daily abnormal trading volume (i.e., buy-sell order imbalance) is positively associated with future daily stock returns. In our context, if more intense ticker search represents information acquisition, trades associated with ticker search should be more likely to impound value-relevant information. Thus, according to the rational expectation framework, we predict that when ticker search is more intense, the power of daily abnormal trading volume in predicting future stock returns should be greater.

To test this prediction, we follow Chordia and Subrahmanyam's (2004) method and run the following time-series regression for each firm:

$$adjReturn_d = \phi_0+\phi_1 NetBuy_{d-1}+\phi_2 NetBuy_{d-1}\times HiSVI_{d-1}+\phi_3 HiSVI_{d-1}+\Sigma Controls+\epsilon_{5d} \tag{3.7}$$

where $adjReturn_d$ is stock return on trading day d, adjusted by the S&P 500 value-weighted composite index, $NetBuy_{d-1}$ is buy minus sell orders on trading day d-1 scaled by the average non-directional volume in prior ten trading days, and $HiSVI_{d-1}$ is a dummy variable equal to one if $\Delta logSVI$ is greater than sample median or zero otherwise. Control variables include higher-order-lags of NetBuy. Following Chordia and Subrahmanyam (2004), we expect a positive coefficient for $NetBuy_{d-1}$ (i.e., $\phi_1 > 0$). More importantly, we expect that the positive association between future stock returns and current NetBuy is greater when ticker search is more intensive (i.e., $\phi_2 > 0$).

Table 3.8 presents the cross-sectional averages and associated t-statistics of estimated coefficients in the time-series regression model (7) for all firms in our sample. All t-statistics are corrected for cross-sectional correlations. In Column (1), we find an insignificant positive coefficient for $NetBuy_{d-1}$. Results in Column (2) show that the insignificant coefficient in our sample is primarily driven by the trading days with low ticker search. We find positive coefficient for the interaction term $NetBuy_{d-1} \times HiSVI_{d-1}$, and the sum of ϕ_1 and ϕ_2 is significantly positive ($t = 2.51$). Results are similar when we include higher-order-lags of NetBuy in Columns (3) and (4). Overall, the evidence in Table 3.8 indicates that when ticker search is relatively more intense, directional daily abnormal trading volume is more positively associated with future stock returns. This evidence supports the prediction that volume associated with ticker-search likely represents informed trading.

3.5 Summary and Conclusion

We study the impact of information acquisition on trading volume by focusing on investors' observable search for firm-specific information on the Internet (i.e., Google ticker search). We also examine how accounting information affects the search-volume relation. We find a positive contemporaneous association between abnormal trading volume and abnormal ticker search after controlling for price reactions. We also find a much weaker impact of lagged abnormal ticker search on abnormal trading volume. In addition, intra-day abnormal volatility of trade size, a measure of asymmetric investor participation, is positively associated with abnormal ticker search, consistent with greater disagreement among different types of investors as information acquisition increases. Consistent with significant impact of accounting information on trading, we find that the search-volume association is stronger for firms with large magnitude of accruals than for those with small magnitude of accruals, during earnings announcement period than during non-earnings announcement period, and for information acquisition by local investors than by distant investors. Further analyses indicate that both abnormal buying and selling volumes increase with ticker search, supporting exacerbated investor disagreement triggered by public information acquisition. We also provide evidence that volume associated with ticker search likely represents informed trading.

We make several contributions to the literature on investor trading. First, we provide direct evidence on how trading activities are associated with information acquisition and support Kim and Verrecchia (1997) as a general characterization of investors' trading and information acquisition. Second, we provide empirical support for significant impact of information environment on trading behaviors associated with investors' information acquisition: a stronger search-volume association for large trades, for firms with large accruals, during earnings announcement periods, and for information acquisition by local investors. These results provide further support for the theory that trading volume associated with idiosyncratic information increases with both the magnitude and the precision of idiosyncratic information. Our study adds to the growing empirical work that examines investors' information gathering activities (Da et al. (2011); Drake et al. (2011)) by showing evidence that ticker search reflects the general information acquisition activities of different types of investors.

3.6 References

Ali, A.; S. Klasa; and O. Li, 2008, Institutional Stakeholdings and Better-Informed Traders at Earnings Announcements, *Journal Of Accounting and Economics* 46, 47-61.

Ayers, B; O. Li; and P.E. Yeung, 2011, Investor Trading and The Post Earnings Announcement Drift, *The Accounting Review* 86 , 385-416.

Ayers, B; S. Ramalingegowda; and P.E. Yeung, 2011, Hometown Advantage: The Effects of Monitoring Institution Location On Financial Reporting Discretion, *Journal of Accounting and Economics*, Forthcoming.

Baik, B.; J. Kang; and J. Kim, 2010, Local Institutional Investors, Information Asymmetries, and Equity Returns, *Journal of Financial Economics* 97, 81-106.

Bamber, L., 1986, The Information Content of Annual Earnings Releases: A Trading Volume Approach, *Journal of Accounting Research* 24, 40-56.

Bamber, L, 1987, Unexpected Earnings, Firm Size, and Trading Volume Around Quarterly Earnings Announcements, *The Accounting Review* 62, 510-32.

Bamber, L.; O. Barron; and T. Stober, 1997, Trading Volume and Different Aspects of Disagreement Coincident With Earnings Announcements, *The Accounting Review* 72, 575-597.

Battalio, B. and Mendenhall, J., 2005, Earnings Expectations, Investor Trade Size, and Anomalous Returns Around Earnings Announcements, *Journal of Financial Economics* 77, 289-319.

Bamber, L.; O. Barron; and D. Steven, 2011, Trading Volume Around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions For Future Research, *Contemporary Accounting Research*, Forthcoming.

Barron, O.; D. Byard; and O. Kim, 2002, Changes In Analysts' Information Around Earnings Announcements, *The Accounting Review* 77, 821-46.

Barron, O.; D. Harris; and M. Stanford, 2005, Evidence That Investors Trade On Private Event-Period Information Around Earnings Announcements, *The Accounting Review* 80 (, 403-421.

Bhattacharya, N., 2001, Investors' Trade Size and Trading Responses Around Earnings Announcements: An Empirical Investigation, *The Accounting Review* 76, 221-245.

Chordia, T. and A. Subrahmanyam, 2004, Order Imbalance and Individual Stock Returns: Theory and Evidence, *Journal of Financial Economics* 72, 485-518.

Coval, J. and T. Moskowitz, 2001, The Geography of Investment: Informed Trading and Asset Prices, *Journal of Political Economy* 109, 811-841.

Da, Z.; J. Engelberg; and P. Gao, 2011, In Search of Attention, *Journal of Finance*, Forthcoming.

Dechow, P.; R. Sloan; and A. Sweeney, 1995, Detecting Earnings Management, *Accounting Review* 70, 193-225.

Drake, M.; D. Roulstone; and J. Thornock, 2011, Investor Information Demand: Evidence From Google Searches Around Earnings Announcements, Working Paper.

Easley, D. and M. O'hara, 1987, Price, Trade Size, and Information In Securities Markets, *Journal of Financial Economics* 19, 69-90.

Grossman, S. and J. Stiglitz, 1980, On The Impossibility of Informationally Efficient Markets, *American Economic Review* 70, 393-408.

Holthausen, R. and R. Verrecchia, 1990, The Effect of Informedness and Consensus On Price and Volume Behavior, *Accounting Review* 65, 191-208.

Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009, Opaque Financial Reports, R2, and Crash Risk, *Journal of Financial Economics* 95, 67-86.

Karpoff, J., 1986, A Theory of Trading Volume, *Journal of Finance* 41, 1069-1087.

Kim, O. and R. Verrecchia, 1991, Trading Volume and Price Reactions To Public Announcements, *Journal of Accounting Research* 29, 302-21.

Kim, O. and R. Verrecchia, 1994, Market Liquidity and Volume Around Earnings Announcements, *Journal of Accounting and Economics* 17, 41-67.

Kim, O. and R. Verrecchia, 1997, Pre-Announcement and Event-Period Private Information, *Journal of Accounting and Economics* 24, 395-419.

Lee, C., 1992, Earnings News and Small Traders, *Journal of Accounting and Economics* 15, 265-302.

Lee, C. and M. Ready, 1991, Inferring Trade Direction From Intraday Data, *Journal of Finance* 46, 733-746.

Malmendier, U. and D. Shanthikumar, 2007, Are Small Investors Naive About Incentives? *Journal of Financial Economics* 85, 457-489.

Mikhail, M.; B. Walther; and R. Willis, 2007, When Security Analysts Talk, Who Listens? *The Accounting Review* 82, 1227-1253.

Sloan, R., 1996, Do Stock Prices Fully Reflect Information In Accruals and Cash Flows About Future Earnings? *The Accounting Review* 71, 289-316.

Verrecchia R., 2001, Essays On Disclosure, *Journal of Accounting and Economics* 32, 97-180.

Table 3.1: Descriptive Statistics

Table 3.1 shows the descriptive statistics of variables of interests. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. DV is total daily trading volume in million U. S. dollars. Δ LogDV is the difference between the natural log of DV and the natural log of average DV in the prior ten trading days. $\Delta\ LogDV0\_5$, $\Delta\ LogDV5\_25$, $\Delta\ LogDV25\_50$, $\Delta\ LogDV50\_100$, $\Delta\ LogDV100\_200$, $\Delta\ LogDV200\_500$, and $\Delta\ LogDV500$ are measures of Δ LogDV within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). NT is total number of daily trades (in thousands). Δ LogNT is defined as the difference between the natural log of NT and the log of average NT in the prior ten trading days. $\Delta\ LogNT0\_5$, $\Delta\ LogNT5\_25$, $\Delta\ LogNT25\_50$, $\Delta\ LogNT50\_100$, $\Delta\ LogNT50\_100$, $\Delta\ LogNT200\_500$, and $\Delta\ LogNT500$ are measures of Δ LogNT within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). StdTS is intra−day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. $\Delta\ Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise.

Variables	Mean	S.D.	Min	25%	Median	75%	Max
SVI	32.95	18.76	0.00	19.13	32.87	46.16	100.00
$\Delta\ logSVI$	0.03	0.27	−0.60	−0.11	0.01	0.13	1.18
DV	200.00	400.00	0.00	38.00	82.00	200.00	1600.00
$\Delta\ logDV$	−0.05	0.39	−1.02	−0.30	−0.07	0.18	1.12
$\Delta\ logDV0\_5$	0.00	0.32	−0.82	−0.20	−0.02	0.17	1.13
$\Delta\ logDV5\_25$	−0.03	0.32	−0.90	−0.23	−0.04	0.15	0.91
$\Delta\ logDV25\_50$	−0.06	0.42	−1.22	−0.32	−0.06	0.19	1.16
$\Delta\ logDV50\_100$	−0.09	0.53	−1.58	−0.40	−0.09	0.22	1.35
$\Delta\ logDV100\_200$	−0.13	0.65	−1.94	−0.50	−0.11	0.27	1.57
$\Delta\ logDV200\_500$	−0.14	0.76	−2.15	−0.60	−0.13	0.33	1.81
$\Delta\ LogDV500$	−0.18	1.02	−2.67	−0.84	−0.18	0.46	2.51
NT	11.64	18.97	2.00	2.71	5.07	11.76	570.00
$\Delta\ logNT$	−0.03	0.30	−0.81	−0.21	−0.03	0.15	0.86
$\Delta\ logNT0\_5$	0.00	0.32	−0.80	−0.20	−0.02	0.17	1.13
$\Delta\ logNT5\_25$	−0.03	0.32	−0.94	−0.22	−0.04	0.15	0.93
$\Delta\ logNT25\_50$	−0.06	0.43	−1.21	−0.32	−0.06	0.19	1.15
$\Delta\ logNT50\_100$	−0.09	0.52	−1.57	−0.40	−0.09	0.22	1.34
$\Delta\ logNT100\_200$	−0.12	0.64	−1.91	−0.50	−0.11	0.26	1.57
$\Delta\ logNT200\_500$	−0.14	0.74	−2.09	−0.59	−0.12	0.33	1.79
$\Delta\ LogNT500$	−0.09	0.82	−2.04	−0.62	−0.10	0.43	2.08
$StdTS$	2.01	3.36	0.06	0.60	1.14	2.26	370.00
$\Delta\ logStdTS$	−0.17	0.71	−1.80	−0.63	−0.21	0.23	1.93
$\|Ret_d\|$	0.01	0.01	0.00	0.00	0.01	0.02	0.06
$Size_{m-1}$	16.45	1.22	9.14	15.60	16.39	17.13	20.06
$Held\_pct_{q-1}$	0.74	0.18	0.01	0.64	0.76	0.87	1.00
$RetVol_{q-1}$	0.02	0.01	0.00	0.01	0.01	0.02	0.07
$Vol5d_d$	0.01	0.01	0.00	0.01	0.01	0.02	0.26
$\Delta\ Turnover_{m-1}$	0.01	0.32	−1.28	−0.19	0.01	0.21	1.96
BM_{m-1}	0.35	0.21	0.00	0.21	0.31	0.47	1.97
Ret_{m-1}	0.01	0.07	−0.41	−0.03	0.01	0.05	0.57
$DRet1dUp$	0.53	0.50	0.00	0.00	1.00	1.00	1.00
$DRet5dUp$	0.62	0.49	0.00	0.00	1.00	1.00	1.00

Table 3.2: Correlation Table

Table 3.2 shows Pearson (above the diagonal) and Spearman (below the diagonal) correlations among variable of interests. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. DV is total daily trading volume in million U. S. dollars. Δ LogDV is the difference between the natural log of DV and the natural log of average DV in the prior ten trading days. Δ $LogDV0\_5$, Δ $LogDV5\_25$, Δ $LogDV25\_50$, Δ $LogDV50\_100$, Δ $LogDV100\_200$, Δ $LogDV200\_500$, and Δ $LogDV500$ are measures of Δ LogDV within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). NT is total number of daily trades (in thousands). Δ LogNT is defined as the difference between the natural log of NT and the log of average NT in the prior ten trading days. Δ $LogNT0\_5$, Δ $LogNT5\_25$, Δ $LogNT25\_50$, Δ $LogNT50\_100$, Δ $LogNT50\_100$, Δ $LogNT200\_500$, and Δ $LogNT500$ are measures of Δ LogNT within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). StdTS is intra−day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. Δ $Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month.

