THREE ESSAYS ON MARKET REACTIONS TO REGULATORY CHANGES IN THE INFORMATION ENVIRONMENT

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ABSTRACT OF THE THESIS

Three Essays on Market Reactions to Regulatory Changes in the Information Environment

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My essays research on the information environment change due to the passage of the Sarbanes-Oxley Act (hereafter, SOX). SOX was enacted in 2002 to reform the financial market following a series of corporate scandals that negatively impacted investors' trust in the integrity of financial reporting. SOX has two main sections that are related specifically to internal control issues within public companies. The two provisions, Sections 302 and 404, focus on Internal Controls over Financial Reporting (hereafter, ICOFR) and were enacted mainly to improve corporate financial reporting (Bedard et al. 2009), and arguably, have a great potential for doing so (Nicolaisen 2004). The effects of SOX in improving financial reporting has been verified by number of papers (e.g. Bedard 2006; Nagy 2010; Bizzaro et al. 2010). In particular, Section 302, which became effective on August 29, 2002, requires top officers of all public firms to disclose quarterly all MWs in the firm's ICOFR. Beginning with fiscal year ending after November 15, 2004, Section 404 requires accelerated filers to assess the effectiveness of the ICOFR, and their auditors to both make their evaluation and to attest to management's findings. In compliance with Section 404, non-accelerated filers are required, starting with fiscal years ending after December 15, 2007, to only document a management report on ICOFR.

Prior literature find SOX increases both financial information quality and internal control efficiency. Based on these results, my essay tests the effects of improved information quality in three different areas. The first essay examines the audit market structure after SOX. Cross-sectional differences in audit fees can represent either the effect of quantity differences (in terms of hours of audit) or price differences in terms of an hourly fee (Simunic 1980a). My second essay examines whether SOX improves the information precision and leads to a faster reaction to information. My third essay examines whether SOX affects the boldness of analysts' stock recommendations.

DEDICATION

To my parents

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1.1 Introduction

Following the enactment of the Sarbanes-Oxley Act in 2002 (hereafter SOX) and the demise of Arthur-Andersen (hereafter AA), audit fees have risen sharply and the market share for the BIG-4 auditors (KPMG, PWC, D&T, and E&Y) has fallen dramatically (Figure 1).[1] In addition, the difference in fees between BIG-4 and other auditors (hereafter, NB-4), usually referred to as the BIG-4 premium, has increased over this period (Ghosh and Pawlewicz 2009). The goal of this paper is to examine whether the fall in market share is primarily a result of the increase in the BIG-4 premium, or whether, after controlling for the effects of the increase in the BIG-4 premium, increased competitiveness of NB-4 has also contributed to the decline in BIG-4 market share.[2] While these two effects have been discussed individually in earlier studies, my paper studies them jointly. As either effect can lead to reduced market share for the BIG-4, it is necessary to show that increased NB-4 competition has led to a reduction above and beyond that resulting from increases in BIG-4 audit fees. By developing a formal model of auditor choice, I am able to identify differences in the pattern of BIG-4 market share losses arising from BIG-4 fee increases as contrasted with losses arising from more effective NB-4 competition.

[1] Papers that have documented fee increases following the enactment of SOX include (Asthana, Balsam and Kim 2009; Griffin and Lont 2007). BIG-4 market share losses have also been noted in earlier literature though I could not find a systematic reference documenting the effects that are categorized in Table 3 of this paper.

[2] Cassell, Giroux, Myers, and Omer (2013) analyze a list of firms they consider to be second-tier auditors and argue that the reference documenting the effects that are categorized in Table 3 of this paper. Competitive position of these second-tier firms has improved post-SOX. Our evidence suggests that this phenomenon is more widespread and applies to other smaller NB-4 audit firms as well.

The fundamental result derived from the model is that if changes in BIG-4 market shares are driven by supply side effects (i.e. BIG-4 fee increases), fee increases, and market share losses will be positively correlated. In contrast, if market share changes are driven not only by supply-side effects (fee increases) but by demand shifts as well, (that is, from an increase in the perceived benefit of an NB-4 audit), the increase in fees and loss of market share can be negatively correlated. My findings are that both at the firm level and industry level, industry market share losses of the BIG-4 are inversely correlated with fee increases. At a firm level, I find that firms that are charged a larger residual premium (after controlling for mean industry fee effects) are less likely to switch to an NB-4 auditor in the following year. I also find that at the industry level, the industries where fees increased the most have the least drop in market share and that industries where the NB-4 held a lower market-share pre-SOX were also the ones where firms were more likely to switch post-SOX (after controlling for the excess BIG-4 premium). This finding is inconsistent with the market equilibrium being driven purely by BIG-4 pricing strategies.

The economic theory of the market for public audits focuses on the fact that audit quality is not observable by investors either before or after the use of audited information (that is, audit services are credence goods (Eamons 1997). This property leads to a theoretical prediction that auditor reputation will be used by the market as a proxy for audit quality and that the "deep pockets" of BIG-4 auditors serves as an observable proxy for auditor reputation (Dye 1993; Datar and Alles 1999; Mayhew 2001, Bar-Yosef and Sarath 2005). The higher perceived quality of BIG-4 audits translates to better market prices for their clients. However, deep pockets also imply greater payouts from litigation (if the plaintiffs succeed) and this expected cost has to be recovered through higher fees. Summarizing, the overall economic consequences of the unobservability of audit quality leads to a theoretical prediction of two components that constitute the BIG-4 premium – (i) a (partial) recapture of the market value to the client-firm associated with higher BIG-4 reputation and (ii) a (partial) recovery of greater expected litigation payouts that act as the implicit guarantee of better quality audits by the BIG-4. All these predicted theoretical factors, namely the existence of a BIG-4 premium, the presence of market benefits for BIG-4 clients, and greater payouts to settle litigation are incorporated in my model. [1]

This model can be used to develop predictions both about the relationship between the probability of switching from a BIG-4 auditor at the individual firm level or in the aggregate as market share shift at the industry level. I first show how, in equilibrium, the BIG-4 premium reflects both the greater risk and the partial recapture of the market value of a BIG-4 audit to client firms (Proposition 1). This equilibrium fee structure can be used to determine the relationship between fee increases due to increased litigation risk and switching probabilities of individual firms or aggregate market share losses at the industry level (Propositions 3 and 4). These results imply that if switching away from the BIG-4 is primarily driven by pricing responses to increased risk, I would expect to see a positive relationship between the increase in the premium charged by the BIG-4 and the propensity to switch to NB-4, or equivalently, with the loss in industry

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[1] The existence of a BIG-4 premium is now a standard feature of Audit Fee models as documented in the next section. There is a considerable stream of empirical literature attempting to document the market value generated by BIG-4 auditors. For example, Beatty (1989) associated BIG-8 auditors with reduced underpricing for their clients at the time of Initial Public Offerings. Teoh and Wong (1993) found the earnings response coefficient (ERC) is higher for firms audited by BIG-4. Pittman and Fortin (2004) and Mansi, Maxwell, and Miller (2004) suggested that debt financing costs are lower for firms audited by BIG-4. Khurana and Raman (2004) showed that the ex-ante cost of equity capital is lower for firms audited by BIG-4 than for companies audited by NB-4 audit firms.

market share. However, the empirical relationships I find are that there are a negative relationship betIen fee increases and the probability of switching and the industry ranking by BIG-4 premium increases and industry ranking by the loss of BIG-4 market share. This negative association is suggestive of a demand side shift (see Figure B1 Panel C of Appendix B).

There are several papers analyzing changes in the levels of audit fees post-SOX (Ghosh and Pawlewicz 2009; Griffin and Lont 2007; Huang, Raghunandan, and Rama 2009). There is also analysis of the prior literature about the types of firms that switched from BIG-4 to NB-4 auditors after the enactment of SOX (Landsman, Nelson, and Rountree 2009). My analysis adds to these prior papers in three ways. First, I focus on the BIG-4 premium and premium changes rather than fees as theory suggest that the premium rather than the level of fees determines the client-firm choice of a BIG-4 or NB-4 auditor. Second I exploit potential heterogeneity in the effects of SOX (and the demise of AA) across industries by correlating the premium (and changes in the premium) with changes in market shares of industries. Last, I analyze the effects of the BIG-4 premium and 2001 NB-4 market share on the probability of an individual firm switching from a BIG-4 to an NB-4 auditor post-2003 adding to earlier research on client-firm behavior.

While I do not directly depend on them, the studies by Maher, Tiessen, Colson, and Broman (1992) and Menon and Williams (1991) had a significant impact on my methodology. Maher et al. (1992) report declining audit fees from 1977 to 1981 because the profession dropped many of its restrictions on competition. Menon and Williams find that audit fees increased in the 1980s but stayed flat in the 1990s. There is a significant increase in 1988 because The Auditing Standards Board issued the “expectation gap” standards. Menon and Williams (1991) also mentioned that BIG-8 mergers had a short-run, instead of a long run, effect on fees. An even longer-term analysis is provided in Ferguson, Pinnuck and Skinner (2014) that argues that increasing concentration with the BIG-4 in the Australian audit market may be a natural evolutionary trend. From this context, it is interesting that following the enactment of SOX and the demise of AA, this trend has "reversed" in the US suggesting that the competitive position of NB-4 may have been strengthened in the period 2003-2011.

To conduct my empirical tests, I first construct a measure of the BIG-4 premium by combining the audit fee model in Blankley, Hurtt, and MacGregor (2012) and combine it with the industry fee effects analysis in Ashbaugh et al. (2003). I estimate a BIG-5/4*industry premium separately for the periods 2001-2002 and the periods 2003-2011. These estimates show that: (i) the BIG-4 premium is significantly different across industries; (ii) that the BIG-4 premium increased in every industry in the 2003-2011 period relative to 2001-2002 and (iii) there were differences in the premium increases across industries. I then compare the correlation between industry rankings based on increases in the BIG-4 premium and rankings based on the level of market share losses using a Spearman Rank Correlation Test. I find that this correlation coefficient is negative and stable across different measures of premium increases and market share losses. [2] As demonstrated through my formal model, this finding is inconsistent with the market equilibrium being driven purely by increases in the BIG-4 premium as a response

[2] Fee Premium I is based on the median BIG-4 excess fees *after controlling for average industry and BIG-4 effects*; Fee Premium Ranking II based on the increase in (the average) BIG-4*industry coefficient across the two periods; and Fee Premium Ranking III based on the level of the BIG-4*Industry coefficient in the period 2003-2011.[2] I next construct three rankings of these industries related to BIG-4 percentage market share losses based on three different ways of computing market share: (i) the proportion of clients choosing BIG-4 in that industry (ii) the proportion of fees collected by the BIG-4 relative to the total industry fees; and (iii) the ratio of BIG-4 fee share (above) divided by BIG-4 market share. I then examine the correlations of each of the fee rankings with each of the market share ranking. All nine coefficients are negative and significant.

to greater post-SOX litigation risk (Proposition 2). I then repeat the analysis using the market share of AA in each of these industries to see if the BIG-4 premium increases are related to AA's market share in 2001. The underlying economic argument is that the competitive strength of the BIG-4 would be higher in industries with a larger proportion of AA clients, and hence, these industries would have seen a greater increase in BIG-4 premium. I find that AA rankings have a less significant, but mainly positive relationship with the premium rankings, that is, premia increases are larger in industries where AA held a greater share pre-2002.

It is important to underline the motivation behind my choice of industry and rank correlation tests to examine the effects of SOX. Given just one observation, it is impossible to determine whether demand or supply effects drive an equilibrium shift. However, the heterogeneity in supply and demand curves across industries allows us to treat each industry as a separate observation on the effects of SOX on the market equilibrium.[3] The overall pattern suggests that the enactment of SOX and the collapse of AA had broadly similar effects across industries resulting in an increase in the BIG-4 premium and a reduction in BIG-4 market share but differed in terms of magnitude. We exploit these cross-sectional differences to test for the relative effects of BIG-4 fee strategies as compared to NB-4 competitive power. In addition, there has been considerable current literature on the effects of factors such as office location (Craswell, Donald and Laughton 2002) or state regulation (Anatharaman and Wans 2012) on audit

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[3] While I consider the enactment of SOX and the collapse of AA as the primary shocks that occurred in this period, I note that there were also other changes such as rule FIN 48 or AS-5 or market-wide effects such as the 2007 recession that might have affected audit fees and/or auditor choice. Our approach does not separate out the effects of these other shocks in any specific way. I do show (Table 6, panel C) that our findings are robust across different time periods so it is likely that the enactment of SOX was the main cause for the market shifts. In any case, this has no bearing on our main empirical findings that demand shifts took place and prior literature has mainly attributed such demand shifts as a consequence of SOX.

fees. By looking at increases in the premium, my results are not sensitive to such fixed effects since they rarely change from year to year.

My second test uses a Logit switching model, based on Landsman, Nelson, and Rountree (2009), to examine the effect of (firm-specific) BIG-4 premium increases (estimated in the first test) on the propensity to switch to an NB-4 auditor. As shown through my formal analysis, if switching is driven solely by fee increases, firms that faced a larger premium increase are more likely to switch to an NB-4 auditor. However, I find that firms whose residual premium (after controlling for mean industry fee and BIG-4 effects) increased more are less likely to switch to an NB-4 auditor in the following year. As shown in Proposition 3, this inverse relationship implies a shift in the perceived benefit of a BIG-4 audit. The Logit model also shows that firms are more likely to switch to NB-4 auditors over the period 2003-2011 in industries where the NB-4 had a low market share prior to 2002. This is additional evidence that in the period 2003-2011, industries where the NB-4 were less competitive pre-SOX, and AA demise are also the ones where the NB-4 are more likely to capture clients in the post-SOX era.

I also examine both my tests for demand shifts in a size quintile-by-quintile basis. As is to be expected, there is very little switching to NB-4 auditors in the highest quintile. However both my main empirical findings hold up in the middle quintiles. The Logit model shows that the effects of fees and NB-4 market power is significant in size quintiles 2, 3, and 4 where there is active competition between the BIG-4 and NB-4 for clients but is not significant in the lowest and highest quintiles. In other words, the effects of SOX and the collapse of AA has realigned economic incentives for medium sized firms but has had relatively little influence on the smallest firms that have historically provided clientele for NB-4 auditors or the largest firms that typically benefit from hiring large auditors.

There have been several earlier papers that have studied the shifts in the audit market post-Sox both concerning fees (Asthana, Balsam and Kim 2009) and client-switching (Etteredge and Li 2007). We contribute to these prior studies in three ways: i) I explore the long-term effects on audit market structure continuing till 2011 as the early period 2003-2005 may be affected by short-term issues; (ii) I develop a formal model to show why a negative correlation between BIG-4 audit fee increase and market share decrease arises from demand shifts rather than BIG-4 price increases (perhaps as a response to greater risk); and (iii) I show a relationship between prior NB-4 market share and firm switching behavior after controlling for the effects of audit fees. I lay out these findings by first discussing related literature (Section II), developing Hypotheses (Section III) and presenting the sample, methodology and results in (Section IV). Section V offers concluding remarks.

1.2 Related Literature

I first review the prior literature on the BIG-4 premium and then the literature pertaining to effects of SOX and AA's collapse on the post-SOX market share held by the BIG-4. Cross-sectional differences in audit fees can represent either the effect of quantity differences (in terms of hours of audit) or price differences in terms of an hourly fee (Simunic 1980a). In addition, there may be quality differences in terms of differentiation of services (DeAngelo 1981) and the association between high fees and high quality may not be straightforward (Choi, J., J. Kim, and Y. Zang. 2010a). As noted earlier, audit quality is unobservable to investors and has to be inferred from differences in prices (Simunic 1980a). It is primarily the observability of audit quality interacting with auditor wealth that supports a BIG-4 premium in equilibrium as argued in both empirical studies (Simunic 1980a; Carcello and Palmrose 1994; Danos and Eichenseher 1986) as well as theoretical studies (Dye 1993, Bar-Yosef and Sarath 2005).

Empirical tests of the existence of a BIG-4 auditor premium include Palmrose (1986) and Beatty (1989). Palmrose found that the BIG-8 audit firms charged higher audit fees and explained it as arising from their monopoly powers. Beatty (1989) however argued that reputation led to better pricing of IPO's audited by the BIG-8. Francis (1984) also found that the BIG-8 charged higher audit fees than non-BIG-8 firms while Blokdijk, Drieenhuizen, Simunic and Stein (2006b) found that NB-4 audit firms are less efficient in their work than BIG-4 firms, which reflect low audit quality. Shockley and Holt (1983) provide evidence that auditors whose client firms represent the highest market value are perceived as providing higher quality audits. However, Dopuch and Simunic (1980a) and DeAngelo (1981) found that the quality of audit services is very difficult to measure. Danos and Eichenseher (1986) found that clients choose auditors for good economic reasons, based on both the (perceived) quality of auditor services and the audit fee as well as client specific factors. For example, they assume a link between audit firm market share and comparative advantages for larger clients (Dopuch and Simunic 1980a, Danos and Eichenseher 1986). A 2006 GAO (Government Accountability Office) report suggests auditees do not want to be audited by NB-4 firms because of the recognized difference in reputation.

In summary, both theory and empirics suggest that big auditors have (or are perceived to have) an advantage that should be reflected as a pricing premium. I rely on this precedent in assuming that a BIG-4 premium is present in audit fees and is determined primarily by the belief that BIG-4 auditors generate market value for their clients.

I rely on the literature on the determinants of audit fees (Simunic 1980a; Francis 1984; Maher et al. 1992; Ashbaugh, LaFond, and Mayhew 2003; Kealey, Lee, and Stein 2007; Ghosh and Pawlowicz 2009) in order to empirically isolate the BIG-4 premium. I use one of the latest published papers in this stream of literature (Blankley et al. 2012), to estimate both an overall BIG-4 premium and an industry-by-industry BIG-4 premium. I emphasize that our goal is not to study the BIG-4 premium per se, but to see how changes in this premium are related to changes in market share across BIG-4 and NB-4 auditors. My methodology is discussed in more depth in the next section.

Danos and Eichenseher (1986) indicated a more generalized movement to the BIG-8 across all client firms from 1973 to 1980 as do Ferguson, Pinnock and Skinner (2014). Both papers argue that the observed change in market share reflects a long-term adjustment to a fairly stable equilibrium distribution of clients across large and small audit firms. In contrast, the enactment of SOX and the collapse of AA disrupted supply and demand patterns in the audit market. This led to both the increases in audit fees and other effects as well. I draw on the evidence in Cassell et al. (2013) to reinforce the popular sentiment that SOX has strengthened NB-4 auditors' competitive position. I bring both these strands of literatures together to analyze whether the shifts in market share can be viewed as primarily driven by new price strategies adopted by the BIG-4 (Choi, Doogar, and Ganguly 2004b) or whether SOX has shifted the preference of client-firms, at least in some section of the markets, towards NB-4 auditors after controlling for the effects of price on market share.

While the overall pattern of shifts in pricing and market shares suggests that SOX was the major event over the long-window 2003-2011, the effects of the collapse of AA also had a significant impact particularly in the period 2003-2004. Several prior studies have examined the switching behavior of Arthur Andersen clients (for example, Blouin, Grein, and Rountree 2007). While the reputation of AA suffered, Krishnamurthy, Zhou and Zhou (2006) found that firms which were former audit clients of Andersen and then switched to other BIG-4 audit firms had higher returns suggesting these were either intrinsically better quality firms (and signaled the high quality by staying with a BIG-4 auditor). My focus is somewhat different but related to this finding. I argue that the (BIG-4) supply curve was disrupted to a greater extent in industries where AA held a larger share and consequently, that changes in audit fees and BIG-4 market shares over the period 2003-2011 should be influenced by AA's pre-2001 footprint in that industry.

1.3 Hypotheses Development

We outline again the basic economic factors that motivate my study. The total market for audit services is (almost) inelastic concerning audit fees, [4] and an increase in the BIG-4 premium should result in a reduction in market share for big auditors. However, such a market share reduction could be further enhanced if the competitive position of NB-4 auditors has been strengthened due to SOX. I abstract away from within BIG-4 competition and view this as a two-firm Stackelberg Oligopoly Equilibrium with the BIG-4 acting as leaders and NB-4 as followers (Vives 1999, 200–205). Firms are

[4] The cost of going private and avoiding the need for an independent audit generally involves costs that are much larger than audit fees, so the effect of an increase in audit fees on the total number of publicly traded firms is generally small.

willing to pay a BIG-4 premium as they recover the costs through a better price in the stock market (e.g. through a lower cost of capital). The main focus of my analysis is to try and see if I can find evidence for stronger market competition from NB-4 auditors post-SOX through a careful analysis of the relationship between premium increases and changes in market share. The formal model developed in Section II demonstrates that the increase in fees without any shift in the strength of preferences across BIG-4 and NB-4 auditors will typically lead to a positive relationship between premium increases and market share losses (Proposition 2). It follows that a negative relationship would suggest a shift in preferences.

In order to further examine the effects of shifts in preferences, I introduce two empirical variables that may plausibly affect the ability of the NB-4 to attract clients in the post-SOX environment: (i) the proportion of the market held by AA (pre-SOX) and (ii) the proportion of the market held by NB-4 auditors pre-SOX. Each of these factors could influence the equilibrium post-SOX, but the direction of influence is unclear from a theoretical perspective. For example, if AA held a larger share of an industry in 2001, the collapse of AA would disrupt the supply curve but could also lower the demand curve because the perceived value of a BIG-4 audit may have fallen due to the Enron scandal. Analogously, the enactment of SOX may have strengthened NB-4 auditors uniformly across all industries, more in industries where they were previously more competitive or more in industries where they were less competitive. For these reasons, I do not have directional predictions based on theory as to which way AA market share and pre-SOX NB-4 market share will influence client-switching behavior from BIG-4 to NB-4 post-SOX (H2, H3, and H4).

Out first hypothesis (in the null form) is that the shift in market shares is primarily attributable to the fee strategies of the BIG-4 post-SOX and AA. If this were the case, industries where the BIG-4 is more selective should see both higher BIG-4 premia and greater losses in market share (Proposition 2).

H1: The fee premium increases charged by the BIG-4 post-SOX will be higher in industries where their market share declined more (i.e., fee premium increases will be positively correlated with (NB-4) BIG-4 market share losses (gains)).

The second hypothesis is connected with the joint effects of the collapse of AA and SOX. The premise is that the larger AA's market share in that industry in 2001, the greater will be the increase in pricing power for the surviving BIG-4 firms. In addition, the lower the shift in competitive advantage to NB-4 auditors, the less the pricing power for BIG-4. This leads to my second hypothesis (in null form):

H2: The relationship between fee premium increases and market share losses (as in H1) will not be affected by AA's market share in that industry in 2001.

The last two hypotheses are associated with the probability of switching from a BIG-4 firm to NB-4 firm in the period 2003-2011. If fee strategies chosen by the BIG-4 are the main factor driving the switch to NB-4 auditors, I expect that firms that are being charged a high premium by the BIG-4 (in the prior year) are more likely to switch to NB-4 auditors. In null form, this reduces to:

H3: A high fee premium increase charged by the BIG-4 will increase the probability of switching to an NB-4 auditor.

My last conjecture related directly to the hypothesis that the enactment of SOX and the overall perception that all auditors Ire now required to do a better job mitigated concerns about the overall quality of audits. Given an increase in audit quality (either real or perceived) the role of reputation and/or deep pockets as a proxy for audit quality would be muted. Therefore, I would expect more switching to NB-4 in industries where the market power of the NB-4 auditors increased the most. To test for this possibility, I use the competitive position of the NB-4 in the pre-SOX period as an instrumental variable for measuring the strength of NB-4 auditors in that industry. I conjecture that SOX helped the competitive position of NB-4 auditors but that it was differential across industries.

H4: The industry strength of NB-4 auditors prior to SOX does not change the probability of switching to an NB-4 auditor post-SOX.

I now describe my methodology and statistical tests to try and reject the null hypotheses H1-H4.

1.4 Sample, Methodology, and Results

1.4.1 Sample and Descriptive Statistics

To form the sample, I collected data from audit analytics covering the period from 2000 to 2011. This resulted in a total of 150,908 observations. If a client had two or more auditors in a sample year (but did not change auditors), I sum the audit fees for the specific year. Therefore, I have a single fee observation for each client-firm for each year. If a client-firm switched auditors, I delete these observations eliminating 6,701 observations from the sample. Next, I merge with Compustat to collect financial data. 55,723 observations were deleted because the financial data was not available. In addition, 26,703 observations did not have information about business segments and were deleted. I use the industry analysis methodology of Ashbaugh et al. (2003) and eliminate the financial services industry (SIC 6000-6999) losing 10,040 observations in this process. In the final step, I exclude firm-years with missing Compustat data in the auditor switch model and as a consequence, 6,714 observations were deleted. My final sample for the audit fee model consisted of 51,732 observations. 8,636 firm-year observations are before 2003 while 43,096 firm-year observations are after 2002. In addition, for the switching model, I delete 2,020 observations before 2001, because of missing data regarding auditor switches. Then I delete 6,735 firm-year observations before 2002 because I focus on the influence of fee premium after 2002. My final sample for switching model is 28,263.[5] The representation of each industry in my sample is closely aligned with the overall industry composition listed in COMPUSTAT.

Table 3 Panel A describes the ratio of audit fees by NB-5/4 audit firms divided by total fees from 2000 to 2011 in different industries. While this also shows the same time-trend, what is striking is that the share of revenues does not exceed 13% in any industry showing the enormous market-share advantage held by the BIG-4. Table 3 Panel B shows the market share audited by NB-5/4 from 2000 to 2011. From this table, it is obvious that the market share of NB-4/5 firms increased significantly post-SOX and AA. (See also Figure 1). Table 3 Panel F shows the increase in the size of BIG-4 firms over the period 2001-2007. The panel shows that firms grew rapidly in the years 2001-2004 when they absorbed the former clients of AA, but this expansion slowed in the years 2005-2007 and reversed slightly in the period 2007-2011. Table 3 Panel G shows

[5] If the firm was a foreign filer or failed to issue a SOX 404 Internal Control report, I define going concern, material weakness and modified opinion as 0, so I did not lose observations in this process.

the number of firms audited by BIG-5/4 on an industry basis from 2000 to 2011. From the evidence in Table 3, it is obvious that the market share of NB-4/5 firms increased significantly post-SOX and AA. (See also Figure 1 Panel B).

1.4.2 Methodology

My methodology involves two different approaches. In both approaches, my goal is first to construct measures for the post-SOX "excess fee" charged by BIG-4 auditors. Then my second step is to see if increases in these excess fees primarily determine the propensity of client-firms to choose NB-4 auditors post-SOX, or whether other factors are also influential.

In the first approach, I use an industry-based model similar to Numan and Willekens (2012). In this approach, I use three measures of differential pricing across BIG-4 and NB-4 auditors in each industry to capture the effects of BIG-4 pricing strategies post-SOX. Then I measure the relationship between BIG-4 premium increases and industry market-share changes using a Spearman Test. Specifically, I examine the relationship between industry rankings related to the BIG-4 premium with both the market-share gains of NB-4 auditors and the market share held by AA before their collapse. In this first set of tests, the underlying idea is that if the increase in the premium was the main factor driving market-share shifts, the industries with the largest premium increases (or levels) should also see the greatest market share reductions.

Industry analysis exploits the fact, established in earlier studies, that there are significant industry differences in both audit fees and BIG-4 market shares (Cahan, Jeter and Naiker 2011). We can, therefore, treat each industry as a "separate" experiment on the shifts following the enactment of SOX on BIG-4 premium increases and BIG-4 market share losses, or equivalently, NB-4 market share gains. As I document in Table 3 Panels F & B, the premium increased in every industry and the NB-4 gained market share in every industry, but there was variation both in terms of the premium increase and market share decrease. If the primary driver of the market realignment post-SOX was the fee strategies set by the BIG-4 auditors, I would typically expect that industries where the premium increased the most are also the ones where the BIG-4 eliminated a larger share of clients, that is, that industry market share losses and industry premium increases are positively correlated. Note that there is a clear alternative possibility here – that NB-4 market share increased because of an increase in client-demand for NB-4 services. Under this second scenario, the increase in the BIG-4 premium will be lowest in industries where NB-4 power increased the most and I would also see a greater market share loss in these industries, in other words, which premium increases and market share losses would be negatively correlated.

The second test follows Landsman et al. (2009) and uses an auditor choice model. Here, I restrict the sample to BIG-4 clients and use the residual from an audit fee regression as a measure of the firm-specific abnormal fees charged by BIG-4 auditors. I then see if an increase in the residual in one year increases the probability of switching in the following year. As shown in Proposition 3, a negative relationship suggests a shift in preferences as well. To analyze this possibility further, I use as a second test variable, the 2001 market share held by the NB-4 firms. If shifts in preferences played little role in determining switch behavior, this variable should be insignificant after controlling for the effect of fee increases.

In both sets of tests, I do not specifically adjust for firms that may have entered or exited the market. Overall, the total number of firms entering or exiting the market is very small relative to the total sample and keeping or removing these firms has no effect on the measure of market shares or the measure of the premium. In my switching model, I only use firms that are BIG-4 clients and then switch to an NB-4 auditor. The length of the audit engagement is a control variable in this model and adjusts for the fact that a new entrant may have a lower probability of switching auditors. In summary, the entry and exit of firms have minimal or zero effects on my tests.

A second point concerns the use of increases in the premium to explain the propensity to switch away from the BIG-4. While we make this choice of explanatory variable primarily to correspond to my formal economic model, it has another benefit in that it reduces the consequences of omitted factors in the audit fee model. Suppose that state liability rules affect audit fees (Anantharaman and Wans 2012). As a firm will not change its location from year to year, the increase in the premium is unaffected by firm location. The same applies to other factors such as audit office quality as these do not change much from year to year. Of course, effects of variables that are likely to change such as acquiring a new business segment, or a growth (or reduction) in assets is controlled when determining the excess premium paid to the BIG-4.

The GAO (2006) report suggests that audit firms are more sensitive to client risk after Arthur Andersen collapsed, so I expect that BIG-4 auditors increased the premium more for clients with high-risk characteristics. However, assuming that their benefits from going to a BIG-4 auditor did not change (or did not increase commensurate with the fee increase), they are more likely to switch to NB-4 auditors. Even otherwise, if the increase in BIG-4 fees were driving firms to the NB-4, I would expect that large abnormal fee increases (after controlling for mean BIG-4 and Industry effects) encourage switching (H3). In addition, if the fee strategies are mainly driving switching behavior, I should see no influence of NB-4 market power on switching behavior. For this reason, I use the NB-4 industry market share in 2001 as a test variable to see if it influences the probability of choosing an NB-4 auditor post-2003 (H4). For similar reasons, I test whether AA's pre-2001 market share either influences the probability of switch directly or in interaction with the abnormal fee.

1.4.3 Audit Fee Models

One of my primary goals is to get an estimate of the fee premium charged by the BIG-4 on an industry-by-industry basis. To isolate the BIG-4 fee premium, it is necessary to estimate what the fee "would be" based on firm and industry characteristics had the firm been audited by a small auditor. Models that tie audit fees with firm characteristics have been extensively developed starting with Simunic (1980a). Most of the models in the following years have used variations of Simunic's model. In particular, the models are log-linear in audit fees and firms' assets. Other variables such as account receivables are used to control for risk. Many recent models extend and improve on Simunic's original model. I use the following model from Blankley et al. (2012) as it provides a convenient reference point for my subsequent industry based analysis:

$$\begin{aligned} LAF_{i,t} = {} & \alpha_0 + \alpha_1 LTA_{i,t} + \alpha_2 CR_{i,t} + \alpha_3 CA\_TA_{i,t} + \alpha_4 ARINV_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 LOSS + \alpha_7 FOREIGN \\ & + \alpha_8 MERGER + \alpha_9 BUSY_{i,t} + \alpha_{10} LEV_{i,t} + \alpha_{11} INTANG_{i,t} + \alpha_{12} SEG + \alpha_{13} OPINION_{i,t} \\ & + \alpha_{14} MATWEAK_{i,t-(t-1)} + \alpha_{15} BIG5/4_{i,t} + \alpha_{16} INDCON_{i,t} + \varepsilon_{i,t} \qquad (1) \end{aligned}$$

I take the natural log of audit fees.[6] If a firm is audited by Arthur Andersen, Deloitte & Touche, Ernst & Young, KPMG, or PricewaterhouseCoopers (or just the last 4 after AA's collapse), the BIG-5 Dummy equals 1 and 0 otherwise; The control variables are consistent with prior research (Simunic 1980a; Palmrose 1986; Whisenant, Sankaragurusuvamy, and Raghunandan 2003; Francis, Reichelt, and Wang 2005; Hay, Knechel, and Wong 2006). The audit effort measures are assets (LTA); the presence of mergers (MERGER) or foreign operations (FOREIGN); the number of business segments (SEG); and the auditors issue a going concern opinion (OPINION).Further, Audit risk measures are CR; CA_TA; ARINV; ROA; LOSS; and INTANG. Financial leverage (LEV) captures the long-term financial structure of the client. I also include industry dummies following Ashbaugh et al. (2003) since my analysis is based on industry premium. To control for internal control quality, I also use a variable as the company has a material weakness in the current year (Ettredge, Li, and Sun 2006; Doyle, Ge, and McVay 2007). Finally, I include a variable if the company's fiscal year end is December 31st. The BIG-4 coefficient estimated over the period 2003-2011 in my sample is significantly higher than a similar BIG-5 dummy coefficient estimate over the years 2000-2002 suggesting that the BIG-4 "premium" increased significantly post-SOX (as documented for a different sample by Ghosh and Pawlewicz 2009).

1.4.4 Industry Effects

Audit fees vary significantly across industries. Different patterns of production, raw materials, and intangible assets change the nature of the external auditor's

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[6] An alternative to transforming the fee variables by their natural log is to scale the fee variables by total assets. (Ashbaugh et al. 2003) I do not use this transformation because our focus is the magnitude of fees instead of the relative cost of audit-related services to the client.

verification process. Less clear are arguments as to how auditor specialization in the industry affects fees. Both Palmrose (1986) and Menon and Williams (1991) find no association is observed between audit fees and industry specialization. Other scholars suggest that fee differences across BIG-4 and NB-4, as well as fee differences within the BIG-4, should vary across industries. Danos and Eichenseher (1986) said that market share differentials are maintained in the public utility, oil and gas, and railroad industries from 1950 to 1980 due to client regulation. They found a significant positive correlation between industry-specific auditor concentration levels and the percentage of industry members listed on the American and New York Stock Exchanges. Previous researches also pointed out the possibility that large audit firms have comparative advantages in highly regulated industries (Danos and Eichenseher 1986). Craswell, Francis, and Taylor (1995) found that BIG-6 auditors could charge a higher price than nonspecialist BIG-6 auditors. They attribute this effect to the fact that industry specialists make investments in order to achieve their industry specific expertise.

