The Value of Independent Analysts

A DISSERTATION
SUBMITTED TO THE FACULTY OF
THE TEPPER SCHOOL OF BUSINESS
AT CARNEGIE MELLON UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

By
Jian Xue

April 2006
To my parents and husband
Acknowledgements

First of all, I would like to specially thank my advisor, Zhaoyang Gu, for his guidance, patience and encouragement through all my years at Carnegie Mellon University. He has always been responsive, shared his time and thoughts with me generously, and given me a great deal of intellectual advice. Working with him helped me develop a broad view of research and made me aware of many debatable issues in the general field of accounting, and more importantly his diligence and insistence on excellence and perfection have undoubtedly influenced me. It has been really a wonderful, challenging, and exciting experience to complete this degree under his supervision.

I would also like to thank my committee members Yuji Ijiri, Carolyn Levine, John O’Brien and Burton Hollifield. Their comments, discussions, and editorial advice concerning my dissertation have been very helpful. I also benefited a great deal from the comments and suggestions of Adam Koch, Jonathan Glover, Pierre Jinghong Liang, and Lin Nan.

Also, I thank my fellow students Carl Brousseau, Min Cao, Ting Chen, Wei Li, Haijin Lin, Jong Chool Park, Hong Qu, Xue Sun, Xiaoyan Wen, Janet Zhao. I also appreciate the friendship of my officemates Tao Chen and Cuiwei Lin, my good friends Caroline Li and Kai Gu. Without them, life at CMU would have been dull and lonesome.

Finally, I wish to express thanks to my family. My parents, Baoku Xue and Xuefen Zhang, encouraged me all through my education, and I would like to dedicate this thesis to them. And of course, thanks to my husband, Fa Wang, whose love and unconditional support were invaluable.
Abstract

Corporate failures in the early 2000s led to a renewed interest in analyst independence, with the presumption that research by independent analysts is “better” than that by their nonindependent counterparts. Recent studies, however, generally fail to find that independent analysts’ earnings forecasts are any better than those by nonindependent analysts in terms of forecast accuracy or bias. This dissertation provides some evidence for the value of independent analysts.

This dissertation shows that independent analysts contribute positively to the earnings forecasting process by disciplining the behavior of nonindependent analysts. Forecasts of nonindependent analysts become significantly more accurate and less biased in the presence of independent analysts than in their absence. Further, the improvement in accuracy or bias does not appear to be attributable to independent analysts’ selective following of firms that provide more public information to make earnings more predictable. Rather, it is due to the higher quality of nonindependent analysts’ private information when independent analysts are following the firms.

Besides forecast accuracy and bias, this dissertation also uses the association between abnormal stock returns and forecast errors as the forecast evaluation criterion. We show that forecast errors of nonindependent analysts are more strongly associated with abnormal returns when independent analysts are following the same firms than when they are not. This evidence is consistent with the disciplining effect of independent analysts documented using the forecast accuracy and bias criterion. We also show that the forecast errors of independent analysts are more strongly associated with abnormal returns than those of nonindependent analysts. This evidence suggests that independent analysts’ forecasts are superior to those by
nonindependent analysts in representing market expectations. Moreover, the effects of independent analysts are more pronounced when earnings news is bad.

The results of this dissertation support the requirements in the recent Global Research Analyst Settlement that independent research should be sponsored along with nonindependent research and that analyst independence should be enhanced.
# Table of Contents

CHAPTER 1 INTRODUCTION ........................................................................................................... 1

1.1. CONTROVERSY OVER ANALYST INDEPENDENCE: A REVIEW OF RELATED LITERATURE .. 1
1.2. ROLES OF INDEPENDENT ANALYSTS ................................................................................. 5
  1.2.1. The disciplining role of independent analysts ................................................................. 5
  1.2.2. Superiority of independent analysts ................................................................................ 8
1.3. FORECAST EVALUATION CRITERIA .................................................................................. 9
1.4. MEASUREMENT OF ANALYST INDEPENDENCE ................................................................. 11
1.5. MAIN FINDINGS ................................................................................................................ 13
1.6. POLICY IMPLICATIONS ..................................................................................................... 15

CHAPTER 2 EVIDENCE FROM FORECAST ACCURACY ......................................................... 18

2.1. INTRODUCTION ............................................................................................................... 18
2.2. SAMPLE SELECTION AND VARIABLE MEASUREMENT ....................................................... 19
  2.2.1. Sample selection ............................................................................................................ 19
  2.2.2. Variable measurement ................................................................................................ 21
2.3. EMPIRICAL RESULTS ....................................................................................................... 25
  2.3.1. Nonindependent vs. independent analysts ................................................................. 25
  2.3.2. The disciplining effect of independent analysts ......................................................... 27
  2.3.3. Sources of forecast accuracy improvement: public vs. private information ............ 30
  2.3.4. Sensitivity tests. .......................................................................................................... 32
2.4. CHAPTER SUMMARY ....................................................................................................... 36

CHAPTER 3 EVIDENCE FROM THE MARKET ASSOCIATION ............................................ 37

3.1. INTRODUCTION ............................................................................................................... 37
3.2. SAMPLE SELECTION, RESEARCH DESIGN AND DESCRIPTIVE STATISTICS .............. 38
  3.2.1. Sample selection ............................................................................................................ 38
  3.2.2. Research design ........................................................................................................... 41
  3.2.3. Descriptive statistics .................................................................................................. 44
3.3. EMPIRICAL RESULTS ....................................................................................................... 46
  3.3.1. The overall effect of independent analysts ................................................................. 46
  3.3.2. The disciplining effect of independent analysts ......................................................... 48
  3.3.3. Individual superiority of independent analysts to nonindependent analysts ......... 50
  3.3.4. Sensitivity tests .......................................................................................................... 53
3.4. CHAPTER SUMMARY ....................................................................................................... 59

CHAPTER 4 CONCLUSIONS AND FUTURE WORK ......................................................... 61

4.1. CONCLUSIONS ................................................................................................................ 61
4.2. UNANSWERED QUESTIONS AND FUTURE WORK ......................................................... 63

REFERENCES ............................................................................................................................. 70

TABLES .................................................................................................................................... 75
Chapter 1

Introduction

Independent analysts, as we define them in this dissertation, refer to those analysts working for pure research firms that are not engaged in any investment banking or brokerage businesses. Numerous anecdotes suggest that nonindependent analysts, especially those with investment banking affiliations with the firms they follow, face conflicts of interest that compromise the quality of their research (e.g., Francis, 2004). Academic studies, however, have generally failed to find that earnings forecasts of independent analysts are of higher quality than those of nonindependent analysts in terms of forecast accuracy and forecast bias. This dissertation contributes to this line of literature by examining two roles of independent analysts: how they discipline the behavior of nonindependent analysts and how they provide forecasts that are superior to those by nonindependent analysts. We use two criteria to evaluate the quality of analyst forecasts: the traditional forecast accuracy and bias criterion that evaluates the \textit{ex post} quality of forecasts, and the market association criterion that evaluates the \textit{ex ante} quality of forecasts. We show that by both criteria independent analysts contribute positively to the earnings forecasting process by affecting the forecast quality of nonindependent analysts. In addition, although forecasts by independent analysts are not as accurate as those by nonindependent analysts \textit{ex post}, they are superior in representing \textit{ex ante} market expectations.