Panel A: Pearson/Spearman correlations among abnormal volume and abnormal ticker search variables

	Δ *logSVI*	Δ *logDV*	Δ *logDV 0_5*	Δ *logDV5_25*	Δ *logDV25_50*	Δ *logDV 50_100*	Δ *logDV100_200*	Δ *logDV200_500*	Δ *LogDV*500
Δ *logSVI*		0.101	0.09	0.099	0.093	0.087	0.081	0.072	0.066
Δ *logDV*	0.12		0.681	0.839	0.838	0.813	0.767	0.699	0.683
Δ *logDV 0_5*	0.108	0.684		0.746	0.613	0.533	0.47	0.4	0.298
Δ *logDV5_25*	0.121	0.861	0.727		0.836	0.738	0.63	0.514	0.37
Δ *logDV25_50*	0.107	0.854	0.617	0.859		0.842	0.711	0.567	0.393
Δ *logDV 50_100*	0.099	0.821	0.531	0.761	0.857		0.788	0.615	0.413
Δ *logDV100_200*	0.088	0.767	0.471	0.649	0.725	0.793		0.687	0.434
Δ *logDV200_500*	0.08	0.705	0.408	0.536	0.583	0.625	0.685		0.477
Δ *LogDV*500	0.069	0.691	0.311	0.395	0.411	0.424	0.439	0.482	

Panel B: Pearson/Spearman correlations among abnormal number of trades and abnormal ticker search variables

	Δ *logSVI*	Δ *logNT*	Δ *logNT0_5*	Δ *logNT5_25*	Δ *logNT25_50*	Δ *logNT50_100*	Δ *logNT100_200*	Δ *logNT200_500*	Δ *LogNT*500
Δ *logSVI*		0.101	0.089	0.098	0.092	0.086	0.081	0.072	0.07
Δ *logNT*	0.123		0.904	0.916	0.801	0.715	0.624	0.522	0.431
Δ *logNT0_5*	0.107	0.873		0.725	0.603	0.527	0.47	0.402	0.339
Δ *logNT5_25*	0.118	0.918	0.674		0.807	0.715	0.605	0.497	0.409
Δ *logNT25_50*	0.106	0.823	0.603	0.829		0.839	0.708	0.569	0.445
Δ *logNT50_100*	0.099	0.735	0.523	0.736	0.855		0.788	0.621	0.47
Δ *logNT100_200*	0.089	0.639	0.47	0.622	0.723	0.794		0.697	0.504
Δ *logNT200_500*	0.08	0.543	0.41	0.517	0.586	0.632	0.697		0.568
Δ *LogNT*500	0.077	0.459	0.351	0.435	0.466	0.483	0.51	0.575	

Panel C: Pearson/Spearman correlations among other regression variables

	$\Delta\ logDT$	$\Delta\ logNT$	$\Delta\ logStdTS$	$\Delta\ logSVI$	$\lvert Ret_d \rvert$	$Size_{m-1}$	$Held\_pct_{q-1}$	$RetVol_{q-1}$	$Vol5d_d$	$\Delta\ Turnover_{m-1}$	BM_{m-1}	Ret_{m-1}
$\Delta\ logDT$		0.861	0.482	0.082	0.279	0.046	0.039	−0.011	−0.022	−0.071	−0.038	0.008
$\Delta\ logNT$	0.879		0.178	0.084	0.29	0.046	0.024	−0.006	−0.027	−0.068	−0.035	0.014
$\Delta\ logStdTS$	0.482	0.176		0.029	0.08	0.023	0.018	−0.014	0.019	0.012	−0.015	−0.005
$\Delta\ logSVI$	0.1	0.105	0.029		0.033	0.283	−0.001	0.011	0.006	0.001	0.001	−0.011
$\lvert Ret_d \rvert$	0.36	0.369	0.096	0.059		0.008	−0.085	0.079	0.28	0.252	0.031	−0.036
$Size_{m-1}$	0.056	0.059	0.023	0.489	0.023		−0.005	0.015	0.008	0.021	−0.001	−0.012
$Held\_pct_{q-1}$	0.033	0.02	0.016	−0.002	−0.121	−0.009		−0.313	−0.299	−0.152	0.003	−0.122
$RetVol_{q-1}$	−0.006	−0.002	−0.011	0.015	0.068	0.021	−0.234		0.277	0.147	−0.004	−0.082
$Vol5d_d$	−0.019	−0.023	0.014	0.014	0.312	0.017	−0.356	0.19		0.503	−0.03	−0.129
$\Delta\ Turnover_{m-1}$	−0.08	−0.074	0.004	0.005	0.266	0.035	−0.197	0.104	0.477		0.053	−0.066
BM_{m-1}	−0.045	−0.042	−0.015	0.002	0.031	0.001	−0.003	−0.013	−0.03	0.052		0.006
Ret_{m-1}	0.001	0.006	−0.005	−0.017	−0.037	−0.019	−0.115	−0.046	−0.118	−0.064	0.004	

Table 3.3: Regressions of Abnormal Trading Volumes (Δ logDV and Δ logNT)

Table 3.3 presents the regression results of abnormal trading volume (Δ LogDV and Δ logNT) on abnormal ticker search (Δ logSVI) and control variables. Results are presented for regressions with two−way clustered standard errors by firm and month, Fama−MacBeth regression with Newey−West adjusted standard errors, and regressions with firm and year fixed effects and standard errors clustered by firm. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. DV is total daily trading volume in million U. S. dollars. Δ LogDV is the difference between the natural log of DV and the natural log of average DV in the prior ten trading days. $\Delta\ LogDV0\_5$, $\Delta\ LogDV5\_25$, $\Delta\ LogDV25\_50$, $\Delta\ LogDV50\_100$, $\Delta\ LogDV100\_200$, $\Delta\ LogDV200\_500$, and $\Delta\ LogDV500$ are measures of Δ LogDV within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). NT is total number of daily trades (in thousand). Δ LogNT is defined as the difference between the natural log of NT and the log of average NT in the prior ten trading days. $\Delta\ LogNT0\_5$, $\Delta\ LogNT5\_25$, $\Delta\ LogNT25\_50$, $\Delta\ LogNT50\_100$, $\Delta\ LogNT50\_100$, $\Delta\ LogNT200\_500$, and $\Delta\ LogNT500$ are measures of Δ LogNT within each trade size categories (i.e., below \$5,000, between \$5,000 and \$25,000, between \$25,000 and \$50,000, and etc.). StdTS is intra−day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. $\Delta\ Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. Monday, Tuesday, Wednesday, and Thursday are Monday through Thursday dummy variables. ***, **, and * denote the coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