Based on these earlier results, I expect to see significant differences across industries in terms of the mean BIG-4 premium and terms of the effects of SOX. To test this, I run the same regression as (1) with industry coefficients.

$$\begin{aligned} LAF_{i,t} = {} & \alpha_0 + \alpha_1 LTA_{i,t} + \alpha_2 CR_{i,t} + \alpha_3 CA\_TA_{i,t} + \alpha_4 ARINV_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 LOSS + \alpha_7 FOREIGN \\ & + \alpha_8 MERGER + \alpha_9 BUSY_{i,t} + \alpha_{10} LEV_{i,t} + \alpha_{11} INTANG_{i,t} + \alpha_{12} SEG + \alpha_{13} OPINION_{i,t} \\ & + \alpha_{14} MATWEAK_{i,t-(t-1)} + \alpha_{15} BIG4{*}INDCON_{i,t} + \varepsilon_{i,t} \qquad (2) \end{aligned}$$

I do not use a separate BIG-4 dummy in this regression because it is the sum of the BIG4*INDCON interactive dummies. I also do not use a separate industry dummy because it is highly correlated with the interactive dummy as the BIG-4 hold a preponderant market share in every industry. The results are tabulated in Table 4 and show that the coefficients varied significantly across industries, that is, the BIG-4 premium was industry dependent. The t-statistics are adjusted for clustering, and the F-test after Table 4 rejects the equality of the BIG-4 dummy coefficient across industries.

1.4.5 Fee Premium Measures

I use the residual from Equations (1) and the BIG-4*Industry coefficient in Equation (2) to construct my empirical measures of the excess fees charged by the BIG-4. As the right-side regressors in Equation (1) include both firm characteristics as well as average BIG-4 and industry effects, the residual measures firm-specific excess fees. If this residual is large, it is indicative of being charged high "excess" fees by the BIG-4 (due to unobservable firm-specific factors). To the extent that the market equilibrium is being driven by BIG-4 pricing strategies, I would expect the firms being charged high excess fees to be the ones that switch to NB-4 auditors. I test this in two ways: first, by determining the correlation between market share changes and excess BIG-4 fees on an industry-by-industry basis, and second, by examining switching probabilities at the firm level.

For the first test, I rank industries concerning the BIG-4 premium in three ways: (i) based on the median residual from Equation 1; (ii) based on the change in the BIG-4*Industry coefficient across the periods 2000-2002 and 2003-2011 in Equation 2; and (iii) based on the level of the BIG-4*Industry coefficient in Equation 2. I compare each of these industry rankings based on the BIG-4 premium with three Industry rankings defined through the percentage loss of BIG-4 market share measured either (i) in terms of the number of firms, or, (ii) by the total fees charged, or, (iii) as a ratio of these variables.

Then I test to see if the rankings of industry based on fee premia corresponds positively or negatively with those on NB-4 market share losses. If fee strategies of the BIG-4 were primarily responsible for market share shifts, I would expect that a positive correlation between BIG-4 excess fee rankings and NB-4 market share gains (H1).

I now turn to the industry-specific market share changes arising out of the effects of exit of AA. I measure the influence of the exit of AA on the market equilibrium based on their market share (either in terms of firms audited or in terms of revenues). I then examine how the rankings of industries based on AA's market share correlate with the post-SOX shifts in market share across BIG-4 and NB-4 (H2).

1.4.6 Audit Switch Model

For the second test, I build on the auditor switch model from (Landsman et al. 2009). The structure of that model and my test variables are described below in Equation 3.

$$\begin{aligned} SWITCH_{i,t} =\ & \alpha_0+\alpha_1\Delta ABAFEE_{i,t-1}+\alpha_2{*}TestVar+\alpha_3 GROWTH_{i,t-1}+\alpha_4 ABSDACC_{i,t-1}+\alpha_5 ARINV_{i,t-1} \\ & +\alpha_6 GC_{i,t-1}+\alpha_7 MODOP_{i,t-1}+\alpha_8 TENURE_{i,t-1}+\alpha_9 ROA_{i,t-1}+\alpha_{10} LOSS_{i,t-1} \\ & +\alpha_{11} LEVERAGE_{i,t-1}+\alpha_{12} CASH_{i,t-1}+\alpha_{13} BIG4{*}MISMATCH_{i,t-1}+\alpha_{14} EXPERT_{i,t-1} \\ & +\alpha_{15} SIZE_{i,t-1}+\alpha_{16} MERGER_{i,t-1}+\varepsilon_{i,t} \end{aligned} \tag{3}$$

TestVar
1.NB-4MarketShare in 2001
2.AAMarketShare in 2001,ABAFEE*AAMarketShare2001
3.AAFeeShare in 2001,ABAFEE*AAFeeShare2001

To control for audit risk, I include GROWTH, ABSDACC, INVREC, GC, MODOP, and TENURE (Stice 1991; DeFond and Subramanyam, 1998). I include other variables to control for client-specific aspects of the audit engagement related to audit risk, like INVREC, GC, MODOP and TENURE (Dopuch, Holthausen, and Leftwich 1987b; Stice 1991; Krishnan 1994a; Krishnan and Krishnan 1997b; Johnstone and

Bedard 2004). To control for financial risk, I include ROA, LOSS, CASH, and LEVERAGE. I also include the MISMATCH variable as a proxy for misalignment (Shu 2000; Landsman et al. 2009) as a further control. Finally, I include industry fixed effects, EXPERT, SIZE and MERGER as additional control variables. (Hogan and Jeter 1999), because companies are more likely to switch auditors after a merger or acquisition if the two companies involved had different auditors prior to the merger. After controlling for all these factors that have been advanced as influencing switching behavior in earlier papers, I focus on the effects of my test variables that measure the effects of fees and market share variables on switching behavior.

1.4.7 Results

Before presenting my results, I outline some statistics that form the background for my analysis. The BIG-4 market share reduced significantly over the period 2003-2011. The descriptive statistics are compelling. [7] The results documented in Tables 3 – 4 show that the cross-sectional variation both in market share losses and BIG-4 premia increases are considerable across industries. My fundamental economic premise is that the enactment of SOX and the demise of AA affected both the demand and supply curves for audit services (as a function of the BIG-4 premia). In particular, I wish to study how strongly changes in the demand curve have affected market structure. If the primary force for change has been cherry picking of profitable clients by the BIG-4 through their fee strategies, I would expect to see a positive association between the level of fee premia increases and changes in market share. If however, demand curve shifts have also been

[7] Although I do not report them here, I formally tested and rejected null hypotheses that there was no change in NB-4 market share from 2001 to 2011 both at an industry level and in aggregate.

influential, I would expect to see more negative correlations between the industry premium and industry market share declines (Proposition 3, Figure B1). Table 5 shows that the correlation between each of the fee rankings and each of the market share rankings is significantly negative (using a non-parametric Spearman test), that is, H1 is rejected. Although the premium has gone up and may have reduced the BIG-4 market share, other factors besides the increase in premium are necessary to explain the negative correlation (such as a downward shift in the demand curve for BIG-4 services for at least a portion of the market). I confirm my findings concerning industries by doing a similar test concerning geographical location.

Analogously, if the demise of AA disrupted the supply curve more than the demand curve, I would expect to see higher premia (and/or premia increase) in industry where AA had a larger market share. In contrast, if NB-4 auditors were better able to compete in industries where AA initially had a greater market share (because the remaining BIG-4 was weaker), I would expect to see a negative association. The results are not very conclusive using a non-parametric Spearman test (Table 5 Panel C), positively significant concerning Fee Premium III but not the others. The finding suggests that the premium is higher in industries where AA had a larger footprint and at least, in this case, supply side effects have led to larger absolute fee levels in industries where AA had a stronger presence. I also examined the relationship between fee premia and the proportion of AA clients switching to NB-4 auditors in the industry (AA-switch-share in Table 5). Again, the results are not very strong but suggest a negative association between high fees and NB-4 auditor choice. That is, industries where larger numbers of

AA clients switched to NB-4 auditors also had low excess fees, perhaps as a consequence of the fact that NB-4 auditors were more competitive in these industries.

Table 6 documents the tests on switching behavior by BIG-4 clients to NB-4 auditors during the years 2001-2011. Although my main focus is on columns C and D, which cover the years 2003-2011, I include the period 2001-2002 for comparison purposes. First, I show that the audit fee residual from Equation 1 has a negative coefficient in the switch model. The inference is that firms with larger residual (i.e., larger abnormal fees paid to BIG-4 auditors) were less likely to switch to NB-4 auditors. This is inconsistent with an assumption that customers were dropped or driven away from the BIG-4 by the use of large audit fees. If firms realized that they were paying excess fees after adjusting for the mean industry and BIG-4 premium, they should be more willing to consider an NB-4 auditor. Instead, I find that such firms are less likely to switch auditors. One possible explanation is that of a survivorship bias. Firms that continue to retain BIG-4 auditors perceive some special benefit from this relationship above and beyond that implied by their observable characteristics.

In this table, it is also shown that industries in which the NB-4 had higher market share in 2001 (the last variable in Table 5 termed as NB-4 market share in 2001) also had a lower probability of switching in the period 2003-2011. The inference from this finding is that NB-4 market power also influences switching behavior. More precisely, SOX seems to have improved the ability of the NB-4 to compete more effectively in industries where they had less influence prior to SOX. To sum up, the overall findings in Table 6, Columns C and D are that switching behavior seems to be influenced by demand-side factors such as a greater attractiveness for BIG-4 audits for some firms (who are willing to pay high excess premia) or a greater preference for NB-4 audits for other firms in industries where the NB-4 were less competitive pre-SOX.

It is also instructive to compare the differences between the coefficients over the period 2001-2002 as compared with 2003-2011 (Table 6, Columns B compared to Columns C and D). I note that the fee residual here has a positive coefficient. My interpretation is that fees were already starting to rise in this period and firms that were fee sensitive switched in 2002. Note also that in Column A, the AA-market share variable is negative and significant at the 10% level, suggesting that firms in industries where AA held a larger share were more likely to stay with other BIG-4 auditors. In other words, I find that the demand for BIG-4 auditing did not shift sharply due to the failure of AA.

I note that all the results in the switching model are derived from controlling for the mismatch variable (Landsman et al. 2009). This variable is determined based on optimal cut-off score (based on certain firm characteristics; see Appendix A) that creates the least misclassification of auditor selection. In other words, the optimal cutoff score is chosen in such a way that a specification that all firms below the cutoff should choose an NB-4 auditor whereas firms above the cutoff should choose BIG-4 produces the smallest number of auditor-auditee misclassifications. Then firms below the cutoff that choose BIG-4 or firms that are above the cutoff but choose NB-4 are classified as mismatched firms. As in Landsman et al. (2009) I find that mismatched firms are more likely to switch but the negative effect of the residual fee holds even after controlling for mismatched firms.

In order to better understand both aspects of the change, I analyze the switching model on a size quintile-by-quintile basis. As may be expected, I find that the switching model, with one or two minor exceptions, is stable across the middle quintiles but is significantly different in the highest and lowest quintiles. First, the key variable of the abnormal fee is significantly negative in the middle quintiles suggesting that higher than normal (lagged) audit fees not induce these firms to switch. In addition, the level of market share held by NB-4 auditors prior to 2001 also significantly influences switching post-SOX, that is, more switching has taken place in industries where NB-4 were more competitive prior to 2001. Firms that were "mismatched" with the BIG-4, that is, firms whose observable characteristics suggested that they would be better off with NB-4 auditors, were significantly more likely to switch in these middle quintiles quintiles (insignificant in the two extreme quintiles). Combining the findings on the explanatory variables: (i) abnormal fees (ii) and 2001 NB-4 market share, analysis of the switching model by size-quintiles confirms the influence of demand-side shifts in the market post-SOX and AA.

While not pertinent to my hypotheses, I comment briefly on some of the other firm-specific control variables in Table 6 Panel A. Growth is negative (or insignificant) in all quintiles suggesting that growing firms are less likely to switch to BIG-4 auditors. Interestingly, Cash is also negative suggesting that cash-rich firms are less willing to pay for a BIG-4 audit. Audit tenure is also negative suggesting that firms who have been with a BIG-4 auditor for longer are less willing to switch to an NB-4 auditor. This is intuitive for two (related) reasons: (1) most firms will stick with an auditor for several years before investigating the possibility of change and (2) firms that are deriving value from BIG-4 audits may become less certain about this (lack of value) of time and thus be less open to switching to an NB-4 auditor. Somewhat surprisingly, the loss variable is not stable in sign suggesting that multiple economic factors may affect the auditor choice of loss-making firms. While such firms may be unwilling to switch to an NB-4 auditor because of the negative signal it sends to the market place, they may also be more sensitive to fees (and hold less readily available cash).

My results show that although the BIG-4 premium has risen significantly, the relative competitive position of NB-4 auditors has strengthened concerning a significant proportion of the market. To augment this finding, I run the switching model separately on each quintile (Table 5 Panel B). The results are consistent with the overall findings across the lowest eight quintiles. In the largest quintiles, there is almost no switching from BIG-4 to NB-4 auditors. This result confirms the common-sense conclusion that the competitiveness of NB-4 auditors has been the dominant feature for about 80% of the market whereas the largest firms are contributing to the significant increase in the BIG-4 premium even after employing the standard controls for size used in prior literature.

1.4.8 Sensitivity Tests

1.4.8.1 Statistical issues

I tested for potential multicollinearity problems by examining the Variable Inflation (VIF) statistic. The VIF for equation (2) is 1.37 and 3.24 in equation (3), so multicollinearity is not a concern. I used several different statistics (such as the Ramsey RESET test) to test the robustness of my results to potential omitted variables. The Breusch-Pagan and White test for heteroskedasticity were positive. However, using heteroskedasticity- robust standard errors did not change the ranking of the Industries based on the BIG-4 incremental premium. I did not find any significant changes in the ranking of the industries by BIG-4 pricing power although there were some occasions when industries changed places with the ones immediately above or below. These changes had some effect on the Spearman ranking correlation score, but the effects were small and did not suggest any changes in the conclusion of a negative association between industry-premium increases and market share changes.

1.4.8.2 Alternative audit fee models

I also checked for alternatives in the Ashbaugh et al. pricing model, but the quantitative impact of these changes were small and were not worth reporting. In particular, the documented increase in the BIG-4 price premium from the 2000-2002 periods to the 2003-2011 periods and the ranking of industries by the level of premium changes was robust across alternative pricing models. I also checked an alternative measure of the premium using a fitted fee model. That is, I estimated a fee model for NB-4 auditors and then measured the premium as the excess charged by the BIG-4 over the predicted fee that would have obtained for an NB-4 auditor using the estimated regression coefficients. Again, the industry fee-premium rankings were stable and did not change the negative coefficient in the Spearman Test. In the switching model, this alternative measure was used to calculate the ABAFEE (here, simply the estimated BIG-4 premium) and it did not change the negative coefficient on this variable or the 2001 NB-4 market share.

1.4.8.3 Second tier auditors

I examine whether the shift to NB-4 is concentrated in Second Tier auditors (See Cassell, Giroux Myers and Omer 2013 for a list of auditors that are considered to be second-tier). Table 3 Panel D&E show that second-tier auditors market share increase, either measured as a proportion of fees or as a proportion of client firms accounted for a very small portion of the shift away from the BIG-4. Therefore, the growth in market share is spread broadly across all NB-4 firms and not just second-tier firms.

1.4.8.4 Switching model robustness

Another robustness check was to run the switching model on all the firms in the sample rather than restricting the sample to only the firms that were with the BIG-4 in 2003. The results were qualitatively unchanged though the significance increased with the inclusion of firms that switched from NB-4 to BIG-4 in the years 2004-2011 (i.e., using the sample of all firms that were with a BIG-4 auditor in at least one of the years from 2003-2011). This set consisted of 545 firms and a total of 2337 firm-year observations that was small relative to the total sample of 28,263 firm-year observations. None of these firms switched back to an NB-4 auditor.

1.4.8.5 Capacity constraints

The collapse of AA led to a sudden shift in demand to the surviving BIG-4 auditors. As documented in Table 3 Panel C, the surviving BIG-4 grew very rapidly in 2003-2004. However, this expansive trend slowed down sharply in 2005-2006 and seemed to have even reversed in a later year. Viewing this evidence from a longer perspective of the entire period 2003-2011, there is little evidence that capacity constraints were a significant economic force in terms of lost market share at least in the later years. To ensure that my findings are robust to capacity constraints, I run my model over different time periods and find that my results are qualitatively similar whether I run it over the period to 2006 when capacity constraints may have been stronger or over longer time periods when these constraints would no longer be part of the economic pressures.

1.4.8.6 Time-Sensitivity

In addition to checking the capacity constraints, I also tested my model over different time periods. Using time periods 2003-2006, 2003-2007 or 2003-2009 did not change any of the results of the switching model (Table 6 Panel C). In particular, the 2001 market share continued to be positive and significant over each of these time periods suggesting that the role of NB-4 market power has exerted a long-term influence on changes in market shares.

1.4.8.7 Other Regulatory Effects

The period covered by my study also saw other changes in regulation both on the market side and on the accounting side. Some of these other events may also have played a part in changing the BIG-4 premium. Specific examples are the requirement of fair value disclosures (Fin 48) or Auditing Standard 5. Such disclosures inevitably involve estimates that may increase audit failure costs, imposing a greater risk on the BIG-4. While I acknowledge this possibility, it does not affect my basic analysis of whether premium increases have resulted in market share shifts or whether NB-4 market power has also played a role. In summary, while there is a legitimate argument that other events besides the enactment of SOX may have added to the increase in the BIG-4 premium, these effects do not affect the main empirical findings of my analysis that market share shifts have been affected by NB-4 market power as well as BIG-4 pricing strategies.

1.5 Conclusion

The market for auditing services is highly concentrated with BIG-4 audit firms. In 2002, one of these auditors, Arthur Andersen, went out of business. In addition, a comprehensive set of new regulations concerning auditing (SOX) went into effect.

Subsequently, in the period 2003-2011, there were significant increases in audit fees (both for BIG-4 and NB-4 auditors) as well as significant decreases in market share for BIG-4. Prior literature has advanced two possible explanations for these shifts in market structure: (i) a deliberate attempt by BIG-4 auditors to concentrate on (fewer) more profitable clients (characterized as "cherry picking"); and (ii) that better regulation and enforcement post-SOX has increased confidence in the reports of NB-4 auditors (characterized as "NB-4 market power"). By examining cross-industry correlation between reductions in market share and increases in the BIG-4 premium, as well as the relationship between audit fees and switching behavior, I are able to provide some new insights on these two effects.

An increase in NB-4 market power should typically lead to a decrease in the BIG-4 premium (the excess oligopoly or other rents) extracted by BIG-4 auditors. However, the BIG-4 premium increased significantly over this period suggesting that the combined effects of the demise of AA and the increased requirements of SOX enhanced the pricing edge for BIG-4 auditors. In addition, the market share of the BIG-4 decreased significantly. Taken together, this pattern suggesting that cherry-picking of high-fee paying clients by the BIG-4 may have been the driving force in reshaping the market for audit services. However, if cherry picking were the dominant influence, I would expect to see that the most selective the BIG-4 became, the higher would be the premium and lower the market share. In contrast, if the increased NB-4 market power played a significant role, then the BIG-4 would lose market share even if they reduced the premium they charged over NB-4 auditors. An industry-by-industry analysis shows that BIG-4 industry premium and market share losses are inversely related (higher premium associated with smaller market share losses) showing that market changes were driven by factors additional to pricing strategy shifts by BIG-4 auditors.

To cross-check this finding, I examine whether higher increases in residual fees (after controlling for firm and industry characteristics), of BIG-4 clients, increases the probability of a client-firm switching from BIG-4 to an NB-4 auditor. As I show through a formal model, if firms switch primarily due to fee increases, I would expect to see a positive association between high firm-specific fee increases and switching to NB-4 auditors. However, if what is happening is that firms that see high (firm-specific) values for BIG-4 audits continue to retain them, it is possible that increases in the BIG-4 premium reflect a capture of this value and that there may be a lower likelihood of switching for firms that pay a high BIG-4 premium or are presented with larger increases in the fee premium. My empirical results show that high residual fee increases reduce the probability of a switch to an NB-4 auditor suggesting that there has been a shift in the perceived value of BIG-4 auditors relative to NB-4 auditors. This finding is further confirmed by the fact that there has been more switching in industries where the NB-4 were weakest pre-2002 suggesting that the enactment of SOX has made it easier for NB-4 to compete in these industries.

While the collapse of AA and enactment of SOX were major economic events, there have been many other changes in the audit environment over the period 2003-2011 as well as a major market recession. I do not examine these features individually but do show that my results are stable across different time windows within this period, and in particular, that excluding or including the recession does not affect my findings. In addition, SOX have changed many other aspects of the corporate structure including governance. Although I control for many firm-specific features connected to audit fees, I do not study the role of governance or management incentives on the decision to retain a BIG-4 auditor. Managers (and/or the Board) may see value in hiring a BIG-4 auditor even if the extra premium is not recovered from the equities market. One of the challenges for the future is to examine whether agency conflicts may lead to the retention of BIG-4 auditors even if such retention does not directly benefit shareholders.

1.6 References

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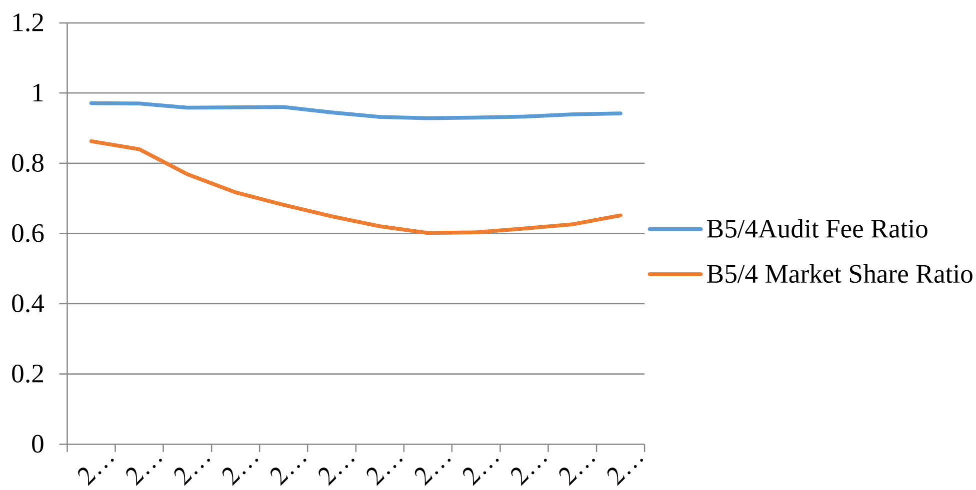
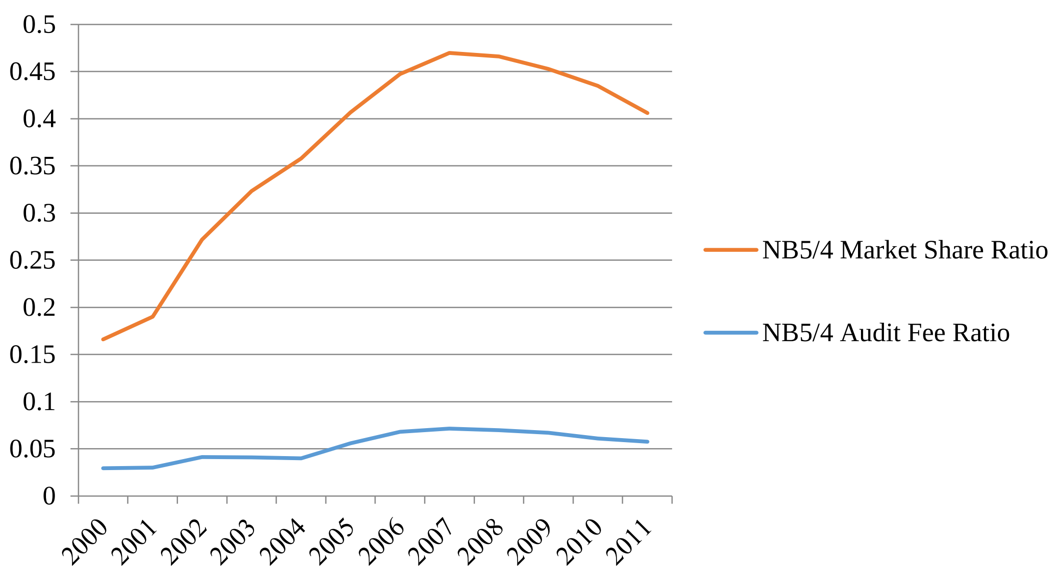
1.7 Figures for Chapter 1

Figure 1.1 - Trends in BIG-5/4Market Share Ratio and Fee Ratio

Panel A: BIG-5/4 Audit Fee Ratio and Market Share Ratio



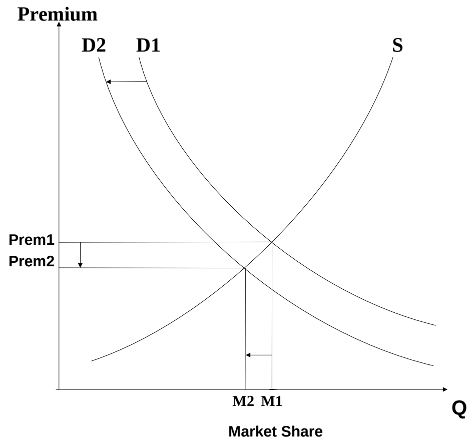
Panel B: NB-5/4 Audit Fee Ratio and Market Share Ratio



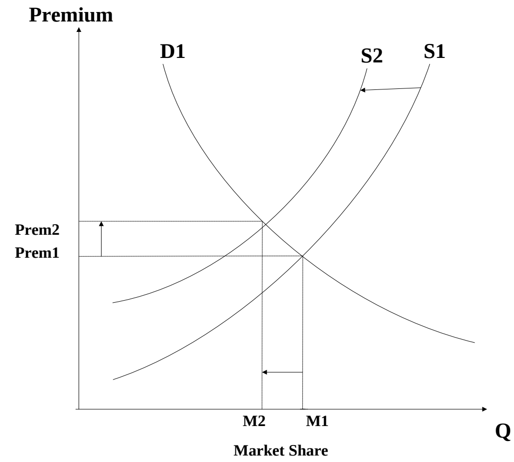
Panel A plots BIG-5/4 Market Share Ratio and BIG-5/4 Fee Ratio from 2000-2011. BIG-5/4 Market Share Ratio is the number of firms audited by BIG-5/4divided by the total number of firms in the audit market. BIG-5/4 Fee ratio is audit fee from BIG-5/4's clients divided by the total audit fees in the audit market from 2000 to 2011. Panel B plots NB-5/4 Market Share Ratio ad Fee Share Ratio for the same time period.

Figure 1.2 - Economic Equilibrium for fee premium and market-share for BIG-4 firms

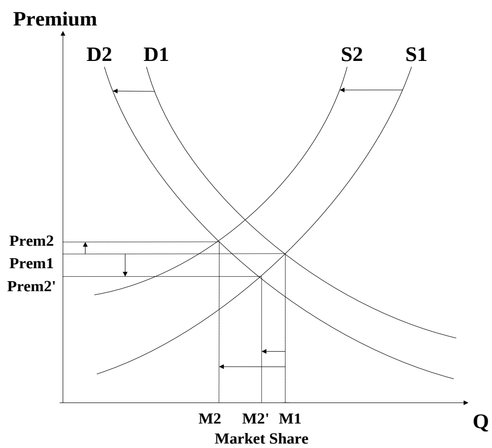
Panel A: Only Demand Curve for BIG-4 Shifts down



Panel B: Only Supply Curve for BIG-4 Shifts up



Panel C: Supply Curve shifts down and Demand Curve Shifts down



This figure shows the effects of demand and supply curve shifts in the BIG-4 premium. Panel A shows the effects of the demand curve shifting down. Panel B shows the effects of the supply curve shifting up while the demand stays constant. Panel C shows that the pattern I observe is consistent with both curves shifting, that is, the changes in market share and premium being inversely correlated (compare Premium 1 with Premium 2).

1.8 Tables for Chapter 1

Table 1.1 - Sample Composition and Attrition

	Audit Fee Model	Switch Model
Firms year observations from Audit Analytics	150,908	
Less:	(6,701)	
One firm one year has more than one audit fee observation in a fiscal year		
No financial data	(55,723)	
No business segment	(26,703)	
Financial Industries have been deleted	(10,040)	
Final firm year observations	51,732	
Missing Compustat data		(14,714)
Final firm year observations		37,018
Firm year observations in 2001		(2,020)
Firm year observations after 2001		34,998
Firm year observations before 2002	(8,636)	(6,735)

I start with 150,908 firm-year observations collected from Audit Analytics covering the period 2000-2011. Then I deleted 55,723 observations since financial data was not available on COMPUSTAT and 26,703 observations were deleted because business segments data was missing. Then I deleted 10,040 observations that belong to financial institutions. My final sample consists 51, 732 firm-year observations. 14,714 of these observations have been deleted for missing the value in the audit switching model. My final sample for the audit switching model consists of 34,998 observations. My subsample has 2,020 observations in 2001, and 6,735 observations in 2002.

Table 1.2 - Descriptive Statistics

Panel A: Univariate Statistics

Variable	Mean	Std	Q1	Median	Q3
LAF	12.98	1.58	11.86	13.02	13.07
NB-4 MARKET SHARE	14.58	4.89	11.83	16.5	16.8
AA MARKET SHARE	0.18	0.06	0.14	0.17	0.23
AA FEE SHARE	0.18	0.1	0.13	0.16	0.23
LTA	5.31	2.75	3.58	5.46	7.20
BIG-5/4	0.69	0.46	0.29	0.5	0.72
CR	3.52	20.71	1.14	1.88	3.24
CA_TA	0.50	0.27	0.25	0.6	0.78
ARINV	0.24	0.20	0.07	0.2	0.35
ROA	-0.79	15.87	-0.23	0.01	0.12
LOSS	0.41	0.50	0.00	0.00	1.00
FOREIGN	0.54	0.50	0.00	1.00	1.00
MERGER	0.15	0.35	0.00	0.00	1.00
BUSY	0.70	0.46	0.00	1.00	1.00
LEV	0.24	3.34	0.00	0.09	0.27
INTANG	0.15	0.20	0.00	0.07	0.24
SEG	1.29	0.00	0.00	0.00	1.10
GOING_CONCERN	0.02	0.67	0.81	0.92	1.91
MATERIAL_WEAKNESS	0.02	0.14	0.00	0.00	0.00
AUDITOR SWITCH	0.01	0.08	0.00	0.00	0.00
GROWTH	0.05	0.04	-0.09	0.04	0.21
ABSDACC	-8.96	13.27	-7.08	-9.95	-0.8
MODOP	0.003	0.06	0.00	0.00	0.00
TENURE	7.49	3.37	5.00	8.00	10.00
CASH	0.23	0.25	0.03	0.13	0.34
EXPERT	2.44	2.59	0.00	2.00	3.00
SIZE	2.50	11.23	0.35	2.12	3.50

Panel B: Correlation among Audit Fee, and Control Variables

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)LAF	**-0.01**	**0.12**	**0.06**	**0.85**	**0.55**	**-0.08**	**-0.26**	**-0.03**	**0.01**	**-0.33**	**0.46**	**0.14**	**0.08**
(2)NB-4 MARKET SHARE		**0.32**	**-0.04**	**-0.02**	**-0.02**	**-0.04**	**0.01**	**0.09**	**0.00**	**0.03**	**-0.02**	**0.01**	**-0.01**
(3)AA MARKET SHARE			**0.79**	**0.23**	**0.09**	**-0.07**	**-0.38**	**-0.12**	**-0.01**	**-0.11**	**0.03**	**-0.02**	**0.11**
(4)AA FEE SHARE				**0.16**	**0.04**	**-0.04**	**-0.35**	**-0.15**	**-0.01**	**-0.12**	**-0.03**	**-0.02**	**0.11**
(5)LTA					**0.61**	**-0.06**	**-0.40**	**-0.09**	**0.03**	**-0.44**	**0.45**	**0.14**	**0.08**
(6)BIG-5/4						**-0.03**	**-0.16**	**-0.10**	**0.01**	**-0.24**	**0.29**	**0.09**	**0.08**
(7)CR							**0.11**	**-0.05**	0.00	**0.04**	**-0.04**	**-0.02**	**-0.02**
(8)CA_TA								**0.44**	**-0.01**	**0.16**	**-0.09**	**-0.11**	**-0.12**
(9)ARINV									**0.01**	**-0.12**	**0.08**	**-0.01**	**-0.17**
(10)ROA										**-0.01**	**0.01**	0.00	0.00
(11)LOSS											**-0.26**	**-0.08**	**0.03**
(12)FOREIGN												**0.11**	**0.01**
(13)MERGER													**0.02**
(14)BUSY													
(15)LEV													
(16)INTANG													
(17)SEG													
(18)GOING_CONCERN													
(19)MATERIAL_WEAKNESS													
(20)AUDITOR SWITCH													
(21)GROWTH													
(22)ABSDACC													
(23)MODOP													
(24)TENURE													
(25)CASH													
(26)EXPERT													
(27)SIZE													

Panel B (countd.): Correlation among Audit Fees, and Control variable

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1)LAF	**-0.02**	**0.23**	**0.42**	**-0.18**	**-0.05**	**-0.03**	**0.01**	**-0.28**	0.00	**0.44**	**-0.24**	**0.35**	**0.35**
(2)NB-4 MARKET SHARE	0.00	**-0.03**	**0.00**	0.00	**0.01**	**0.01**	0.00	**0.03**	**0.00**	**0.01**	**-0.05**	**0.00**	**-0.01**
(3)AA MARKET SHARE	**0.01**	**-0.06**	**0.11**	**-0.03**	**-0.01**	**0.00**	0.00	**-0.11**	0.00	**0.04**	**-0.29**	**0.01**	**0.01**
(4)AA FEE SHARE	**0.01**	**-0.01**	**0.11**	**-0.02**	**-0.01**	**-0.01**	**0.00**	**-0.05**	**-0.01**	**0.03**	**-0.26**	**-0.02**	-0.03
(5)LTA	**-0.05**	**0.19**	**0.43**	**-0.23**	**-0.09**	**-0.02**	**0.01**	**-0.30**	**-0.01**	**0.44**	**-0.33**	**0.36**	**0.36**
(6)BIG-5/4	**-0.02**	**0.08**	**0.22**	**-0.17**	**-0.11**	**0.05**	**0.01**	**-0.11**	**-0.03**	**0.44**	**-0.07**	**0.62**	**0.15**
(7)CR	**-0.01**	**-0.05**	**-0.04**	**-0.01**	**-0.01**	**0.00**	0.00	**0.02**	**0.00**	**-0.01**	**0.16**	**-0.01**	**-0.02**
(8)CA_TA	**-0.01**	**-0.37**	**-0.20**	**0.03**	**0.02**	**0.01**	**-0.01**	**0.14**	0.00	**-0.12**	**0.68**	**-0.05**	**-0.11**
(9)ARINV	**-0.01**	**-0.13**	**0.07**	**-0.01**	**0.02**	**0.00**	0.00	**0.08**	**0.01**	**-0.05**	**-0.33**	**-0.07**	**-0.06**
(10)ROA	**-0.02**	**0.01**	**0.01**	**0.00**	0.00	0.00	0.00	**0.00**	0.00	**0.01**	**-0.01**	**0.01**	0.00
(11)LOSS	**0.02**	**-0.05**	**-0.26**	**0.14**	**0.07**	**0.02**	**0.00**	**0.04**	**0.02**	**-0.24**	**0.25**	**-0.12**	**-0.15**
(12)FOREIGN	**-0.02**	**0.11**	**0.27**	**-0.12**	**-0.03**	**-0.01**	**0.00**	**-0.11**	0.00	**0.20**	**-0.16**	**0.15**	**0.15**
(13)MERGER	0.00	**0.27**	**0.09**	**-0.02**	**-0.01**	**0.01**	**0.01**	**-0.03**	**-0.01**	**0.05**	**-0.10**	**0.06**	**0.04**
(14)BUSY	0.00	**0.03**	**0.01**	0.00	0.00	0.00	**0.00**	**-0.03**	**0.00**	**0.05**	**0.01**	**0.06**	**0.01**
(15)LEV		**0.00**	**-0.01**	**0.05**	**0.02**	**0.00**	0.00	0.00	0.00	**-0.01**	**-0.01**	**-0.01**	**0.00**
(16)INTANG			**0.13**	**-0.02**	**0.00**	0.00	**0.01**	**-0.04**	**0.01**	**0.06**	**-0.28**	**0.06**	**0.08**
(17)SEG				**-0.09**	**-0.03**	0.00	**0.01**	**-0.15**	**0.00**	**0.24**	**-0.26**	**0.11**	**0.18**
(18)GOING_CONCERN					**0.27**	**0.02**	0.00	**0.02**	**-0.01**	**-0.17**	**0.02**	**-0.11**	**-0.03**
(19)MATERIAL_WEAKNESS						**0.08**	0.00	**0.02**	**0.24**	**-0.15**	0.00	**-0.07**	**-0.03**
(20)AUDITOR SWITCH							0.00	**0.00**	**0.00**	**-0.08**	**0.01**	**0.04**	**-0.01**
(21)GROWTH								**-0.01**	0.00	0.00	**0.00**	0.00	**0.01**
(22)ABSDACC									**0.01**	**-0.08**	**0.09**	**-0.06**	**-0.46**
(23)MODOP										**-0.06**	**-0.01**	**-0.02**	**-0.01**
(24)TENURE											**-0.07**	**0.35**	**0.17**
(25)CASH												**0.03**	**-0.07**
(26)EXPERT													**0.09**
(27)SIZE													

Table 2 Panel A shows the descriptive statistics of audit fee, test variable and other control variables. Panel B shows the correlation among these variables. Bold indicates statistical significance at 10% level or higher.