1.1. Controversy Over Analyst Independence: A Review of Related Literature

Although conflicts of interest faced by sell-side analysts have long been of concern to academics, regulators, and practitioners (e.g., Schipper, 1991), the corporate scandals in recent years and analysts’ failure to warn investors in time have exacerbated such concerns.
Analyst bias is often held partly responsible for the stock market debacle in the early 2000’s. To mitigate worries and promote analyst independence, regulators have taken a series of actions, including the U.S. Congress hearing “Analyzing the Analysts” in 2001, Regulation Fair Disclosure in 2001, Sarbanes-Oxley Act (Section 501) in 2002, and new Self-Regulation Organization rules of NYSE and NASDAQ in 2002. The culmination of the new regulations imposed directly on analysts was the Global Research Analyst Settlement between the SEC and ten of the largest investment banks (Bear Stearns, Citigroup, Credit Suisse First Boston, Goldman Sachs, J.P. Morgan Securities, Lehman Brothers, Merrill Lynch, Morgan Stanley, UBS Warburg, U.S. Bancorp Piper Jaffray). Finalized on April 28, 2003, the settlement required the banks to pay a total of $1.4 billion for their past misconduct. Another two banks (Deutsche Bank and Thomas Weisel) settled in August 2004 for $100 million. In addition to financial terms, the banks agreed to institute a number of reforms to increase analyst independence.

While the Global Settlement clearly indicates that analyst independence has been seriously sacrificed in the past, academic evidence on the value of analyst independence, however, is mixed. For stock recommendations and long-term growth forecasts, almost all studies confirm that affiliated analysts are more optimistic than unaffiliated analysts. However, there is no consistent evidence that affiliated analysts are able to mislead the market with their biased stock recommendations. For example, Iskoz (2003) finds that only “strong buy” recommendations by affiliated analysts for IPOs underperform those by unaffiliated analysts, as similarly found in Michaely and Womack (1999). There is no significant difference for other recommendations for IPOs or any kind of recommendations for SEOs. Barber, Lehavy

---

1 Although Regulation Fair Disclosure is targeted at managers, the main issue was to prevent selective disclosure by management to certain investment professionals, especially financial analysts, so that they would not bias their reports and compete for management favor to gain informational advantages over each other or over the general public.
and Trueman (2005) find that investment bank “buy” recommendations underperform those by independent research firms during 2000-2003 but that their “hold” and “sell” recommendations outperform those by independent research firms. Agrawal and Chen (2005) find no difference in stock returns following recommendation revisions. Clarke et al. (2004) find that the market reacts more to recommendation revisions by investment banks and that their upgrades are even followed by one-year positive abnormal returns.\(^2\) Overall, stock recommendations by affiliated analysts only underperform those by nonaffiliated analysts for certain categories of stock recommendations, for a certain type of investment business, or during a specific period. Often, stock recommendations by affiliated analysts are actually more informative and better received by institutional investors.

For near-term *earnings forecasts*, the preponderance of empirical evidence actually suggests that forecasts by independent analysts are either not different from, or mostly worse (less accurate and more optimistically biased) than, those by nonindependent analysts. For example, Jacob, Rock and Weber (2005) separate analysts into affiliated investment bank analysts, unaffiliated investment bank analysts, and independent analysts. They find that affiliated investment bank analysts are the most accurate and least optimistic, with mean (absolute) forecast error of -0.034 (0.164), followed by unaffiliated investment bank analysts, with mean (absolute) forecast error of -0.035 (0.176). Independent analysts produce the worst forecasts, with mean (absolute) forecast error of -0.076 (0.230). Using revenue sources to identify the types of analyst firms, Agrawal and Chen (2004) find that the mean absolute forecast error is 0.0030 for analysts without investment banking business and 0.0028 for those with investment banking business. Clarke et al. (2004) find that analysts at large investment banks provide less biased and more accurate forecasts, and are more likely to provide the first

forecast. Cowen, Groysberg and Healy (2006) separate the total sample into more detailed
categories of security firms: underwriter, syndicate, brokerage, and pure research firms. They
find that analysts at firms with underwriting and trading business are less optimistic than
those at pure brokerage houses. And most of the forecast optimism by nonindependent analyst
firms is attributable to sales and trading activities used to fund research departments.
Malmendier and Shanthikumar (2005) similarly find that affiliated analysts’ earnings
forecasts are more biased than unaffiliated analysts. Lin and McNichols (1998) focus on SEO
firms and compare earnings forecasts between lead and co-underwriters and unaffiliated
analysts. No significant difference in forecast accuracy is found between the two groups of
analysts. Perhaps the only study that finds more optimistic bias in earnings forecasts by
affiliated analysts than unaffiliated analysts is Duger and Nather (1995). But their sample is
very limited with only 250 observations. Generally it is not clear if and how analyst
independence adds value to the analyst earnings forecasting process. In fact, many of these
studies conclude by casting doubt on the potential effectiveness of the Global Settlement to
achieve the underlying goals.

Overall, while regulators believe that analyst independence is valuable, academic
evidence suggests the forecasts by independent analysts are less accurate and more biased
than those by nonindependent ones. Some interesting questions arise: Are regulators wrong in
advocating analyst independence? If they are right, where does analyst independence add
value to the earnings forecasting process? Does the accuracy and bias criterion capture all the
relevant elements of forecast quality?

This dissertation tries to answer the above questions. We focus on earnings forecasts
and differ from the literature in two aspects. First, we study a role of independent analysts that
has been relatively unexplored previously: their disciplining effect on nonindependent
analysts. Second, in addition to the typical forecast accuracy and bias criterion used in prior studies, we also use the market association criterion to evaluate forecast quality.

1.2. Roles of Independent Analysts

Independent analysts are likely to be different from nonindependent analysts in many aspects. For example, their incentives are different. Independent analysts generate revenues from the sale of their research, while analysts from investment banks or brokerage firms have (or used to have) their compensation tied to the underwriting business they bring to their firms or commissions from trade execution services (Cowen, Groysberg and Healy, 2006). In addition, the information sources are likely to be different. Nonindependent analysts have (or used to have) preferential access to the private information of management personnel. The investment banking business that nonindependent analysts are doing for firms or the brokerage services they provide may require them to invest more in firm-specific information. They may also have more financial resources on private information acquisition than independent analysts. In addition, the capability of independent and nonindependent analysts could differ, with investment banks/brokerages possibly attracting more talented individuals.

1.2.1. The disciplining role of independent analysts

Prior studies typically compare independent analysts directly with nonindependent analysts to examine the effect of analyst independence. Given their findings that earnings forecasts of independent analysts are no more accurate than those of nonindependent analysts, where does analyst independence add value to the earnings forecasting process? We argue that although independent analysts may not necessarily provide more accurate forecasts by themselves, they can still contribute positively by changing the behavior of others. Our argument is motivated by one of the requirements in the Global Settlement. According to the
SEC press release on April 28, 2003,³

“To ensure that individual investors get access to objective investment advice, the firms will be obligated to furnish independent research. For a five-year period, each of the firms will be required to contract with no fewer than three independent research firms that will make available independent research to the firm’s customers.”

Out of the $1.5 billion to be paid by the 12 investment banks, about $478 million will be used by the banks for the acquisition and distribution of independent research reports along with their own reports for every company they cover. Many of the previously cited studies interpret this requirement as implying a comparison between independent and nonindependent analysts and that independent research should be of higher quality than nonindependent research. The opposite empirical findings from earnings forecasts led many of these studies to specifically question the necessity of this requirement and more generally the value of analyst independence.

In this study we offer a different interpretation of the requirement of making research reports from both investment banks and independent analyst firms simultaneously available. It is not useful, and may not be the main intention of regulators, to force investment banks to identify a source of higher quality research just to contrast their own low quality research, unless the presence of other research would make a difference to their research quality. We believe that a more important and subtle message embedded in the requirement is the regulators’ belief that the presence of independent analysts following the same firms will change the behavior of nonindependent analysts and lead to improved quality of their research relative to the situation where independent analysts are absent. That is, independent analysts will have a disciplining effect on nonindependent analysts and in this way contribute

positively to the earnings forecasting process. This interpretation suggests that, to study the
effect of independent analysts, the comparison should not be made between independent and
nonindependent analysts, but between nonindependent analysts in the presence and the
absence of independent analysts.