	Two−Way Clustering		Fama−MacBeth		Firm and Time Fixed Effects	
	Δ logDV (1)	*Δ logNT* (2)	*Δ logDV* (3)	*Δ logNT* (4)	*Δ logDV* (5)	*Δ logNT* (6)
Constant	−0.273***	−0.141***	−0.225***	−0.104***	−0.401***	−0.286***
	(−7.77)	(−4.66)	(−7.62)	(−4.17)	(−5.31)	(−4.81)
$\Delta logSVI_d$	0.097***	0.080***	0.071***	0.058***	0.101***	0.082***
	(−10.01)	(9.46)	(16.26)	(17.50)	(12.68)	(12.12)
$\|Ret_d\|$	14.504***	11.232***	15.401***	11.581***	14.479***	11.486***
	(15.24)	(15.38)	(45.84)	(46.65)	(56.97)	(56.52)
$\Delta logSVI_{d-1}$	0.033***	0.026***	0.022***	0.017***	0.040***	0.030***
	(6.07)	(5.76)	(5.55)	(6.21)	(8.17)	(7.45)
$Size_{m-1}$	0.010***	0.004***	0.009***	0.004***	0.016***	0.010**
	(7.63)	(3.15)	(6.13)	(3.35)	(3.25)	(2.58)
$Held\_pct_{q-1}$	0.001	0.004	−0.008	0.000	0.026*	0.015
	(0.11)	(0.58)	(−1.16)	(0.03)	(1.70)	(1.19)
$RetVol_{q-1}$	−4.175***	−3.945***	−4.585***	−4.132***	−3.247***	−2.700***
	(−4.77)	(−4.76)	(−15.39)	(−17.11)	(−15.17)	(−13.50)
$Vol5d_d$	−5.729***	−4.108***	−5.643***	−3.804***	−5.651***	−3.365***
	(−11.46)	(−9.11)	(−25.81)	(−24.45)	(−24.45)	(−20.33)
$\Delta\ Turnover_{m-1}$	−0.063***	−0.045***	−0.069***	−0.045***	−0.067***	−0.047***
	(−7.83)	(−7.35)	(−11.52)	(−9.98)	(−20.06)	(−17.99)
BM_{m-1}	0.010**	0.012**	0.013**	0.013***	(0.01)	0.01
	(2.01)	(2.56)	(2.30)	(3.23)	(−0.56)	(1.39)
Ret_{m-1}	0.067	0.076*	0.019	0.015	0.065***	0.018*
	(1.56)	(1.91)	(1.05)	(1.10)	(4.56)	(1.80)
DRet1dUp	−0.009	−0.025***	0.015***	0.002	−0.008***	−0.024***
	(−1.22)	(−3.59)	(6.35)	(1.27)	(−4.65)	(−18.71)
DRet5dUp	0.009	−0.007	0.005**	−0.005***	0.007***	−0.012***
	(1.20)	(−1.05)	(2.15)	(−2.60)	(3.09)	(−6.53)
Monday	−0.026	0.018			−0.027***	0.017***
	(−1.59)	(1.14)			(−8.58)	(8.51)
Tuesday	0.062***	0.079***			0.063***	0.078***
	(3.99)	(5.58)			(23.08)	(43.93)
Wednesday	0.083***	0.093***			0.083***	0.093***
	(7.50)	(8.93)			(27.72)	(42.85)
Thursday	0.061***	0.076***			0.061***	0.076***
	(4.26)	(5.96)			(21.37)	(39.13)
Observations	179,031	179,031	179,031	179,031	179,031	179,031
R-squared	0.188	0.201	0.214	0.235	0.192	0.218

Table 3.4: Regression of Abnormal Trading Volume for Different Trade Size Categories

Table 3.4 presents the regression results of abnormal trading volume for different trade size categories on abnormal ticker search (Δ LogSVI) and control variables. Results are presented for regressions with two−way clustered standard errors by firm and month. Dependent variables are measures of abnormal trading volume for different trade size categories in Panel A and measures of abnormal number of trades for different trade size categories in Panel B. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. DV is total daily trading volume in million U. S. dollars. Δ LogDV is the difference between the natural log of DV and the natural log of average DV in the prior ten trading days. Δ $LogDV0\_5$, Δ $LogDV5\_25$, Δ $LogDV25\_50$, Δ $LogDV50\_100$, Δ $LogDV100\_200$, Δ $LogDV200\_500$, and Δ $LogDV500$ are measures of Δ LogDV within each trade size categories (i.e., below $5,000, between $5,000 and $25,000, between $25,000 and $50,000, and etc.). NT is total number of daily trades (in thousand dollars). Δ LogNT is defined as the difference between the natural log of NT and the log of average NT in the prior ten trading days. Δ $LogNT0\_5$, Δ $LogNT5\_25$, Δ $LogNT25\_50$, Δ $LogNT50\_100$, Δ $LogNT50\_100$, Δ $LogNT200\_500$, and Δ $LogNT500$ are measures of Δ LogNT within each trade size categories (i.e., below $5,000, between $5,000 and $25,000, between $25,000 and $50,000, and etc.). StdTS is intra−day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. Δ $Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. Monday, Tuesday, Wednesday, and Thursday are Monday through Thursday dummy variables. ***, **, and * denote the coefficient is statistically significant at two-tailed 1%, 5%, and 10% level, respectively.

Panel A: Regression of Stratified Abnormal Dollar Trading Volume (Δ logDV)

	(1) < 5k	(2) [5k, 25k]	(3) [25k, 50k]	(4) [50k, 100k]	(5) [100k, 200k]	(6) [200k, 500k]	(7) ≥ 500k
Constant	−0.195***	−0.211***	−0.502***	−0.747***	−0.831***	−0.322**	0.852***
	(−5.69)	(−5.48)	(−9.14)	(−11.78)	(−8.63)	(−2.41)	(3.91)
$\Delta logSVI_d$	0.078***	0.084***	0.094***	0.101***	0.106***	0.124***	0.148***
	(8.26)	(9.56)	(9.28)	(8.29)	(7.91)	(9.06)	(9.30)
$\|Ret_d\|$	10.181***	11.827***	15.086***	17.460***	19.372***	20.054***	18.607***
	(15.88)	(14.99)	(15.43)	(16.30)	(16.23)	(15.39)	(13.42)
$\Delta logSVI_{d-1}$	0.027***	0.025***	0.031***	0.039***	0.047***	0.040***	0.052***
	(5.46)	(5.11)	(5.50)	(5.67)	(5.54)	(4.41)	(3.90)
$Size_{m-1}$	0.008***	0.007***	0.020***	0.033***	0.036***	0.01	−0.050***
	(4.48)	(4.11)	(8.35)	(11.49)	(9.04)	(1.13)	(−4.50)
$Held\_pct_{q-1}$	0.022**	−0.001	−0.003	−0.023	−0.052	−0.067*	−0.131**
	(2.07)	(−0.09)	(−0.23)	(−1.59)	(−1.50)	(−1.66)	(−2.53)
$RetVol_{q-1}$	−3.380***	−4.053***	−4.207***	−3.696***	−3.434***	−4.361***	−5.884***
	(−4.88)	(−4.69)	(−4.49)	(−3.45)	(−2.99)	(−3.60)	(−3.46)
$Vol5d_d$	−3.375***	−4.437***	−5.544***	−6.574***	−7.770***	−9.732***	−9.963***
	(−9.22)	(−9.22)	(−10.11)	(−10.66)	(−11.83)	(−12.30)	(−11.25)
$\Delta Turnover_{m-1}$	−0.032***	−0.047***	−0.057***	−0.064***	−0.073***	−0.079***	−0.117***
	(−5.10)	(−7.15)	(−7.50)	(−6.28)	(−6.45)	(−6.78)	(−6.10)
BM_{m-1}	0.001	0.007	0.012	0.007	0.002	−0.005	−0.012
	(0.17)	(1.27)	(1.63)	(0.78)	(0.17)	(−0.28)	(−0.32)
Ret_{m-1}	0.103***	0.082*	0.077*	0.06	0.04	0.05	0.02
	(2.62)	(1.95)	(1.70)	(1.13)	(0.73)	(0.82)	(0.21)
DRet1dUp	−0.023***	−0.016**	−0.005	0.006	0.008	0.010	0.014
	(−3.63)	(−2.34)	(−0.56)	(0.66)	(0.80)	(1.12)	(1.16)
DRet5dUp	−0.006	0.007	0.017**	0.023***	0.023***	0.016**	0.018
	(−0.78)	(1.07)	(2.31)	(3.03)	(2.67)	(1.98)	(0.87)