Table 1.3 - SOX Effect in Industries

Panel A: Specific Industry Audit Fees Shares for NB-5/4 (2000-2011)

Year	Agri	Minin	Food	Textile	Chem	Pharm	Extrac	Durab	Trans	Utilit	Retail	Servic	Comp
2000	0.00	6.37	1.73	5.93	1.04	3.03	1.01	2.65	2.82	0.89	4.60	3.28	3.28
2001	1.45	1.48	2.13	5.04	2.74	3.71	1.73	2.92	2.34	0.82	3.48	4.37	2.36
2002	1.27	3.90	1.78	4.31	2.19	5.39	9.02	3.89	4.81	0.52	5.83	4.79	3.39
2003	2.21	3.32	2.33	4.05	1.86	7.41	9.71	3.77	2.44	0.92	5.91	5.86	3.76
2004	1.57	6.39	2.05	3.90	1.55	9.28	3.55	3.58	1.75	1.32	7.04	4.31	4.89
2005	1.20	5.87	1.68	3.35	3.48	11.33	4.83	5.49	3.51	3.16	6.41	7.08	6.94
2006	3.25	6.13	3.32	4.34	4.05	9.75	7.51	6.87	3.99	3.70	8.07	9.68	8.98
2007	4.18	7.55	3.95	4.94	5.14	9.84	9.04	6.82	4.23	3.53	9.20	10.38	8.77
2008	11.95	7.18	5.19	4.28	4.24	9.47	7.14	6.82	3.89	3.82	9.37	10.46	8.99
2009	10.57	8.47	5.02	5.43	3.67	8.92	7.33	6.56	3.99	3.48	7.75	9.59	8.57
2010	7.33	8.34	4.58	5.24	3.53	8.44	5.95	6.05	3.94	2.88	7.32	8.88	7.30
2011	6.52	7.03	4.58	6.11	3.62	5.84	6.29	5.52	3.80	2.88	8.10	7.99	7.14

TABLE 1.3 - Continued

Panel B: Specific Industry Number of Firms Shares for NB-5/4 (2000-2011)

Yea	Agri	Mini	Food	Textile	Chem	Phar	Extrac	Durabl	Tran	Utilit	Retail	Service	Comp
2000	0.00	25.93	25.81	15.58	13.21	13.53	12.64	12.86	6.45	6.74	15.67	15.38	12.98
2001	7.69	17.78	22.95	14.17	20.51	16.80	22.88	16.50	9.49	8.47	13.50	19.01	11.83
2002	23.81	30.93	24.44	14.38	24.79	23.73	34.50	24.09	14.07	9.18	18.09	26.91	21.06
2003	28.57	40.31	30.00	17.65	28.06	28.53	43.90	30.01	17.87	11.26	21.58	30.96	25.52
2004	28.57	46.58	31.31	19.89	31.03	32.37	46.64	33.82	20.40	14.35	24.01	33.80	30.35
2005	19.05	49.39	33.03	20.00	33.33	35.11	47.39	37.26	22.53	16.88	27.49	38.63	35.33
2006	31.82	45.30	34.86	22.16	36.54	36.78	50.92	40.94	25.25	18.26	31.45	39.83	39.31
2007	42.86	50.54	39.09	26.92	41.18	38.19	50.92	43.62	26.56	19.51	33.12	41.99	39.17
2008	57.14	50.84	43.27	26.54	43.26	38.21	46.79	45.98	23.50	21.23	32.77	40.05	38.12
2009	48.00	51.46	40.38	27.16	41.18	41.87	43.90	44.89	25.43	19.05	29.87	40.09	35.78
2010	46.15	53.00	44.76	25.32	38.28	41.79	42.26	43.63	24.71	17.48	27.64	39.35	34.64
2011	50.00	49.38	40.22	25.53	36.84	38.07	39.66	40.62	19.87	14.21	25.61	36.34	34.65

Panel C: Growth of Number of Firms Shares BIG-5/4 Clients (2000-2011)

Year	Market Shares Change				
	Ernst & Young LLP	Deloitte & Touche LLP	PricewaterhouseCoopers LLP	KPMG LLP	Arthur Andersen LLP
2001-2003	163.11	184.54	157.07	184.47	-100.00
2003-2007	102.46	102.09	84.85	91.43	0.00
2011-2007	85.01	85.23	86.44	86.75	0.00

TABLE 1.3 - Continued

Panel D: Audit Fee Percentage audited by Second Tier Auditors (2000-2011)

Year	Agri	Minin	Foo	Textil	Chem	Pharm	Extrac	Dura	Transp	Utilit	Retail	Service	Compu
2000	0.00	3.97	1.12	4.15	0.68	1.75	0.61	1.65	1.31	0.58	2.55	1.51	1.80
2001	0.00	0.50	1.70	3.61	0.47	2.25	0.52	1.64	1.61	0.52	2.09	1.97	1.18
2002	0.12	0.54	1.07	2.96	0.20	2.18	0.53	2.06	2.95	0.28	3.27	1.73	1.44
2003	0.18	0.61	0.98	2.81	0.15	3.39	0.93	1.71	1.70	0.45	3.69	2.46	1.68
2004	0.00	4.21	0.80	3.05	0.15	4.66	1.64	2.04	0.94	0.97	4.77	2.24	2.50
2005	0.00	3.46	0.50	1.85	1.46	6.04	2.25	2.86	2.00	2.53	4.36	3.26	3.97
2006	0.00	3.02	1.06	2.82	2.11	5.72	4.53	3.56	2.35	2.80	5.41	4.20	5.15
2007	0.00	3.73	1.53	3.38	2.21	5.28	4.65	3.94	2.26	2.60	5.68	6.16	5.32
2008	3.90	3.52	2.50	2.95	0.54	4.79	3.99	3.82	2.00	2.59	5.87	6.58	4.65
2009	3.66	4.71	2.12	3.94	0.66	4.60	3.93	3.59	2.08	2.24	5.07	5.55	4.47
2010	2.64	2.79	1.17	2.73	0.53	2.33	2.44	2.65	1.53	1.62	3.29	2.89	2.64
2011	2.59	2.27	1.48	2.53	0.44	1.24	2.96	2.53	1.56	1.84	2.42	2.18	2.29

Panel E: Percentage of firms audited by Second Tier Auditors (2000-2011)

Year	Agr	Mining	Food	Textil	Chem	Phar	Extrac	Dura	Trans	Utilit	Retail	Servi	Comp
2000	0.00	7.41	12.90	6.49	5.66	6.47	6.90	6.90	0.81	4.49	6.72	5.49	5.34
2001	0.00	2.22	14.75	5.51	3.85	6.97	5.93	6.80	3.80	5.08	6.11	6.34	4.93
2002	4.76	3.09	8.89	4.38	2.48	8.54	5.85	8.00	4.07	2.90	6.72	6.23	5.45
2003	4.76	2.33	8.00	4.71	2.16	9.60	6.34	9.27	4.08	3.90	7.91	6.63	6.94
2004	0.00	4.11	7.07	4.97	1.38	9.42	8.52	10.05	4.82	4.78	8.39	7.28	8.96
2005	0.00	4.27	5.50	4.74	4.00	8.89	8.84	10.30	6.08	5.19	9.74	9.71	9.98
2006	0.00	3.87	5.50	6.70	5.13	9.50	9.89	10.82	6.19	5.02	10.90	10.27	11.56
2007	0.00	4.35	5.45	9.89	3.92	9.28	9.89	12.04	6.25	5.37	10.11	12.19	11.29
2008	9.52	4.47	6.73	8.64	2.84	9.20	10.19	12.55	5.74	5.19	11.08	13.51	11.14
2009	8.00	6.43	5.77	10.49	3.68	10.05	10.98	11.62	6.29	4.29	9.37	12.59	10.68
2010	7.69	4.00	4.76	7.14	3.13	6.52	6.79	9.02	4.07	2.91	7.04	7.52	7.32
2011	7.69	4.32	5.43	7.80	2.63	5.68	7.76	9.95	3.97	3.68	5.39	6.76	7.20

TABLE 1.3 - continued

Panel F: Total audit fee table for different industries for BIG-5/4 (2000-2011)

Year	Agri	Minin	Food	Textile	Chem	Pharm	Extrac	Durabl	Transp	Utility	Retail	Service	Compu
2000	4,489,000	5,188,605	28,327,147	54,613,767	47,706,490	50,986,620	62,971,233	212,759,956	69,591,055	65,182,115	42,363,690	71,214,547	91,294,671
2001	6,702,886	17,409,901	51,452,004	75,037,095	84,948,778	85,736,615	73,334,586	373,367,310	100,081,944	100,671,491	122,118,431	99,199,385	220,853,774
2002	16,913,267	34,790,136	84,343,876	128,509,167	167,016,826	158,158,338	130,926,946	601,865,909	316,294,284	232,688,674	153,453,638	156,993,580	324,913,352
2003	12,756,418	50,638,380	104,252,681	165,976,071	218,493,450	183,253,263	168,401,567	879,445,839	401,179,144	278,025,180	195,153,909	201,769,517	445,018,135
2004	25,848,954	89,677,840	136,287,636	257,105,978	335,034,201	288,781,052	323,778,231	1,465,735,851	612,845,372	458,146,783	292,745,671	442,490,111	708,472,222
2005	29,610,815	112,457,738	213,534,169	309,972,073	358,046,941	351,000,205	384,162,849	1,719,456,092	699,531,230	456,478,147	477,291,134	547,245,077	938,138,942
2006	35,739,218	149,428,569	208,214,695	373,395,466	433,066,440	406,700,952	466,039,877	1,911,116,134	801,449,741	432,282,058	525,736,552	537,949,499	1,118,682,426
2007	35,476,170	194,513,936	195,201,801	321,442,092	323,749,042	420,651,011	461,086,800	1,919,911,262	763,443,678	419,210,122	516,171,058	498,597,970	1,189,518,764
2008	23,423,780	215,011,703	184,604,418	319,143,421	309,970,135	407,295,929	478,802,955	1,866,496,865	745,589,887	444,419,391	481,841,667	483,627,160	1,212,841,814
2009	27,163,039	191,866,525	189,240,229	280,417,687	280,668,018	382,224,344	441,332,908	1,746,561,025	672,681,041	414,015,391	476,429,842	455,208,889	1,069,287,024
2010	35,436,198	184,598,898	182,619,072	274,253,269	272,122,081	413,761,995	470,462,088	1,675,586,959	647,124,436	396,891,117	474,163,015	449,171,519	1,094,718,111
2011	34,279,904	183,974,237	171,394,021	247,289,024	252,725,227	408,773,028	460,768,178	1,681,624,963	637,196,806	395,481,490	438,406,263	432,335,465	1,063,084,238

Panel G: The number of firms in the audit market by different industries for BIG-5/4 (2000-2011)

Year	Agri	Mining	Food	Textile	Chem	Pharm	Extrac	Durabl	Transp	Utility	Retail	Service	Compu
2000	6	20	23	65	46	147	76	366	116	83	113	154	228
2001	12	37	47	109	62	203	91	602	143	108	269	230	447
2002	16	67	68	137	91	241	112	712	232	188	317	258	536
2003	15	77	70	140	100	268	115	702	262	205	327	281	569
2004	15	78	68	145	100	280	119	724	281	197	326	282	560
2005	17	83	73	152	100	292	131	719	306	192	335	278	551
2006	15	99	71	151	99	306	134	688	302	179	327	287	562
2007	12	91	67	133	90	293	134	623	282	165	311	257	528
2008	9	88	59	119	80	262	141	551	280	167	279	253	500
2009	13	83	62	118	80	243	138	555	261	170	277	257	499
2010	14	94	58	115	79	241	153	544	259	170	288	242	500
2011	13	82	55	105	72	218	140	519	242	163	276	226	445

Panel A&B describes the market shares (the ratio of the NB-5/4 market share divided by the total market share) and fee shares (the ratio of fee share divided by the total audit fee) by each industry from the 2000 to 2011(in percentage), which I define as SOX effect. Panel C indicates the declines of market share for surviving BIG-4 firms. Panel D&E shows the market share and fee share for second tier audit firms (in percentage). Panel F&G shows the whole market audit fees and number of clients for BIG-5/4.

Table 1.4 - Determinants of Fee Premium Metrics (2000-2011)

Dependent Variable: LAF	E.	Full 2000-2011	Sub Sample 2000-2002		Sub Sample 2003-2011	
		(A)	(B)	(C)	(D)	(E)
Test Variables						
BIG-5/4	+		0.07**		0.40***	
			(2.25)		(20.82)	
BIG-4*AGRICULTURE	?			-0.07		0.26**
				(-0.54)		(1.98)
BIG4*MININGANDCONSTRUCTION	?			-0.14**		0.11*
				(-2.19)		(1.89)
BIG-4*FOOD	?			0.08		0.33***
				(1.25)		(4.93)
BIG-4*TEXTILE	?			0.07		0.36***
				(1.64)		(7.90)
BIG-4*CHEMICALS	?			0.22***		0.59***
				(4.09)		(10.95)
BIG-4*PHARMA	?			-0.06*		0.32***
				(-1.73)		(10.21)
BIG-4*EXTRACTIVE	?			-0.13***		0.33***
				(-2.67)		(6.99)
BIG-4*DURABLE	?			0.07***		0.46***
				(2.66)		(17.81)
BIG-4*TRANSPORTATION	?			-0.12***		0.21***
				(-3.05)		(5.34)
BIG-4*UNILITIES	?			-0.25***		0.05
				(-5.45)		(1.10)
BIG-4*RETAIL	?					0.20***
						(5.93)
BIG-4*SERVICES	?					0.40***
						(12.01)
BIG-4*COMPUTER	?					0.43***
						(15.37)
Control Variables						
LTA	+	0.48***	0.43***	0.43***	0.45***	0.45***
		(116.89)	(60.69)	(96.04)	(90.54)	(90.82)
CR	+	-0.00***	-0.01***	-0.01***	-0.00***	-0.00***
		(-3.13)	(-2.71)	(-11.97)	(-3.36)	(-3.18)
CA_TA	+	0.61***	0.19***	0.25***	0.54***	0.64***
		(16.15)	(2.78)	(5.71)	(13.86)	(17.14)
ARINV	+	-0.05	0.39***	0.34***	0.07*	0.02
		(-1.24)	(5.68)	(6.99)	(1.70)	(0.43)
ROA	+	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(-3.47)	(-2.32)	(-5.63)	(-3.66)	(-3.50)
LOSS	+	0.20***	0.26***	0.26***	0.23***	0.22***
		(16.60)	(13.56)	(15.23)	(18.44)	(17.64)
FOREIGN	+	0.23***	0.20***	0.19***	0.20***	0.20***
		(16.06)	(9.14)	(11.10)	(13.44)	(13.16)
MERGER	?	-0.03**	-0.01	-0.01	-0.00	-0.00
		(-2.08)	(-0.54)	(-0.67)	(-0.02)	(-0.35)
BUSY	+	0.08***	0.12***	0.12***	0.08***	0.09***
		(5.45)	(5.86)	(7.02)	(5.31)	(5.61)
LEV	+	0.01***	0.00	-0.01*	0.01***	0.01***
		(3.48)	(-0.96)	(-1.91)	(4.18)	(3.98)
INTANG	+	0.66***	0.40***	0.43***	0.61***	0.69***
		(16.65)	(6.21)	(8.77)	(14.89)	(17.70)
SEG	+	0.15***	0.12***	0.12***	0.16***	0.15***
		(12.53)	(7.93)	(10.07)	(12.95)	(12.39)
GOING_CONCERN	+	0.11***	0.25***	0.25***	0.07**	0.08**
		(3.34)	(3.74)	(4.46)	(2.12)	(2.17)
MATERIAL_WEAKNESS	+	0.12***	1.00*	1.03***	0.09***	0.08**
		(3.80)	(1.78)	(3.61)	(2.76)	(2.53)
INTERCEPT		9.57***	9.51***	9.39***	9.60***	9.58***
		(193.40)	(132.61)	(245.69)	(190.41)	(262.82)
INDUSTRY DUMMY		YES	YES	YES	YES	NO
N		51732	8636	8636	43096	43096

Adjusted R2 (%)	75.25	72.64	72.44	78.81	78.54
F Test: Column (C) equals Column (D) (p-value)		4.89(<0.001)			
F Test: Industry Dummy equals (p-value)		5.43(<0.001)			

This table shows the results of audit fee model in different samples. Sample A is from 2000 to 2011. I get the similar results as Blankley et al. (2012). I add BIG-4*Industry in Sample B, I would like to show that after SOX, BIG-4 auditors charge a higher premium over some industries, while charge a lower premium over some other industries. I add Big-4 dummy in Sample C&D. I would like to show that after SOX, Big-4 auditors charge a higher premium. My results prove the hypothesis. F test shows that the coefficient of BIG-5/4 is significantly different before and after SOX at 10% level. ***, **, * Indicate statistical significance at 1%, 5% and 10% level, respectively.

Table 1.5 - Spearman Rank Order Test

Panel A: Fee Premium Rank Table by Industry

Industry	**Rank**			
	Fee Premium I	**Fee Premium II**	**Fee Premium III**	**Fee Premium IV**
Agriculture	11	7	9	7
Chemicals	1	5	1	4
Computers	3	11	3	6
Durable manufactures	4	4	2	3
Extractive	5	1	7	8
Food	8	13	6	9
Mining and Construction	12	12	12	13
Pharmaceuticals	7	3	8	6
Retail	10	9	11	12
Services	2	2	4	2
Textiles and Printing	6	10	5	1
Transportation	9	6	10	11
Utilities	13	8	13	13

Panel B: Fee Premium Rank Table by Geography

Geography	**Rank**			
	Fee Premium I	**Fee Premium II**	**Fee Premium III**	**Fee Premium IV**
New York	6	21	18	6
Los Angeles	5	8	12	5
Chicago	7	18	13	7
Houston	9	10	7	9
Phoenix	11	9	15	11
Philadelphia	10	17	6	10
San Antonio	15	4	21	15
San Diego	8	5	3	8
Dallas	18	13	11	18
San Jose	2	11	2	2
Detroit	21	14	17	21
Jacksonville	13	3	20	13
Indianapolis	20	7	19	20
San Francisco	3	16	4	3
Columbus	17	12	16	17
Austin	12	6	5	12
Memphis	4	19	9	4
Fortworth	16	2	8	16
Baltimore	1	20	1	1
Charlotte	19	15	0	19
Other	14	1	14	14

Panel C: Independent Variable Rank Table by Industry

Industry	**Rank**			
	Fee	**Market**	**Fee/Market**	**AA Switch Share**
Agriculture	2	11	1	12
Chemicals	13	8	9	8
Computers	3	6	4	2
Durable manufactures	7	9	3	3
Extractive	5	2	8	6
Food	8	5	7	1
Mining and Construction	1	3	2	7
Pharmaceuticals	9	12	5	5
Retail	4	4	10	9
Services	6	7	6	4
Textiles and Printing/Publishing	12	13	11	11
Transportation	11	10	12	10
Utilities	10	1	13	13

Panel D: Independent Variable Rank Table by Geography

Geography	**Rank**			
	Fee	**Market**	**Fee/Market**	**AA Switch Share**
New York	21	20	18	17
Los Angeles	20	17	12	11
Chicago	19	19	13	12
Houston	18	2	7	6
Phoenix	17	16	15	14
Philadelphia	16	15	6	13
San Antonio	15	12	21	20
San Diego	14	4	3	2
Dallas	13	18	11	15
San Jose	12	21	2	16
Detroit	11	13	17	12
Jacksonville	10	5	20	19
Indianapolis	9	7	19	10
San Francisco	8	1	4	3
Columbus	7	6	16	9
Austin	6	14	5	4
Memphis	5	9	9	7
Fortworth	4	10	8	8
Baltimore	3	11	1	1
Charlotte	2	3	0	0
Other	1	8	14	5

Table 1.5 - Continued

Panel E: Spearman Rank-Order Correlation

	Fee Premium I (Medium)		**Fee Premium I I (Mean)**	
	Industry	Geography	Industry	Geography
Fee	**-0.79**	**-1.00**	0.21	**-0.38**
Market	**-0.63**	**-0.48**	**-0.26**	**-0.61**
Fee/Market	**-0.37**	**-0.37**	**-0.37**	0.20
AA	**-0.23**	**-0.46**	0.01	**-0.24**
	Fee Premium III (Change_Medium)		**Fee Premium IV (Change_Mean)**	
	Industry	Geography	Industry	Geography
Fee	**-0.23**	**-0.56**	-0.02	0.16
Market	**-0.24**	**-0.27**	-0.19	0.25
Fee/Market	**-0.57**	**-0.81**	-0.22	**-0.36**
AA	**-0.23**	**-0.35**	**-0.23**	**-0.24**

Panel A shows three measures of Fee Premium. Fee Premium I is ranking based on the median of the Industry residual in Table 4 Column D; Fee Premium II is ranking based on the magnitude of the coefficient of BIG-4*INDUSTRY after 2002 in table 4 Column (B); Fee Premium III is ranking based on the change of median of the Industry residual in Table 4 Column D before 2002 and after 2002; Fee Premium IV is ranking based on the change in the coefficient of BIG-4*INDUSTRY before 2002 and after 2002 in equation (2). Panel B shows Fee Premium I, II, III, IV by geography, which is measured as the top 20 cities in U.S., and the others. Panel C presents three measures of SOX effect and one measure of AA effect. Fee Share is ranking based on the increase in NB-4 fee share between 2001 and 2001. Market Share in 2001 and with the same ratio in 2011. Fee/Market is ranking based on the difference of NB-4 Audit Fee divided by Market Share is ranking based on the increase in NB-4 market share between 2001 and 2011; Arthur Andersen Switch Share is ranking based on prior AA clients in the industry switching to NB-4 as a proportion of AA clients in the industry in 2003. Panel D presents Fee, Market, Fee/Market, and AA switch share by geography. Panel E presents the Spearman rank test results, which is used in this table to indicate the relationship between Fee premium, SOX effect, and Arthur Andersen collapse effect. The results are presented both by industry and geography.

Bold indicates statistical significance at 10% level or higher.

Table 1.6 - Auditor Switch Model

Panel A: Audit Switching Model

	Full Sample	**2001-2002**	**Sub Sample 2003-2011**	
	(A)	(B)	(C)	(D)
Test Variables				
DABAFEE	-0.28**	-0.35	-0.35***	-0.23**
	(-2.36)	(-0.78)	(-2.73)	(-2.55)
NB-4 MARKET SHARE in 2001	-0.15**	-0.06	-0.23***	-0.23***
	(-2.32)	(-0.05)	(-2.91)	(-2.90)
AA MARKET SHARE in 2001	-0.28	-2.77	0.41	
	(-0.55)	(-1.61)	(0.71)	
DABAFEE*AAMARKET 2001	1.26*	-0.32	0.76	
	(1.83)	(-1.01)	(1.01)	
AA FEE SHARE in 2001				0.25
				(0.66)
DABAFEE*AAFEE2001				0.05
				(0.09)
Control Variables				
GROWTH	-0.001	-0.00	-0.005	-0.004
	(-0.90)	(-0.51)	(-0.95)	(-0.86)
ABSDACC	0.00**	-0.00	0.0001**	0.0001**
	(2.32)	(-1.56)	(2.37)	(2.42)
ARINV	0.37**	-1.45**	0.57***	0.54***
	(2.38)	(-6.23)	(3.22)	(3.03)
GOING_CONCERN	0.46***	-0.43	0.43**	0.42**
	(2.66)	(-0.62)	(2.19)	(2.05)
MODOP	0.98***	-11.250	0.79**	0.78**
	(2.83)	(-0.00)	(2.17)	(2.13)
TENURE	-0.40***	-1.20***	-0.44***	-0.44***
	(-29.39)	(-4.25)	(-29.01)	(-28.31)
ROA	-0.001	-0.00	-0.002	-0.002
	(-0.99)	(-1.22)	(-1.36)	(-1.54)
LOSS	-0.04	-0.27	-0.02	-0.02
	(-0.49)	(-0.72)	(-0.20)	(-0.19)
LEVERAGE	-0.01	-0.17	-0.004	-0.004
	(-0.77)	(-1.18)	(-0.95)	(-0.92)
CASH	-0.35***	-1.04**	-0.36**	-0.37**
	(-2.70)	(-5.08)	(-2.45)	(-2.46)
MISMATCH*BIG-5/4	1.89***	2.92***	1.91***	1.88***
	(22.01)	(7.93)	(20.47)	(19.74)
EXPERT	0.14***	0.06	0.14***	0.14***
	(11.67)	(1.54)	(10.41)	(10.17)
SIZE	-0.16***	-0.40***	-0.15***	-0.16***

	(-10.37)	(-5.44)	(-8.28)	(-8.38)
MERGER	-0.14	-0.33	-0.10	-0.14
	(-1.26)	(-1.14)	(-0.80)	(-1.09)
INTERCEPT	-1.83***	-0.19	-1.56***	-1.45***
	(-11.81)	(-0.23)	(-9.11)	(-8.88)
N	34998	6735	28263	27367
Pseudo R2 (%)	27.82	45.14	29.88	29.60
F Test:		5.67		
Column(B)≠Column(C) (p-value)		(0.01)		

Panel B: Auditor Switch Model by 5 Asset Quintiles

Switch Model 2003-2011					
	AT 1	**AT 2**	**AT 3**	**AT 4**	**AT 5**
Test Variables					
DABAFEE	-0.38***	-0.30***	-0.17**	0.02	-1.62**
	(-3.35)	(-4.34)	(-2.02)	(0.10)	(-2.12)
NB-4 MARKET SHARE in 2001	0.05	-0.49***	-0.33**	-0.02	1.97
	(0.31)	(-3.39)	(-2.23)	(-0.10)	(1.53)
MISMATCH*BIG-5/4	0.00	4.25***	0.33*	-0.20	0.00
	(0.00)	(10.74)	(1.94)	(-0.45)	(0.03)
Control Variables					
STAND BY CONTROL VARIABLES ARE INCLUDED	Yes	Yes	Yes	Yes	Yes
INTERCEPT	1.28***	-2.78***	-0.92***	-1.94***	-6.58*
	(3.35)	(-6.21)	(-2.67)	(-3.57)	(-1.82)
N	2706	5372	6617	7158	6410
Pseudo R2 (%)	24.31	30.10	18.05	19.81	38.89

Panel C: Auditor Switch Model by Year Trends

Switch Model 2003-2011						
	2003-2006	2003-2007	2003-2008	2003-2009	2003-2010	2003-2011
Test Variables						
DABAFEE	-0.15***	-0.11**	-0.14***	-0.18***	-0.18***	-0.23***
	(-3.01)	(-2.34)	(-3.11)	(-3.89)	(-4.00)	(-5.22)
NB-4 MARKET SHARE in 2001	-0.15	-0.19**	-0.20**	-0.24**	-0.22***	-0.22***
	(-1.57)	(-2.25)	(-2.42)	(-2.99)	(-2.88)	(-2.85)
MISMATCH*BIG-5/4	1.80***	1.79***	1.83***	1.87***	1.90***	1.91***
	(16.01)	(17.66)	(18.58)	(19.64)	(20.27)	(20.43)
Control Variables						

STANDBY CONTROL VARIABLES ARE INCLUDED	Yes	Yes	Yes	Yes	Yes	Yes
INTERCEPT	-1.24***	-1.21***	-1.25***	-1.32***	-1.42***	-1.48***
	(-6.94)	(-7.43)	(-8.11)	(-8.92)	(-9.78)	(-10.44)
N	13219	16507	19617	22637	25557	28263
Pseudo R2 (%)	35.01	33.22	32.05	31.19	30.38	29.86

This table shows the results of auditor choice model over the years 2001-2011 (I omit 2000 because the model uses lagged fees). Panel A Sample A covers the period 2001 to 2011 whereas Samples C & D shows the clients switching behavior across 2003-2011. Sample B considers the period 2001-2002 to examine whether switching behavior changed after SOX. DABAFEE is the change in residual. The Mismatch variable is based on Landsman et al. (2012) in Appendix A. As I only consider BIG-4, I use Mismatch*BIG-5/4 in my regressions (i.e., to see if mismatched clients with the BIG-5/4 were more likely to switch to NB-5/4). My sample exhibits properties similar to the previous study (see Appendix). My results show that clients are less likely to switch if they are paying a higher premium (in the post-SOX period) and less likely to switch in the years 2003-2011 in industries where NB-4 had a large market share in 2001. Panel B shows the audit switch behavior broken out for five assets quintiles. The results show that NB-4 2001 market share decreases the probability of switching in the low size quintiles. Panel C shows the same results across the different period. F-test shows that the difference in abnormal fees on audit switching model before and after SOX is significant at 1% level. ***, **, *, indicate statistical significance at 1%, 5% and 10% level, respectively.

Table 1.7 - Supply and Demand Function

Panel A: Reasons for Demand Curve Shifts

Trends of Demand for BIG-4 Auditors	Reasons	Market Share & Premium for BIG-4
Down	Tarnished reputation as a result of AA collapse & scandals	
Down	Work of regulators & others to increase NB-4 reputation	Drop
Down	Overall fees going up with addition of 404 requirement	
Up	"Tried and true" in face of new regulatory requirements	Increase

Panel B: Reasons for Supply Curve Shifting up

Trends of Supply for BIG-4 Auditors	Reasons	Market Share & Premium for BIG-4
Up	Capacity constraints (Excess demand shifts pricing curve up)	
Up	Fewer BIG auditors more Oligopoly power	Market Share drops, but less clear what happens with fees and premiums
Up	Cost of risk audits have gone up—charge higher risk premium for clients	

Chapter 2: Is there a Post Earnings Announcement Drift after SOX?
2.1 Introduction

This study investigates the relation between accruals quality and Post Earnings Announcement Drift for a large sample of firms over the period - 2011. My study is motivated by a recent empirical research that shows that rational investor responses to information uncertainty (IU) explain properties of and returns to the post-earnings-announcement-drift (PEAD) trading anomaly (Francis, Lafond, Olsson, and Schipper 2007). By information risk, I mean the likelihood that firm-specific information that is pertinent to investor pricing decisions is of poor quality. I assume that cash flow is the primitive element that investors price and identify accruals quality as the measure of information risk associated with a key accounting number - earnings. That is, accruals quality tells investors about the mapping of accounting earnings into cash flows. Relatively poor accruals quality weakens this mapping and, therefore, increases information risk.