The disciplining effect of independent analysts on nonindependent analysts can come
from at least two sources related to the differences between the two groups of analysts. First,
the presence of independent analysts provides a monitoring device for nonindependent
analysts. Although it may not be independent analysts’ intention to explicitly monitor
nonindependent analysts, implicit monitoring arises when both sets of forecasts for the same
firms are available to investors. Since forecasts reflect the underlying incentives, deviation
from independent analyst forecasts is more likely to reveal the incentive-specific biases of
nonindependent analysts than when there are no independent analyst forecasts. If such biases
are not desirable to investors, nonindependent analysts will be constrained from building in as
much bias when independent analyst forecasts are available as when they are not. Thus,
holding the information of nonindependent analysts constant, an overall improvement of their
forecast performance is expected when independent analyst forecasts are available. In this
sense, nonindependent analysts are monitored. Second, the presence of independent analysts
is likely to increase the information competition among analysts. Nonindependent analysts
may increase their private information acquisition to maintain their informational advantage.
Although more analysts will increase the competition in general, the effect may be especially
strong for independent analysts since their incentives and information sources are different
from those of nonindependent analysts. Thus, the presence of independent analysts can also
change the information available to nonindependent analysts, leading to an overall
improvement of forecast performance.
1.2.2. Superiority of independent analysts

In addition to the financial payment by the investment banks, the Global Settlement also required numerous reforms to sever the ties between the investment banking and research departments within investment banks. For example:

“The firms will physically separate their research and investment banking departments to prevent the flow of information between the two groups; The firms’ senior management will determine the research department’s budget without input from investment banking and without regard to specific revenues derived from investment banking; Research analysts’ compensation may not be based, directly or indirectly, on investment banking revenues or input from investment banking personnel, and investment bankers will have no role in evaluating analysts’ job performance; Research management will make all company-specific decisions to terminate coverage, and investment bankers will have no role in company-specific coverage decisions; Research analysts will be prohibited from participating in efforts to solicit investment banking business, including pitches and roadshows. During the offering period for an investment banking transaction, research analysts may not participate in roadshows or other efforts to market the transaction; The firms will create and enforce firewalls restricting interaction between investment banking and research except in specifically designed circumstances.”

All of these reforms are intended to promote the independence of analysts. Clearly, regulators believe that enhanced analyst independence itself is valuable. This implies that forecasts by independent analysts should be superior to those by nonindependent ones. Nonetheless, previous studies find the puzzling result that independent analysts on average are less accurate

---

or more biased in their forecasts than nonindependent analysts. Accuracy and bias are a criterion of \textit{ex post} forecast performance and do not capture all aspects of the quality of forecasts. Forecasts by nonindependent analysts may be more accurate or less biased \textit{ex post}. However, \textit{ex ante}, do their forecasts represent better market expectations? We also use an alternative criterion, market association, to evaluate the \textit{ex ante} superiority of independent analyst forecasts from the market perspective. We argue below that the two criteria need not yield the same results on the relative superiority of two groups of analysts.

\subsection*{1.3. Forecast Evaluation Criteria}

Forecast accuracy and bias is perhaps the most commonly used criterion in evaluating forecast quality, especially in the context of comparing independent and nonindependent analysts. Forecast accuracy is usually measured as the absolute or squared value of the difference between forecasts and actual earnings. Competing forecasts are compared with actual earnings and whichever forecast is closer to actual earnings is regarded as the better forecast. A closely related measure is forecast bias, or the signed difference between forecasts and actual earnings. If analysts have incorporated all available information into their forecasts, then forecast errors will be purely unpredictable random shocks and should be zero on average. Systematically positive (negative) forecast errors imply that the forecasts are pessimistically (optimistically) biased. Usually forecasts with the smaller bias are regarded as better forecasts. Both accuracy and bias evaluate the \textit{ex post} performance of forecasts. We will examine both forecast accuracy and bias in this dissertation, but will especially focus on forecast accuracy.

An alternative forecast evaluation criterion is which forecast is closer to the \textit{ex ante} market expectation. As a matter of fact, a primary motivation for studying analyst forecasts in the early literature was to find an alternative and better proxy of market expectations than
proxies from a mechanical model (e.g., Brown and Rozeff, 1978). According to this criterion, the error in the forecast that is more aligned with market expectation should better capture the surprise to the market with less measurement error. Consequently, there would be a stronger association between abnormal returns and the error in the better-aligned forecast. This should be reflected in a higher coefficient on the forecast error (referred in the accounting literature as earnings response coefficient or ERC) since larger measurement error would bias the coefficient downward toward zero. Thus this criterion is operationalized as the market association or ERC comparison. The forecast that produces stronger market association or higher ERC is regarded as the better forecast. Although this criterion is seldom used in most other studies on analyst independence, it has been commonly applied in prior studies to evaluate alternative forecasts (e.g., Brown et al., 1987b; O’Brien, 1988; Philbrick and Ricks, 1991, among others). In evaluating alternative forecasts, the actual earnings are usually held constant to see which forecast error yields stronger association with abnormal returns (Brown et al., 1987b; O’Brien, 1988). Actual earnings from alternative sources can also be compared see which forecast-actual pair yields the strongest association (Philbrick and Ricks, 1991). This latter technique has been widely used in recent years to evaluate competing actual earnings (e.g., GAAP vs. pro forma earnings) by holding the forecast constant (Bhattacharya et al., 2003; Bradshaw and Sloan, 2002; Brown and Sivakumar, 2003). The idea underlying the criterion remains the same, i.e., whichever actual earnings best capture the surprise to the market is regarded as the best.

Previous research suggests that the market association criterion does not always yield results consistent with those from the accuracy or bias criterion (e.g., O’Brien, 1988). Similarly, we find in this dissertation that the results for the superiority role of independent analysts are “inconsistent” between the two criteria: nonindependent analyst forecasts are
more accurate and less biased *ex post*, but independent analyst forecasts represent *ex ante* market expectation better. One possible reason for the divergence between the *ex post* and *ex ante* superiority is the different interaction of independent and nonindependent analysts with management. Affiliated analysts may have better access to the private information of management personnel, be guided more intensively by management, or be more capable in information processing. *Ex post*, their forecasts may be more accurate and less biased. However, they may be overly guided by management due to an interest in maintaining the investment banking relationship. Management may also manipulate earnings to meet or just beat forecasts by these analysts. The market may not value the guided or manipulated part of earnings and regard it as of low quality or value irrelevant. Independent analysts, on the other hand, may participate less in the guidance game and have less preferred information access. The market may perceive them to be more objective and stand by their beliefs. Thus, it is possible that forecasts by independent analysts are less accurate/more biased *ex post*, but are closer to *ex ante* market expectations. Thus their forecast errors are more strongly associated with abnormal returns. Given the importance of analyst independence, the two criteria we use are likely to give us a more complete picture about the quality of analyst forecasts than using either criterion alone.

1.4. Measurement of Analyst Independence

To study the effect of analyst affiliation or independence, some studies separate analysts into affiliated and unaffiliated based on the actual investment banking business, such as equity offering, that the analyst firms are doing for the corporation they follow (e.g., Dechow et al., 2000; Dugar and Nathan, 1995; Lin and McNichols, 1998; Michaely and Womack, 1999). Other studies have a more direct measure of independent analysts by excluding or separately considering unaffiliated investment bank analysts (e.g., Barber et al.,
2005; Clarke et al., 2004; Jacob et al., 2005; Cowen et al., 2006). These unaffiliated investment bank analysts are not free from conflicts of interest as their firms constantly compete for potential future investment banking business or compete for clients for trading commissions.