Panel A: Regression of Stratified Abnormal Dollar Trading Volume (Δ logDV)

	(1) < 5k	(2) [5k, 25k]	(3) [25k, 50k]	(4) [50k, 100k]	(5) [100k, 200k]	(6) [200k, 500k]	(7) ≥ 500k
Monday	0.017	0.020	0.024	0.018	0.003	−0.017	−0.318***
	(1.06)	(1.25)	(1.47)	(1.05)	(0.19)	(−0.97)	(−10.34)
Tuesday	0.067***	0.083***	0.090***	0.095***	0.106***	0.114***	−0.089***
	(4.69)	(5.60)	(6.02)	(5.68)	(6.23)	(6.52)	(−3.32)
Wednesday	0.081***	0.099***	0.106***	0.110***	0.123***	0.135***	−0.056***
	(7.41)	(8.88)	(9.70)	(9.11)	(9.82)	(9.56)	(−2.68)
Thursday	0.068***	0.079***	0.084***	0.088***	0.097***	0.103***	−0.097***
	(5.35)	(6.03)	(6.14)	(5.83)	(6.32)	(6.63)	(−3.83)
Observations	105,521	177,622	178,267	178,340	176,562	171,490	158,670
R-squared	0.144	0.189	0.169	0.149	0.124	0.099	0.060

Panel B: Regression of Stratified Abnormal Number of Trades (Δ logNT)

	(1) < 5k	(2) [5k, 25k]	(3) [25k, 50k]	(4) [50k, 100k]	(5) [100k, 200k]	(6) [200k, 500k]	(7) ≥ 500k
Constant	−0.193***	−0.176***	−0.488***	−0.728***	−0.804***	−0.265*	1.258***
	(−5.53)	(−4.53)	(−8.81)	(−11.46)	(−8.30)	(−1.94)	(6.24)
$\Delta logSVI_d$	0.077***	0.082***	0.094***	0.100***	0.106***	0.119***	0.143***
	(8.20)	(9.54)	(9.33)	(8.15)	(7.90)	(8.73)	(10.25)
$\lvert Ret_d \rvert$	10.111***	11.449***	14.952***	17.338***	19.279***	19.958***	17.298***
	(16.14)	(14.80)	(15.41)	(16.28)	(16.26)	(15.32)	(13.59)
$\Delta logSVI_{d-1}$	0.027***	0.026***	0.032***	0.038***	0.047***	0.041***	0.033***
	(5.62)	(5.17)	(5.58)	(5.64)	(5.77)	(4.42)	(3.22)
$Size_{m-1}$	0.008***	0.005***	0.020***	0.032***	0.035***	0.01	−0.076***
	(4.52)	(3.17)	(7.97)	(11.18)	(8.65)	(0.69)	(−7.33)
$Held\_pct_{q-1}$	0.024**	−0.005	−0.003	−0.024	−0.052	−0.071*	−0.110**
	(2.07)	(−0.51)	(−0.23)	(−1.55)	(−1.48)	(−1.73)	(−2.29)
$RetVol_{q-1}$	−3.228***	−4.145***	−4.252***	−3.751***	−3.536***	−4.465***	−7.311***
	(−4.64)	(−4.79)	(−4.50)	(−3.52)	(−3.09)	(−3.69)	(−4.99)
$Vol5d_d$	−3.225***	−4.322***	−5.525***	−6.546***	−7.711***	−9.686***	−10.316***
	(−8.15)	(−8.97)	(−10.04)	(−10.72)	(−11.74)	(−12.44)	(−13.20)
$\Delta\ Turnover_{m-1}$	−0.029***	−0.046***	−0.057***	−0.064***	−0.073***	−0.080***	−0.105***
	(−4.54)	(−7.15)	(−7.55)	(−6.32)	(−6.42)	(−6.86)	(−5.52)
BM_{m-1}	0.003	0.006	0.012	0.008	0.002	−0.002	−0.010
	(0.37)	(1.14)	(1.64)	(0.87)	(0.21)	(−0.12)	(−0.28)
Ret_{m-1}	0.101**	0.088**	0.080*	0.06	0.04	0.04	0.03
	(2.50)	(1.98)	(1.75)	(1.12)	(0.72)	(0.78)	(0.42)
DRet1dUp	−0.032***	−0.019***	−0.006	0.01	0.01	0.01	0.00
	(−4.96)	(−2.63)	(−0.71)	(0.58)	(0.79)	(1.17)	(−0.01)
DRet5dUp	−0.021***	0.00	0.015**	0.022***	0.022***	0.016**	0.017*
	(−2.74)	(0.62)	(2.17)	(2.93)	(2.67)	(2.02)	(1.76)
Monday	0.02	0.02	0.03	0.02	0.00	−0.017	−0.067***
	(1.04)	(1.23)	(1.49)	(1.12)	(0.23)	(−0.99)	(−3.87)
Tuesday	0.068***	0.082***	0.090***	0.095***	0.106***	0.111***	0.092***
	(4.78)	(5.49)	(6.03)	(5.72)	(6.27)	(6.34)	(5.07)
Wednesday	0.079***	0.098***	0.105***	0.110***	0.123***	0.132***	0.121***
	(7.33)	(8.57)	(9.66)	(9.12)	(9.83)	(9.68)	(8.81)
Thursday	0.068***	0.079***	0.084***	0.088***	0.097***	0.100***	0.085***
	(5.25)	(5.86)	(6.12)	(5.85)	(6.28)	(6.49)	(5.66)
Observations	105,521	177,622	178,267	178,340	176,562	171,490	158,670
R-squared	0.147	0.176	0.166	0.148	0.125	0.101	0.082

Table 3.5: Regressions of Intra-day Abnormal Volatility of Trade Size (Δ logStdTS)

Table 3.5 presents the regression results of intra-day abnormal volatility of trade size (Δ LogStdTS) on abnormal ticker search (Δ LogSVI) and control variables. StdTS is intra-day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. Results are presented for regressions with two-way clustered standard errors by firm and month, Fama-MacBeth regression with Newey-West adjusted standard errors, and regressions with firm and year fixed effects and standard errors clustered by firm. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F-filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. $\Delta\ Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. Monday, Tuesday, Wednesday, and Thursday are Monday through Thursday dummy variables. ***, **, and * denote the regression coefficient is statistically significant at two-tailed 1%, 5%, and 10% level, respectively.