My paper makes three contributions. First, consistent with theories that demonstrate a role for information risk in asset pricing, I show that firms with poor accrual quality have higher PEAD than do firm with good accruals quality. This result is consistent with the view that information risk (as proxied by accruals quality) is a priced risk factor. Second, I find that accruals quality increase after SOX, which is contrasting with the previous literature that information is more precise after SOX (Bedard et al. 2009). While I find earnings volatility decreases, earnings persistence and smoothness increases after SOX which is consistent with prior studies (Ashbaugh et al. 2008), I shed light on accrual quality measure, which is well documented in previous literatures

(Francis, Lafond, Olsson, and Schipper 2005). While theory does not distinguish between the sources of information risk, prior research on discretionary accruals (e.g. Guay et al., 1996; Subramanyam, 1996) provides a framework in which discretionary accruals quality and innate accruals quality will have distinct cost of capital effects. Briefly, this body of work suggests that, in broad samples, discretionary accrual choices are likely to reflect both opportunism (which exacerbates information risk) and performance measurement (which mitigates information risk); these conflicting effects will yield accrual quality is actually higher after SOX. Consistent with this view, I find that innate accruals quality has a larger effect than does discretionary accruals quality. I argue managers may sacrifice accruals quality to smooth earnings, which conflicts with prior studies. (Paul and Tucker). Third, I find that earnings response coefficient increases in the short window (-1, +1) but decrease in the long window (+2, +60).

The accruals quality (AQ) metric I use is based on Dechow and Dichev's (2002) model which shows a relation between current period working capital accruals and operating cash flows in the prior, current and future periods. Following Francis (2005) and McNichols (2002) model, I include the change in revenues and property, plant and equipment (PPE) as an additional variable. In this frame, working capital accruals reflect the difference between managerial estimates of cash flows and the factors driven cash flows, changes in revenues and PPE, the estimation errors are the opposite of accruals quality due to managers intended or estimation errors.

Our tests show the relation between AQ and ERC. I find that firms with poorer AQ have higher PEAD than firms with better AQ (all differences significant at the 0.001 level). Previous literature well documented that there is a drift on the market reaction to the earnings announcement since market needs time to react to the news (Dontoh, Ronen and Sarath 2003). Because of the noise in the earnings announcement, the market tends to wait, so the information quality determines the speed of the market reacts to the news. If the information is not precise, the investors will wait for future confirmative of information, there will a delay reaction to the earnings news. Sarbanes-Oxley applies to publicly held companies and their audit firms. The statute creates the Public Company Accounting Oversight Board (PCAOB). The Securities and Exchange Commission (SEC) has oversight and enforcement authority over the PCAOB and is authorized to give it additional responsibilities. SOX effect is broad in four channels: 1) audit committee. These requirements relate to: the independence of audit committee members; the audit committee's responsibility to select and oversee the issuer's independent accountant; procedures for handling complaints regarding the issuer's accounting practices; the authority of the audit committee to engage advisors; and funding for the independent auditor and any outside advisors engaged by the audit committee. The rule implements the requirements of Section 10A (m) (1) of the Securities Exchange Act of 1934, as added by Section 301 of the Sarbanes-Oxley Act of 2002. Each member of the audit committee must be an “independent” member of the board of directors, which is strictly defined and requires that audit committee members receive no fees from the company other than those for serving on the board. At least one audit committee member must be designated as a financial expert. 2) Board of directors. Directors were required to adhere to three basic duties: the duty of loyalty, the duty of care, and the duty of obedience. In addition to these three duties, when a liability case was before a court, the business judgment rule applied. Directors must obey the law and ensure that the corporations in which they are also involved obey the law. They are obligated to ensure that all actions are taken and decisions made follow a thorough process. In liability cases, courts do not examine the outcome of a decision as much as the process that led to the result. The role of chairman of the board has clearly become more demanding. Sarbanes-Oxley prohibits registered public accounting firms from providing any non-audit services to an issuer contemporaneously with an audit. Exceptions permit firms to engage in non-audit services, including tax services, but only if the activity is approved in advance by the audit committee of the issuer. 3) A panel of CEO has strengthened. The CEO and CFO are required to prepare a statement for inclusion in the audit report that certifies the appropriateness of the financial statements and any disclosures contained in the periodic report. These certifications must state that financial statements and disclosures present, in all material respects, the operations and financial condition of the issuer. 4) The importance of responsibilities of the board and senior management as a corporation approaches the zone of insolvency cannot be overstated. Warning signs of a business failure are present between one and three years before a company runs out of capital sources and fails. One consequence may be that additional board oversight will increase instances of identifying the warning signs earlier in the zone of insolvency, which may reduce the number of business failures in future years, especially among those not married by fraud. Prior research documents Sarbanes-Oxley Act (SOX) create a faster reaction to information, Bedard et al. (2009) find that information is more precise after SOX. If SOX improves information environment, I should observe a faster reaction to the earnings announcement. In this paper, I examine the speed of market reaction to earnings announcement news before and after SOX, therefore, if I observe an increase/improve the speed of market reaction to earnings announcement after SOX, this indicate that market perceives that information to be more precise. Francis et al. (2007) employ a similar scenario about accrual quality, by the hypothesis that the market will react faster to higher quality information than lower quality information. Consistent with previous papers, I find that earnings response more quickly in the short window, but more slowly in the long window.

2.2 Literature Review

Ball and Brown (1986) first discover the post-earnings announcement drift. A strand of research which is related to post earnings announcement drift concerns whether the market understands the earnings announce. The idea is that the market initially misunderstands the signal, the markets full response to the disclosure comes much later. Bernard and Thomas (1997) concentrate on the market lagged reaction to some information, for example, "post-earnings announcement drift: delayed price response or risk premium? Two explanations have been documented in the literature about the existence of PEAD. The first is that investors underreact to the information in earnings. Bernard and Thomas (1990) find that PEAD is caused by investors failing to include the earnings surprises into their earnings expectations. Abarbanell and Bernard (1992) find that PEAD is driven by analyst failure to incorporate earnings surprises in forecasting earnings. Consistently, Bartov (1992) and Ball and Bartov (1996)) suggest that investors cause PEAD because they fail to incorporate the time-series properties of earnings. By contrary, Jacob et al. (1999) argue that previous literature findings are driven mistakenly by their research method. Based on previous arguments, Livnat and Mendenhall (2006) find that the PEAD is larger when using analysts' forecasts data to predict earnings surprises. This argument is marked in both finance and accounting literatures (Latané and Jones 1979; Bernard and Thomas 1989; Bhushan 1994; Bartov et al 2000, Ng, Rusticus, and Verdi 2008; Chordia et al. 2009). Different firm characteristics will also be driven factors of Post Earnings Announcement Drift, such as firm size, market to book ratio, liquidity, the number of analysts following.

The second explanation is the risk-premium hypothesis. It suggests that the delayed reaction to earnings announcement just compensate the risk premium (Sadka 2006). Ball, Sadka, and Sadka (2009) argue that the subsequently abnormal returns are just simply a fair compensation for information asymmetry risk and liquidity risk. Livnat and Mendenhall (2006), Konchitchki et al. (2012) argue that the PEAD is driven by risk-premium instead of under pricing, since they find that using reformed measure of earnings surprises, the PEAD reduced dramatically. In summary, there is no single story could fully explain PEAD. In my settings, I use ERC to measure PEAD. Coll and Koth JAE (1989) relate ERC to a number of commonly assumed ARIMA models, time-series properties of earnings. They examine temporal as well as cross-sectional determinants of ERC. Predict and document evidence that ERC is a function of riskless interest rates and riskiness, growth and/or persistence of earnings, so I use ERC as a measure for the market reaction to the information.

My paper research is based on information economy theory and focuses on the information environment change due to SOX (Sarbanes-Oxley Act). SOX law was enacted in 2002 to establish reforms in the financial market following a series of corporate scandals that negatively impacted investors' trust in the integrity of financial reporting. SOX has two main sections that are related specifically to internal control issues within public companies. The two provisions, Sections 302 and 404, focus on ICOFR (Internal Controls over Financial Reporting) and were enacted mainly to improve corporate financial reporting (Bedard et al. 2009) and they are argued to have the greatest potential for doing so (Nicolaisen 2004). In particular, Section 302, which became effective on August 29, 2002, requires top officers of all public firms to disclose quarterly all MWs in the firm's ICOFR. Beginning with fiscal year ending after November 15, 2004, Section 404 requires accelerated filers to assess the effectiveness of the ICOFR, and their auditors to both make their evaluation and to attest to management's findings. In compliance with Section 404, non-accelerated filers are required, starting with fiscal years ending after December 15, 2007, to only document a management report on ICOFR.

Prior literature examine whether SOX compliance results in better financial reporting quality. Using unexpected total and current accruals as measures of earnings quality, Bedard (2006) finds that internal control requirements lead to improved earnings quality. Similarly, Nagy (2010) provides evidence that firms with mandated audits of MW disclosures are less likely to restate their financial statements than noncomplying firms, and that MW disclosure is positively associated with the likelihood of future restatements. Ronen (2013) documents that SOX reduce earnings management.[1] Finally, Bizzaro et al. (2010) find a significant association between the incidence as well as the frequency of MWs and the probability of financial restatements. In all, SOX increase the financial information quality and increase the internal control efficiency. I would argue that after SOX, improved information environment will reduce the delay regression of the

[1] The book has a detail literature review of the literatures relates to whether SOX reduce earnings management or not.

market, more timely reaction to the news in the short run and fewer post earnings announcement drift will be observed in the long run.

2.3 Research Method and Hypothesis Development

Hypothesis Development:

SOX is associated with better quality (Ashbaugh 2008). SOX is designed to decrease the noise in reported earnings around fundamentals. SOX will increase the predictability, persistence, and smoothing. IU is an ambiguous measure. It increases opaque. IU is not sure to measure the good quality of earnings. Managers may intensive the informativeness of earnings by using accruals to predict future earnings, and smooth earnings.

IU is the inverse noise of reported earnings to economic earnings (fundamentals). The decrease of noise in the process, the fewer accruals in order to reflect economic earnings. IU could reflect a lower quality of earnings, accrual volatility increase to bias earnings or to officiate earnings quality. Managers use earnings discretion to change accruals to smooth earnings over time. IU is a measure of disclosure, transparency, degree to which economic earnings are reported. Cash generating ability, IU future cash flows. Economic earnings, which foretell future cash flows to test whether the latter is the cash, I look at the IU post Sox, and persistence, smoothing and find IU is ambiguous measure, it could be used to reflect better quality and smoothing.

H1: After SOX, the information uncertainty increases.

SOX improves information quality in general. PEAD effect is a noise earnings quality story. Accounting signal. SOX results in better accounting earnings reflect economic earnings. Current cash flows and future cash flows; eventually SOX reduce PEAD.

H2: After SOX, the ERC increases in the short term window.

H3: After SOX, the ERC decreases in the long term window.

H4: After SOX, the hedge portfolio returns decreases.

2.4 Sample and Descriptive Statistics

2.4.1 Sample Details

My sample is obtained from COMPUSTAT from 1993 to 2011. I use 2002 as a cut-off year; I define 1993-2001 as prior SOX period. I define 2003-2011 as post-SOX period. I begin by calculating IU before and after SOX.

2.4.2 Descriptive Statistics

Table 1 reports descriptive statistics for information uncertainty.

2.4.3 Measuring Information Uncertainty

My measure of information uncertainty is based on Dechow and Dichev's (2002) model, the variables come from the modified Jones(1991) model, to PPE and change in revenues (average assets scale all variables). I follow Francis (2007)'s measure for information uncertainty, I view that if three years cash flow can not explain the total current accruals, change in revenue and PPE, the variance of the unexplained portion is the reverse measure of information quality.

$$TCA_{j,t} = \varnothing_0 + \varnothing_1 CFO_{j,t-1} + \varnothing_2 CFO_{j,t} + \varnothing_3 CFO_{j,t+1} + \varnothing_4 \Delta Rev_{j,t} + \varnothing_5 PPE_{j,t} + v_{j,t} \quad (1)$$

Where:

$TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ = firm j's total current accruals in year t

$CFO_{j,t} = NIBE_{j,t} - TA_{j,t}$=firm j's cash flow from operations in year t

$NIBE_{j,t}$ =firm j's net income before extraordinary items (Compustat #18) in year t

$TA_{j,} = (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t})$=firm j's total accruals in year t

$\Delta CA_{j,t}$= firm j's change in current assets (Compustat #4) between year t-1 and year t

$\Delta CL_{j,t}$= firm j's change in current liabilities (Compustat #5) between year t-1 and year t

$\Delta Cash_{j,t}$= firm j's change in cash (Compustat #1) between year t-1 and year t

$\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities (Compustat #34) between year t-1 and year t

$DEPN_{j,t}$ = firm j's depreciation and amortization expense (Compustat #14) in year t

$\Delta Rev_{j,t}$ = firm j's change in revenues (Compustat #12) between year t-1 and year t

$PPE_{j,t}$ =firm j's gross value of property, plant and equipment (Compustat #7) in year t

I follow Francis et.al. (2005; 2007)'s paper to form my information uncertainty metric: $IU_{j,t}=\sigma(V_j)_t$, which is the standard deviation of firm j's residuals, calculated over years t-4 to t. Larger standard deviation of firm j's residuals, the lower quality of information..

I calculate IU for all firms with available data for years between 1993 - 2011; Table 1 Panel A reports the number of observations each year. The number of firms ranges from 6269 to 9851. Panel B reports descriptive statistics about IU before and after SOX. The mean of IU before SOX equals to 0.3429(0.4279). The mean of IU after SOX equals to 0.5449(0.4775). It indicates that after SOX, the information quality increases rather than decreases.

Insert Table 1 Here

2.4.4 Measuring Earnings Persistence

This study follows prior literature and measure earning persistence as the slope coefficient from a regression of current earnings on previous earnings (Francis et al. 2004, Richardson et al. 2005):

$$Earn_{j,\,t} = \o_0 + \o_{1*}Earn_{j,\,t-1+}v_{j,\,t} \quad (2)$$

Where:

$Earn_{j,\,t}$ is net income before extraordinary items of a firm in year t.

$Earn_{j,\,t-1}$ is net income before extraordinary items of a firm in year t-1.

Equation (2) is estimated for each firm-year by using maximum likelihood estimation and rolling ten-year windows. Firms with a higher value of $\o_1$ have higher earnings persistence, hence, higher earnings quality (Francis et al. 2004).

2.4.5 Earnings Smoothness

I measure earnings smoothness as the ratio of standard deviation of earnings of a firm, to its standard deviation of cash flow operations, both deflated by beginning total assets (Francis et al. 2004, Pincus and Rajgopal 2002).

$$\text{Smooth}\ j,t = \frac{\sigma(\text{Earn}\ j,t/\text{Total Assets}\ j,t-1)}{\sigma(\text{CFO}\ j,t/\text{Total Assets}\ j,t-1)} \quad (3)$$

Where:

Smooth j, t = earnings smoothness of a firm in year t.

σ = standard deviation of a firm calculated over rolling ten-year windows.

Earn j, t = net income before extraordinary items of a firm in year t.

CFO j, t = operating cash flows of a firm in year t.

According to Equation (3), smoothness is considered as a ratio of earnings variability to cash flow variability; hence, firms with higher values of earnings smoothness have poorer earnings quality.

To compare coefficient estimates across earnings quality proxies, I rank each proxy each year and form deciles. Firms in the bottom decile (decile 10) have the largest values of the proxy while firms in the top decile (decile 1) have the lowest values of the proxy. Given the definitions of my proxies' measures, this ordering places firms with the worst (best) outcome for the proxy in the bottom (top) deciles. Earnings persistence is designed to be in the same direction as other three earnings quality proxies. Using the decile rank of each proxy rather than its raw value alleviates the effects of extreme observations (Francis et al. 2004, Francis et al. 2005).

2.5 Empirical Results

2.5.1 Abnormal Returns to PEAD Strategy

I follow Livnat (2007)'s paper Post Earnings Announcement Drift. The standard return is calculated based on six portfolio returns. (Two size high low, and three market to book, high media and low).

Table 1 Panel B shows that more observation with large SD before than after. Small variation (0.09-1.09), less variation after SOX (0.47-1.18). Less variation of IU after SOX. 0.7<Half<1.18, threshold, after SOX, there is less variation, IU does not matter, volatility matters more after SOX than it is before.

2.5.2 Tests of Hypotheses 2-3

In order to test my hypothesis; I add the interaction of UE with SOX, and UE with IU in the model. 2

$$CAR(0,1) = \gamma_0 + \gamma_1 UE_{j,q} + \gamma_2 UE_{j,q} \times SOX + \zeta_{j,q} (4)$$
$$CAR(0,1) = \gamma_0 + \gamma_1 UE_{j,q} + \gamma_2 UE_{j,q} \times SOX + \gamma_3 UE \times IU_{j,q} + \gamma_4 UE \times IU_{j,q} \times SOX + \zeta_{j,q} (5)$$

Where:

CAR (-1, 0) j,q = Absolute value of cumulative 2-day market-adjusted return around firm j's quarter q earnings announcement;

UE j,q = Unexpected earnings news revealed in firm j's quarter q earnings announcement, scaled by firm j's share price 20 days before the earnings announcement date. Expected earnings = the consensus analyst forecast for quarter q;

IU j,q =Decile rank of IU; observations with the highest (lowest) values of IU are included in decile 10 (decile 1);

SOX = Dummy variable; equals to 1 after 2002, 0 before 2002.

SOX make the market more precise. High IU stands for the poor information environment. UE*SOX*IU is negative in the short window and positive in the long window.

In the short window, the coefficient of UE*SOX is positive, given an introduction of SOX to the improvement in expected earnings. I know that there is a positive reaction to unexpected earnings on CAR. If you consider information uncertainty, if SOX

[2] Positive r_2 means that CAR response more to UE in the presence of SOX. However, the increase in response of UE in the presence of SOX decreases in IU.

increases the market response to unexpected earnings, Information uncertainty will decrease the positive contribution of SOX to UE, you expect less reaction. Table 2 Panel A shows that the coefficient of the interaction UE*IU*sox is -0.62 and significant. So my second hypothesis has been supported.

Insert Table 2 Here

In the long window, I find that IU influences the contribution of SOX on the price response to Unexpected Earnings[3]. r3 is the coefficient on the cross term UE*IU, which equals to -1.10 in the long term window and -0.50 in the short term window, and both are negative, which means if information environment is uncertain, there is lower reaction to unexpected earnings. If you put SOX on top of this, if the environment is better, the negative correlation on UE*IU will be less, you expect the coefficient on UE*IU*SOX is positive in the long term window. Table 2 Panel B shows that the coefficient on the interaction term equals to 0.16, although it is not significant in the long term window. 4 So my third hypothesis has been supported.

Table 2 Panel C SUE_After is 9.30 and significant in the short window (-1, 0), the -3.65 is significant, which means it decreases after SOX. SUE_Before*IU is -0.50 and significant, it decreases in IU. SOX did increase internal control. SOX influence information quality.

[3] Negative r_3 means that in a high IU environment the incremental effect of SOX is reduced.
[4] The presence of SOX reduces in the long window dependent on CAR decreases SOX in the long window, because market reacts quickly due to SOX in the short window. If I introduce information environment, the dependence of UE decreases, but not much with information uncertainty.

Table 2 shows smaller influences of SOX(R Square increase a limited amount), however, add SOX is better. If IU is high UE*SOX, check the IU environment across without condition on IU. Effect of IU is highlighted; SOX should lower IU. IU increase more predictions for future, business uncertainty, high IU, more noise information. Low IU, more precise information, the variance of the residual, higher volatility in the business. Three items interaction term, SOX mitigate the negative effect. SOX effect is stronger; results are positive. More uncertainty of the environment. SOX offset the effect of the impact of IU, IU more offsets the effect of SOX, IU is not sufficient. In theory, IU Coefficient increase will lead to a decrease in PEAD. Coefficient not only could predict one year, it could also predict four years.

Insert Table 2 Here

2.5.3 Market Responses to Hedge Portfolio Returns

Then I build the hedge portfolios for the long and short portfolio based on UE. Moreover, I calculate hedge portfolio returns based on the hedge portfolio returns using long minus short. I test the hedge portfolio returns using different models before and after SOX, and my results are consistent.

I report the mean monthly abnormal return to the extreme UE portfolios (short, long, and long-short). Long security is in the top quantile. Short security is in the bottom quartile. I report abnormal returns based on CAPM, 3-factor, and 4-factor models of expected returns.

$$(R_L - R_S)_m = \alpha_{LS}^{CAPM} + \beta_{LS} RMRF_m + \varepsilon_{LS}^{CAPM}$$
$$(R_L - R_S)_m = \alpha_{LS}^{3f} + b_{LS}^{3f} RMRF_m + s_{LS}^{3f} SMB_m + h_{LS}^{3f} HML + \varepsilon_{LS,m}^{3f}$$
$$(R_L - R_S)_m = \alpha_{LS}^{4f} + b_{LS}^{4f} RMRF_m + s_{LS}^{4f} SMB_m + h_{LS}^{4f} HML + e_{LS}^{4f} AQ + \varepsilon_{LS,m}^{4f} \quad (6)$$

Table 3 for each period, you would estimate matched group, book to market correspondent, contemporaneous matched cross section returns Passed average/Beta.

IU increase, persistence increase. Table 3 shows that the difference between High IU and Low IU shrinking after SOX. After SOX, high IU, more accrual management, lower PEAD. Decrease more for high IU. The nature of IU changed; IU reflect better accruals, which caused persistently. After SOX, IU increase, earnings persistence increases. IU helps better predict future.

IU is proxy for business uncertainty, a high risk. High IU increases underlining volatility of firm.

Insert Table 3 Here

2.5.4 Volatility Test

Three measures of volatility have been used; the first is the standard deviation of quarterly earnings; the second is implied volatility; the third is stock return volatility; Sensitivity, different uncertainty regimes. SOX is greater for high volatility. Implied volatility surprise market reaction to sue both before and after. Implied volatility leads to higher perceived risk. I expect the coefficient both before and after to be negative in a short window. I expect sue_after to be negative. I get 0.99=1.55=-0.56, which means incremental effect if I measure uncertainty by implied volatility. Higher implied volatility, higher price reaction to SUE. IU leads to market volatility and earnings volatility, consistent results in short/ long window.

Table 4 volatility test, in the long window, there is a negative loading on SUE without any interaction. Is SUE reaction after, in the long window, IU will be greater. If earnings volatility are high or low, earnings volatility in the long window. In the short window, market reaction to SUE is positive, Nobody believes in IU, interact with earnings volatility. Noise measure of IU, that is why 7.44 is different from -0.92. Table 4 Volatility Test, You assuming firm-specific cash flows, the relationship between is the same the fact, high residual cross-sectional relationship.

Insert Table 4 Here

2.5.4.1 Earnings Persistence

Correlation of the errors

$$SUE_t = \alpha_0 + \alpha_1 SUE_{t-1}$$

As error term becomes more correlated, it is easier to predict earnings

Correlation of the earnings

$$E_t = \alpha_0 + \alpha_1 E_{t+1}$$

2.5.4.2 Other factors included in the model

For table 5, Big-5 observe opposite, people are misled with Big5, people over react with Big-5, so it is opposite effect as PEAD. Big-5 overreact both cases. Interaction term before and after SOX. Consistently, I see an overreaction after SOX. TA is not significant, in the long run, which means there is no overreaction in the long run due to SOX.

SOX effect is greater if BIG-5 is responsible. Provision of SOX is followed. Before SOX, I need presence of auditor to improve information environment, that's why I got 0.28 ***for SUE_Before, SUE_After, you don't need auditor as before, If you are going to hire the auditor, it doesn't give extra effect.

2.5.4.3 Robust Tests

Milian J. (2014) finds that investors overreact to earnings announcement news for firms with active exchange-traded options. I untangle option trading volume with SOX. I find in both high and low trading volumes, SOX still contributes negatively, but it will contribute lower for high option trading volume. The magnitude/contribution is great for low volume than for high volume, but it is still there. I control for high option trading volume relative to low trading volume. SOX effect exists for both high and low trading volumes as suggested in the previous literature. The low value to justify, PEAD is weaker for firms with SUE high/low interact with SOX. So I do the test after control for options trading volume, and I find my results about SOX still hold. I use two models to capture the effect of option trading, first is the absolute value of trading volume; second is a dummy variable, if the trading volume is higher than the mean, I code it as 1,otherwise I code it as 0. My previous results still hold.

The correlation metrics (Table 6 Panel D) show the smoothing and other measures increase with IU increase. IU increases with persistence, predictability, and smoothness after SOX.

Since the SOX adoption year varies for firm size and large firms' adoption period may postpone to 2006. I split my sample into large and small size firms based on the media of the sample firm size. Moreover, the results show different patterns for small and large firms in 2006.

2.6 Conclusions

I find that after SOX, the information environment becomes more precise. So the investors respond more quickly to the earnings announcement in the short window (-1, 0), which means investors have more confidence in the market. On the other hand, in the long window (+2, +60), I get the lower returns. Because SOX increases the transparency of information, less profit could be extracted from the market.

2.7 References

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2.8 Figures for Chapter 2

Figure 2.1 - Hedge Portfolio Returns to PEAD strategy before and after SOX

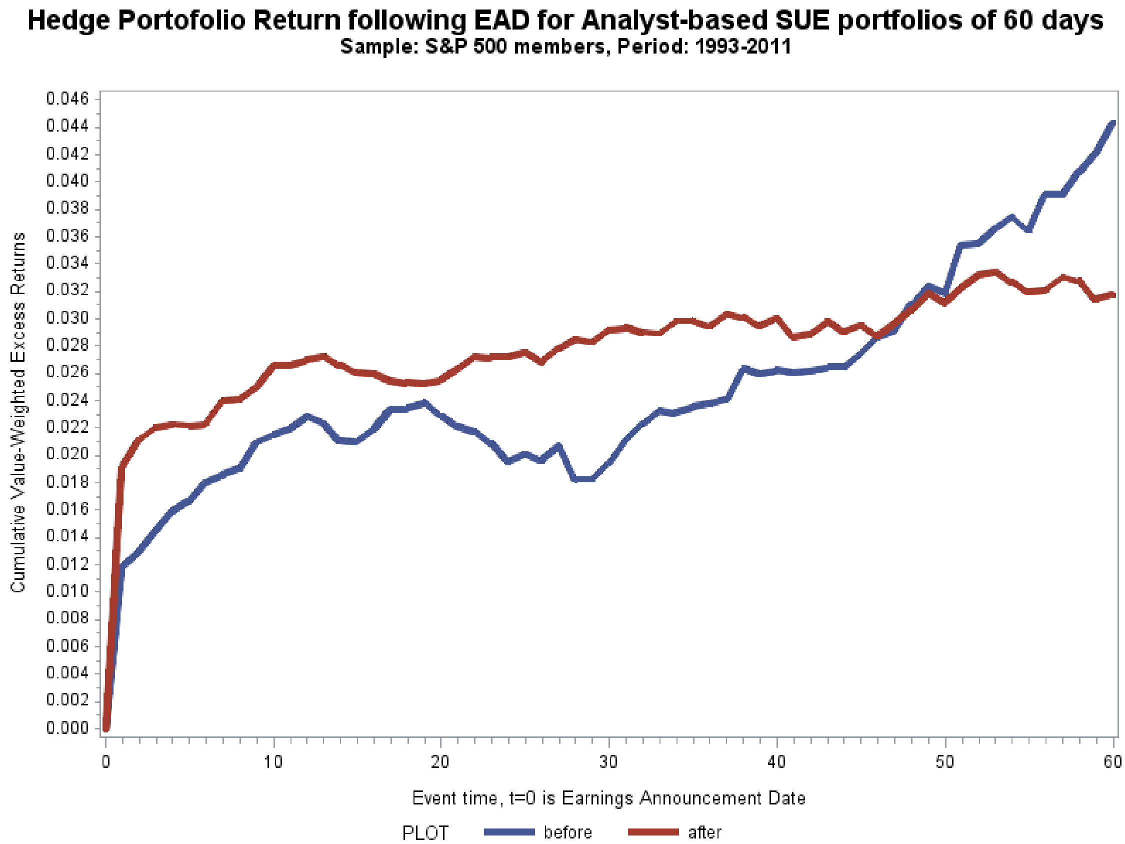
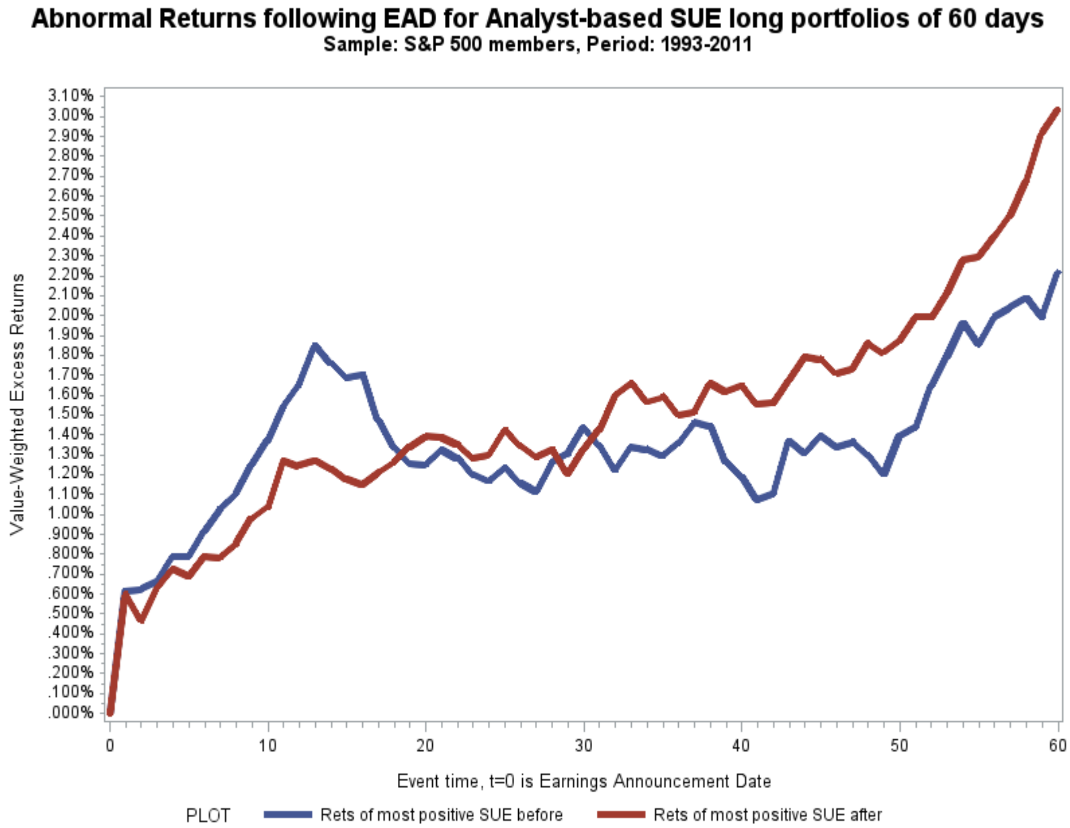