We follow the second approach to categorizing analysts by focusing on independent analysts vs. all other (nonindependent) analysts. We choose to do this because our research question, derived from the Global Settlement on the effects of analyst independence, requires a relatively clean measure of independent analysts.\(^5\) According to the Attorney General of the State of New York (Addendum A, 2003, p. 25),

“The Independent Consultant will seek to procure research reports on the Common Stock of all Covered Companies from Independent Research Providers. Independent Research Providers may not perform *investment banking business of any kind* and may not provide *brokerage services in direct and significant competition with the firm*” (emphasis added).

It is clear that any investment business, actual or potential (and affiliated or unaffiliated), would preclude a firm from being considered independent. In addition, certain pure brokerage houses may be considered not independent if they compete for the same clients. Thus, we focus only on pure independent research firms as identified by Nelson’s Directory of Investment Research and regard all others as nonindependent. While identifying firms with actual investment banking relationships is likely to yield a measure of the most severe conflict of interest, our classification better allows us to isolate the effect of analyst independence. We note that certain pure brokerage houses may be regarded as independent of one investment bank but not independent of another investment bank, depending on the nature of competition.

\(^5\) We choose to do this also for a practical reason. Data availability at our school constrains us from accessing data on analyst affiliations.
Identifying such relations, however, is difficult and subjective. Our grouping them together as being nonindependent may have some noise, but such noise would work against our findings. Nonetheless, as part of our analysis, we separately examine analysts from the 12 investment banks specifically targeted in the Global Settlement to determine whether independent analysts have an effect on these banks.

1.5. Main Findings

We obtain our earnings forecasts from First Call Historical Database and analyst independence status from Nelson’s Directory of Investment Research. For every firm quarter that is followed by both independent and nonindependent analysts, we match with a nearby quarter of the same firm followed only by nonindependent analysts. In this way, we isolate the effects of the presence and absence of independent analysts while controlling for other firm and time-specific characteristics.

Our first set of results is based on the forecast accuracy and bias criterion. We confirm prior findings that forecasts by independent analysts are less accurate than those by nonindependent ones. However, we show that forecast accuracy of nonindependent analysts is significantly higher when independent analysts are following the same firms than when they are not. On average, the increase in accuracy is about 13.5% to 25.4% by the measures we use. Forecast bias of nonindependent analysts is also reduced with independent analyst following. Further, we estimate the accuracies of the public and private components of nonindependent analysts’ information. We find that the accuracy of public information in the presence of independent analysts is actually slightly lower than in the absence of independent analysts. This is inconsistent with the selection effect of independent analysts. On the other hand, the accuracy of the private information of nonindependent analysts is higher by 20.9%
on average in the presence of independent analysts than in their absence. This lends support to the disciplining effect of independent analysts.

Our second set of results is based on the market association criterion. We show that the overall ERC for the consensus forecast error by all analysts is higher by nearly 40% when the firms are followed by both independent and nonindependent analysts than when the same firms are followed by only nonindependent analysts in nearby quarters. The ERC improvement reaches over 120% when the earnings news is negative. The economically and statistically significant improvement of the ERC strongly suggests that forecasts are better aligned with market expectations when independent analysts are present. The improvement in the face of bad news is especially comforting since O’Brien et al. (2005) find from stock recommendations that nonindependent analysts are slower to convey unfavorable news than favorable news. Consequently, the room for improvement and the value of analyst independence is expected to be greater for bad news.

Further, we explore the sources of the ERC improvement related to the two roles played by independent analysts. For the disciplining effect of independent analysts, we focus on the ERC for only nonindependent analysts and compare their forecasts in the presence and in the absence of independent analysts for the same group of firms in nearby quarters. We find that the presence of independent analysts improves the ERC for nonindependent analysts by about 25%. Again, the improvement is much more pronounced when earnings news is negative (about 100%). We conclude that nonindependent analysts behave differently and provide forecasts better aligned with market expectations when independent analysts are following the same firms, consistent with the disciplining role of independent analysts documented using the analyst forecast accuracy and bias criterion.
We then examine the superiority of independent analysts to nonindependent analysts by comparing forecasts by independent and nonindependent analysts simultaneously following the same firms. Since the number of nonindependent analysts is well above the number of independent analysts per firm, it is important to control for the level of following so that the comparison is on equal footing. We show that the ERC for independent analysts is about 20% higher than the ERC for nonindependent analysts. The difference is 33% and 24% for good and bad news, respectively. We also calculate a measure of incremental contribution by a group of analysts relative to the forecasts by the remaining analysts. We find that incremental contribution by independent analysts is about 30% larger than that by nonindependent analysts. The difference is significant only for bad news. These results suggest that independent analysts are individually superior to nonindependent analysts: their forecasts may not be as accurate as those by nonindependent analysts, but their forecasts are closer to market expectations.

We also conduct a number of additional tests to corroborate our results. We repeat the analysis to analysts from the 12 investment banks targeted in the Global Settlement since the settlement suggests that analysts from these banks are likely to have the most severe conflicts of interest. To ensure that the same nonindependent analysts will behave differently in the presence of independent analysts, we also extend our analysis to the sub-samples when nonindependent analysts are held to be constant in the presence and in the absence of independent analysts. Some other sensitivity checks are also conducted and our results are robust in various tests.

1.6. Policy Implications

Overall, we present findings that are different from those in the extant literature. Many existing studies cast doubt on the effectiveness of the independence requirements in the
Global Settlement. Our study suggests that independent analysts do add value to the forecasting environment through at least two roles they play: the disciplining role and superiority role. Our results have important policy implications. First, the disciplining role of independent analysts documented here supports the Global Settlement’s requirement that investment banks should provide independent research reports along with their own. Although the financial resources needed to fulfill this requirement appear large ($478 million), the economic significance of the improved quality of nonindependent research also appears large. It is unreasonable to expect investment banks to spin off their research departments since such departments play a vital informational role in the firms’ activities. If both the investment banking and research departments are going to co-exist, constraining analysts from these firms with independent research reports appears an effective policy choice.

Second, our sample covers the period before 2003. If the disciplining effect of independent analysts was already at work before the Global Settlement, should nonindependent analysts be required to acquire independent analysts’ service and show along with their own reports? It is important to note that although our sample of firms followed by both independent and nonindependent analysts is not small per se, it represents only 10% of the firms with available data. In other words, for the vast majority of the firms during our sample period, nonindependent analysts were free from the disciplining of independent analysts. This implies, 1) untapped economic potential of independent analyst research is likely to be large; and 2) the Global Settlement’s requirement is likely to spur the demand for such research and significantly change the industry horizon looking ahead.

Third, our results on the superiority of independent analysts support the various analyst reforms delineated in the Global Settlement that aim to sever the ties between investment banking and research departments. Given that both departments are likely to co-
exist, research departments in investment banks may perhaps never achieve the status of full-
fledged independent research firms. However, promoting their independence to bring them
closer to independent research firms is likely to improve their research quality beyond the
disciplining effect of independent analysts.

The remainder of the dissertation is organized as follows. Chapter 2 investigates the
disciplining role of independent analysts based on the forecast accuracy and bias criterion.
Chapter 3 uses the market association criterion and further examines the disciplining role and
superiority of independent analysts. Chapter 4 concludes the dissertation and proposes some
further research.
Chapter 2

Evidence from Forecast Accuracy

2.1. Introduction

This chapter investigates the disciplining role of independent analysts on nonindependent analysts using the forecast accuracy and bias as the evaluation criterion. As discussed in Chapter 1, we examine whether the forecasts by nonindependent analysts become more accurate and less biased when independent analysts are following the same firms compared to when they are not.