Regressions of Intra-day Abnormal Volatility of Trade Size (Δ logStdTS)			
	Two-Way Clustering (1)	Fama-MacBeth (2)	Fixed Effects (3)
Constant	−0.230***	−0.548***	−0.299**
	(−3.56)	(−12.48)	(−2.11)
$\Delta logSVI_d$	0.044***	0.019**	0.043***
	(4.03)	(2.54)	(4.83)
$\|Ret_d\|$	6.597***	7.197***	6.682***
	(11.84)	(29.96)	(32.61)
$\Delta logSVI_{d-1}$	0.032***	0.022***	0.032***
	(3.54)	(3.17)	(4.38)
$Size_{m-1}$	0.013***	0.019***	0.021**
	(4.69)	(6.39)	(2.42)
$Held\_pct_{q-1}$	−0.047***	(0.01)	(0.01)
	(−3.15)	(−0.63)	(−0.71)
$RetVol_{q-1}$	−0.196	0.544	−0.768**
	(−0.22)	(1.41)	(−2.30)
$Vol5d_d$	−1.153***	−0.705**	−0.803***
	(−2.74)	(−2.53)	(−3.69)
$\Delta\ Turnover_{m-1}$	−0.041**	−0.051***	−0.053***
	(−2.52)	(−7.15)	(−9.36)
BM_{m-1}	0.000	0.007	−0.014
	(−0.03)	(0.75)	(−0.69)
Ret_{m-1}	−0.029	−0.043	−0.036*
	(−0.58)	(−1.59)	(−1.69)
DRet1dUp	0.02	0.01	0.018***
	(1.59)	(1.28)	(5.10)
DRet5dUp	−0.006	−0.016***	−0.014***
	(−0.36)	(−4.01)	(−3.84)
Monday	−0.332***		−0.334***
	(−12.19)		(−36.02)
Tuesday	−0.191***		−0.196***
	(−9.47)		(−24.26)
Wednesday	−0.182***		−0.185***
	(−9.93)		(−24.17)
Thursday	−0.196***		−0.198***
	(−10.27)		(−26.52)
Observations	179,031	179,031	179,031
R-squared	0.033	0.04	0.037

Table 3.6: Impact of Accruals, Earning Announcement, and Local Ticker Search on Abnormal Trading Volume

Table 3.6 presents the regression results of abnormal trading volume. Dependent variables (Δ LogDV, Δ LogNT and Δ LogStdTS) are measures of abnormal trading volume, abnormal number of trades, intra−day abnormal volatility of trade size respectively. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. DV is total daily trading volume in million U. S. dollars. Δ LogDV is the difference between the natural log of DV and the natural log of average DV in the prior ten trading days. NT is total number of daily trades (in thousands). Δ LogNT is defined as the difference between the natural log of NT and the log of average NT in the prior ten trading days. StdTS is intra−day standard deviation of trade size (in thousand dollars). Δ logStdTS is the difference between the natural log of StdTS and the natural log of average StdTS over prior ten trading days. $|Accruals|$ is the tercile rank of the average absolute discretionary accruals (Dechow et al. (1995)) of prior three years. EA is a dummy variable equal to one if the trading day is within the (−5, +5) trading day window centered on Compustat earning announcement date. HiLocal is a dummy variable equal to one if local ticker search is above sample median in a given year and zero otherwise. Local search is defined as the search from any locations in the state of the firm's headquarter. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. Δ $Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. Monday, Tuesday, Wednesday, and Thursday are Monday through Thursday dummy variables. All t−statistics are calculated with two−way clustered standard errors by firm and month. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ *logDV*	Δ *logNT*	Δ *logDV*	Δ *logNT*	Δ *logDV*	Δ *logNT*
Constant	−0.295***	−0.158***	−0.291***	−0.155***	−0.272***	−0.135***
	(−6.62)	(−4.16)	(−8.28)	(−5.24)	(−5.64)	(−3.25)
$\Delta logSVI_d$	0.077***	0.063***	0.088***	0.074***	0.128**	0.128***
	(5.31)	(4.78)	(8.93)	(8.55)	(2.56)	(2.67)
$\|Ret_d\|$	15.827***	12.268***	14.383***	11.138***	14.488***	11.162***
	(15.28)	(15.05)	(15.45)	(15.50)	(15.56)	(16.09)
$\Delta logSVI_{d-1}$	0.033***	0.027***	0.032***	0.025***	0.099***	0.075***
	(5.29)	(4.80)	(5.89)	(5.64)	(4.76)	(4.47)
$\Delta logSVI \times \|Accruals\|$	0.036***	0.032***				
	(3.34)	(3.05)				
$\|Accruals\|$	−0.005***	−0.004***				
	(−3.32)	(−3.69)				
$\Delta logSVI \times EA$			0.072***	0.053***		
			(4.51)	(4.07)		
EA			0.077***	0.060***		
			(6.99)	(6.24)		
$\Delta logSVI \times HiLocal$					0.083***	0.053**
					(2.79)	(2.25)
HiLocal					0.024***	0.018***
					(4.06)	(3.66)
$Size_{m-1}$	0.010***	0.004***	0.010***	0.004***	0.007***	0.001
	(6.04)	(2.74)	(7.65)	(3.45)	(5.11)	(1.00)
$Held\_pct_{q-1}$	0.014	0.012	0.007	0.009	0.010	0.020
	(1.17)	(1.21)	(0.90)	(1.39)	(0.37)	(0.85)
$RetVol_{q-1}$	−4.434***	−4.076***	−3.818***	−3.664***	−4.572***	−4.291***
	(−4.79)	(−4.68)	(−4.50)	(−4.51)	(−7.97)	(−7.99)
$Vol5d_d$	−6.311***	−4.526***	−6.086***	−4.389***	−4.834***	−3.670***
	(−12.60)	(−9.79)	(−11.93)	(−9.73)	(−6.18)	(−6.23)
Δ $Turnover_{m-1}$	−0.068***	−0.050***	−0.060***	−0.043***	−0.059***	−0.041***
	(−8.67)	(−7.83)	(−6.83)	(−6.41)	(−6.30)	(−6.44)
BM_{m-1}	0.012*	0.011*	0.008*	0.010**	0.039***	0.032***
	(1.95)	(1.94)	(1.73)	(2.37)	(4.07)	(3.23)
Ret_{m-1}	0.062	0.073**	0.068*	0.077**	0.019	0.033
	(1.52)	(1.96)	(1.65)	(2.03)	(0.43)	(0.90)
DRet1dUp	−0.010	−0.027***	−0.009	−0.025***	−0.003	−0.019***
	(−1.32)	(−3.50)	(−1.22)	(−3.60)	(−0.44)	(−3.07)
DRet5dUp	0.011	−0.006	0.009	−0.007	0.010	−0.004
	(1.52)	(−0.87)	(1.19)	(−1.05)	(1.01)	(−0.53)
Monday	−0.020	0.024	−0.027	0.018	−0.027	0.024
	(−1.08)	(1.25)	(−1.62)	(1.12)	(−1.36)	(1.23)
Tuesday	0.068***	0.086***	0.061***	0.078***	0.072***	0.090***
	(3.83)	(5.04)	(3.96)	(5.55)	(4.01)	(5.40)
Wednesday	0.088***	0.100***	0.083***	0.093***	0.087***	0.099***
	(6.86)	(7.87)	(7.51)	(8.93)	(6.19)	(7.16)
Thursday	0.069***	0.085***	0.060***	0.075***	0.065***	0.079***
	(4.18)	(5.36)	(4.22)	(5.92)	(3.96)	(5.05)
Observations	139,173	139,173	179,031	179,031	33,850	33,850
R-squared	0.203	0.213	0.192	0.206	0.204	0.22