Figure 2.2 - Cumulative Abnormal Returns to PEAD strategy before and after SOX

Panel A: Positive SUE



Panel B: Negative SUE

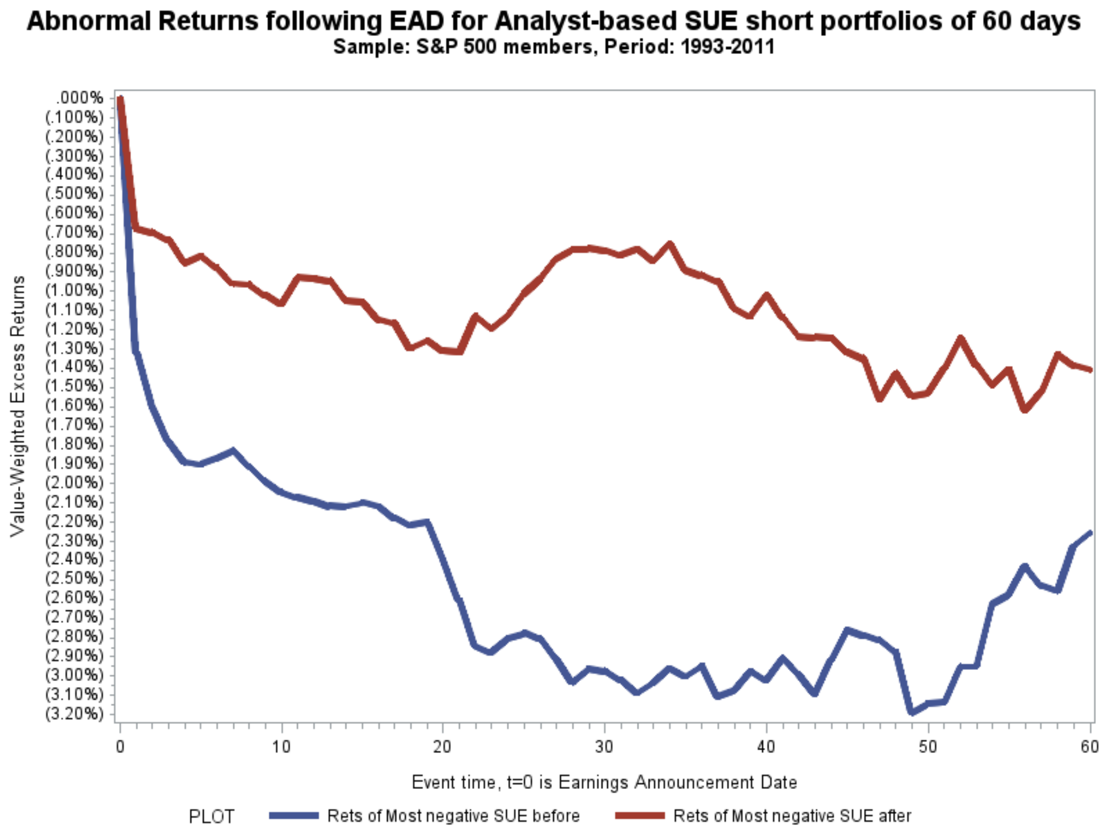
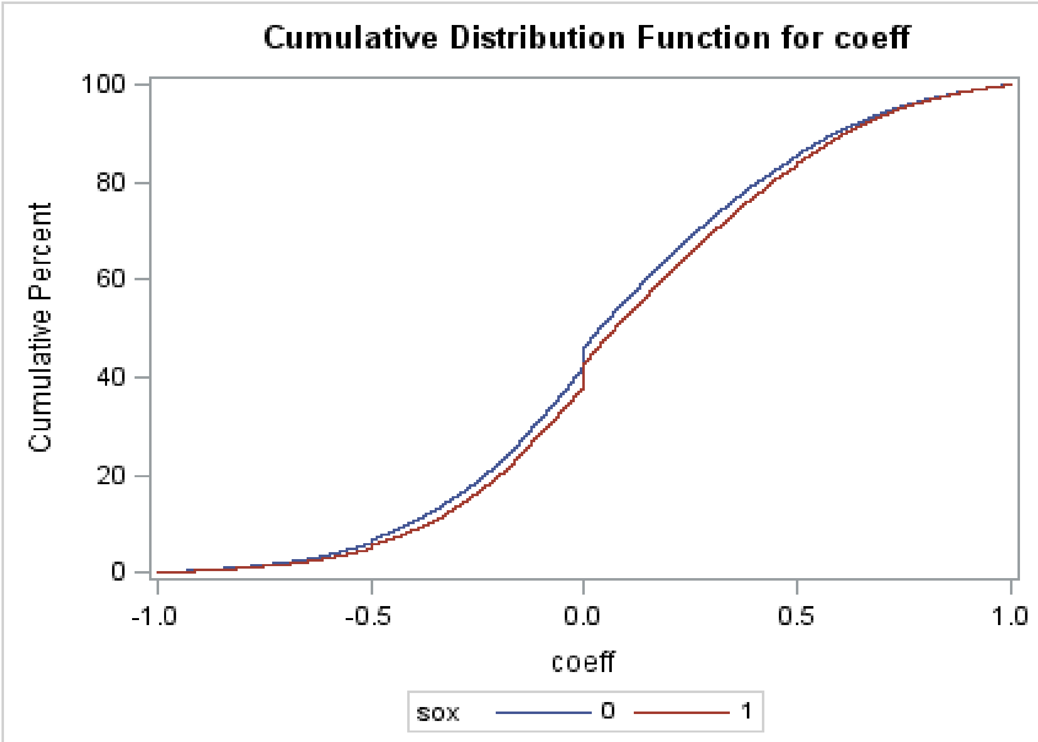
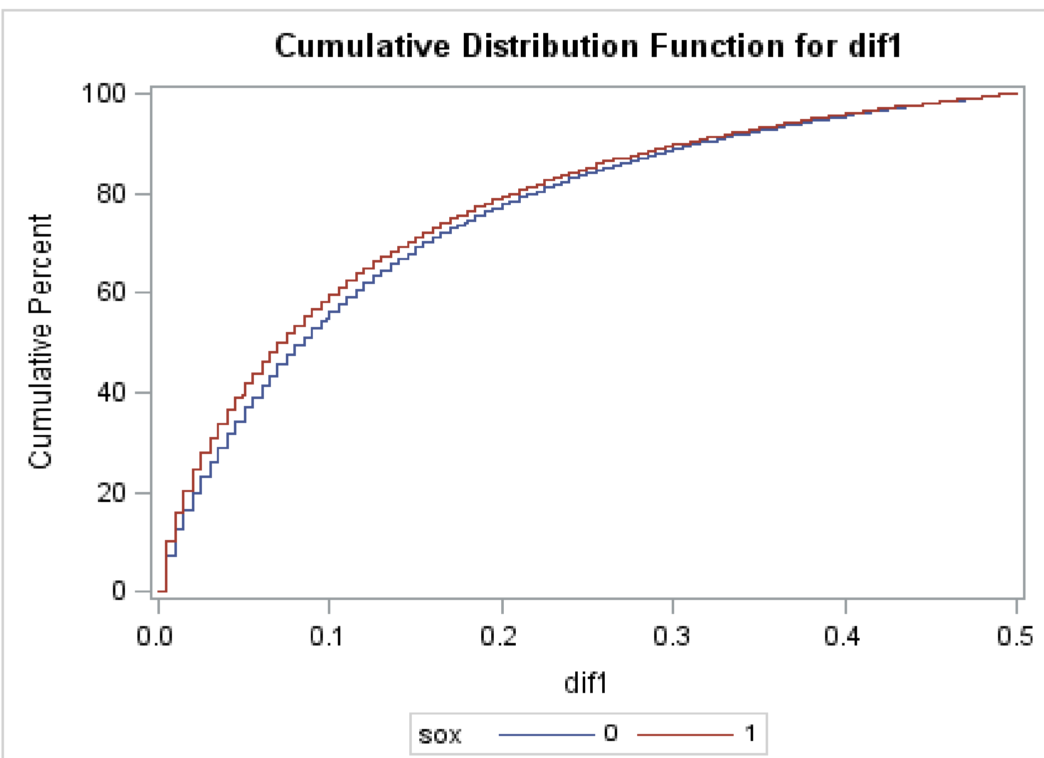


Figure 2.3 - Comparison before and after SOX

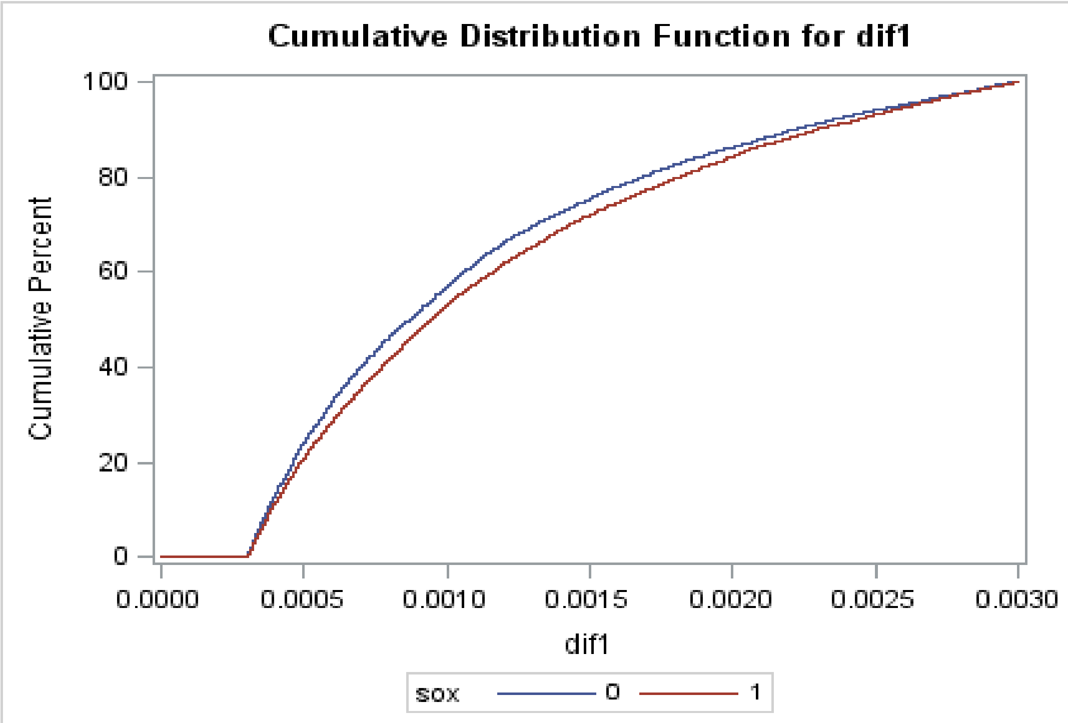
Panel A: Earnings Persistence before and after SOX



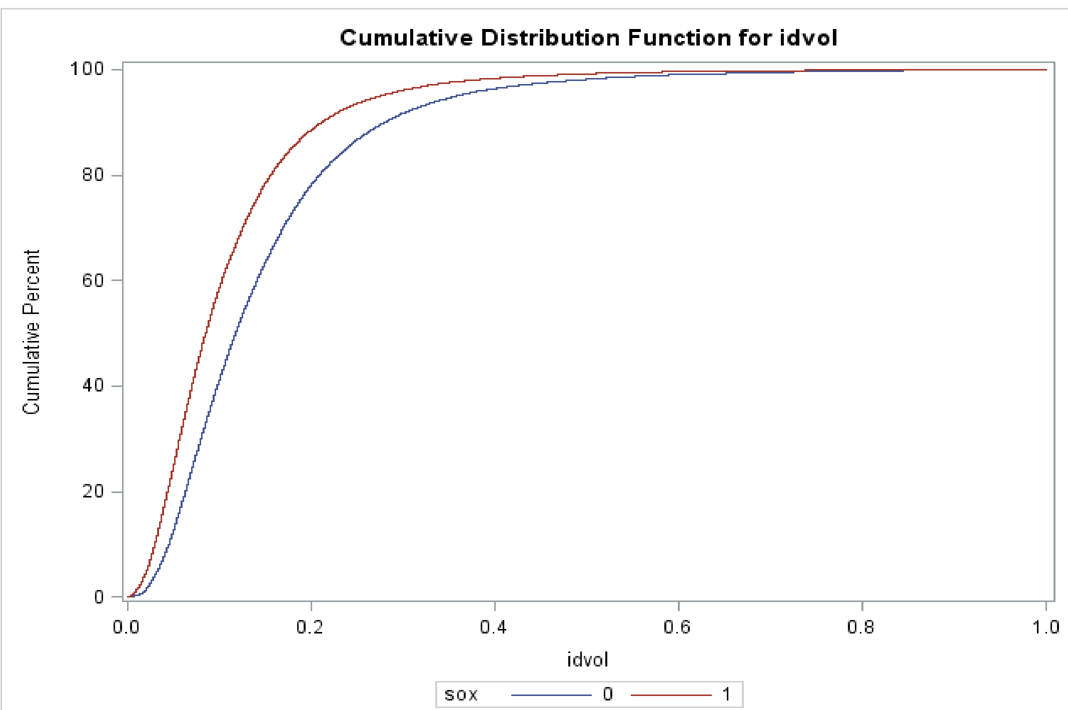
Panel B: Earnings Prediction Errors before and after SOX



Panel C: SUE Persistence before and after SOX



Panel D: Idiosyncratic volatility



2.9 Tables for Chapter 2

Table 2.1 - Descriptive Statistics about the Information Uncertainty Metric

Panel A: Number of Firms with Data on the Information Uncertainty Metric, by Year

Year	No. of Firms	Year	No. of Firms
1993	9748	2003	9865
1994	10221	2004	9851
1995	10585	2005	9609
1996	11078	2006	9498
1997	10833	2007	9513
1998	10399	2008	9559
1999	10361	2009	9356
2000	10257	2010	9224
2001	10049	2011	6269

Panel B: Distribution of the Information Uncertainty (IU) Metric

Before SOX	Mean	Std. Dev.	10%	25%	Median	75%	90%
IU	0.3429	0.4279	0.000	0.0141	0.0985	0.8467	1.0132
After SOX	Mean	Std. Dev.	10%	25%	Median	75%	90%
IU	0.5449	0.4775	0.000	0.0000	0.4749	0.9662	1.1847

IU=σ(v) is the standard deviation of the residuals from rolling five-year regressions of current accruals on lagged, current and future cash flows from operations. The IU sample consists of all firms with the necessary data to calculate IU in years.

Panel C: Distribution of Volatility

Volatility	Mean	STD	10%	25%	Median	75%	90%
Before SOX	0.106	0.056	0.051	0.066	0.094	0.129	0.175
After SOX	0.095	0.0526	0.0456	0.061	0.082	0.114	0.157

Panel D: Idiosyncratic Volatility

Volatility	Mean	STD	10%	25%	Median	75%	90%
Before SOX	0.151	0.137	0.051	0.066	0.094	0.129	0.175
After SOX	0.111	0.106	0.0456	0.061	0.082	0.114	0.157
Dif	0.04	Sig.	***				

Panel E: Distribution of Earnings Persistence

Volatility	Mean	STD	10%	25%	Median	75%	90%
Before SOX	0.199	0.488	-0.264	-0.073	0.161	0.440	0.723
After SOX	0.284	0.487	-0.232	-0.040	0.244	0.569	0.883

Panel F: Smoothing

	Correlation of idiosyncratic volatility and residual
Before SOX	-0.022***
After SOX	-0.040***

Panel A shows the summary statistics of the comparison of IU (standard deviation of residual from Dechow and Dichev 2002 and Francis et al. 2005's model) before and after SOX. Panel B shows the distribution of IU. Panel C shows the comparison of distribution of volatility (standard deviation of quarterly earnings over the year ending at the end of year t) before and after SOX. Panel D shows the idiosyncratic volatility (average by each firm) before and after SOX. Panel E presents the distribution of earnings' persistence. Earnings' persistence is measured using the following equation: $E_t=\alpha+\beta E_{t-4}$, β represents earnings persistence. Panel F describes smoothing measure before and after SOX. My measure of smoothing include four steps: 1) residual from DD's model 2) draw a trend line of earnings less the residuals 3) calculate deviation of the residual from the trend line 4) deviation correlated with residual.

Table 2.2 - Market Responses to Unexpected Earnings Conditional on the SOX of the Unexpected Earnings Signal

Panel A: Short Term Window

(0,+1) days	(1)	(2)	(3)	(4)
Intercept	-0.007	-0.000	-0.000	-0.000
	(-0.01)	(-0.00)	(-0.00)	(-0.00)
(1)SUE	0.140***	0.136***	0.136***	0.132***
	(47.27)	(45.65)	(44.81)	(42.70)
(2)SUE*SOX5		0.210***	0.178*	4.072***
		(8.63)	(1.80)	(6.04)
(3)SUE*IU			0.003	0.014
			(0.34)	(1.40)
(4)SUE*IU*SOX				-0.402***
				(-5.84)
N	26204	26204	26204	26204
R Square	0.12	0.12	0.12	0.12

Panel B: Long Term Window

(+2,+60)days	(1)	(2)	(3)	(4)
Intercept	0.331*	0.330*	0.330*	0.330*
	(1.76)	(1.75)	(1.75)	(1.75)
(1)SUE	0.005	0.003	0.005	0.008
	(0.53)	(0.33)	(0.53)	(0.93)
(2)SUE*SOX		-0.456***	-0.152	-3.947**
		(-6.66)	(-0.55)	(-2.08)
(3)SUE*IU			-0.031	-0.041
			(-1.13)	(-1.48)
(4)SUE*IU*SOX				0.392**
				(2.02)
N	26204	26204	26204	26204
R Square	0.12	0.12	0.12	0.12

[5] These results are based on the SOX adoption years. If the firm's market value of equity is smaller than 75 million, then I define SOX adoption year in 2003; If the firm's market value of equity is higher than 700 million, then I define SOX adoption year in 2006; If the firm's market value of equity is higher than 75 million but lower than 700 million, then I define SOX adoption year in 2004.

Panel C: Separate SUE Before and After

Window	(0,+1)	(+2,60)
Intercept	0.021	0.345*
	(0.32)	(1.86)
(1)SUE_Before	4.549***	4.469*
	(5.22)	(1.88)
(2)	-0.745***	-0.962**
SUE_Before*IU	(-4.10)	(-1.94)
(3) SUE_After	7.443***	-3.941
	(8.50)	(-1.65)
(4) SUE_After*IU	-1.422***	0.699
	(-8.09)	(1.46)
Firm Fixed Effect	Yes	Yes
Quarter Fixed Effect	Yes	Yes
Industry Fixed Effect	Yes	Yes
N	26135	26140
R Square	0.05	0.12
Dif:(1)-(2)	5.261	8.111
F Test	3.78	5.12
Sig.	***	***

This table shows whether information uncertainty is associated with PEAD begins by investigating whether signals with higher information uncertainty have more muted immediate market responses but less profit in the long run after SOX. I define CAR (0, +1) as cumulative 2-day market adjusted return around firm j's quarter q earnings announcement. The earnings surprise (SUE) is actual earnings minus expected earnings, scaled by stock price. Expected earnings are set to the consensus analyst forecast for quarter q. IU is decile ranking of IU; observations with the highest(lowest) values of IU are included in decile 10 (decile 1); SOX is defined as 1 after 2002; 0 otherwise.

Table 2.3 - High IU Low IU

Window (0,+1)	Low IU	Middle IU	High IU
Intercept	0.08	0.04	0.02
	(0.85)	(1.3)	(0.34)
(1)SUE_Before	24.53***	9.68	3.62***
	(3.24)	(1.97)	(2.78)
(2) SUE_Before*IU	-6.23***	-1.13	-0.29**
	(-2.81)	(-1.57)	(-2.09)
(3) SUE_After	106.02	19.38	14.53***
	(1.34)	(4.04)	(15.74)
(4) SUE_After*IU	-24.44	-2.70	-1.42***
	(-1.22)	(-3.84)	(-15.36)
Firm Fixed Effect	Yes	Yes	Yes
Quarter Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
N	256	3412	8700
R Square	0.06	0.12	0.07

In this table, I divide the whole IU into low, middle and high IU group and I find my results are shown stronger in high IU group, which is consistent with the theory that SOX effect is strongest in high IU group.

Table 2.4 - Average Monthly Abnormal Returns to High and Low Information Uncertainty Securities

Panel A: Average Monthly Abnormal Returns to Securities before and after SOX

Contemporaneous Matched Cross section Return

	Long	Short	Dif	Sig
After	0.120	0.076***	0.044	***
	(0.22)	(2.11)	(4.18)	
Before	0.122	-0.086*	0.208	***
	(1.02)	(1.55)	(4.24)	
Dif	0.002	-0.162**	0.164	**
	(1.53)	(2.22)	(2.93)	

Three Factors

$$(R_L - R_S)_m = \alpha_{LS}^{3f} + b_{LS}^{3f} RMRF_m + s_{LS}^{3f} SMB_m + h_{LS}^{3f} HML + \varepsilon_{LS,m}^{3f}$$

	Long	Short	Dif	Sig
After	0.021	0.006	0.015	***
	(1.11)	(1.23)	(4.39)	
Before	0.141	-0.002**	0.143	**
	(1.45)	(1.78)	(3.34)	
Dif	0.12	-0.008*	0.128	**
	(1.14)	(1.60)	(2.54)	

CAPM

$$(R_L - R_S)_m = \alpha_{LS}^{CAPM} + \beta_{LS} RMRF_m + \varepsilon_{LS}^{CAPM}$$

	Long	Short	Dif	Sig
After	0.009	-0.004***	0.013	**
	(1.21)	(2.78)	(4.0)	
Before	0.101	-0.001***	0.102	***
	(1.06)	(2.35)	(3.67)	
Dif	0.092	0.003***	0.089	**
	(1.18)	(2.58)	(2.07)	

Four Factor

$$(R_L - R_S)_m = \alpha_{LS}^{4f} + b_{LS}^{4f} RMRF_m + s_{LS}^{4f} SMB_m + h_{LS}^{4f} HML + e_{LS}^{4f} AQ + \varepsilon_{LS,m}^{4f}$$

	Long	Short	Dif	Sig.
After	0.019***	0.007***	0.012	**
	(2.12)	(3.42)	(4.33)	
Before	0.125***	0.005***	0.120	**
	(2.22)	(4.23)	(3.91)	
Dif	0.106***	-0.002***	0.108	**
	(2.10)	(3.44)	(2.00)	

Additional Accrual Quality Factor

$$(R_L - R_S)_m = \alpha_{LS}^{4f} + b_{LS}^{4f} RMRF_m + s_{LS}^{4f} SMB_m + h_{LS}^{4f} HML + e_{LS}^{4f} AQ + \varepsilon_{LS,m}^{4f}$$

	Long	Short	Dif	Sig
After	0.015	0.001*	0.014	**
	(1.44)	(1.60)	(4.43)	
Before	0.122	-0.007**	0.129	**
	(1.25)	(2.10)	(3.52)	
Dif	0.107	-0.008*	0.115	**
	(1.35)	(2.00)	(2.71)	

I report the mean monthly abnormal return to the extreme UE portfolios (short, long, long-short). Long security is in the top quantile. Short security is in the bottom quantile. I report abnormal returns based on CAPM, 3-factor, and 4 factor models of expected returns.

Significance at *** at 0.01, ** at 0.05, * at 0.1.

Panel B: Average Monthly Abnormal Returns to High and Low Information Uncertainty Securities before and after SOX

Contemporaneous Matched Cross section Return

	Long		**Short**		**Dif**		**Sig**	
	High IU	Low IU	High IU	Low IU	High IU	Low IU	High IU	Low IU
After	0.101	0.076	-0.002	0.005	0.103	0.071		
	(0.32)	(0.11)	(-0.08)	(0.09)	(0.35)	(0.10)		
Before	0.142	0.086	-0.011	0.003	0.153	0.083	*	
	(1.02)	(0.88)	(-0.03)	(0.005)	(1.83)	(0.78)		
Dif	0.041	0.010	0.09	-0.002	-0.049	0.012	*	*****
	(1.53)	(1.47)	(1.23)	(-0.02)	(1.95)	(1.60)		

CAPM

$$(R_L - R_S)_m = \alpha_{LS}^{CAPM} + \beta_{LS} RMRF_m + \varepsilon_{LS}^{CAPM}$$

	Long		**Short**		**Dif**		**Sig**	
	High IU	Low IU	High IU	Low IU	High IU	Low IU	High IU	Low IU
After	0.126	0.058***	-0.003	-0.001	0.129	0.061	**	
	(1.73)	(1.41)	(-0.10)	(-0.06)	(2.02)	(1.43)		
Before	0.106	0.016	-0.053	-0.021	0.159	0.037	**	
	(1.11)	(0.44)	(-0.98)	(-0.96)	(1.99)	(0.88)		
Dif	-0.020	-0.142**	-0.050	-0.010	0.030	-0.141		******
	(-1.40)	(-2.83)	(-1.75)	(-1.02)	(1.42)	(2.80)		

3 Factor

$$(R_L - R_S)_m = \alpha_{LS}^{3f} + b_{LS}^{3f} RMRF_m + s_{LS}^{3f} SMB_m + h_{LS}^{3f} HML + \varepsilon_{LS,m}^{3f}$$

	Long		Short		Dif		Sig	
	HighIU	Low IU	High IU	LowIU	High IU	LowIU	HighU	Low IU
After	0.158	0.076	-0.102	0.011	0.260	0.065	**	
	(2.01)	(1.56)	(-1.99)	(1.21)	(3.42)	(1.23)		
Before	0.153	0.054	-0.124	0.101	0.277	-0.047	**	
	(2.36)	(1.15)	(-1.55)	(1.43)	(3.53)	(-1.04)		
Dif	0.102	0.010**	0.09	-0.005	0.012	0.015		
	(1.82)	(0.47)	(0.73)	(-0.21)	(0.48)	(0.53)		

I report the mean monthly abnormal return to the extreme UE portfolios (short, long, and long-short). Long security is in the top quantile. Short security is in the bottom quantile. I report abnormal returns based on CAPM, 3-factor models of expected returns. Significance at *** at 0.01, ** at 0.05, * at 0.1.

Panel A reports the mean monthly abnormal return to the securities within each of the extreme UE portfolios (short, long, long-short) before and after SOX. I report abnormal returns based on Contemporaneous matched cross section return (calculated as the raw return from the Center for Research in Security Prices (CRSP) minus the daily return on the portfolio of firms with approximately the same size and book-to-market ratio (Based on classification of the population into six (two size and three B/M) portfolios; 3-factor, CAPM, 4-factor, and a 4-factor model that adds an accruals quality (AQ) mimicking factor to the 3-factor model. To the traditional CAPM, I add a variable capturing accruals quality. Specifically, I calculate an AQfactor-mimicking portfolio equal to the difference between the monthly excess returns of the top two AQ quintiles (Q4 and Q5) and the bottom AQ quintiles (Q1 and Q2). This procedure (similar to that used by Fama and French (1993) to construct size and book-to-market factor-mimicking portfolios) yields a series of 228 monthly AQfactor returns. Panel A shows the results of regressions which include AQfactor as an additional independent variable; these tests allow us to assess the degree to which accruals quality overlaps with and adds to the market risk premium in explaining returns. Specifically, I report the mean of the J=9,540 loadings, βj and λj, from firm-specific estimations of Eq. Panel B reports the mean monthly abnormal return to the High IU and low IU securities within each of the extreme UE portfolios (short, long,

long-short). Low IU securities are those in the bottom two deciles of the ranked distribution of the IU metric, while High IU securities are in the top two deciles. Variable definitions and sample description are shown in Appendix A.

Table 2.5 - Market Responses to Unexpected Earnings Conditional on the Volatility Signal

Panel A: Standard Deviation of Quarterly Earnings

$$CAR = \gamma_0 + \gamma_1 SUE\_BeforeSOX_{j,q} + \gamma_2 SUE\_BeforeSOX_{j,q} \times IU_{j,q} + \gamma_3 SUE\_AfterSOX_{j,q}$$
$$+\gamma_4 SUE\_AfterSOX_{j,q} \times IU_{j,q} + \gamma_5 SUE\_Before_{j,q} * StdEPS_{j,q} + \gamma_6 SUE\_After_{j,q} * StdEPS_{j,q} + \zeta_{j,q}$$

CAR	Short Window (0,+1)			Long Window (2,60)		
	Coeff.	t Statis.	Sig.	Coeff.	t Statis.	Sig.
Intercept	0.01	0.1		0.34	1.85	*
sue_before	1.46	8.38	***	1.10	2.03	**
sueiu_before	0.73	1.08		-4.37	-2.42	**
sue_after	0.19	2.53	**	-0.35	-1.71	*
sueiu_after	0.79	5.06	***	-0.30	-0.69	
suestdeps_before	-0.33	-3.81	***	-0.82	-2.14	**
suestdeps_after	0.01	2.48	**	0.00	0.25	
Fixed Effect Included	Yes			Yes		
N			25762			25767
R Square			0.06			0.12

$Step1: \mathrm{Re}gress$

$$IU = \gamma_0 + \gamma_1 StdEPS_{j,q} + \gamma_2 \mathrm{Re}sidual_{j,q}$$

$Step2: Plugin\ \mathrm{Re}sidual\ \ from\ step1$

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_Before_{j,q} \times \mathrm{Re}sidual_{j,q} + \gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q} \times \mathrm{Re}sidual_{j,q} + \gamma_5 SUE\_Before_{j,q} \times StdEPS\_Before_{j,q} + \gamma_6 SUE\_After_{j,q} \times StdEPS_{j,q}\_After_{j,q} + \zeta_{j,q}$$

Intercept	0.01	0.1		0.34	1.85	*
sue_before	1.73	8.25	***	-0.58	-0.92	
sue*residual_before	0.73	1.08		-4.37	-2.42	**
sue_after	0.49	13.9	***	-0.46	-4.89	***
sue*residual_after	0.79	5.06	***	-0.30	-0.69	
suestdeps_before	-0.33	-3.78	***	-0.83	-2.16	**
suestdeps_after	0.01	3.11	***	0.00	0.18	
Fixed Effect Included	Yes			Yes		
N			25762			26030
R Square			0.06			0.12

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_After_{j,q} + \gamma_3 SUE\_Before_{j,q} \times StdEPS\_Before_{j,q} + \gamma_4 SUE\_After_{j,q} \times StdEPS_{j,q}\_After_{j,q} + \zeta_{j,q}$$

Intercept	0.02	0.32		0.34	1.86	*
sue_before	1.56	11.02	***	0.49	1.04	
sue_after	0.33	12.92	***	-0.46	-6.69	***
suestdeps_b	-0.33	-3.84	***	-0.72	-1.92	*
suestdeps_a	0.02	5.01	***	0.00	0.08	
Fixed Effect Included	Yes			Yes		
N			26025			26030
R Square			0.05			0.12

Panel B: Implied Volatility

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_Before_{j,q} \times IU_{j,q} + \gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q} \times IU_{j,q} + \gamma_5 SUE\_Before_{j,q} \times \text{Im}\, pVol\_Before_{j,q} + \gamma_6 SUE\_After_{j,q} \times \text{Im}\, pVol\_After_{j,q} + \zeta_{j,q}$$

	Short Window Coeff.	t Statis.	P-Value	Long Window Coeff.	t Statis.	P-Value
Intercept	-0.02	-1.39		-0.05	-1.3	
sue_before	2.11	4.03	***	-2.86	-1.24	
sueiu_before	0.53	0.53		-6.18	-2.05	**
sue_after	4.43	6.33	***	-2.42	-1.32	
sueiu_after	-0.75	-1.02		-1.52	-0.98	
suevolatility_before	0.02	0.02		9.20	2.54	**
suevolatility_after	-2.96	-4	***	4.83	1.9	*
N			8906			8943
R Square			0.10			0.17

$Step1: \text{Re}\,gress$

$$IU = \gamma_0 + \gamma_1 \text{Im}\, pVol_{j,q} + \gamma_2 \text{Re}\,sidual_{j,q}$$

$Step2: Plugin\ \text{Re}\,sidual\ \ from\ step1$

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_Before_{j,q} \times \text{Re}\,sidual_{j,q} + \gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q} \times \text{Re}\,sidual_{j,q} + \gamma_5 SUE\_Before_{j,q} \times \text{Im}\, pVol\_Before_{j,q} + \gamma_6 SUE\_After_{j,q} \times \text{Im}\, pVol_{j,q}\_After_{j,q} + \zeta_{j,q}$$

	Short Window Coeff.	t Statis.	P-Value	Long Window Coeff.	t Statis.	P-Value
Intercept	-0.02	-1.39		-0.05	-1.3	
sue_before	2.39	4.05	***	-6.24	-2.8	***
sue*residual_before	0.53	0.53		-6.18	-2.05	**
sue_after	4.03	8.34	***	-3.25	-2.14	**
sue*residual_after	-0.75	-1.02		-1.52	-0.98	
suevolatility_before	-0.09	-0.1		10.28	2.86	***
suevolatility_after	-2.81	-3.58	***	5.09	1.98	**
N			8906			8943
R Square			0.10			0.17

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_After_{j,q} + \gamma_3 SUE\_Before_{j,q} \times \text{Im}\, pVol\_Before_{j,q} + \gamma_4 SUE\_After_{j,q} \times \text{Im}\, pVol_{j,q}\_After_{j,q} + \zeta_{j,q}$$

	Short Window Coeff.	t Statis.	P-Value	Long Window Coeff.	t Statis.	P-Value
Intercept	-0.02	-1.37		-0.05	-1.27	
sue_before	2.22	4.59	***	-4.78	-2.26	**
sue_after	3.90	8.35	***	-3.42	-2.27	**
suevolatility_b	0.01	0.01		10.12	2.81	***
suevolatility_a	-3.10	-4.28	***	4.72	1.86	*
N			8906			8943
R Square			0.10			0.17

Panel C: Stock Return Volatility

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_Before_{j,q} \times IU_{j,q} + \gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q} \times IU_{j,q} + \gamma_5 SUE\_Before_{j,q} \times Sto\,\mathrm{Re}\,tVol\_Before_{j,q} + \gamma_6 SUE\_After_{j,q} \times Sto\,\mathrm{Re}\,tVol\_After_{j,q} + \zeta_{j,q}$$

	Short Window Coeff.	t Statis.	P-Value	Long Window Coeff.	t Statis.	P-Value
Intercept	0.02	0.45		0.03	0.31	
sue_before	2.77	9	***	0.67	0.78	
sueiu_before	1.06	1.61		-5.06	-2.73	***
sue_after	3.19	17.81	***	0.57	1.17	
sueiu_after	-0.86	-4.28	***	-0.26	-0.47	
suevolatility_before	-8.05	-6.3	***	-1.16	-0.27	
suevolatility_after	-5.69	-14.04	***	-3.44	-3.08	***
N			24651			24650
R Square			0.06			0.13

$Step1 : \mathrm{Re}\,gress$

$$IU = \gamma_0 + \gamma_1 Sto\,\mathrm{Re}\,tVol_{j,q} + \gamma_2\,\mathrm{Re}\,sidual_{j,q}$$

$Step2 : Plugin\ \mathrm{Re}\,sidual\ \ from\ step1$

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_Before_{j,q} \times \mathrm{Re}\,sidual_{j,q} + \gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q} \times \mathrm{Re}\,sidual_{j,q} + \gamma_5 SUE\_Before_{j,q} \times Sto\,\mathrm{Re}\,t\_Before_{j,q} + \gamma_6 SUE\_After_{j,q} \times Sto\,\mathrm{Re}\,t_{j,q}\_After_{j,q} + \zeta_{j,q}$$

Intercept	0.02	0.45		0.03	0.31	
sue_before	3.22	9.1	***	-1.46	-1.44	
sue*residual_before	1.06	1.61		-5.06	-2.73	***
sue_after	2.82	19.58	***	0.46	1.15	
sue*residual_after	-0.86	-4.28	***	-0.26	-0.47	
suevolatility_before	-8.54	-6.46	***	0.85	0.19	
suevolatility_after	-5.29	-12.63	***	-3.33	-2.89	***
N			24651			24650
R Square			0.06			0.13

$$CAR = \gamma_0 + \gamma_1 SUE\_Before_{j,q} + \gamma_2 SUE\_After_{j,q} + \gamma_3 SUE\_Before_{j,q} \times Sto\,\mathrm{Re}\,t\_Before_{j,q} + \gamma_4 SUE\_After_{j,q} \times Sto\,\mathrm{Re}\,tVol_{j,q}\_After_{j,q} + \zeta_{j,q}$$

Intercept	0.03	0.93		0.03	0.3	
sue_before	2.92	9.84	***	0.10	0.13	
sue_after	2.52	17.99	***	0.70	1.83	*
suevolatility_b	-8.03	-6.27	***	-2.44	-0.58	
suevolatility_a	-6.31	-15.71	***	-3.67	-3.33	***
N			24905			24902
R Square			0.06			0.13

Panel D: Correlation Table

Before SOX			
	Predictability	Persistence	Smoothing
IU	-0.03621	-0.0767	-0.05634
After SOX			
	Predictability	Persistence	Smoothing
IU	0.05421	0.06544	0.06789

This table shows whether volatility is associated with PEAD begins by investigating whether signals with high volatility have more muted immediate market responses, and does it substitute IU's influence on PEAD. I use three measures of volatility: standard deviation of quarterly earnings, implied volatility and stock return volatility. The dependent variable is CAR in the short window (0,+1) and long window (+2,60). Panel A shows standard deviation of quarterly earnings in the fiscal year t as a measure of volatility; Panel B shows implied volatility, where the theoretical option price is set equal to the midpoint of the best closing bid price offer price for the option. The Black-Scholes formula is then inverted using a numerical search technique to calculate the implied volatility for the option. Panel C shows stock return volatility which represents total stock return volatility in the last 24 months. Panel D shows the correlation table among IU and three volatility measures (Standard deviation of quarterly earnings, implied volatility, and stock return volatility) both in the short term and long term. Residual equals to the residual from IU regress on volatility measures.