The disciplining effect of independent analysts can come from at least two sources. The presence of independent analysts not only provides a monitoring device for nonindependent analysts but also increases the information competition among analysts. Differentiating between the above two sources empirically is difficult because in either case we expect to observe improved quality of private information of nonindependent analysts in the presence of independent analysts. There is yet a third possibility that the presence of independent analysts may be associated with better forecast performance of nonindependent analysts. That is, the following decision by independent analysts may not be random. If independent analysts systematically choose to follow firms whose earnings are relatively easy to forecast, we can also observe that the forecast performance of nonindependent analysts improves when independent analysts are present. An implication of this possibility is that the ease of forecasting considered by independent analysts should be related to the quality of public information available to all analysts rather than the private information available only to nonindependent analysts. Thus, to examine whether any forecast performance improvement of nonindependent analysts is due to the selection effect or the disciplining effect of
independent analysts, we follow Gu (2004) and decompose total earnings forecast accuracy of nonindependent analysts into accuracy of public information and accuracy of private information. We expect an improvement in the accuracy of private (common) information for the disciplining (selection) effect of independent analysts.

2.2. Sample Selection and Variable Measurement

2.2.1. Sample selection

We gather analyst forecasts of quarterly earnings per share from the March 2003 version of First Call Historical Database covering the period from 1989 to 2002. Actual earnings are also collected from First Call to be consistent with forecasts in the treatment of nonrecurring items (Gu and Chen, 2004). Earnings surprise, measured by forecast error ($FE$), is the difference between actual earnings and forecasted earnings. To minimize the effect of stale forecasts, we require forecasts to be made within 90 days of the earnings announcements. If an analyst makes several forecasts within this window, only the most recent one is retained in the sample. The initial sample consists of 145,332 firm quarters with nonmissing values of forecasts, actual earnings, and earnings announcement dates. For each forecast, First Call provides an identity code for the analyst firm. In a separate “Brokers” file, First Call provides the full names of the analyst firms in the database.

We use Nelson’s Directory of Investment Research from 1993 to 2002 to identify the types of analyst firms. The directory profiles more than 14,000 publicly-traded security firms worldwide and classifies each into an “Independent Research Firm,” an “Investment Bank/Broker,” or an “Investment Manager.” Following Jacob et al. (2005), we treat Investment Managers as independent based on the incentives they receive relative to
investment banks.\textsuperscript{6} Thus, analyst firms classified as “Investment Bank/Broker” by Nelson’s Directory are regarded as nonindependent because they either generate revenues from investment banking business or compete in the brokerage business. An analyst firm may change its business type during our sample period. When this occurs, we also reclassify its type accordingly. After merging with First Call data, we obtain 141,954 firm quarters with at least one forecast made by an analyst firm identifiable as independent or nonindependent.

We also require each firm quarter to have stock prices and market capitalization at the beginning of the quarter from the Center for Research in Security Prices (CRSP). After merging data from First Call, CRSP, and Nelson’s Directory we have a total of 132,351 firm quarter observations with nonmissing values of the variables required. Out of these firm quarters, 120,568 are followed only by nonindependent analysts (IND = 0), 9,661 followed by both independent and nonindependent analysts (IND = 1), and 2,122 followed only by independent analysts. Table 2-1 summarizes our sample selection process described above and Panel A of Table 2-2 provides the time profile for this sample. We combine observations before 1993 with those of 1993 since First Call’s coverage is relatively incomplete before 1993. About 8.9\% of firm quarters are followed by independent analysts (1.60\% exclusively by independent analysts and 7.30\% by both independent and nonindependent analysts). However, independent analyst following has gradually increased over time, perhaps because independent analyst firms have expanded, and/or First Call has increased its coverage of such firms. Firm quarters followed only by nonindependent analysts have been rather stable in absolute numbers, but decreased relative to total available quarters.

We use a matched sample design to capture the effect of the presence of independent analysts on forecast performance of nonindependent analysts. For each of the 9,661 firm

\textsuperscript{6} In our final sample, there are only two firms classified as Investment Managers. Excluding them from independent firms does not qualitatively affect our results.
quarters followed by both independent and nonindependent analysts (IND = 1), we match it by a quarter followed only by nonindependent analysts (IND = 0) and examine whether forecast performance is different between the two quarters. To control for firm- and time-specific characteristics and seasonality of earnings, the match is chosen as, if available, the closest quarter from the same fiscal quarters of the same firm within three years surrounding the current quarter. To mitigate the effect of outliers, our matching excludes extreme observations as described below. The matching process yields a total of 6,149 pairs of observations. These 6,149 pairs comprise our Match Sample 1 with the most available observations.

The empirical decomposition of total forecast accuracy into accuracies of public and private information requires the imposition of additional conditions as described below. Not all firm quarters have empirical measures. Thus, our examination of the sources of the accuracy improvement is based on a second matched sample (Match Sample 2) comprising 4,104 pairs of observations from Matched Sample 1 for which the empirical measures are possible.

Panel B of Table 2-2 provides the time profile for the two matched samples. The number of firm quarters with independent analysts following increases gradually similar to the overall sample. Note that the number of matched quarters does not exhibit the increasing trend because the match is obtained from the surrounding years. More observations of the base sample in later years tend to have their matches obtained from earlier years.

2.2.2. Variable measurement

2.2.2.1. Forecast error and forecast accuracy

For each analyst i in a firm quarter, we measure forecast error (FEi) as actual earnings (A) minus the forecast by the analyst (Fi). To study forecast bias (signed forecast errors) of an
analyst group, we average the forecast errors across individual analysts, $FE = A - \Sigma F_i/N$, where $N$ is the number of analysts in that group for the quarter. We denote the mean forecast error of all analysts, only nonindependent analysts, and only independent analysts as $FE_{ALL}$, $FE_{NI}$, and $FE_{IND}$, respectively. To obtain our two matched samples, we do not include any observation in the top and bottom extreme 1% of any of these three variables in the overall sample. Extreme forecast errors in either direction will translate into extreme values of absolute forecast errors, which are the basis of our accuracy measures. To allow for cross-firm comparability, all earnings and forecasts are deflated by the price at the beginning of the quarter (adjusted for stock splits and stock dividends) and multiplied by 100.

We measure forecast accuracy in two ways. The first one (ACCY1) is absolute error in the mean forecast multiplied by $-1$, or $-|FE| = -|A - \Sigma F_i/N|$. This is commonly used in prior studies and measures the accuracy of consensus forecast for an analyst group. The second measure (ACCY2) is the mean of the inverse of absolute errors in individual forecasts, or $(\Sigma 1/|A - F_i|)/N$. In cases where the actual earnings are exactly equal to a forecast, we assume the inverse is twice as large as the maximum of the finite measures from the remaining forecasts. Using other reasonable multiples or excluding such observations does not affect our results qualitatively.

There are two differences between ACCY2 and ACCY1. The first is obvious. Instead of multiplying the absolute error by $-1$ as in ACCY1, we use the inverse in ACCY2 so that in each case the higher the measure, the higher the accuracy. The second and more subtle difference is that instead of aggregating individual forecasts into a consensus and then measuring its accuracy as in ACCY1, ACCY2 measures accuracies of individual forecasts first and then aggregates them into an average. This is done for two reasons. One, decomposition of total accuracy into accuracies of public and private information, discussed
below, is done at the individual forecast level similar to ACCY2. Two, ACCY2 controls for any accuracy difference merely due to the difference in the number of forecasts included. This is because the consensus forecast $\sum_i F_i / N$ will become more accurate simply as the number of forecasts grows larger. Thus, even if all individual analysts are identical in their accuracy, a group with more analysts will have a higher ACCY1 than a group with fewer analysts. The ACCY2 measure is not subject to this problem. Our empirical results indicate that the number of analysts indeed differs across groups in the various comparisons. We use suffixes _ALL, _NI, and _IND for ACCY1 and ACCY2 to denote accuracy measures for all analysts, nonindependent analysts, and independent analysts, respectively.