Table 3.7: Impact of Ticker Search on Directional Abnormal Trading Volumes

Table 3.7 presents the regression results of abnormal trading volumes for buy and sell orders. In Panel A, Δ logBuyDV (Δ logSellDV) is the difference between the natural log of buy (sell) orders (in million dollars) and the natural log of average buy (sell) orders in prior ten trading days. In panel B, Δ logBuyN (Δ logSellN) is the difference between the natural log of number of buy (sell) orders (in thousands) and the natural log of average number of buy (sell) orders in prior ten trading days. We classify trades into buyer−initiated or seller−initiated trades using the Lee and Ready (1991) and Lee (1992) algorithm. SVI is ticker search intensity defined as the daily search volume index of a stock ticker on Google, scaled from 0 to 100 by Google. Δ logSVI is the difference between the natural log of SVI and the natural log of average SVI in the prior ten trading days. Large is a dummy variable equal to one if the average trade size of a trading day is above the mean daily trade size of prior month. $|Accruals|$ is the tercile rank of average absolute discretionary accruals (Dechow et al. (1995)) of prior three years. EA is a dummy variable equal to one if the trading day is within the (-5, +5) trading day window centered on Compustat earning announcement date. HiLocal is a dummy variable equal to one if local ticker search is above sample median in a given year and zero otherwise. Local search is defined as the search from any locations in the state of the firm's headquarter. $|Ret_d|$ is the absolute value of contemporary daily stock return. $Size_{m-1}$ is the natural log of market value of equity at the beginning of the month. $Held\_pct_{q-1}$ is the percentage of stocks held by all 13F−filing institutional shareholders at the end of last quarter. $RetVol_{q-1}$ is the daily individual stock return standard deviation in the prior quarter. $Vol5d_d$ is daily return standard deviation over prior five days. $\Delta\ Turnover_{m-1}$ is the difference between the natural log of share turnover of prior month and the natural log of share turnover of the month before the prior month. BM_{m-1} is the book value of equity from the latest available financial statement. Ret_{m-1} is stock return during the prior month. $DRet1dUp_{it}$ ($DRet5dUp_{it}$) is a dummy variable equal to one if the stock returns during the prior (prior five) trading day(s) are positive, and zero otherwise. DWeekDay represents Monday through Thursday dummy variables and for brevity the estimated coefficients ant t−statistics are not reported. All t−statistics are calculated with two−way clustered standard errors by firm and month. ***, **, and * denote the regression coefficient is statistically significant at two-tailed 1%, 5%, and 10% level, respectively.

	Abnormal Buy Volume (Δ logBuyDV)					Abnormal Sell Volume(Δ logSellDV)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	−0.243***	−0.390***	−0.223**	0.065	−0.268***	−0.101	−0.240***	0.018	0.055	−0.128
	(−4.36)	(−7.15)	(−2.52)	(0.90)	(−5.17)	(−1.17)	(−2.84)	(0.14)	(0.95)	(−1.59)
$\Delta logSVI_d$	0.100***	0.064***	0.086***	0.188***	0.092***	0.096***	0.063***	0.074***	0.157***	0.083***
	(9.53)	(6.68)	(5.50)	(3.89)	(8.64)	(8.37)	(5.51)	(3.86)	(2.72)	(7.50)
$\Delta logSVI_{d-1}$	0.033***	0.025***	0.033***	0.070***	0.032***	0.035***	0.026***	0.031***	0.097***	0.033***
	(4.95)	(3.86)	(3.96)	(3.38)	(4.76)	(4.10)	(3.15)	(3.38)	(4.80)	(3.98)
$\Delta logSVI \times Large$		0.057***					0.054***			
		(4.16)					(3.93)			
Large		0.336***					0.319***			
		(26.36)					(27.44)			
$\Delta logSVI \times \lvert Accruals \rvert$			0.032***					0.040***		
			(2.62)					(2.59)		
$\lvert Accruals \rvert$			−0.008**					0.00		
			(−2.01)					(0.60)		
Δ *logSVI* × *EA*				0.114***					0.187***	
				(2.68)					(3.29)	
EA				0.024***					0.020***	
				(3.35)					(2.72)	
Δ *logSVI* × *HiLocal*					0.061***					0.092***
					(3.71)					(3.95)
HiLocal					0.099***					0.119***
					(9.04)					(8.32)
$\lvert Ret_d \rvert$	15.228***	12.826***	16.125***	19.907***	15.071***	14.093***	11.799***	14.892***	19.685***	13.875***
	(14.84)	(15.12)	(14.24)	(13.21)	(15.07)	(13.39)	(13.23)	(13.83)	(12.98)	(13.57)
$Size_{m-1}$	0.008***	0.008***	0.007*	−0.008**	0.009***	−0.002	−0.002	−0.008	−0.007**	−0.001
	(3.59)	(3.60)	(1.74)	(−2.30)	(4.15)	(−0.35)	(−0.44)	(−1.23)	(−2.30)	(−0.24)
$Held_pct_{q-1}$	−0.022	−0.010	−0.029	0.020	−0.015	−0.044*	−0.032	−0.056	0.024	−0.035*
	(−1.37)	(−0.68)	(−1.08)	(1.18)	(−0.99)	(−1.92)	(−1.44)	(−1.58)	(1.37)	(−1.66)
$RetVol_{q-1}$	−4.891***	−3.778***	−5.059***	−7.247***	−4.406***	−4.405***	−3.338***	−4.864***	−7.345***	−3.775***
	(−5.12)	(−4.66)	(−4.29)	(−9.72)	(−4.89)	(−3.49)	(−2.98)	(−3.12)	(−8.68)	(−3.21)
$Vol5d_d$	−6.149***	−6.196***	6.848***	−5.405***	−6.627***	−6.433***	−6.472***	−7.452***	−5.462***	−7.054***
	(−12.54)	(−14.38)	(−11.75)	(−6.23)	(−13.57)	(−9.70)	(−11.03)	(−9.48)	(−6.14)	(−10.83)
$\Delta\ Turnover_{m-1}$	−0.071***	−0.050***	0.074***	−0.076***	−0.068***	−0.065***	−0.044***	−0.078***	−0.071***	−0.061***
	(−8.44)	(−6.73)	(−8.35)	(−6.73)	(−8.24)	(−4.49)	(−3.53)	(−4.49)	(−5.43)	(−4.85)

	Abnormal Buy Volume (Δ logBuyDV)					Abnormal Sell Volume(Δ logSellDV)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BM_{m-1}	−0.015	−0.015	−0.033	−0.001	−0.018	0.004	0.005	0.004	0.003	0.003
	(−1.35)	(−1.35)	(−1.55)	(−0.10)	(−1.61)	(0.31)	(0.37)	(0.16)	(0.13)	(0.20)
Ret_{m-1}	0.083	0.117**	0.082	−0.078	0.085	0.130**	0.157***	0.098	0.020	0.130**
	(1.49)	(2.35)	(1.35)	(−1.49)	(1.63)	(2.22)	(3.06)	(1.59)	(0.38)	(2.44)
DRet1dUp	0.004	0.000	0.004	0.018**	0.004	−0.024***	−0.028***	−0.026***	−0.017**	−0.025***
	(0.55)	(−0.03)	(0.49)	(2.40)	(0.54)	(−3.32)	(−3.82)	(−3.34)	(−2.12)	(−3.32)
DRet5dUp	0.006	0.007	0.011	0.012	0.006	0.027***	0.029***	0.028***	0.018	0.027***
	(0.74)	(1.01)	(1.38)	(1.08)	(0.75)	(3.44)	(4.13)	(3.36)	(1.49)	(3.43)
DWeekDay	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,003	170,003	131,221	32,189	170,003	158,155	158,155	124,472	31,000	158,155
R-squared	0.123	0.229	0.101	0.192	0.127	0.077	0.143	0.058	0.162	0.081