Table 2.6 - Comparison of Earnings Persistence, Earnings Prediction Errors, SUE Persistence before and after SOX and corresponding coefficients

Panel A: Earnings Persistence Before and After SOX

	Et=α+βEt-4				
	Q1	**Q2**	**Q3**	**Q4**	**Total**
(1)Before SOX	0.09	0.07	0.05	0.00	0.05
(2)After SOX	0.12	0.11	0.08	0.03	0.08
Dif (1)-(2)	-0.03	-0.04	-0.03	-0.03	0.03
T Statistic	-1.25	-3.43	2.41	-2.76	-4.36
P Value	0.21	0.00	0.02	0.01	<0.00
Sig.		***	**	***	***

$$CAR=\gamma_0+\gamma_1 SUE\_Before_{j,q}+\gamma_2 SUE\_Before_{j,q}\times IU_{j,q}+\gamma_3 SUE\_After_{j,q}+\gamma_4 SUE\_After_{j,q}\times IU_{j,q}$$
$$+\gamma_5 SUE\_Before_{j,q}\times Beta\_Before_{j,q}+\gamma_6 SUE\_After_{j,q}\times Beta\_After_{j,q}+\zeta_{j,q}$$

		Short Window			**Long Window**		
		Coeff.	**t Stat.**	**Sig.**	**Coeff.**	**t Stat.**	**Sig.**
	Intercept	-0.01	-0.28		0.26	2.16	**
$\mathbf{r_1}$	sue_before	4.64	5.89	***	6.49	3.02	***
$\mathbf{r_2}$	sueiu_before	-0.36	-4.3	***	-0.63	-2.73	***
$\mathbf{r_3}$	sue_after	12.65	15.68	***	-2.64	-1.19	
$\mathbf{r_4}$	sueiu_after	-1.23	-15.08	***	0.24	1.09	
$\mathbf{r_5}$	sue_b*beta_b	-0.38	-1.55		-3.03	-4.84	***
$\mathbf{r_6}$	sue_a*beta_a	-0.29	-3.04	***	-0.73	-2.73	***
	F test: B_3+B_6	11.32	15.26	***	-3.01	-1.42	
	N			24914			24683
	R Square			0.06			0.11

$Step1: \mathrm{Re}\,gress$

$IU=\gamma_0+\gamma_1 Beta_{j,q}+\gamma_2 \mathrm{Re}\,sidual_{j,q}$

$Step2: Plugin\ \mathrm{Re}\,sidual\ \ from\ step1$

$$CAR=\gamma_0+\gamma_1 SUE\_Before_{j,q}+\gamma_2 SUE\_Before_{j,q}\times \mathrm{Re}\,sidual_{j,q}+\gamma_3 SUE\_After_{j,q}$$
$$+\gamma_4 SUE\_After_{j,q}\times \mathrm{Re}\,sidual_{j,q}+\gamma_5 SUE\_Before_{j,q} * Beta\_Before_{j,q}+\gamma_6 SUE\_After_{j,q} * Beta_{j,q}\_After_{j,q}+\zeta_{j,q}$$

	Intercept	-0.01	-0.28		0.26	2.16	**
$\mathbf{r_1}$	sue_before	1.54	11.07	***	1.10	2.93	***
$\mathbf{r_2}$	sue_b*residual_before	-0.36	-4.3	***	-0.63	-2.73	***
$\mathbf{r_3}$	sue_after	1.27	19.85	***	-0.37	-2.1	**
$\mathbf{r_4}$	sue_a*residual_after	-1.23	-15.08	***	0.24	1.09	
$\mathbf{r_5}$	sue_b*beta_b	-0.31	-1.29		-2.93	-4.66	***
$\mathbf{r_6}$	sue_a*beta_a	0.05	0.47		-0.80	-2.83	***
	N			24914			24683

Panel B: Earnings Prediction Errors before and after SOX (E Stands for Earnings)

	$\varepsilon_1 = \left\lvert \frac{E_2 + E_3 + E_4}{3} - E_1 \right\rvert$	$\varepsilon_2 = \left\lvert \frac{E_2 + E_3 + E_4 + E_5}{4} - E_1 \right\rvert$	$\varepsilon_3 = \left\lvert \frac{E_2 + E_3 + E_4 + E_5 + E_6}{5} - E_1 \right\rvert$	$\varepsilon_4 = \left\lvert \frac{E_2 + E_3 + E_4 + E_5 + E_6 + E_7}{6} - E_1 \right\rvert$
(1)Before SOX	0.1798	0.1777	0.1856	0.1935
(2)After SOX	0.178	0.1726	0.1791	0.1838
Dif (1)-(2)	0.00187	0.00511	0.00645	0.0097
T Statistic	2.4	6.73	8.32	12.19
P Value	0.0163	<.0001	<.0001	<.0001
Sig.	**	***	***	***
Dif (Scaled by Price[1])	0.00025***	0.00035***	0.00036***	0.00054***
and Sig.	(2.99)	(3.03)	(2.89)	(4.64)

[1] Price is the same date as E_1's report date.

Panel C: SUE Persistence Before and After SOX

	$SUE_t = \alpha + \beta * SUE_{t-4}$				
	Q1	**Q2**	**Q3**	**Q4**	**Total**
(1)Before SOX	0.26	0.29	-0.25	0.14	0.11
(2)After SOX	0.36	0.57	-0.06	0.19	0.265
Dif (1)-(2)	-0.10	-0.28	-0.19	-0.05	-0.155
T Statistic	-1.25	-2.35	5.21	-3.10	-0.3725
P Value	0.20	0.02	0.0002	0.005	0.045
Sig.		***	***	***	**

Panel D: Overall distribution

	DISTRIBUTION								
	Earnings Persistence			**Earnings Prediction Errors**			**SUE Persistence**		
	Total	**Before SOX**	**After SOX**	**Total**	**Before SOX**	**After SOX**	**Total**	**Before SOX**	**After SOX**
Mean	0.12	0.11	0.14	0.27	0.27	0.27	0.21	0.24	0.18
Median	0.07	0.05	0.08	0.11	0.11	0.1	0.19	0.24	0.16
SD	0.69	0.72	0.64	0.43	0.42	0.45	1.91	1.92	1.90
Q1	-0.17	-0.18	-0.15	0.03	0.04	0.03	-0.11	-0.07	-0.15
Q3	0.40	0.39	0.42	0.29	0.30	0.29	0.57	0.60	0.55
N	680144	365382	314762	691830	400457	291373	26061	11336	14725

This table shows comparison of earnings signals before and after SOX. Panel A shows summary statistics of earnings persistence and regression analysis of whether earnings persistence is associated with PEAD begins by investigating whether signals with higher earnings persistence have more muted immediate market responses. I measure earnings persistence using the coefficient of quarterly earnings regress on last quarterly earnings. Panel B show summary statistics of earnings prediction errors before and after SOX. Panel C shows comparison statistics of SUE persistence before and after SOX. Panel D shows overall distributions of Earnings Persistence, earnings prediction errors and SUE persistence.

Table 2.7 - Comparison of Earnings Smoothing, Smoothness Before and After SOX

Panel A: Smoothing

Before SOX	0.53
After SOX	1.56

$$Accruals_t = a(1/Assets_{t-1}) + b\Delta Sales_t + cPPE_t + dROA_t + \mu_t$$

In regression (3), the total accruals (Accruals)(Accruals=NI(Data 18)-CFO(Data 308)); change in sales (ΔSales(Data 12)); and gross property, plant, and equipment(PPE)(Data 7) are each deflated by the beginning-of-year total assets(Assets) (Data 6). NDAP are the fitted values of Regression (3) and the discretionary accruals (DAP) are the deviations of actual accruals from NDAP. The pre-discretionary income (PDI) is calculated as net income minus discretionary accruals (PDI=NI-DAP). The income-smoothing measure is the correlation between the change in discretionary accruals and the change in pre-discretionary income: Corr(ΔDAP, ΔPDI), using the current year's and past four years' observations.

Panel B: Smoothing (See Appendix B)

Before SOX	0.37
After SOX	1.10

Methodology is presented in Appendix C

Panel C: Smoothness (See Appendix B)

Before SOX	0.21
After SOX	0.45

Methodology is presented in Appendix C

This table shows comparison of earnings smoothing, smoothness before and after SOX. Panel A shows statistics of earnings smoothing following Tucker and Zarowin (2006)'s measure. Panel B describes the comparison of other measures of smoothing, which is documented in Ronen & Sadan (1981). I also show comparison of how smooth a series is, following Ronen & Sadan (1981). The detail method is presented in Appendix B.

Table 2.8 - Different Measures of IU

Panel A: Summary Statistics

Measures	IU_TCA	IU_TA	IU_ROA
1993	0.29	0.19	0.18
1994	0.30	0.19	0.18
1995	0.28	0.15	0.15
1996	0.30	0.18	0.16
1997	0.31	0.20	0.17
1998	0.30	0.19	0.17
1999	0.29	0.20	0.17
2000	0.28	0.20	0.19
2001	0.36	0.32	0.24
2002	0.74	0.52	0.48
2003	0.76	0.60	0.57
2004	0.79	0.65	0.60
2005	0.80	0.62	0.57
2006	0.50	0.59	0.54
2007	0.46	0.52	0.43
2008	0.38	0.40	0.34
2009	0.39	0.48	0.42
2010	0.39	0.48	0.54
2011	0.33	0.44	0.51
Before SOX	0.03	-0.001	0.07
After SOX	0.3	0.08	0.43
Sig.	***	***	***

Panel B: Hedge Portfolio Returns

TCA Model			
DIFFERENCE	LOW IU	MIDDLE	HIGH IU
AFTER SOX	0.0314	0.0281	0.0145
BEFORE SOX	0.0423	1.0276	1.4758
DIFFERENCE	0.0109	0.9995	1.4613
SIG.		*	***
TA Model			
DIFFERENCE	LOW IU	MIDDLE	HIGH IU
AFTER SOX	-0.01	0.10	0.45
BEFORE SOX	0.02	0.14	0.58
DIFFERENCE	0.03	0.04	0.13
SIG.		*	*

This table shows robust tests on different measures of IU use different models. Panel A shows the summary statistics of IU measures using TA, TCA and add ROA in the TA model. I use total accruals (TA) instead of total current accruals (TCA), the difference is TA equals to TCA minus depreciation and amortization expense. Panel B presents hedge portfolio returns using different IU models.

Table 2.9 - Option Trading Volume

Panel A: Option Trading

Absolute Trading Volume							
Parameter	Estimate	t Value	Pr > |t|	Parameter	Estimate	t Value	Pr > |t|
Intercept	0.020867847	0.31	0.7531	Intercept	0.346462012	1.87	0.0621
sue_before	3.379084053	4.11	<.0001	sue_before	5.520727007	2.67	0.0076
sueiu_b	-0.242732399	-2.61	0.0089	sueiu_b	-0.646082495	-2.86	0.0042
sueot_b	-0.000040656	-1.91	0.056	sueot_b	0.000434079	2.96	0.0031
sue_after	9.541346305	13.94	<.0001	sue_after	-3.832905171	-2.05	0.0405
sueiu_a	-0.930517454	-13.5	<.0001	sueiu_a	0.344345209	1.83	0.0676
sueot_a	0.000006372	6.83	<.0001	sueot_a	-0.000009736	-1.68	0.0933
volume1	0.000000012	0.6	0.5498	volume1	-0.000000058	-1.05	0.2928
		N	26135			N	26140
		R Square	0.06			R Square	0.124

Dummy Variable							
Parameter	Estimate	t Value	Pr > |t|	Parameter	Estimate	t Value	Pr > |t|
Intercept	0.020969	0.32	0.7515	Intercept	0.345149	1.86	0.0631
sue_before	4.192452	4.97	<.0001	sue_before	5.661011	2.57	0.0102
sueiu_b	-0.35116	-3.61	0.0003	sueiu_b	-0.66772	-2.68	0.0075
sueot1_b	0.074384	0.34	0.7367	sueot1_b	0.823377	1.44	0.1489
sue_after	9.072271	13.29	<.0001	sue_after	-3.96279	-2.12	0.0342
sueiu_a	-0.8949	-13.03	<.0001	sueiu_a	0.342929	1.82	0.0683
sueot1_a	0.65922	11.76	<.0001	sueot1_a	0.365739	2.39	0.0167
volume2	0.002175	2.25	0.0247	volume2	-0.00791	-2.98	0.0029
		N	26135			N	26140
		RSquare	0.063			RSquare	0.125

Panel B: Hedge Portfolio Returns

High Volume					Low Volume			
	4 Factor					4 Factor		
	Long	Short	Dif	Sig		Long	Short	Dif
After	**1.19**	**-0.38**	1.57		After	**0.9**	**-1.58**	2.48
Before	**3.71**	2.2	1.51		Before	**2.36**	**-1.43**	3.79
Dif	-2.52	-2.58	0.06		Dif	-1.46	-0.15	-1.31
	3 Factor					3 Factor		
	Long	Short	Dif	Sig		Long	Short	Dif
After	**1.02**	-0.28	1.3		After	**0.85**	**-1.44**	2.29
Before	**3.12**	1.74	1.38		Before	**2.12**	-0.35	2.47
Dif	-2.1	-2.02	-0.08		Dif	-1.27	-1.09	-0.18
	CAPM					CAPM		
	Long	Short	Dif	Sig		Long	Short	Dif
After	1.17	-0.53	1.7		After	1.21	-1.64	2.85
Before	2.23	2.56	-0.33		Before	2.48	-1.19	3.67
Dif	-1.06	-3.09	2.03		Dif	-1.27	-0.45	-0.82

Chapter 3: Bold Recommendations that Lead the Market
3.1 Introduction

The association between security returns and analysts' recommendations suggests that the market values analysts' private information and personal skills. In particular, investors may respond more strongly to stock recommendations that appear to reflect knowledge that has not yet been impounded in concurrent market prices. To explore this hypothesis, I study bold recommendations, that is, recommendations that diverge from the consensus prevailing at the time of the recommendation. However, divergences from the consensus by individual analysts could also represent an incorrect assessment of future price movements. The goal of my analysis is to examine the extent to which investors are able to separate out bold recommendations that are driven by private information (or superior analysis) from those that are less reliable. I examine this issue by splitting bold recommendations into market leaders and others (leading bold and contra-bold) based on ex-post information and documenting differential market reactions at the time of the recommendation (when investors react based on their perceptions regarding these recommendations).[1]

I classify recommendations as bold if the analysts recommendation is significantly different from consensus recommendations 30 days prior to the analyst's recommendation, non-bold otherwise. To explain this further, observe that recommendations are classified a buy (1 or 2), hold (3), or sell (4 or 5). Given this numbering, a buy recommendation (1 or 2) at a time when the market consensus is above

[1] On December 15, 1998, Amazon (AMZN) stock price was $242. On that day, Henry Blodget, an analyst, made a strong buy recommendation and predict that the stock price would rise to $400. This was considered a bold recommendation. One month later, the price had hit a high of $553 and the analyst consensus was that Blodget had made a good call. One could say that his boldness led him to better career advancement.

3 would be classified as bold. In contrast, a recommendation of sell (4 or 5) when the market consensus is below 3 is classified as non-bold. My classification of recommendations is based on the classification of forecasts as bold or non-bold (Clement and Tse 2005)[2]. That paper finds that bold forecasts are more accurate than herding forecasts[3]. Clarke and Subramanian (2006) find that both very accurate and very inaccurate forecasters produce bold forecasts. However, recommendations are different from forecasts. Forecasts deal solely with accounting information and typically focus on quarterly or annual accounting performance. In contrast, recommendations analyze stock price movements and may contain information that will not be reflected in accounting numbers in the near future (such as, say, a successful initial trial of a pharmaceutical product). So my first test examines whether markets react differently to bold recommendations as compared with non-bold recommendations (that is, conforms to what has already been established for assessments).

The second research question is whether the market reaction to all bold recommendations is similar or whether there is some ability to discern between less profitable and more profitable recommendations. I argue that some bold recommendations maybe based on analysts' private information or experience while others may be based on mistakes, and so, not all bold recommendations would create higher market returns.[4] I separate bold ratings into two categories: leading bold and

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[2] Clement and Tse classify forecasts as bold if they are above both the analyst's own prior forecast and the consensus of forecast prior to the analyst's forecast, others which move away from the analyst's prior forecast and toward the consensus are classified as herding forecast.

[3] My study and Clement et al. (2005) are not directly comparable, since analysts' bold forecasts are not directly linked to bold recommendations. In addition, the sample periods are different. While Clement et al. (2005) use data from 1989 to 1998; my sample is from 1992 to 2011. Furthermore, instead of arguing that bold recommendations are more accurate than non-bold recommendations, I use ex-post consensus to divide bold recommendations into contra-bold and leading-bold.

[4] Clarke and Subramanian (2006) find that bold forecasts could also be less accurate.

contra-bold. These are ex-post measures based on the consensus recommendations thirty days after the original bold recommendation. If the recommendation is opposite from the consensus of other analysts at the end of the thirty day period, I classify the recommendation as contra-bold, which could also be defined as a bold recommendation that does not influence other analysts. If in contrast, the consensus rating after thirty days is similar to the original bold recommendation, then I classify it as leading-bold, which can also be considered as a bold recommendation that is followed by other analysts. I argue that contra-bold recommendations may be more likely to be caused by inaccurate information or analysis whereas leading-bold recommendations may reflect analysts' superior private information.

The third research question is to establish which analyst characteristics are related with the likelihood of making leading bold recommendations. If these characteristics are similar to those that are related to superior forecasts, it could explain why the market reacts more strongly to leading-bold recommendations as compared with contra-bold recommendations. [5] I find that analysts who issue contra-bold and leading-bold recommendations have similar characteristics and the same analyst may issue a leading bold in one period and a contra-bold in another. Nevertheless, I find that leading-bold creates a higher market returns than contra-bold recommendations both at the time of the recommendation (when the fact that other analysts' reactions are not observable) and in the long-term after the market becomes aware that other analysts have been influenced by this leading-bold recommendation. I infer from this that at least some investors in the market are able to confirm which recommendations reflect superior information perhaps

[5] Factors such as prior forecasting performance and the type of brokerage firm the analyst belongs to have been associated with forecast accuracy in earlier studies (Clement and Tse 2005).

through their own private information search rather than through observable characteristics of analysts.

The results show that the CAR associated with leading bold recommendations is higher both in the event window (-1 to +1 days) and in the long term (6 months) as compared with contra-bold and non-bold recommendations. However, contra-bold recommendations also earn a positive CAR in the short window relative to non-bold recommendations but not in the long window. This result suggests that the market is partially, but not perfectly, able to distinguish between bold recommendations driven by superior private information or analytic skills from those that may be mistakes.

The results also demonstrate a complex relation between analyst characteristics and bold behavior. It is documented in previous literature that the likelihood of analysts' forecast boldness increases with their prior accuracy, brokerage size, and experience, but declines with the number of industries that the analysts follow (Clement and Tse 2005). On the other hand, Jegadeesh and Kim (2010) find that the likelihood of analysts' herding behavior increases with the size of brokerage firms, smaller stock price dispersions, and less frequent forecast revisions.[6] Due to the conflicting findings regarding factors such as brokerage size, it is interesting to examine their relationship with leading-bold and contra-bold recommendations.

First, I find that the correlation between forecast boldness and recommendation boldness is positive and partially significant. Second, I find that information asymmetry is positively correlated with analysts' bold recommendations. This result is consistent with the theory that analysts' private information will give them advantage in becoming

[6] Other papers that examine factors underlying bold forecasts include (Scharfstein and Stein 1990; Hirshliefer and Tse 2003; Jegadeesh and Kim 2010; Lundholm and Rogo 2014).

market leaders when there is more uncertainty. Third, I find that risk factors have a complex relationship with the likelihood of making a leading bold recommendation where some risk factors increase the probability (perhaps because of greater incentives to acquire private information) whereas others decrease it (perhaps due to a greater risk of being wrong). Fourth, I find that general experience will increase the likelihood of bold recommendations, which is consistent with the theory that analysts experience allow them to become market leaders. Fifth, consistent with Clement and Tse (2005)'s findings, I find that the more industries the analysts pursue, the less probability the analysts will make a bold recommendation.

This paper contributes to the literature in several ways. First, this study sets up a new classification of analysts' bold recommendations. I divide analysts' bold recommendations into contra-bold and leading-bold recommendations based on the consensus of other analysts' 30 days after the recommendation. Second, I find that analysts' bold recommendations create higher market returns than non-bold recommendations both at the time of recommendation and in the long run. In particular, I find at the recommendation date, the market reacts positively to all bold recommendations but that there is a stronger reaction to leading-bold recommendations. In addition, by identifying a variable that is more strongly associated with leading-bold recommendations as opposed to contra-bold recommendations, I am able to create a hedge portfolio that earns abnormal returns at least with regard to bold sell recommendations.

Together, these findings suggest that analysts who issue leading bold recommendations are more likely to possess private information or have expertise in either the firm or the industry. These characteristics provide a potential explanation for the findings that bold recommendations create higher market returns than non-bold recommendations in the short run. Not surprisingly, bold recommendations that later turn out to be inaccurate (contra-bold) lead to negative long run returns as compared with leading-bold or non-bold ratings. The more interesting finding is that investors react more strongly in the short-run to leading-bold recommendations even before other analysts confirm the accuracy of this recommendation.

The next section discusses the literature review and hypotheses. Section III shows sample selection and research methodology. Section IV describes the results. Section V discusses additional tests and robustness tests and conclusions are presented in section VI.

3.2 Literature Review and Hypotheses Development

Financial analysts play a key role in the price formation process even though their recommendations do not always agree (Brown 1993; Schipper 1991). Sometimes, analysts may simply herd toward the consensus, either due to career security concern or because they think that the consensus is a good aggregator of private information (Scharfstein and Stein 1990; Hirshliefer and Teoh 2003; Jegadeesh and Kim 2010; Lundholm and Rogo 2014). Welch (2001) finds that analysts herd toward the consensus when there is little information available. Analysts may also herd because they may be concerned about their reputation, or because their private information may be inconsistent with contemporaneously available public signals (Graham 1999).

Prior literature has mostly studied bold recommendations and advanced several factors that may lead to bold assessments. Hong, Jeffrey, and Kubik (2003) show that once analysts become confident in their own models, they become bolder and attempt to lead rather than follow the consensus. Analysts may privately acquire information that is not available to other analysts leading them to diverge from the consensus (Chen and Jiang 2006). Palmon and Yezegel (2012) look at the value of recommendations and R&D intensity and find that experience, expertise and education contribute to analysts' ability to provide more informative recommendations for R&D intensive firms. On the other hand, Clarke and Subramanian (2006) find that analysts may make non-rational recommendations just to attract the attention from the investment community, or alternatively, analysts may respond too aggressively to new information due to saliency bias (Kahneman and Tversky 1973).

Prior research has focused on analysts' forecasts rather than their recommendations,[7] and finds that return responses are weaker for herding forecast than for bold forecast (Clement and Tse 2005). Gleason and Lee (2003) find that market returns are lower for forecast revisions that herd toward a prior consensus than for forecast revisions that deviate from the consensus. Market does react differently to bold forecasts than to herding forecasts, so it is likely the same holds for recommendations. So my first hypothesis is as following:

H1: The market reacts more strongly to bold recommendations than to non-bold recommendations in the short run and in the long run.

[7] Hong et al. (2003) find that inexperienced analysts are more likely to be fired for issuing "bold" forecasts, giving them an incentive to herd toward the consensus. Lundholm and Rogo (2013) suggest that information variation is a factor that leads to bold forecasts. Alternatively, analysts may make different forecasts or change their forecasts for reasons unrelated to their private information, or they may respond non-rationally to the information available. Bernhardt et al. (2006) report evidence of anti-herding, in which analysts' forecasts move away from the consensus. Chen and Jiang (2006) confirm that anti-herding can be another relevant behavior that leads to bold forecasts from analysts. Trueman (1994) suggests that forecast boldness is related to analysts' self-confidence.

The market reacts to boldness in general because of a perception that bold recommendations may involve superior private information. However, the market is able to separate out more accurate (i.e. leading-bold) recommendations from less accurate ones (i.e. contra-bold). This differentiation may stem from the fact that leading-bold assessments are made by analysts that the market perceives as being more able. Thus my third hypothesis is as following:

H2: Market has the ability to distinguish leading-bold recommendations because analysts who make these recommendations have characteristics that distinguish them as better analysts.

In addition, not all bold recommendations are the same and some could reflect analysts' accurate private information while others may reflect analysts' inaccurate private information or overreaction. To separate out these different types of recommendations, I divide bold recommendations into two types: leading-bold and contra-bold based on the consensus of other analysts' recommendations 30 days after. A leading-bold recommendation is one where other analyst consensus moves towards the recommendation. If a recommendation has a lot of followers, it is likely that it is accurate and so, I view leading-bold recommendations as being based on superior private information.[8] On the other hand, if the bold recommendation is an outlier, which means other analysts do not follow it, I classify this recommendation as a contra-bold recommendation. Therefore, leading-bold recommendations could trigger higher market returns than contra-bold recommendations. Another possible explanation could be that

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[8] Reputable analysts have more access to private information (Barber, Lehavy, McNichols, and Trueman 2007). Clement and Tse (2005) argue that bold forecasters are more likely to be more accurate although Clarke and Subramanyam argue this may not be the case.

the market reacts to the bold recommendation, and then other analysts observe the market reaction and decide to follow the bold recommendation. However, if this were the case, leading-bold recommendations should earn negative long-run returns. So my second hypothesis is as following:

H3: The market reacts more strongly to leading-bold recommendations than to contra-bold recommendations both at the time of recommendation (i.e. before learning that other analysts are also following this recommendation) and in the long run.

3.3 Sample Selection and Research Methods

3.3.1 Sample Selection

To create the data needed for this study, I start with the I/B/E/S Recommendations Database and a sample of 589,197 U.S. firm observations taken between 1992 and 2011. Next, 21,130 observations are deleted due to missing CUSIP. Then the sample is limited to recommendations without actual earnings announcements in the (-2, +4) days window,[9] leaving 458,375 observations. In order to categorize the recommendations into contra-bold, leading-bold or non-bold recommendations, 274,567 observations are deleted because they have no other analysts' recommendations within the 30-day window prior and post,[10] leaving a final sample of 183,808 stock recommendations.[11] Table 1 shows the data selection process.

[9] Francis and Soffer (1997) examine 556 analyst research reports available in the Investext database between 1989 and 1991. They find that 3-day returns centered on the report announcement date are significantly associated with both the recommendations and earnings forecast revisions.

[10] Different windows are used to calculate the consensus of analysts' stock recommendations. When a 60-day window prior to analyst's stock recommendations are used to calculate the consensus of analysts' stock recommendations, non-tabulated results show that my results still hold.

[11] Because I use the consensus of other analysts' recommendations as a benchmark to classify analysts' recommendations into contra/leading and non-bold recommendations, 47% of the observations are deleted since no other analysts issue recommendations for the firm in a 30-day window prior and post. In order to address the sample selection bias due to the classification of bold recommendations, I used analysts' prior

[Table 1]

3.3.2 Research Methodology

3.3.2.1. Leading Bold, Contra Bold, Non-Bold Recommendations Classifications

After deleting the firm years with earnings announcement during the (-2, 4) days window around analysts' recommendations, the consensus of other analysts' stock recommendations is used to define analysts bold recommendations. [12] I define bold recommendations to be those that are significantly above or below the consensus of other analysts' recommendations made during the previous month. All other recommendations (i.e., those that move away from the analysts' own prior recommendations and toward the consensus of other analysts' recommendations) are classified as non-bold recommendations (Gleason and Lee 2003; Clement and Tse 2005). In order to distinguish bold recommendations as outstanding recommendations, I try different benchmarks and select only the most extreme 5% of equity recommendations as bold.[13] As a result of this selection, 2 scales difference for buy, 2 scales difference for hold, and 2.5 scales difference for sell from the consensus of other analysts' stock recommendations 30 days before are defined as bold recommendations. All other recommendations are defined as non-bold.

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recommendations as a benchmark for analysts' bold recommendations in the robustness test. Since this study focuses on analysts' private information, I don't selection this classification as the main test, but in robust test. I define the non-bold recommendations are either the same as the analysts' previous recommendations or the same as other analysts' recommendations consensus 30 days ex-ante. Thus, no observations were deleted, and the results are consistent.

[12] Thomson Reuters maintains a standard set of recommendations: 1 = Strong Buy; 2 = Buy; 3 = Hold; 4 = Underperform; and 5 = Sell.

[13] When alternative scales are used, the results remain the same.

Then the bold recommendations are subdivided into contra-bold and leading-bold based on the consensus of other analysts' stock recommendations 30 days post. If the recommendations are at least 2 degrees different for buy, 2 degrees different for hold, and 2.5 degrees different for sell from the consensus of other analysts' stock recommendations 30 days later, they are defined as contra-bold recommendations. Otherwise, they are defined as leading-bold recommendations. In simply terms, contra-bold recommendations are the bold recommendations without followers; leading-bold recommendations are the bold recommendations with followers.

[Appendix A]

3.3.2.2 Market Performance of Leading-Bold Recommendations

The first research question is how to measure the market performance of analysts' bold recommendations. Previous literature frequently uses return on investment to evaluate the performance of analysts, investors, and other market participants. Thus, this measure allows reliable inferences and serves as a benchmark to judge the performance of analysts. Fama, Fisher, Jensen, and Roll's (1969) event study on dividend announcements and Fama's (1970) efficient market hypothesis gives rise to studies on the effects of analysts' stock recommendations on market performance. Liu, Smith and Syed (1990) confirm those results using data from 1982-1985. Beneish (1991) also finds similar results using data from 1978 to 1979. I test short term performance using the CAPM model. I run an event study in the three days window (-1, +1) [14]around the recommendation date to evaluate the market reaction to contra-bold, leading-bold and non-bold recommendations. For the CAPM-based abnormal returns, the average

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[14] We use (-1, +1) days window since we would like to focus on analysts' private information. We run the window (-5, +5) as a robust test and the results still hold.

abnormal return equals to the intercept from regressing the excess return on the excess market return for period t which is shown in equation 1 (Brown and Warner 1985).

$$R_{i,t} - R_{F,t} = \alpha_i^{CAPM} + \beta_i RMRF_t + \varepsilon_{i,t}^{CAPM} \tag{1}$$

To test the long-term performance of stock recommendations, I build a calendar-time portfolio and use Fama French four factor model, the intercept capture the average returns as shown in equation 2. (Jaffe 1974; Mandelker 1974; Mitchell and Stafford 2000).

$$R_{pt} - R_{ft} = \alpha + \beta_i (R_{mt} - R_{ft}) + s_i SMB_i + h_i HML_i + u_i UMD_i + \varepsilon_{it} \tag{2}$$

3.3.2.3 Cross-sectional analyses

Market does react differently to bold and non-bold forecasts. It's likely to test if it happens to recommendations. A logistic model is used to run the regression in three different subsamples: contra-bold, leading-bold, and non-bold recommendations. The dependent variable is a dummy variable that equals to 1 if the recommendation is leading-bold, contra-bold, or non-bold recommendations and 0 otherwise. All the control variables are described in Appendix B.

Gleason and Lee (2003) find that forecast boldness is related to investors' under-reaction to analysts' earnings forecast revision. Truman (1994) finds that analysts' self-confidence will lead to forecast boldness. Clement and Tse (2005) find that bold forecasts conveying more of the analysts' private information about the firm. Analysts obtain information from earnings and SEC filings, industry reports indicating macro-economic conditions, conference calls and other management transmissions (Lawrence et al. 2014). Clark and Subramanian (2006) find that analysts' prior forecasting performance is related to the degree of boldness in future forecasts. I include boldness (Boldness) in the model and argue that the boldness of analysts' forecasts will lead to bold recommendations. Hong et al. (2003) suggest that career concerns may inhibit analysts' boldness. I argue that more information asymmetry (BidAskSpread), analysts will have more opportunity to process private information and issue more bold recommendations. Ramnath, Rock, and Shane (2008) find that higher forecasts dispersion is generally an indicator of analysts' uncertainty with respect to firm earnings. I include Forecast dispersion in the regression (AnalystsDisperion). Williams (1996) finds that analysts' dependence on management earnings forecasts relates to the reliability of the forecast as measured by past management earnings forecast accuracy. I include management earnings forecast frequency (FrequencyCIG) in the model since analysts obtain information from management guidance. The more frequently managers publicly issue earnings guidance; the less likely analysts will be able to process private information and issue bold ratings. I include industry risk factor (Beta) and standard deviation of Beta (BetaStd) in the prediction model since high industry risk will offer analysts more priority to access private information, while the high variance of risk may lead analysts to herd due to career security concerns (Hong et al 2003). Givoly and Lakonishok (1979) and Brown, Foster, and Noreen (1985) observed a relationship between forecast revisions and lagged changes in stock prices. I include stock price changes (Pctchng) from previous recommendations as an important information resource for analysts to make recommendations, if the stock price signal confirms with the analysts, they will have more confident to issue bold recommendations. Brown (1993) and Schipper (1991) find it's important to understand the role of analysts' earnings forecast, macroeconomic and industry factors and other information in formulating stock recommendations. I extend prior research (Clement and Senyo 2005; Hong et al. 2003) explaining analysts' bold recommendations by including several analysts characteristics (Broker size, analysts forecast frequency, firm experience, general experience, companies following, and general industry experience). Brawshaw (2002) finds that analysts most frequently justify their recommendations with reference to P/E ratios and long-term growth rate forecasts. I include analysts' forecasts frequency (ForFrequency) in the prediction model to better understand the factors influencing analysts' bold recommendations. The argument is the higher frequency of management earnings forecast, the more access of the analysts to the firm, the more probability the analysts could process private information and issue bold recommendations. Cooper, Day and Lewis (2001) also find that the market respond to forecast revisions by following analysts in one high-tech industry (semiconductors and printed circuit boards) and one low-tech industry (restaurants). In order to control for the industry difference in market reactions, I control industry dummy variables in the prediction model (IndustryFE).

$$\begin{aligned} Dummy_{ijt} = {} & \alpha_0 + \alpha_1 Boldness_{ijt} + \alpha_2 BidAskSpread_{it} + \alpha_3 AnalystsDispersion_{ijt} + \alpha_4 FrequencyCIG_{it} \\ & + \alpha_5 Beta_{it} + \alpha_6 BetaStd_{it} + \alpha_7 Pctchng_{it} + \alpha_8 Bro\ker Size_{it} + \alpha_9 ForFrequency_{ijt} \\ & + \alpha_{10} FirmExperience_{ijt} + \alpha_{11} GenExperience_{ijt} + \alpha_{12} Companies_{ijt} + \alpha_{13} Industries_{ijt} \\ & + \alpha_{14} IndustryFE_{it} \quad (3) \end{aligned}$$

[Appendix B]

3.4 Results

3.4.1 Market Performance

I use market adjusted returns [15] to measure short-term abnormal performance of stock recommendations and four factor model (Fama 1970)[16] to measure long-term (6 months) performance.