2.2.2.2. Accuracies of analysts’ public and private information

Barron et al. (1998) build a model of analyst forecast and propose a way to measure the accuracies of analysts’ public and private information. In this model, each analyst observes two signals about future actual earnings $A$. One is the public information shared by all analysts that $A$ is normally distributed with mean $\tilde{A}$ and variance $1/h$. The other is the private information $z_i = A + \varepsilon_i$ observable only by analyst i, where $\varepsilon_i$ is normally distributed with mean zero and variance $1/s_i$, and independent of all other information. Note that the inverses of the variances, $h$ and $s_i$, provide natural measures of accuracies of analyst i’s public and private information. Weighing her two signals, analyst i will make a forecast of future earnings based on her conditional expectation, $F_i = (h\tilde{A} + s_i z_i) / (h+s_i)$, with accuracy of each signal as the weight. Variance of the forecast error is $\text{Var}(FE_i) = 1/(h+s_i)$. Its inverse, or total accuracy $h+s_i$, is simply the summation of the two accuracies. Barron et al. (1998) show how $h$ and $s_i$ can be measured under the assumption that $s_i$ is identical across all analysts.

Gu (2004) relaxes Barron et al.’s (1998) assumption that all analysts have identical accuracy of private information and provides the following generalized measures of $h$ and $s_i$:
where N is total number of analysts; Var(FE) is variance of the mean forecast error; and DISP is expectation of dispersion (sample variance) of the N forecasts. The relaxation of the assumption of equal accuracy of private information is particularly relevant in our context. Prior studies show that forecasts of nonindependent analysts are more accurate than those of independent analysts. Since public information is, by definition, identical for all, any difference in accuracy must be caused by a difference in the accuracy of private information. Thus, it is problematic to assume that independent and nonindependent analysts have identical accuracy of private information.

Note that total variance of error in an individual forecast $F_i$, $\text{Var}(\text{FE}_i) = 1/(h+s_i)$, can be estimated by observed squared forecast error $\text{FE}_i^2 = (A - F_i)^2$. The inverse of the absolute forecast error, $1/|A - F_i|$, provides an estimate of the square root of $h+s_i$, or total accuracy of the analyst. Measures of $h$ and $s_i$ are the direct decomposition of this total accuracy. Our second total accuracy measure ACCY2, or $1/|A - F_i|$ averaged across analysts, is an aggregate of individual total accuracies. While $h$ is the same for all analysts, we can similarly aggregate (average) $s_i$ across analysts and thus obtain a decomposition of total accuracy ACCY2.

Although Var(FE) and DISP in the $h$ measure are in expectations, we can use their observed realizations as their proxies and obtain estimates of $h$ (and $s_i$). In particular, we can use squared error in the mean forecast $(A - \Sigma_i F_i/N)^2$ to replace Var(FE) and sample variance of the N forecasts $[\Sigma_i(F_i - \Sigma_i F_i/N)^2]/(N-1)$ to replace DISP in the expression for $h$.

Estimation of $h$ and $s_i$ imposes additional conditions on our sample. In particular, there must be at least two forecasts available for a firm quarter to have enough degree of freedom.
for measuring forecast dispersion. There must also be at least two forecasts that are not exactly equal to actual earnings (zero forecast errors); otherwise both the denominator and numerator of $h$ will be zero. Following Gu (2004), we make several further treatments of the empirical estimates of $h$ and $s_i$ since these estimates use observed realizations instead of expectations as in the theoretical constructs. First, although $h$ and $s_i$ are positive theoretically, empirical estimates can be negative. In this case, we assume they take a value of zero (i.e., no public or private information). Second, when a forecast error is zero, $s_i$ will be infinity. In this case, we assume that it takes a value that is twice as large as the maximum of the finite measures from the remaining forecasts. Third, since $h$ and $s_i$ are skewed to the right, we report our results based on square roots of these measures, $H = \sqrt{h}$, $S_i = \sqrt{s_i}$. We use $S_{NI}$ and $S_{IND}$ to denote the across-analyst mean of $S_i$ for nonindependent and independent analysts, respectively. Finally, to mitigate the effect of outliers, for our second matched sample we remove observation in the highest 1% of any of the $H$, $S_{NI}$ and $S_{IND}$ measures.

2.3. Empirical Results

2.3.1. Nonindependent vs. independent analysts

We first confirm prior findings that forecasts of nonindependent analysts are less optimistically biased and more accurate than those of independent analysts. To do this, we consider only those firm quarters simultaneously followed by independent and nonindependent analysts ($IND = 1$) from our two matched samples. This allows us to control for any firm specific characteristics.

The results are reported in Table 2-3. For the larger sample in Panel A, the mean (median) forecast error by nonindependent analysts ($FE_{NI}$) is 0.024 (0.030), whereas the

---

Using raw measures of $H$ and $S_i$ without taking the square roots or measuring ACCY2 by the mean of the inverse of squared (rather than absolute) errors does not affect our results qualitatively.
mean (median) forecast error by independent analysts (FE_IND) is 0.002 (0.026). The positive mean forecast errors suggest that both independent and nonindependent analysts are on average pessimistic rather than optimistic in our sample. More importantly, the comparison between independent and nonindependent analysts indicates that forecasts of nonindependent analysts are more pessimistic. This ordering is consistent with prior findings that forecasts of nonindependent analysts are less optimistic. The mean paired differences in forecast errors are significant at the 0.01 level. For forecast accuracy, the mean (median) ACCY1_NI for nonindependent analysts is -0.235 (-0.091), which is significantly higher than the mean (median) ACCY1_IND of -0.269 (-0.105) for independent analysts. Similarly, the mean (median) ACCY2_NI is 15.855 (10.339), again significantly higher than the mean (median) ACCY2_IND of 15.175 (8.347). In terms of percentages, forecast accuracy of nonindependent analysts is higher by a median of 16.7% and 7.1% for the two accuracy measures. As we discuss before, the first measure yields larger differences partly because it does not adjust for number of forecasts included in the measure. Table 2-3 shows that the vast majority of firms have only one independent analyst (mean 1.03 and median 1), whereas nonindependent analysts are more numerous (mean 5.44 and median 4).

The results on forecast bias and accuracy for the smaller sample in Panel B are qualitatively similar. Overall, these results are consistent with prior findings that forecasts of nonindependent analysts are more pessimistic/less optimistic and more accurate than those of independent analysts.

---

8 The positive mean forecast error is due to our removal of extreme observations in the top and bottom 1% of forecast errors. If the outliers were retained, the mean forecast errors would be negative, consistent with forecast optimism. Abarbanell and Lehavy (2003) similarly show that negative mean forecast errors are driven by a few extreme observations in the left tail and would disappear if outliers were removed.

9 Since the denominator is small for some quarters, the mean of the percentages is very large and not used.
2.3.2. The disciplining effect of independent analysts

2.3.2.1. Univariate results

Our main prediction is that the role of independent analysts is not necessarily to provide more accurate or less biased forecasts by themselves, but to discipline the behavior of nonindependent analysts and make their forecasts better. This is tested by comparing the forecast error and forecast accuracy of nonindependent analysts in the presence of independent analysts (IND = 1) and in the absence of independent analysts (IND = 0) based on the matched samples. The results are reported in Table 2-4.