Panel B: Regressions of Abnormal Number of Buy Orders and Sell Orders

	Abnormal Number of Buy Orders (Δ logBuyN)				Abnormal Number of Sell Orders (Δ logSellN)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	−0.067	−0.102*	−0.042	−0.088*	−0.206**	0.060	0.030	0.163	0.037	−0.262***
	(−1.25)	(−1.89)	(−0.54)	(−1.80)	(−2.13)	(0.68)	(0.34)	(1.27)	(0.44)	(−3.18)
$\Delta logSVI_d$	0.086***	0.056***	0.076***	0.080***	0.139***	0.078***	0.055***	0.053***	0.068***	0.117**
	(9.05)	(6.13)	(5.09)	(8.42)	(2.67)	(7.38)	(5.39)	(2.87)	(6.38)	(2.26)
$\Delta logSVI_{d-1}$	0.027***	0.024***	0.027***	0.026***	0.084***	0.027***	0.025***	0.024***	0.026***	0.089***
	(4.60)	(4.15)	(3.62)	(4.47)	(4.39)	(3.49)	(3.22)	(2.73)	(3.36)	(4.26)
$\Delta\ logSVI \times Large$		0.064***					0.047***			
		(5.73)					(3.30)			
Large		0.085***					0.072***			
		(14.67)					(10.83)			
$\Delta logSVI \times \lvert Accruals \rvert$			0.025**					0.039**		
			(2.10)					(2.57)		
Accruals			−0.007*					0.00		
			(−1.85)					(0.61)		
$\Delta\ logSVI \times EA$				0.046***					0.073***	
				(3.12)					(3.54)	
EA				0.082***					0.104***	
				(8.02)					(7.37)	
$\Delta\ logSVI \times HiLocal$					0.074**					0.101**
					(2.27)					(2.06)
HiLocal					0.018***					0.020***
					(3.45)					(2.70)
$\lvert Ret_d \rvert$	11.844***	11.210***	12.415***	11.714***	12.531***	10.612***	10.073***	11.092***	10.424***	11.312***
	(14.57)	(14.39)	(13.68)	(14.72)	(13.73)	(12.46)	(12.16)	(12.85)	(12.55)	(14.00)
$Size_{m-1}$	0.000	0.000	−0.001	0.001	0.005	−0.009**	−0.009**	−0.015**	−0.008**	0.006*
	(0.02)	(−0.07)	(−0.28)	(0.30)	(1.46)	(−1.99)	(−2.04)	(−2.21)	(−1.98)	(1.95)
$Held\_pct_{q-1}$	−0.026*	−0.023	−0.039	−0.020	0.008	−0.044*	−0.041*	−0.059*	−0.035*	−0.004
	(−1.70)	(−1.54)	(−1.62)	(−1.44)	(0.16)	(−1.85)	(−1.74)	(−1.67)	(−1.65)	(−0.09)
$RetVol_{q-1}$	−4.788***	−4.511***	4.690***	−4.383***	−5.042***	−4.132***	−3.894***	−4.396***	−3.581***	−2.681**
	(−5.09)	(−4.94)	(−4.11)	(−4.88)	(−6.01)	(−3.20)	(−3.08)	(−2.83)	(−2.93)	(−2.41)
$Vol5d_d$	−4.542***	−4.557***	5.081***	−4.942***	−4.040***	−4.763***	−4.773***	−5.580***	−5.306***	−4.122***
	(−10.03)	(−10.60)	(−8.81)	(−11.19)	(−6.10)	(−7.21)	(−7.47)	(−6.92)	(−8.26)	(−4.58)
$\Delta\ Turnover_{m-1}$	−0.053***	−0.047***	0.054***	−0.050***	−0.050***	−0.048***	−0.043***	−0.059***	−0.045***	−0.040***
	(−6.80)	(−6.24)	(−6.26)	(−7.11)	(−3.73)	(−3.11)	(−2.85)	(−3.30)	(−3.29)	(−3.05)
BM_{m-1}	−0.014	−0.014	−0.035*	−0.016	0.018	0.003	0.004	0.001	0.002	0.028
	(−1.25)	(−1.25)	(−1.73)	(−1.47)	(0.77)	(0.26)	(0.28)	(0.05)	(0.16)	(1.09)
Ret_{m-1}	0.112**	0.121**	0.111*	0.114**	0.034	0.125**	0.132**	0.091	0.125**	0.139**
	(1.99)	(2.20)	(1.83)	(2.15)	(0.65)	(2.04)	(2.20)	(1.39)	(2.25)	(2.17)
DRet1dUp	−0.023***	−0.024***	0.024***	−0.023***	−0.017***	−0.027***	−0.028***	−0.029***	−0.027***	−0.030***
	(−3.20)	(−3.33)	(−3.52)	(−3.20)	(−3.11)	(−3.70)	(−3.78)	(−3.60)	(−3.69)	(−3.16)
DRet5dUp	−0.010	−0.009	−0.005	−0.010	−0.007	0.008	0.008	0.009	0.007	0.003
	(−1.35)	(−1.34)	(−0.64)	(−1.35)	(−0.70)	(1.01)	(1.08)	(1.09)	(1.00)	(0.28)
DWeekDay	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,003	170,003	131,221	170,003	32,189	158,155	158,155	124,472	158,155	31,000
R-squared	0.111	0.121	0.082	0.115	0.127	0.057	0.061	0.04	0.061	0.067

Table 3.8: Search Intensity, Directional Abnormal Net Buy, and Future Returns ($adjReturn_d$)

Table 3.8 presents the cross−sectional averages of estimated coefficients (t−statistics) from firm−specific regression of daily market−adjusted returns. The dependent variable $adjReturn_d$ is stock return on trading day d adjusted by the S&P 500 value−weighted composite index. $NetBuy_{d-1}$ is buy minus sell orders (in million dollars) on trading day d−1 scaled by the sum of buy and sell orders in prior ten trading days. $HiSVI_{d-1}$ is a dummy variable equal to one if Δ logSVI is greater than sample median within each year or zero otherwise, where Δ logSVI is the difference between the natural log of SVI on trading day d−1 and the natural log of average SVI in the prior ten trading days. All t−statistics are corrected for cross−sectional correlations. ***, **, and * denote the regression coefficient is statistically significant at two−tailed 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Constant	0.017**	0.012**	0.083***	0.105**
	(2.06)	(2.02)	(2.84)	(2.45)
$NetBuy_{d-1}$	0.071	−0.220	−0.139	−0.192*
	(0.49)	(−1.58)	(−0.83)	(−1.92)
$NetBuy_{d-1} \times HiSVI_{d-1}$		0.397***	0.456***	0.757***
		(2.91)	(2.87)	(2.76)
$HiSVI_{d-1}$		−0.007	−0.050	−0.022
		(−0.27)	(−1.12)	(−0.75)
$NetBuy_{d-2}$			−0.148***	−0.147
			(−2.88)	(−1.62)
$NetBuy_{d-3}$				−0.067
				(−0.85)
Average R-squared	0.014	0.046	0.056	0.071
$NetBuy_{d-1} + NetBuy_{d-1} \times HiSVI_{d-1}$		0.177**	0.317**	0.565**
		(2.51)	(2.35)	(2.66)