3.4.1.1 Short term market performance

I use equation (1) to estimate cumulative abnormal returns. In order to prevent new information bias, firm-year observations with earnings announcement for the (-2, +4) days window around stock recommendations are deleted. [17] The short-term abnormal returns are analyzed in three parts. First, the pre-publication behavior, corresponding to the interval between five days and one day before the publication (-5, -1) is investigated. Next, the publication effect is explored by investigating the three-day period centered on the publication date (-1, +1). Finally, the reversal process is studied by looking at the day intervals (-1, +5), (-1, +10), (-1, +20), and (-1, +30). I only report the results in (-1, +1) day window to show market instant reaction to analysts' recommendations. Consistent with prior literatures, the results indicates a higher market reaction to sell recommendations than to buy recommendations (Hirschey et al. 2009).

Table 2 shows the market performance to stock recommendations with/without earnings announcement in the (-2, +4) days window. The results show that the market performance of bold recommendations is significantly higher than that to non-bold

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[15] First, a simple market adjustment method based on the S&P 500 is used to evaluate investment performance for contra-bold, leading-bold and non-bold recommendations. This method is most commonly used by the financial press to measure the investment performance. In this method, the return of the S&P 500 during a given period is subtracted from the raw returns of the recommended stocks to find the abnormal portion of the returns for each type of recommendation.

[16] The long-term (6 months) performance of recommendations is calculated using the calendar time portfolio regression approach.

[17] Elgers, Lo, and Pfeiffer (2003) find the delay reaction of investors to analysts' earnings forecasts is related to characteristics of firms' information environment. I delete earnings announcement in order to focus on market reaction to analysts' private information. Table 2 Panel C shows the results without deleting observations with earnings announcement in (-2, +4) days window, and the results are consistent.

recommendations.[18] Panel A shows CAR for recommendations without earnings announcements in (-2, +4) days window. Column a, b, c and g show the number of buy, sell, hold and total number of recommendations separately. Row A, B, C and D show descriptive statistics for the bold, non-bold, contra-bold and leading-bold recommendations. Row A/E shows the bold ratio, which is the number of bold recommendations divided by total number of recommendations in the corresponding category. Results show that bold stock recommendations have higher cumulative abnormal returns than non-bold recommendations for both buy and hold[19] recommendations without earnings announcement in the (-2, 4) window: CAR 1.85 > 0.84 for buy recommendations; CAR -1.76 < -1.46 for hold recommendations; CAR -2.62 > -2.65 for sell recommendations. This result is consistent with the information hypothesis, which argues that bold forecasts are made by analysts with more private information (Clement et al. 2005).[20] Three reasons could explain the insignificant results on the sell side. First, it's easier to buy than to sell. Second, the investors need to pay higher tax for the profit which impedes them to sell. Third, the negative news is harder to believe until it's confirmed. From the above reason, the market is more conservatism to sell recommendations, which reduce the information advantage from leading-bold recommendations (Core 2001). Thus my first hypothesis has been partially supported. Panel B confirms the finding in Panel A using CAPM model.

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[18] In robustness test, I hand collect data from Barron's Picks and Pans magazine and find results are consistent. Bold recommendations create significantly higher cumulative abnormal returns than non-bold stock recommendations (2.66% > 0.33% for buy recommendations; -3.57 % < 0.21% for sell recommendations).

[19] Since hold and sell is similar in nature. I only report sell in the future analyses.

[20] Given the data used, it is not possible to distinguish whether the market reaction is to analysts' reputations or to their private information.

Furthermore, Panel C shows that the market reacts more strongly to leading-bold recommendations than to contra-bold recommendations for both buy and sell recommendations (CAR 1.96 > 1.58 for buy recommendations; CAR -2.15 < -1.47 for hold recommendations; CAR -2.84 < -0.52 for sell recommendations). The results show that market reacts positively to leading-bold than to contra-bold ratings even before they are classified. Another explanation could be that the subsequent analysts are simply observing the market reaction and then deciding whether to follow or not. If it is the truth, I should not observe leading-bold assessments create higher market returns in the long run. Similar results are found if analysts' recommendations with earnings announcement in the (-2, +4) days window are included. The results show that the market reacts more strongly to leading-bold than to contra-bold than to non-bold recommendations at the time the ratings are issued.

In order to test if the market reaction to leading-bold recommendations is significantly higher than to contra-bold than non-bold, for each bold recommendation, I find a random firm of the same size in the same industry. I use a similar procedure and match each non-bold recommendation with a firm of the same size in the same industry. Then I compare the performance of the randomly matched firms over the same calendar period as of the bold and Non-bold. Panel D shows that the leading-bold recommendations create significantly higher market reactions than the matched sample with the same size and industry portfolio (CAR 1.96 > 0.27 for the buy; CAR -2.15 < -1.17 for the sell), and the t statistic show that the difference is significant. (t = 2.56 for the buy ratings; t = 3.45 for the sell ratings) The results provide additional evidence that the stronger market reaction to bold recommendations is driven by (firm specific) information rather than general characteristics like size or industry.

Finally, in order to control the sample selection bias, I include the recommendations with earnings announcement in the (-2, +4) days window and the results reported in Table 2 Panel E are consistent with previous findings. Therefore the second hypothesis has been validated.

[Table 2]

3.4.1.2 Long term performance of contra-bold, leading-bold and non-bold recommendations

Assuming that long-term performance measures the accuracy of analysts' stock recommendations, the Fama and French three factor model (equation 2) is used to measure long-term performance of analysts' recommendations. In this model, the intercept measures the annual abnormal returns, and six month from the announcement date is used to measure long-term performance.[21] The results in Table 3 show that leading-bold buy recommendations provide practically significant abnormal stock returns (α = 0.39%) in six months, while leading-bold sell recommendations create abnormal returns (α = -1.08%) which is partially significant in six months. The results show that the stronger market reaction to leading-bold recommendations is not due to investors mistakenly under- or overreacting to stock recommendations. On the other hand, long term results show that leading-bold recommendations could generate the highest market return and indeed are more accurate than non-bold and contra-bold recommendations. I find contra-bold buy recommendations provide significant -1.31% stock returns, whereas

[21] This test was also performed using 12 months, and the results remain the same.

non-bold buy recommendations create 0.11% non-significant abnormal returns in the test period. Similar results are shown for the sell sample (contra-bold sell α = 0.32% and t =0.63, non-bold sell α = -0.94% and t = -3.88). The results show that non-bold recommendations create higher market returns than contra-bold, which reflects that market over-reaction to contra-bold recommendations when they are issued. After the analysts have time to revise their ratings, the market knows that they are not accurate and they reverse their reaction in the long run. So my second hypothesis has been partially supported.

[Table 3]

[Figure 1]

3.4.2 Cross Sectional Analyses for Analysts' Recommendations

Table 5 shows the regression results from equation (3), which is used to detect factors that lead to leading-bold recommendations and compare it with the other two groups. I find that analyst characteristics are similar for leading-bold and contra-bold recommendations (but different for non-bold). However market characteristics differ both across leading-bold and contra-bold recommendations and across bold and non-bold recommendations. Analysts' forecast dispersion is included as a factor influencing analysts' bold recommendations. The results shows that the odds-ratio of Boldness is 1.29 and significant in the contra-bold recommendation subsample, which means that analysts forecast boldness will increase the likelihood of contra-bold recommendations instead of leading-bold recommendations, whereas it is 0.84 and significant in the non-bold recommendation subsample. The odds ratio of BidAskSpread for leading-bold recommendations is 0.19, while 1.84 for non-bold. The result is consistent with the theory about analysts' private information (Lundholm and Rogo, 2013). Higher information asymmetry creates an unstable environment, so analysts tend to herd with other analysts to compensate for the increased risk. Consistent with this theory, the coefficient of capital beta is significantly positive (odds ratio = 1.30) for leading bold recommendations and 1.15 for non-bold recommendations, but not significant for contra-bold recommendations. Because beta measures industry risk, this result suggests that there is no difference in the likelihood of analysts leading and non-bold recommendations, which could be consistent with two opposite streams of literatures: 1) more dispersion in the industry may drive analysts less likely to issue contra-bold recommendations if the industry risk is higher due to job safety concerns (Hong et al. 2003). 2) More industry dispersion will provide analysts more opportunity to collect private information advantage (Brown, Call, Clement, and Sharp 2014). Consistent with Clement et al. (2005), I find that the more frequent of analysts forecasts (odds ratio = 1.04 and z stat. = 3.25), the longer period of general experience (odds ratio = 1.00 and z stat. = 2.56), the smaller the company following (odds ratio = 0.99 and z stat. = -3.82), and the less industries the analysts following (odds ratio = 1.00 and z stat. = -2.56), the higher the likelihood that analysts will issue leading-bold recommendations. By contrast, the longer firm experience (odds ratio = 0.96 and z stat. = -3.73), the less likely they are to issue bold recommendations. But the empirical results show that there is no difference in brokerage house, analysts forecast frequency, firm experience, the company following, and the number of industries following between leading-bold and non-bold recommendations except general experience partially could increase the likelihood of analysts be market leaders (odds ratio = 1.00 and z stat. = 2.33). But I do find the coefficient is not significant for contra-bold recommendations, which show similar nature of analysts' leading-bold and non-bold recommendation: analysts' private information or expertise.

[Table 4]

3.4.3 An Implementable Trading Strategy

My definition of a leading bold recommendation is based on information that becomes available a month after the recommendation. Therefore, it is impossible to construct a trading strategy based on a portfolio of stocks that attract leading bold recommendations since the definition of leading-bold and contra-bold recommendations is ex-post. Category 1 dummy variable is loaded significant in the cross-sectional analyses. In order to address this issue, I turn to study how the investors can devise a trading strategy to make a profit based on the analysts' likelihood to be market leaders. Lion and Mian (2006) find that monthly abnormal returns on hedge portfolios based on recommendations of analysts in the top (bottom) quintile of earnings forecast accuracy are, on average, approximately 0.74% (-0.53%). Using the same type of approach, I build a hedge portfolio by going long on the recommendations which have a higher possibility to be leading-bold (category 1), and short on the recommendations which have a higher possibility to be contra-bold (category 2) where these categories are defined as follows:

Category 1: At least one other company in the same industry (industry Y) as company X was upgraded at the same time that the bold recommendation was made for company X

Category 2: No other company in the same industry (industry Y) as company X was upgraded at the same time that the bold recommendation was made for company X

Category 1 and Category 2 are mutually exclusive. Table 3 Panel A show that category 1 is more likely to become leading-bold than category 2 in the buy sample, I use the ratio of the number of leading-bold recommendations to that of contra-bold as the benchmark, and the results are significant at the 0.10 level for buy recommendations (Category 1 equals to 3.97; Category 2 equals to 3.06). Similarly, I find that category 1 is four times more likely than category 2 to issue leading-bold recommendations for sell sample (Category 1 equals to 15.22; Category 2 equals to 3.93), and the significance is at 0.01 level. Based on these results, I set up a hedge trading strategy.

Since I know that category 1 is more likely to be associated with leading-bold recommendations than category 2, and leading-bold recommendations are always more likely to create higher market returns, my trading portfolio is based on going long on category 1 and short on category 2 for the buy recommendations, while going short in category 1 and long in category 2 for the sell recommendations. Table 4 Panel B presents that the six months buy and hold returns is -4% for buy recommendations, and 10% for sell recommendations. Thus, I find that my ex-ante hedge portfolio earns significant abnormal returns on the sell side recommendations.

[Table 5]

3.4.4 Additional Tests

Additional tests will find out the private information channels for analysts to issue leading-bold recommendations. Another question will be affiliated analysts are more likely to issue leading-bold recommendations?

3.4.4.1 Star Analysts

I hand collect data from Institutional Investor Magazine about star analysts. The sample contains 89 distinct star analysts from 2000 to 2013 and a total of 340 rankings. The leading-bold recommendations in my sample contain 3,671 observations and 332 different analysts. In this case, I do not find a significant correlation between leading-bold recommendations and star analysts.[22] However, compared to non-star analysts, non-tabulate results show that star analysts create higher market returns both in contra-bold and leading-bold recommendations, which shows that the market overreacts to star analysts.

3.4.4.2 Classification as independent and non-independent analysts

Table 6 shows the results of the number of recommendations and CAR for independent and affiliated analysts separately. The bold ratio is similar between independent and affiliated analysts (5.8% for independent analysts' buy sample and 5.2% for affiliated analysts' buy recommendations; 6.3% vs. 6.7% for sell recommendations). This suggests that, although affiliated analysts may have the advantage of better access to private information, independent analysts may work harder to build their own reputation in order to compensate the information disadvantage (Barber et al. 2007). Thus, independent analysts and affiliated analysts have a similar likelihood of issuing bold recommendations.

In addition, I find that market reaction to bold buy recommendations from independent analysts is stronger than to affiliated analysts, and these results hold both for

[22] Another reason for this insignificant correlation could be due to the large number of analysts in my sample.

bold buy recommendations (2.41 > 1.54), and bold sell recommendations (-3.68 < -3.50). These findings suggest that the market reacts more strongly to investment banks' downgraded bold recommendations than to their non-bold recommendations because affiliated banks are reluctant to downgrade their own client's stock recommendations. Barber et al. (2007) find that average daily abnormal returns related to independent research firms' buy recommendations exceeds that of investment banks' buy recommendations by 3.1 basis points. They show that investment bank analysts' hold and sell recommendations outperform those of analysts at independent research firms, and suggest that investment banks are reluctant to downgrade stocks, so the market reacts more strongly to their recommendations. Consistently, I find that the market reacts more strongly to independent analysts' upgrade bold stock recommendations, because their decision is more independent than affiliated banks. In additional, I find the stronger market reaction comes mainly from leading-bold recommendations than from contra-bold ratings.

[Table 6]

[Figure 2]

[Figure 3]

3.4.4.3 Classification by R&D

Table 5 shows the results of the market reaction to recommendations if the firm has research and development (R&D) in the current year. Column a shows the results for the buy sample and column b shows the results for the sell sample. Comparing it with the firms without R&D, it shows that market reaction to leading-bold recommendations is stronger if the firm has R&D investment (CAR = 1.98 comparing with CAR = 1.96 and t stat. = 2.68 for buy recommendations; CAR = -4.60 comparing with CAR= -2.84 and t sta. = 3.54 for sell recommendations. It shows that if a firm has R&D in the current year, analysts could have more channels to process private information, and the market reaction to leading-bold recommendations will be stronger. The observed difference mainly comes from sell recommendations, since rational investors react strongly to bad news recommendations (Core 2001).

[Table 7]

3.4.4.4 Classification by industry expertise

Kadan, Madureira, Wang, and Zach (2012) demonstrate that analysts present across-industry expertise, and they find the portfolio based on industry recommendations creates abnormal returns both in the short and long term. Therefore, a sub-sample of recommendations from analysts with specific industry expertise is tested. Non-tabulated results suggest that abnormal market return for leading-bold buy recommendations is 3.4 with industry expertise, compared to 1.96 for the whole sample. For sell recommendations, CAR is -4.20 with industry expertise, compared to -3.60 for the whole sample. F tests show that the difference is significant at 0.01 level. This evidence is consistent with the argument that the market reacts more strongly if the analysts have industry expertise.

3.4.4.5 Effect of Regulation FD[23]

[23] Since 2000, Regulation FD has required firms to disclose private information to the public, reducing analysts' private information advantage.

To evaluate the effect of Regulation FD on both analysts and the market, the number of bold recommendations and the market reaction to these recommendations are tested before and after Regulation FD. Table 6 indicates that after Regulation FD, fewer bold sell recommendations are issued (bold ratio is 10.66% before Reg. FD while it is 5.50% after Reg. FD). However, bolder buy recommendations have been provided before Reg. FD (bold ratio is 3.15 % before Reg. FD while it is 7.11% after Reg. FD). It could be explained as downgraded recommendations contain more of analysts' private information, analysts are not allowed to withhold private information after Reg. FD, and analysts' bold ratio in the sell sample has been influenced more than the buy sample after Reg. FD. [24]

When the market abnormal returns are compared before and after Regulation FD, results show that CAR actually increases for both buy and sell bold recommendations (0.42 before Reg. FD < 2.30 after Reg FD for buy recommendations; -1.23 before Reg. FD > -3.31 after Reg. FD for sell recommendations). Results show that after Reg. FD, analysts are less likely to withhold private information and the information advantage is valued higher after Reg. FD. The results are consistent in both buy and sell samples.

[Table 8]

[Figure 4]

[Figure 5]

3.4.4.6 Stock price increase/decrease before stock recommendations

[24] Another reason for analysts bold ratio for buy ratings increase after Reg. FD could be that upgrade recommendations come mainly from public information

Liu, Smith, and Syed (1990) document the influence of stock price on equity recommendations. To test stock price influence on analysts' bold recommendations, I include stock price change in the analyses to test market reaction to bold recommendations. In the first stage, to determine whether the stock price is increasing or decreasing, the stock price on the recommendation date is compared to the stock price on the last recommendation date. Table 10 shows that when the stock price goes up, the market reacts more positively to bold buy recommendation (CAR 3.68 >1.17).[25] Consistently, the cumulative abnormal returns for bold sell recommendations are positive when stock price actually increases (CAR = 0.34). When stock price goes down, the market reacts positively to bold sell recommendations (CAR = -5.64).

In the second stage, I include analysts' last stock recommendations, the results show that if analysts last issued buy recommendations and do not upgrade their recommendations after the stock price went down, the market reacts more negatively than if the analysts upgrade their recommendations (e.g. -3.72 < -2.11 for analysts upgrade their recommendations from buy to sell if the stock price drops). Similar trends were found in sell recommendations (CAR -3.19<4.00). The results are consistent with the theory that if analysts upgrade their stock ratings in a timely fashion after a stock price change, the market will react positively to the updated information.

In the third stage, my empirical findings show that if the stock price increases more than 3%, analysts' bold behavior disappears. A possible explanation could be that the large change in stock price provides such a strong signal to the market that analysts

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[25] The market reaction to bold recommendations is originally assessed when a 3% stock price increase provided a consistent or a conflicting signal to the market. The same tests are also performed for a 5% increase in stock price. Non-tabulated results show that the findings remain the same.

decide to issue the ratings on the same trend as the stock price change, so it is impossible for a stock recommendation to be bold. In order to test this explanation, analysts' dispersion before stock price increase is included in the analysis. Table 7 conduct that analysts' dispersion is lower when stock price increases rather than decreases (Up CAR = 2.76 smaller than Down CAR = 3.05), and the F-test shows that the difference is significant at 0.01, which shows less disagreement between analysts after the stock price goes up. Thus, one reason that analysts' bold recommendations disappear after a price increase could be that analysts all agree to issue buy recommendations after stock price goes up.

[Table 9]

3.5 Robustness Tests

This section describes tests that are conducted to determine whether the main results are robust when the parameters are changed.

3.5.1 Separation of Market Reaction to Analysts' Forecast to Recommendations

It may be that market responds to analysts' bold forecasts rather than to bold recommendations. Mikhail et al. (1997) find consistent evidence that analysts with greater firm-specific forecasting experience may not issue more profitable stock recommendations. To compare analysts' forecasts to their recommendations, a sample of forecasts is classified into bold and non-bold, following Clement et al. (2005).[26] Table 8 Panel A shows the joint distribution of the number of analysts' forecast and

[26] Clement et al. (2005) define bold forecasts as above (below) both the analyst's prior forecast and the mean forecast immediately before the forecast revision. The mean forecast is based on forecasts issued in the 90 days prior to analysts' forecast revision.

recommendations. The column shows the number of analysts' forecasts and the rows shows the number of recommendations in different categories. The results show that 60% analysts who issue bold forecasts will issue bold recommendations, which is similar to a random 50% which means bold forecasts are not associated with bold ratings.

Next, the market returns for the joint bold and non-bold forecasts and recommendations are tested. Table 6 Panel B shows that the market reaction to bold forecast is stronger than to non-bold forecast, which is consistent with previous literatures that bold forecasts are more accurate than herding forecasts. (Clement et al. 2005) In addition, the market reaction to joint bold forecasts and leading-bold recommendations are the strongest among the combinations (e.g. CAR 2.30 > 1.53 > 0.61).

In all, empirical results show that bold forecasts may not correlated to bold recommendations, and there are two distinguishable differences between analysts' forecasts and their recommendations. First, the time period is different. Analysts make forecast based on previous performance and make predictions about the future, so limited horizon is used to make a judgment. By contrast, analysts' recommendations are based on the business cycle of the company. Second, the market reaction to analysts' forecasts is informed by forecast errors, which are the differences between expected forecasts and real earnings. Little other content is included in the forecasts. Actually, forecasts represent only one component of recommendations. Thus, analysts' forecasts differ from analysts' recommendations.

[Table 10]

3.5.2 Super Bold Recommendations

I use two definitions for super bold recommendations: First, if a bold recommendation is two scales different from the consensus, I define it as super bold recommendations. Non-tabulate results show that there is no difference in the market reaction if the analysts update their recommendations by one scale or two scales, which means that the market reacts mainly to good/bad news, not to recommendations themselves. Second, I define a super bold recommendation as the first bold recommendation in the last five years. Table 9 shows that super bold recommendations create higher market returns than regular bold recommendations for the sell side (CAR -3.45 for Super Leading-bold < -2.15 for Leading-bold and t stat. = -2.73. But I don't find the results on the buy side, probably downgraded ratings contain more analysts' private information. These results give additional support that bold recommendations create higher market returns.

[Table 11]

3.5.3 Excluding Boldness in Forecasts

In order to distinguish the market reaction to analysts' recommendations from forecasts, if there are analysts' forecast within 6 days of the recommendations, those observations are excluded. Non-tabulated results show that bold recommendations still create a stronger market reaction than non-bold recommendations.

3.5.4 SOX

I include SOX in my study, since SOX improves overall information quality (Ashbaugh, Collins, Kinney, and LaFond 2008). A time trend of analysts' following stock recommendations has been drawn, and non-tabulate results show that analysts' following increased because of SOX, and the bold ratio increased due to SOX since information quality increased, more accurate information will lead to more bold recommendations. In addition, I use the propensity score matching the firm size and industry before and after SOX. However, I find no significant improvement of analysts' recommendation profitability due to SOX, which shows the market reacts no difference for bold recommendations after SOX is issued in 2002.

3.6 Conclusion

Bold recommendations are an important aspect of sell-side research. They could be composed of both analysts' ability to acquire accurate private information or it could be driven by behavioral considerations that are unrelated to information. This paper first shows that market reacts more strongly to bold recommendations suggesting that investors believe that bold recommendations are driven considerably by private information. I then provide a new characterization of analysts' bold recommendations that tries to separate those driven by accurate private information from those that may be driven by less accurate private information or non-informational factors.

I divide analysts' bold recommendations into leading-bold and contra-bold recommendations. Leading bold recommendations are those where the consensus moves towards the bold recommendation in the subsequent month as compared with contra-bold recommendations that do not move the consensus towards them. Leading-bold recommendations are more likely to reflect accurate private information compared with contra-bold recommendations. Consistent with this hypothesis, I find that the market reacts more strongly ex-ante (in a short-window around the recommendation) to leading-bold recommendations as compared with contra-bold recommendations. In addition, leading-bold ratings earn positive abnormal returns in the long run whereas contra-bold earn negative abnormal returns. Taken together, these results suggest that leading-bold ratings incorporate superior private information and that the market is able to at least partially separate out leading-bold recommendations from contra-bold ones at the time of the recommendation (before the market observes whether other analysts are following this recommendation).

In order to understand how the market can separate out leading bold from contra-bold recommendations ex-ante, I conduct cross-sectional tests about analysts characteristics such as industry expertise, or the number of companies they follow that might drive the ability to make leading-bold recommendations. I find that characteristics associated with forecast accuracy increase the probability of making a bold recommendation but that they do not differentiate between leading bold and contra bold recommendations. However, differences in market or firm conditions are associated with leading-bold recommendations, and I use this fact to construct an implementable trading strategy.

Since this is the first paper to study analysts' bold recommendations, several interesting questions remain. First, given the importance of leading-bold recommendations, what is their role in analysts' compensation and reputation? Second, what is the impact of leading-bold recommendations on the careers and reputation of analysts? For example, given the importance of leading-bold recommendations in creating stronger market returns, it would be interesting to explore the relationship between these leading analysts and achieving all-star status. These are questions to be addressed in future research.

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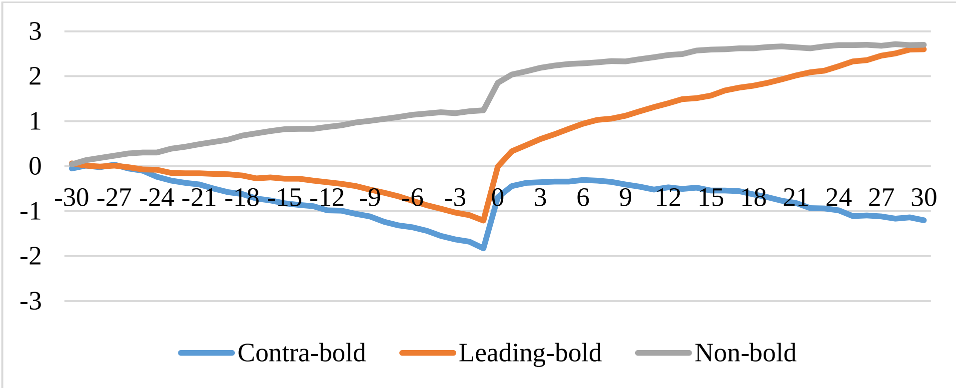
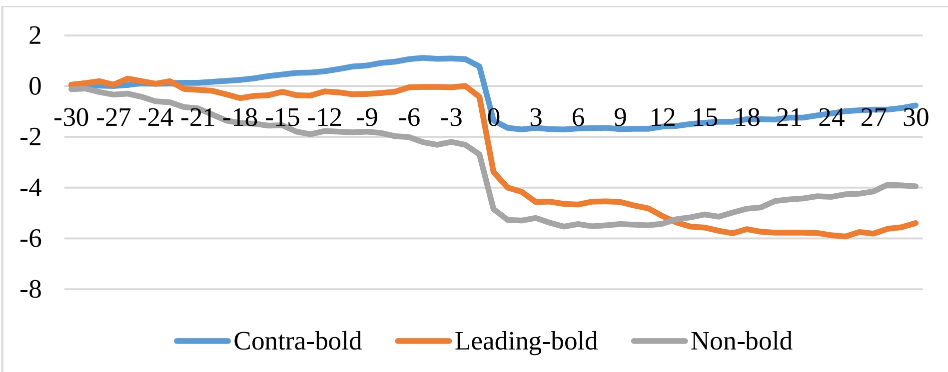
3.8 Figures for Chapter 3

Figure 3.1 CAR for Analysts' Stock Recommendations

Panel A: CAR for buy recommendations in (-30,+30) days



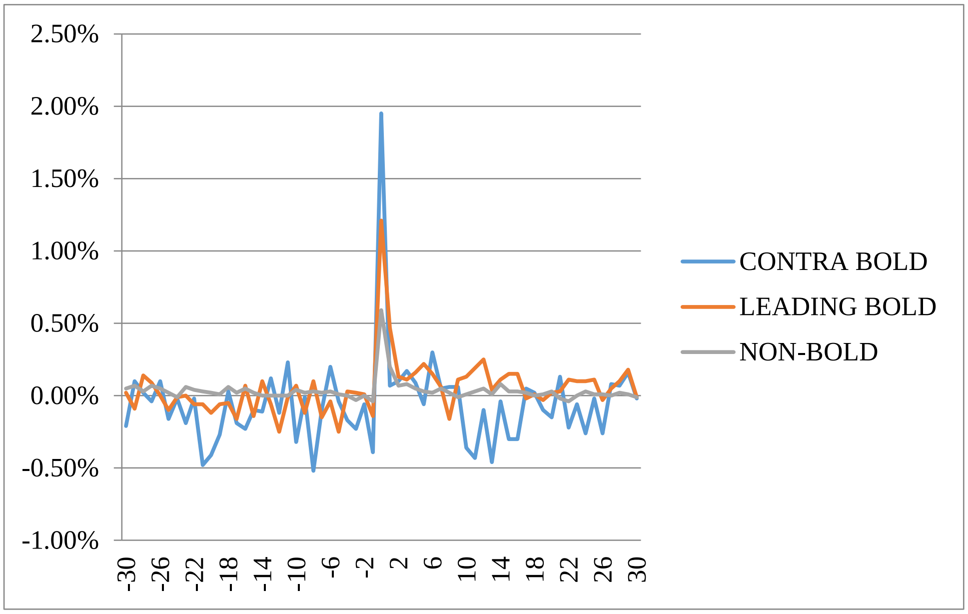
Panel B: CAR for sell recommendations in (-30,+30) days



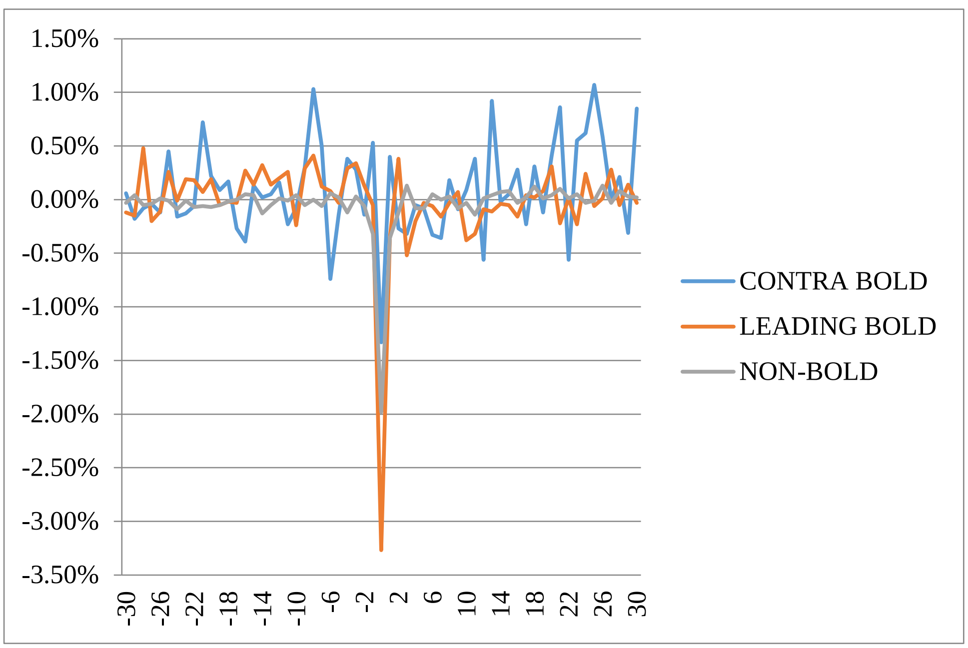
This figure shows the market reaction comparison of contra-bold, leading-bold and non-bold recommendations in both buy and sells recommendations. My results show that market reaction to contra and leading-bold recommendations are higher than to non-bold recommendations.

Figure 3.2 AR for Non-Independent Analysts' Stock Recommendations

Panel A: Comparison of AR from buy recommendations from non-independent investment banks



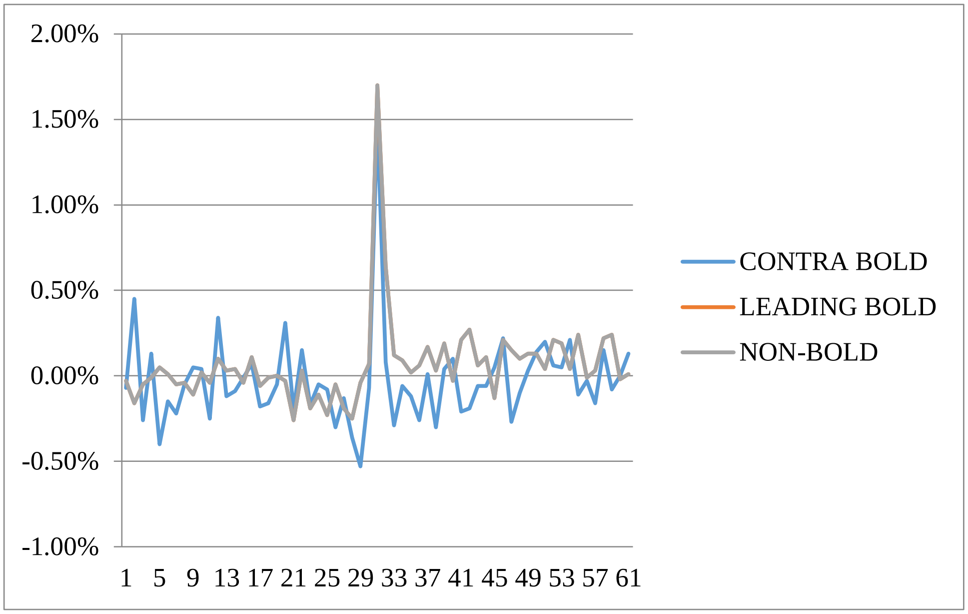
Panel B: Comparison of AR from sell recommendations from non-independent investment banks



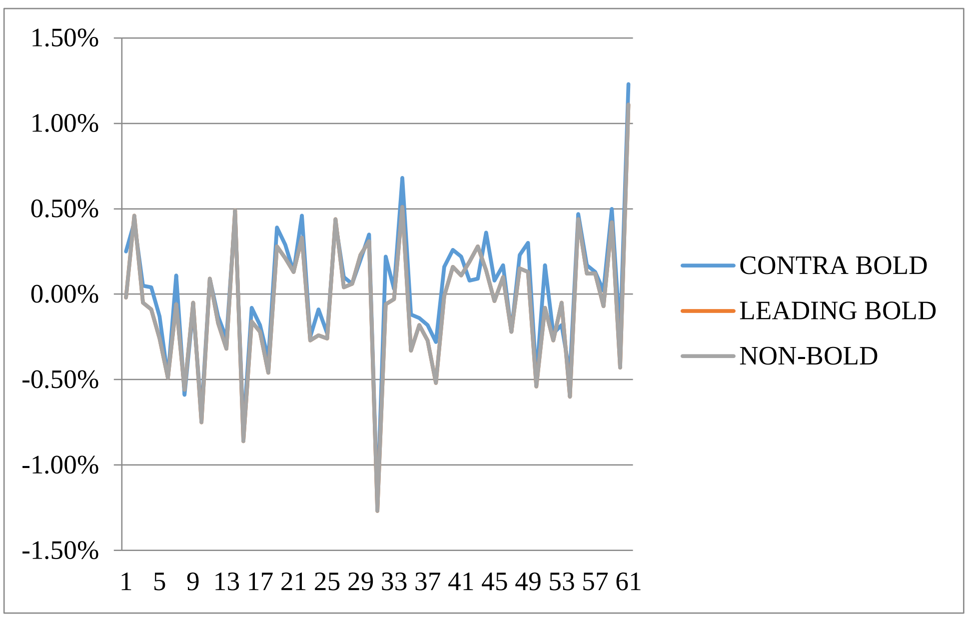
This figure shows the market reaction comparison of contra-bold, leading-bold and non-bold recommendations in both buy and sells recommendations from affiliated analysts. My results show that market reaction difference to contra and leading-bold recommendations and non-bold recommendations are reduced for affiliated analysts.