In Panel A for Matched Sample 1, mean (median) forecast error for all analysts (FE_ALL) is 0.019 (0.029) when independent analysts are following the firm and 0.046 (0.034) when independent analysts are not. The differences are significant at the 0.01 level. The reduction in forecast bias with IND = 1 could be because independent analysts with less biased forecasts (see Table 2-3) are joining the forecasting, or because nonindependent analysts become less biased. When only nonindependent analysts are considered, the mean (median) forecast error (FE_NI) is 0.024 (0.030) with IND = 1, significantly smaller than the mean (median) forecast error of 0.046 (0.034) with IND = 0. Thus, it appears that nonindependent analysts become less biased in the presence of independent analysts, contributing to the smaller bias in the overall consensus forecast.

Improvements in forecast accuracy related to independent analyst following are also observed. Mean (median) ACCY1_ALL for all analysts is -0.233 (-0.091) when independent analysts are following the firms, significantly higher than the mean (median) of -0.275 (-0.098) when independent analysts are not following the firms. Results for ACCY2_ALL are similar. Table 2-3 indicates that such improvement in forecast accuracy should not be attributable to the quality of independent analyst forecasts since their forecast accuracy is worse than that of
nonindependent analyst forecasts. Rather, the improvement should be attributable to the higher accuracy of forecasts of nonindependent analysts in the presence of independent analysts. The results are consistent with this argument. Mean (median) ACCY1_NI is -0.235 (-0.091) for IND = 1 and -0.275 (-0.098) for IND = 0. Similarly, ACCY2_NI has a mean (median) of 15.855 (10.339) for IND = 1, as opposed to 14.482 (8.854) for IND = 0. The differences are all significant at the 0.01 level. In terms of percentages, the presence of independent analysts increases ACCY1_NI by a median of 25.4% and ACCY2_NI by a median of 13.5%.

Since decomposition of total accuracy into accuracies of public and private information is conducted for Matched Sample 2, we want to make sure that the results documented for the larger sample apply equally to the smaller sample and are not driven by sampling differences. Panel B indicates that the results for Matched Sample 2 are indeed consistent. We do not discuss them in detail here. Overall, we conclude that there is a significant disciplining effect of independent analysts on nonindependent analysts. The presence of independent analysts makes forecasts of nonindependent analysts less biased and more accurate, leading to an improvement in the overall consensus forecast.

2.3.2.2. Regression results

In Panels A and B of Table 2-4, we also provide information on some other variables. We discuss those in Panel A for Match Sample 1 in detail here. Firm size (SIZE), measured by the market capitalization at the beginning of the quarter, is similar between IND = 0 and IND = 1 quarters. This is not surprising given our matching criteria. There are, however, significantly more analysts when independent analysts are present than when they are not.

The mean (median) number of analyst following (N) is 6.5 (5.0) with IND = 1, and 4.7 (3.0) with IND = 0. Note that the majority of firm quarters have only one independent analyst
(Table 2-3). Thus, even if we do not count independent analysts, there are still more nonindependent analysts ($N_{NI}$) when independent analysts are present. Forecast horizon ($HORIZON$ and $HORIZON_{NI}$ for all and nonindependent analysts), measured as days from the forecast date to earnings announcement averaged across analysts, is slightly shorter when independent analysts are following the firm. Average experience of all analysts ($EXP$), measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across analysts, is slightly shorter when independent analysts are present. But experience of nonindependent analysts ($EXP_{NI}$) is slightly longer. Prior studies find that these variables are related to forecast bias and forecast accuracy (e.g., Kang et al., 1994; Lim, 2001; Jacob et al., 1999).

To make sure that the forecast performance improvement in the presence of independent analysts is driven by the disciplining effect of independent analysts rather than the above factors, we pool observations in our matched sample and run regressions based on the following model:

$$\text{Forecast Performance}_{i} = b_0 + b_1 \text{IND} + b_2 \text{LGSIZE} + b_3 \text{LGN} + b_4 HORIZON_{(-NI)} + b_5 \text{EXP}_{(-NI)} + \sum_k \lambda_k Q_k + \sum_m \rho_m Y_{rm} + \epsilon$$  \hspace{1cm} (2.1)

Logarithm of firm size (LGSIZE) and logarithm of number of analysts following (LGN) are used to mitigate the effect of their skewed distribution. We also include dummy variables $Q_k$ for fiscal quarters ($k = 2, 3$ and $4$) and $Y_{rm}$ for fiscal years to control for fixed quarter and year effects. We separately run the regressions for all analysts and nonindependent analysts, and correspondingly use explanatory variables measured for each group.\(^{10}\)

The regression results are reported in Panels C and D of Table 2-4. For brevity, coefficients on yearly dummies are not reported. For Matched Sample 1 in Panel C, the

\(^{10}\) We use total number of analysts (LGN) in the regression for nonindependent analysts since it may capture an aspect of the overall forecasting environment such as degree of information competition. Using number of nonindependent analysts does not change the results qualitatively.
coefficient $b_1$ is significantly negative for forecast bias FE\_ALL and significantly positive for both forecast accuracy measures ACCY1\_ALL and ACCY2\_ALL. This suggests that the overall consensus forecasts of all analysts become less biased and more accurate when independent analysts are present. When forecasts of only nonindependent analysts are considered, the coefficient $b_1$ is again significantly negative for forecast bias FE\_NI (-0.019, p < 0.1) and significantly positive for both forecast accuracy measures ACCY1\_NI and ACCY2\_NI (0.041 and 1.123, p < 0.01). The results for Matched Sample 2 in Panel D are qualitatively similar. Thus, even after controlling for other variables, the disciplining effect of independent analysts remains highly significant and consistent with the univariate results.

2.3.3. Sources of forecast accuracy improvement: Public vs. private information

To further examine the sources of the forecast accuracy improvement by nonindependent analysts in the presence of independent analysts, we decompose the total accuracy ACCY2\_NI into accuracy of information public to all analysts and accuracy of information private to individual analysts. This is done for Matched Sample 2 where the empirical decomposition is possible. If the improvement is due to independent analysts’ selective following of firm quarters with easy-to-forecast earnings, we expect that the accuracy of public information that they have access to is higher when they are present. If the improvement is due to the disciplining effect of independent analysts, we expect that the accuracy of private information of nonindependent analysts is higher.

The results are reported in Table 2-5. In Panel A, the mean (median) accuracy of public information (H) is 6.306 (3.773) when independent analysts are following the firm quarter and 6.654 (3.895) when they are not. The differences are significant in the mean but not in the median. Thus, instead of choosing to follow firm quarters with more public information to make earnings more predictable, there is some weak evidence that independent
analysts choose to follow firm quarters with less public information. This is reasonable since they are likely to contribute more in such situations. On the other hand, the mean (median) accuracy of private information of nonindependent analysts (S_NI) is 8.749 (5.084) when independent analysts are present and 7.322 (3.734) when independent analysts are absent. The differences are significant at the 0.01 level. The median percentage difference is 20.9%.\textsuperscript{11}

Thus, the improvement in total forecast accuracy of nonindependent analysts is attributable only to increased accuracy of their private information. This result is further confirmed by the regression results in Panel B after controlling for other variables. The coefficient $b_1$ on IND is insignificant when H is the dependent variable, but significantly positive when S_NI is the dependent variable (0.879, p < 0.01).

It can also be noted from Panel A that accuracy of private information of independent analysts is, as expected, lower than that of nonindependent analysts when both follow the same quarters. However, the difference is not obvious if we compare the accuracy of private information of independent analysts with that of nonindependent analysts in the absence of independent analysts (mean 7.902 and median 2.412 vs. mean 7.332 and median 3.734). It appears that the information advantage of nonindependent analysts over independent analysts takes effect only if independent analysts are joining the forecasting.