Figure 3.3 AR for Independent Analysts' Stock Recommendations

Panel A: Comparison of CAR from buy recommendations from independent research firms



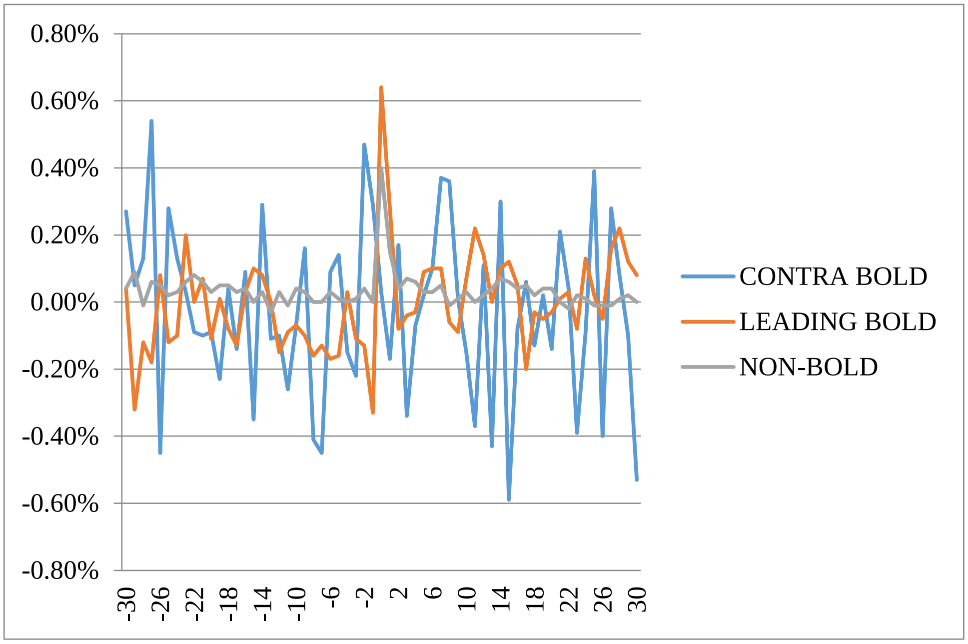
Panel B: Comparison of CAR from sell recommendations from independent research firms



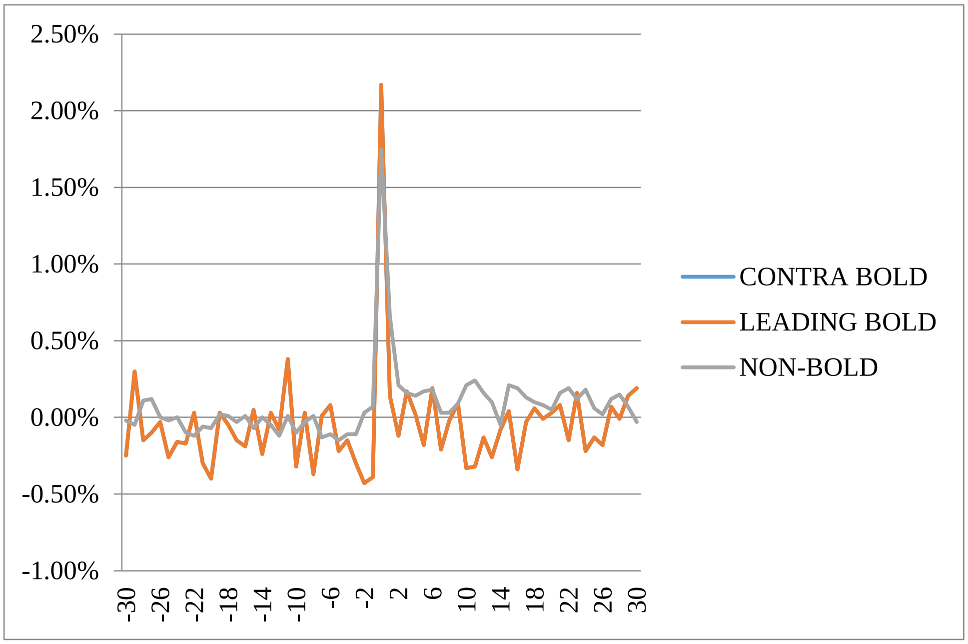
This figure shows the market reaction comparison of contra-bold, leading-bold and non-bold recommendations in both buy and sells recommendations from independent analysts. My results show that market reaction to contra and leading-bold recommendations from independent analysts are higher than to non-bold recommendations.

Figure 3.4 AR for Analysts' Stock Recommendations before Reg. FD

Panel A: Comparison of CAR from buy recommendations before Reg. FD



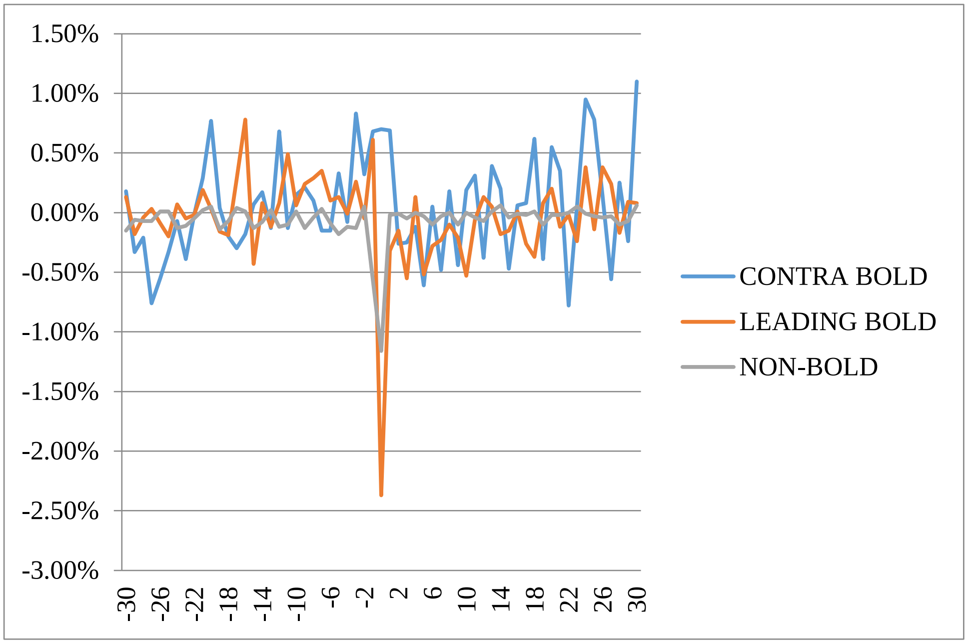
Panel B: Comparison of CAR from buy recommendations after Reg. FD



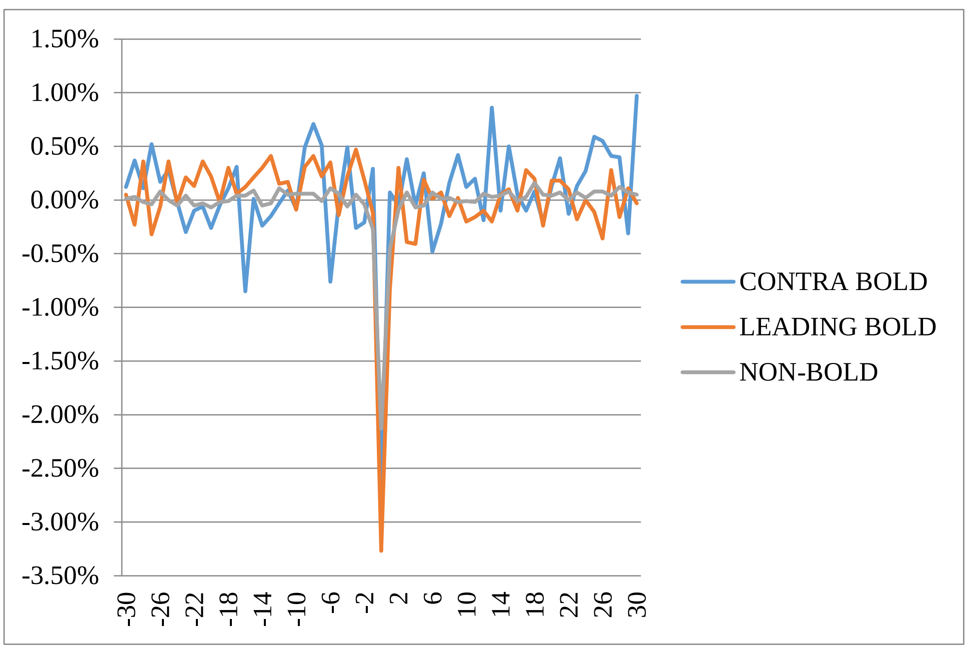
This figure shows the market reaction to buy stock recommendations before Reg FD and after Reg FD. I find that the variance of market reaction to stock recommendations is higher before Reg FD. Than after Reg FD.

Figure 3.5 AR for Analysts' Stock Recommendations after Reg. FD

Panel A: Comparison of CAR from sell recommendations before Reg. FD



Panel B: Comparison of CAR from sell recommendations after Reg. FD



This figure shows the market reaction to sell stock recommendations before Reg FD and after Reg FD. I find that the variance of market reaction to stock recommendations is higher before Reg. FD than after Reg FD.

3.9 Tables for Chapter 3

Table 3.1 - Sample Composition and Attrition

This table shows the data selection process. I start from I/B/E/S and get 589,197 firm year observations. I delete 21,130 observations because of missing cusip. Then I delete observations which have earnings announcement in (-2, +4) days window, this process result in loss of 109,692 observations. Next, I classify stock recommendations into bold and non-bold, and subdivide bold recommendations into contra-bold and leading-bold, 274,567 observations are deleted when there is no other analysts stock recommendations in 30 days window ex-ante and ex-post. My final sample consists of 183,808 observations.

	No of observations
Firm year Observations from I/B/E/S	589,197
Less:	
cusip is not available	21,130
Earnings announcement in (-2, +4) days window	109,692
Missing other analysts stock recommendations in 30 days window ex-ante and ex-post	274,567
Final Sample	183,808

Table 3.2 - CAR Comparison between Recommendations Window without Earnings Announcement

Panel A: CAR without Earnings Announcement (-2, 4)

		BUY RECOMMEN	CAR%	HOLD RECOMMEND	CAR%	SELL RECOMMEN	CAR%	TOTAL
		a		b		c		g=a+b+c
A	BOLD	4,716	**1.85**	12,479	**-1.76**	908	**-2.62**	18,103
B	NON-BOLD	81,842	**0.84**	5,512	**-1.46**	12,970	**-2.65**	100,324
E=A+B	TOTAL	86,549	**0.90**	67,573	**-1.51**	13,876	-2.65	167,998
A/E	RATIO	5.44%		18.47%		6.54%		

Panel B: Buy and Hold Return (Market Model)

		BUY RECOMMENDATIONS CAR%			SELL RECOMMENDATIONS CAR%		
	DAYS	0-2	0-30	0-180	0-2	0-30	0-180
A	BOLD	2.53	4.86	7.20	-2.67	-1.93	1.16
B	NON-BOLD	1.31	2.20	4.75	-2.49	-1.84	4.33
F=C-D	DIFF	1.22	2.66	2.45	-0.18	-0.09	-3.17

Panel C: CAR without Earnings Announcement

		BUY RECOMMEN	CAR%	HOLD RECOMMEND	CAR%	SELL RECOMMEN	CAR%	TOTAL
		a		b		c		g=a+b+c
C	CONTRA-BOLD	857	**1.58**	2,973	**-1.47**	83	**-0.52**	3,913
D	LEADING-BOLD	2,447	**1.96**	6,112	**-2.15**	490	**-2.84**	9,049
C+D=A	BOLD	4,716	**1.85**	12,479	**-1.76**	908	**-2.62**	18,103

Panel D: Market Reaction of Matched Sample

		BUY RECOMMENDATIONS	CAR%	SELL RECOMMENDATIONS	CAR%	TOTAL
		a		b		g=a+b
A	MATCHED BOLD	2117	**0.16**	603	**-0.21**	2720
B	MATCHED NON-BOLD	70877	**0.20**	5549	**0.06**	76426
C	MATCHED CONTRA BOLD	393	**0.29**	74	**-0.26**	467
D	MATCHED LEADING BOLD	1162	**0.27**	331	**-1.17**	1493
E=A+B	MATCHED TOTAL	72994	**0.20**	6152	**0.03**	79146
A/E	MATCHED BOLD RATIO	2.90%		9.80%		3.44%
Panel D Row A=Panel D Row B	t		2.56	***		
Panel D Row C=Panel D Row D	t		3.45	***		

Panel E: CAR Comparison between Recommendations Window with Earnings Announcement (-2, 4)

		BUY RECOMMENDATION	CAR%	SELL RECOMMENDATION	CAR%	TOTAL
		a		b		g=a+b
A	BOLD	230	**0.55**	340	**-2.55**	570
C	CONTRABOLD	99	**0.97**	300	**-0.82**	399
D	LEADINGBOLD	131	**0.58**	40	**-5.10**	171
E	TOTAL	4613		5680		10293
A/E	BOLD RATIO	5.22%		5.82%		5.54%

This table Panel A shows the cumulative abnormal returns without earnings announcement in (-2, 4) window. Column a and b shows the number of observations in each column. Row A stands for bold recommendations; Row B stands for non-bold recommendations; Row C stands for contra-bold recommendations; Row D stands for leading-bold stock recommendations; Row E is the whole sample. Row A/E shows the percentage of bold recommendations. CAR% shows accumulative abnormal returns in percentage. Panel B shows Buy and Hold Return for different days. Panel C shows market reaction to the leading-bold and contra-bold. Panel D shows market reaction to the matched sample. Panel E displays the CAR for contra-bold, leading-bold, and non-bold recommendations without deleting the recommendations having earnings announcement in the (-2, +4) days window. The significance is higher or equals to 0.1 levels.

Table 3.3 - Long Term Performance of Recommendation
(Calendar Time Portfolio Regression Approach with Fama French Three Factor Model)

	(Intercept)	Beta	SMB	HML	Adjusted R2
Contra-bold Buy	-1.31%	1.34	0.69	0.54	0.57
OLS t	-3.24***	14.77***	5.35***	4.14***	
t(HC)	-3.30***	13.46***	2.75**	3.31***	
Leading-bold					0.84
Buy	0.39%	1.28	0.37	0.06	
OLS t	2.10*	31.12***	6.45***	1.07	
t(HC)	2.12*	28.24***	4.09***	0.91	
Non-Bold Buy	0.11%	1.28	0.36	-0.16	0.94
OLS t	0.98	51.64***	10.40***	-4.49***	
t(HC)	0.97	40.95***	6.40***	-3.34***	
Buy	0.001	1.29	0.36	-0.1	0.94
OLS t	0.87	52.06***	10.65***	-3.95***	
t(HC)	0.86	41.01***	6.59***	-2.94**	
Contra-bold Sell	0.32%	0.99	0.12	-0.44	0.34
OLS t	0.63	8.66***	0.74	-2.37**	
t(HC)	0.64	8.70***	0.55	-2.15*	
Leading-bold					0.41
Sell	-1.08%	1.32	0.54	0.23	
OLS t	-1.98*	10.93***	3.29***	1.32$	
t(HC)	-2.00*	12.98***	2.00*	1.05	
Non-Bold Sell	-0.94%	1.36	0.43	0.19	0.78
OLS t	-3.88***	25.51***	5.90***	2.47**	
t(HC)	-4.02***	22.07***	4.19***	1.89*	
Sell	-0.01	1.36	0.43	0.18	0.80
OLS t	-3.96***	26.52***	6.10***	2.45**	
t(HC)	-4.11***	23.04***	4.24***	1.87*	

This table reports the results of the Calendar Time Portfolio Regression Approach using Fama French three factor model. The intercepts, factor coefficients, r-squared values and the corresponding t-statistics are listed for the one-year performance of recommendations. The intercept, coefficients, t-ratios and R-square of the regression of monthly excess returns on the CRSP equally weighted index are reported in each set of rows. Intercept of the regression, reported in the second column, indicates the average monthly abnormal return of each type of recommendations (I report it in percentage in order to present exact CAR). The symbols ***, **, and*, denote statistical significance at the 0.001, 0.01 and 0.05 levels respectively, using a generic one-tail test.

Table 3.4 - Comparison of Factors influencing Analysts Recommendation Dispersion

Dependent Var:	**Bold (A)**			**Leading-bold (B)**			**Contra-bold (C)**			**Non-bold (D)**		
	Odds Ratio	z-stat	sig.	Odds Ratio	z-stat	sig.	Odds Ratio	z-stat	sig.	Odds Ratio	z-stat	sig.
Boldness	1.12	1.94	*	1.09	1.09		1.29	2.24	**	0.84	-7.98	***
BidAskSpread	0.19	-4.95	***	0.21	-3.45	***	0.69	-0.75		1.84	7.2	***
AnalystsDispersion	1.37	4.86	***	1.71	6.77	***	1.03	0.28		1.02	0.88	
FrequencyCIG	0.98	-2.02	**	0.98	-1.60		1.06	3.05	***	1.02	5.44	***
Beta	1.15	2.56	***	1.30	3.81	***	0.98	-0.17		1.15	7.28	***
BetaStd	0.22	-6.85	***	0.25	-5.05	***	0.15	-3.43	***	0.76	-4.17	***
Pctchng	1.39	2.27	**	1.50	2.40	**	1.85	2.59	***	0.89	-1.7	*
BrokerSize	1.00	-3.58	***	1.00	-2.19	**	1.00	-0.07		1.00	-8.73	***
ForFrequency	1.04	3.25	***	1.06	3.68	***	1.12	2.37	**	0.98	-9.1	***
FirmExperience	0.96	-3.73	***	0.95	-3.42	***	0.86	-3.23	***	1.01	7.53	***
GenExperience	1.00	2.56	***	1.00	2.33	**	0.99	-1.93	*	1.00	-2.36	**
Companies	0.99	-3.82	***	0.99	-3.35	***	1.00	-0.02		1.00	1.71	*
Industries	1.00	-2.56	**	1.00	-1.34		1.01	1.63		1.00	7.34	***
Category 1	1.01	2.78	**	1.21	2.29	***	0.87	-1.01		0.65	-0.89	
Intercept	0.10	-13.93	***	0.02	-15.92	***	0.05	-8.48	***	1.23	3.63	***
IndustryFE	Included			Included			Included			Included		
N	22,503			22,503			22,503			22,503		
Pseudo R^2 (%)	7.19			7.17			15.53			2.26		

This table shows the logistic regression results for the factors influencing leading-bold/contra-bold/non-bold recommendations. The definition of variables is in Appendix B. My results are shown as follows: (*** significant at p-value 0.001 level, ** significant at p- value 0.05 level, * significant at p-value 0.1 level)

Table 3.5 - Trading Strategy

Panel A: Descriptive statistics about the number of recommendations belong to each category.

	Buy		**Sell**	
	Leading-Bold	Contra-Bold	Leading-Bold	Contra-Bold
Category 1	2269	572	274	18
Category 2	52	17	181	46
t	1.69	1.70	4.53	1.80
Sig.	*	*	***	*

Panel B: Hedge portfolio returns

	6 months		**12 months**	
	Buy	Sell	Buy	Sell
Category 1	-0.02	0.14	0.05	0.26
Category 2	0.02	0.04	0.03	0.12
Buy and Hold Returns	-0.04	0.10	0.02	0.14

This table shows the results of trading strategy. Panel A shows descriptive statistics about the number of recommendations belong to each category. The definition of Categories are as following: Category 1 means at least one other company in the same industry (industry Y) as company X was upgraded at the same time that the bold recommendation was made for company X; Category 2 refers to o other company in the same industry (industry Y) as company X was upgraded at the same time that the bold recommendation was made for company X. Panel B shows hedge portfolio returns in each category.

Table 3.6 - Comparison of CAR between Independent Analysts and Non-Independent Analysts

		BUY RECOMMENDATIONS						**SELL RECOMMENDATIONS**						**TOTAL**
		INDEPENDE		AFFILIATE		Total		INDEPEN		AFFILIATE		Total		
		a	CAR	b	CAR	c=a+b	CAR	d	CAR	e	CAR	f=d+e	CAR	g=c+f
A	CONTRA	357	**1.50**	500	**1.64**	857	**1.58**	37	-0.67	46	-0.40	83	**-0.52**	**940**
B	LEADIN	1185	**2.41**	1262	**1.54**	2447	**1.96**	227	**-3.50**	263	**-3.68**	490	**-3.60**	**3253**
C	BOLD	2199	**2.15**	2517	**1.58**	4716	**1.85**	392	**-2.81**	516	**-2.49**	908	**-2.62**	**5624**
D	NONBOLD	35871	**0.97**	45964	**0.75**	81842	**0.84**	5809	**-2.65**	7159	**-2.65**	12970	**-2.65**	**94812**
E=C+D	TOTAL	38066	**1.03**	48476	**0.79**	86549	**0.90**	6201	**-2.66**	7675	**-2.64**	13876	-2.65	**100427**
C/E	RATIO	5.8%		5.2%		5.5%		6.3%		6.7%		6.5%		5.6%

This table shows the cumulative abnormal returns (-1, +1) days for independent research firm and affiliated investment banks from 1992 to 2001. Non-tabulated results show that all the CARs are significant, p-value=0.001.Column a shows the number of independent buy recommendations; Column b shows the number of affiliated buy recommendations; Column c is the sum of column a and column b; Column d shows the number of independent sell recommendations; Column e shows the number of affiliated sell recommendations; Column f is the sum of column d and column e. Bold means significant at higher than 0.10 level. Row A shows the results for contra-bold; Row B shows the results for leading-bold; Row C shows the results for bold; Row D shows the results for non-bold; Row E shows the results for total; Row C/E shows bold ratio.

Table 3.7 - Market Reaction to Recommendations with R&D

		BUY RECOMMENDATIONS	CAR%	SELL RECOMMENDATIONS	CAR%	TOTAL
		a		b		g=a+b
A	CONTRA	384	0.32	41	-1.64	425
B	LEADING	1197	1.98	224	-4.60	1421
C	BOLD	2236	1.75	408	-3.49	2644
D	NON-BOLD	36997	0.96	5840	-2.75	42837
E=C+D	TOTAL	39230	1.01	6248	-2.80	45478
C/D	BOLD RATIO	5.70%		6.53%		
F Test	t	2.68	***	3.54		***

Row A shows the results for contra-bold; Row B shows the results for leading-bold; Row C shows the results for bold; Row D shows the results for non-bold; Row E shows the results for total; Row C/E shows bold ratio. F test show the CAR difference with or without R&D is significant at 0.01 level.

Table 3.8 - Comparison of CAR between bold and non-bold recommendations before and after Reg FD

Panel A: Comparison of CAR after Reg FD.

		BUY RECOMMENDATIONS						**SELL RECOMMENDATIONS**						**TOTA**
		INDEPEND		AFFILIATE		Total		INDEPEN		AFFILIATE		Total		
		a	CA	b	CA	c=a+b	CA	d	CAR	e	CAR	f=d+e	CAR	g=c+f
A	CONTR	309	1.49	382	2.27	691	**1.92**	22	-2.47	27	-2.18	49	**-2.31**	740
B	LEADING	928	2.80	850	2.12	1778	**2.48**	186	-3.89	162	-4.60	348	**-4.22**	2126
C	BOLD	1789	2.41	1787	2.19	3576	**2.30**	302	-3.41	307	-3.21	609	**-3.31**	4185
D	NON-BOLD	22715	1.20	24061	0.93	46776	**1.06**	4986	-2.85	5476	-2.87	10462	**-2.86**	57238
E=C+D	TOTAL	24502	1.28	25846	1.01	50348	**1.14**	5288	-2.88	5783	-2.89	11071	**-2.89**	61419
D/E	RATIO	7.30%		6.91%		7.11%		5.7%		5.31%		5.50%		6.30%
F-test:	(a=b)	t		2.56		***		d=e		t		3.46		***

Panel B: Comparison of CAR before Reg FD.

		BUY RECOMMENDATIONS						**SELL RECOMMENDATIONS**						**TOT**
		INDEPEND		AFFILIATE		Total		INDEPEND		AFFILIATE		Total		
		a	CAR	b	CAR	c=a+b	CAR	d	CAR	e	CAR	f=d+e	CAR	g=c+f
A	CONTR	48	1.55	118	-0.42	166	**0.15**	15	1.98	19	2.13	34	**2.07**	200
B	LEADING	257	1.00	412	0.34	669	**0.59**	41	-1.75	101	-2.22	142	**-2.08**	811
C	BOLD	410	1.03	730	0.08	1140	**0.42**	90	-0.77	209	-1.43	299	**-1.23**	1439
D	NONBOLD	13156	0.58	21903	0.55	35059	**0.56**	823	-1.43	1683	-1.90	2506	**-1.75**	37565
E=C+D	TOTAL	13564	0.59	22630	0.53	36194	**0.55**	913	-1.37	1892	-1.85	2805	**-1.69**	38999
D/E	RATIO	3.02%		3.23%		3.15%		9.86%				10.6%		6.91%
F-test:	(a=b)	t		5.35		***		(d=e)				6.45		***

This table compares the Cumulative abnormal returns between bold, herd, bold, leading, independent research firm, and affiliated investment banks before and after Regulation Fair Disclosure. Panel A shows the comparisons between different categories of recommendations after Reg FD; Panel B shows the comparisons before Reg FD.

Table 3.9 - Market Reaction to Bold Recommendations after Stock Price Changes

				BUY RECOMMENDATIONS				SELL RECOMMENDATIONS			
		Dispersion			**CAR**	**3%**	**CAR**		**CAR**	**3%**	**CAR**
A	**UP**	2.76	CONTRA-BOLD	389		0		42		0	
			LEADING-BOLD	1159		0		336		0	
			TOTAL	2189	3.68	0		384	0.34	0	
B	**DOW**	3.05	CONTRA-BOLD	525		301	-1.56	43		29	-1.77
	N		AFTER BUY			80	-3.72			1	-3.19
			AFTER SELL			29	-2.11			1	4.00
			LEADING-BOLD	1413		817	0.01	501		199	-6.77
			AFTER BUY			247	-1.05			40	-4.66
			AFTER SELL			43	-0.32			22	-1.74
			Total	2753	1.17	1600	0.05	563	-5.64	382	-4.84
			AFTER BUY			450	-1.51			73	-3.82
			AFTER SELL			100	-0.20			40	-2.20
	F Test		t		4.57	***			t	3.56	***

This table shows the market reaction differently after stock price change. First, I compare the market reaction to the analysts' ratings if their stock price signal consistent with their recommendations; second, I include the previous ratings and test if analysts update the recommendations consistent with the stock price change, the market will respond positively to the analysts' updated recommendations. Third, I also compare the analysts' dispersion before stock recommendations. I find when stock price increase, there will be less disagreement between analysts, and bold recommendations finally disappear.

Table 3.10 - Joint Distribution of analysts forecast and recommendations

Panel A: Joint Distribution of analysts forecast and recommendations

	Forecast		
Recommendations	**Contra-bold**	**Leading-bold**	**Non-Bold**
Contra-bold	1775	12023	8600
Leading-bold	932	4968	3896
Non-Bold	4298	25570	19305

Panel B: Joint CAR to analysts forecast and recommendations.

	Forecast		
Recommendations	**Contra-bold**	**Leading-bold**	**Non-Bold**
Contra-bold	1.05%***	1.53%	1.25%
Leading-bold	1.79%***	2.30%	2.06%
Non-Bold	0.27%***	0.61%	0.41%

This table shows a joint distribution of analysts' forecast and recommendations. In Panel A, the rows present the number of recommendations in contra-bold, leading-bold and non-bold categories. The columns present the number of analysts forecast in contra-bold, leading-bold and non-bold categories following Clement et al. (2005). In Panel B, the rows show CAR to contra-bold, leading-bold and non-bold recommendations. The columns present CAR to contra-bold, leading-bold and non-bold forecasts. The symbols ***, **, and*, denote statistical significance at the 0.001, 0.01 and 0.05 levels respectively, using a generic one-tail test.

Table 3.11 - Market Reaction to Super Bold Recommendations

		BUY RECOMMENDATIONS	CAR%	SELL RECOMMENDATIONS	CAR%	TOTAL
		a		b		g=a+b
A	CONTRA	1493	1.17	600	-2.51	2093
B	LEADING	3500	1.24	253	-3.45	3750
C	NON-BOLD	84490	0.94	13376	-2.77	97866
D=A+B+C	TOTAL	89483		14229		103712
C/D	BOLD RATIO	5.58%		6.02%		5.74%
F	SUPER BOLD	1338	0.91	310	-2.73	

I define super bold recommendations as the first bold recommendations in the last five years. I find that super bold recommendations could create higher market returns than other recommendations. And I find the results only in the sell side not in the buy side, which shows market have more confidence in the downgraded ratings than upgraded ratings.

Appendix

Appendix 1 Chapter 2 Variable Definitions

TCA	ΔCA j,t-CL j,t-Cash j,t+STDEBT j,t =firm j's total current accruals in year t
TA	ΔCA j,t-CL j,t-Cash j,t: +STDEBT j,t-DEPN j,t= firm j's total accruals in year t
CFO	Firm j's cash flow from operations in year t
ΔCA	Firm j's change in current assets (Compustat #4) between year t-1 and year t
ΔCL	Firm j's change in current liabilities (Compustat #5) between year t-1 and year t
ΔCash	Firm j's change in cash (Compustat #1) between year t-1 and year t
DEPN	Firm j's depreciation and amortization expense (Compustat #14) in year t
ΔRev	Firm j's change in revenues (Compustat #12) between year t-1 and year t
PPE	Firm j's gross value of property, plant and equipment (Compustat #7) in year t
CAR (0,+ 1)	Absolute value of cumulative 2-day market-adjusted return around firm j's quarter q earnings announcement
CAR (+2,+60)	Absolute value of cumulative 59 days market-adjusted return around firm j's quarter q earnings announcement
UE	Unexpected earnings news revealed in firm j's quarter q earnings announcement, scaled by firm j's share price 20 days before the earnings announcement date. Expected earnings = the consensus analyst forecast for quarter q
IU	Decile rank of IU; observations with the highest (lowest) values of IU are included in decile 10 (decile 1)
SOX	Dummy variable; equals to 1 after 2002, 0 before 2002
AQ factor-mimicking portfolio	Equal to the difference between the monthly excess returns of the top two AQ quintiles (Q4 and Q5) and the bottom AQ quintiles (Q1 and Q2). This procedure (similar to that used by Fama and French (1993) to construct size and book-to-market factor-mimicking portfolios) yields a series of 228 monthly AQfactor returns.

Appendix 2 Definition of Bold and Non-bold Stock Recommendations

	Ratings	Other Analysts' Consensus 30 days before	First Classification	Other Analysts' Consensus 30 days after	Second Classification
Buy	1, 2	> 3	BOLD	> 3	CONTRA-BOLD
				< 3	LEADING-BOLD
		< 3	NON-BOLD		
Hold	3	< 2 or > 4	BOLD	< 2 or > 4	CONTRA-BOLD
				> 2 and < 4	LEADING-BOLD
		> 2 and < 4	NON-BOLD		
Sell	4, 5	< 1.5	BOLD	< 1.5	CONTRA-BOLD
				> 2.5	LEADING-BOLD
		> 2.5	NON-BOLD		

Appendix 3 Chapter 3 Variable Descriptions

Dependent Variable

Contra-bold/leading-bold/non-bold: A dummy variable equals to 1 if analyst i's recommendation belongs to contra-bold/leading-bold/ non-bold recommendations; 0 otherwise.

Control Variables

Boldness: defined as the distance of the analyst's revised forecast from the prerevision consensus forecast.
BidAskSpread: For tests requiring Nasdaq quote data, days without a valid bid and ask quote are discarded. A valid quote is defined as having a bid and ask greater than zero, the ask greater than the bid, and the ask minus the bid less than five dollars.
AnalystsDispersion: Variance of analysts forecast, which equals to the variance of analysts forecast minus the consensus of analysts forecast (Barron, Kim, Lim and Stevens 1998; Palmon et al. 2012).
FrequencyCIG: The number of management earnings forecast every year.
Beta: Industry Risk.
BetaStd: Standard deviation of industry beta.
Pctchng: Stock price percentage change.
BrokerSize: Analyst's brokerage size, calculated as the number of analysts employed by the brokerage employing analyst i following firm j in year t.
ForFrequency: Analyst i's forecast frequency for firm j, calculated as the number of firm j forecasts made by analyst i following firm j in year t.
FirmExperience: Analyst i's firm-specific experience, calculated as the number of years of firm-specific experience for analyst i following firm j in year t.
GenExperience: Analyst i's general experience, calculated as the number of years of experience for analyst i following firm j in year t.
Companies: The number of companies analyst i follows in year t, calculated as the number of companies followed by analyst i following firm j in year t.
Industries: The number of industries analyst i follows in year t, calculated as the number of two-digit SICs followed by analysts who follow firm j in year t.
IndustryFE: Industry membership is determined by SIC code, and follows Ashbaugh et al. (2003). It is determined as follows: Agriculture (0100-0999), mining and construction (1000-1999), excluding 1300-1399), food (2000-2111), textiles and printing/publoishing (2200-2799), chemicals (2800-2824; 2840-2899), pharmaceuticals (2830-2836), extractive (1300-1399; 2900-2999), durable manufactures (3000-3999, excluding 3570-3579 and 3670-3679), transportation (4000-4899), retial (5000-5999), services (7000-8999, excluding 3570-739), computers (3570-3579; 3670-3679; 7370-7379), and utilities (49000-4999).