As we discuss in the introduction, there could be two explanations for the higher accuracy of private information of nonindependent analysts in the presence of independent analysts. First, for a given level of private information, they may build less bias into their forecasts since deviation from forecasts of independent analysts is likely to reveal their bias related to their private incentives. This would result in improved accuracy of private information measured by us. Second, they may spend more resources on private information

\textsuperscript{11} Calculation of percentage changes excludes observations with a zero value of S_NI before the median is taken.
acquisition to maintain their informational advantage over independent analysts. Although we are not able to differentiate these two possibilities, both are consistent with the disciplining effect of independent analysts.

2.3.4. Sensitivity tests

2.3.4.1. Analysts from the 12 investment banks targeted in the Global Settlement

Given the attention that the 12 investment banks targeted in the Global Settlement have received and the magnitude of financial penalties they agreed to pay, analysts from these banks were likely to have the most severe conflicts of interest during our sample period (before the Global Settlement). It is interesting to examine whether independent analysts exerted any disciplining effect on these analysts. Focusing on these analysts also mitigates the concern that some nonindependent analysts as we define them may not necessarily be nonindependent (for example, analysts from certain pure brokerage firms not in direct competition with other firms).

We repeat the earlier analysis but calculate forecast performance measures for nonindependent analysts using forecasts of analysts from the 12 investment banks. For brevity, we do not report the univariate results but only report the regression results in Table 2-6 based on Match Sample 2 where accuracies of public and private information can be calculated. The sample is reduced to 2,744 pairs. For forecast bias FE_NI, the coefficient on IND is negative (-0.015) but insignificant. For the two total forecast accuracy measures ACCY1_NI and ACCY2_NI, the coefficients on IND are both positive and highly significant (0.029 and 2.955, p < 0.01), suggesting that total forecast accuracy is significantly increased in the presence of independent analysts. When total forecast accuracy is decomposed into accuracies of public information (H) and private information (S_NI), IND is unrelated to H but positively related to S_NI, again suggesting that the improvement in total forecast accuracy is due to improved
accuracy of private information. Note that the coefficients on IND are 2.955 for ACCY2_NI and 1.385 for S_NI, much larger than the corresponding coefficients of 0.918 and 0.879 reported in Tables 3 and 4 for all nonindependent analysts. Thus, the disciplining effect on forecast accuracy of analysts from these 12 investment banks appears to be larger than the average nonindependent analysts.

2.3.4.2. Holding nonindependent analysts constant

In our earlier tests nonindependent analysts in the presence of independent analysts may not necessarily be the same nonindependent analysts in the absence of independent analysts. This itself does not go against the general disciplining effect of independent analysts on nonindependent analysts. To make sure that the same nonindependent analysts would be affected by the presence of independent analysts, we repeat the analysis by using the subset of forecasts by the same nonindependent analysts following both the matching and matched quarters. The results based on a reduced sample of 3,665 pairs are reported in Table 2-7. The disciplining effect of independent analysts remains highly significant on forecast accuracy of nonindependent analysts, though not on their forecast bias.

2.3.4.3. Regulation Fair Disclosure and private information of nonindependent analysts

One of the possible ways for nonindependent analysts to improve the accuracy of their private information in the presence of independent analysts is through increased private communication with management. The preferential access to management’s private information is possible because of the investment banking affiliations they may have. Alternatively, nonindependent analysts could improve their accuracy through increased analytical skills and efforts. Regulation Fair Disclosure (Reg FD), introduced in October 2000, prohibits management from disclosing private information to only selective groups. Thus, if preferential access to management’s private information is the only source of improved
accuracy of private information of nonindependent analysts, we should not observe any such improvement after Reg FD.

We re-run the regressions based on the earlier model but include an additional interaction variable between IND and the dummy for the post-Reg FD period. The coefficient on IND captures the disciplining effect in the pre-Reg FD period and the coefficient on the interaction variable captures the incremental disciplining effect in the post-Reg FD period. The results are reported in Table 2-8. For forecast bias, the coefficients on both IND and the interaction variable are negative as expected but insignificant. The disciplining effect on forecast bias appears small. For total forecast accuracy, the coefficient on IND is positive and significant for both ACCY1_NI and ACCY2_NI. The coefficient on the interaction variable is also significantly positive for both measures. Thus, while total forecast accuracy of nonindependent analysts improves in the presence of independent analysts before Reg FD, the improvement becomes even more pronounced after Reg FD. For accuracy of public information, neither IND nor the interaction variable is significant. Thus, there does not appear to be any evidence that independent analysts choose to follow firm quarters with more public information in either period. On the other hand, the coefficients on both IND and the interaction variable are significantly positive for accuracy of private information, suggesting that improved accuracy of private information in the presence of independent analysts applies to the pre-Reg FD period and even more so to the post-Reg FD period. This is broadly consistent with the findings of Gu (2004) that Reg FD led to increased acquisition of private information by analysts. The disciplining effect we are interested in does not appear to be driven by nonindependent analysts’ increased private communication with managers which is prohibited after Reg FD.
2.3.4.4. Forecasting sequence and presence of independent analysts

We determine the presence of independent analysts by at least one forecast by independent analysts. We find that the timing of forecasts is rather random. Nearly half of the forecasts of nonindependent analysts are made before, and another half are made after, the forecasts of independent analysts. It is possible that some nonindependent analysts are unaware of the presence of independent analysts if their forecasts are made earlier. Although this would introduce noise into our measure and bias against our findings of the disciplining effect of independent analysis, we conduct an additional check by using only those forecasts made by nonindependent analysts later than the first (and in most cases the only) independent analyst forecast. This reduces Match Sample 2 to 3,195 pairs. The regressions results are reported in Table 2-9. While the disciplining effect on forecast bias is insignificant, significant disciplining effect on forecast accuracies remains.

2.3.4.5. Additional matching for IND = 0 quarters

To provide further evidence that any difference in forecast bias and accuracy we document is attributable to the presence of independent analysts and not to random sampling errors, we match those firm quarters followed only by nonindependent analysts (IND = 0) to other firm quarters also followed only by nonindependent analysts. The criteria for matching are the same as before, with the match being the closest quarter from the same fiscal quarters of the same firm within three years. This yields a sample 2,893 pairs. Since there is no independent analyst involved, we expect no difference in forecast performance between the two groups of firms.

We designate the indicator variable IND = 1 for the matched quarters and IND = 0 for the matching quarters. We run the regressions and report the results in Table 2-10. For all the forecast performance measures, the coefficients on IND are insignificant. There does not
appear to be any difference in forecast quality between the two groups. This suggests that the significance of IND in our earlier results is unlikely caused by random sampling errors. Rather, it is likely to be driven by “real” disciplining effect of independent analysts.

2.4. Chapter Summary

The loss of independence of financial analysts due to investment banking affiliations has raised considerable controversy in the investment community in recent years. It is widely believed that independence is a valuable trait of analysts. However, academic studies have generally failed to find that earnings forecasts of independent analysts are any better than those of nonindependent analysts. This chapter examines a role of independent analysts that has received little attention before. We show that while independent analysts may not provide more accurate or less biased forecasts by themselves, they add value to the forecasting environment by disciplining the behavior of nonindependent analysts. Relative to cases where independent analysts are not following the firms, the forecast quality of nonindependent analysts is significantly improved when independent analysts are following the same firms. In particular, their forecast accuracy is improved by 13.5% to 25.4% on average. Moreover, the increase in forecast accuracy does not appear to be attributable to independent analysts’ selective following of firms with more predictable earnings due to more public information. Rather, it is attributable to the higher quality of nonindependent analysts’ private information. There is also some weak evidence that nonindependent analysts’ forecasts become less biased in the presence of independent analysts.
Chapter 3

Evidence from the Market Association

3.1. Introduction

In this chapter we use the strength of association between abnormal stock returns and forecast errors as our forecast evaluation criterion and examine the disciplining role of independent analysts and the superiority of their forecasts. The idea about the market association criterion is that forecasts that are more aligned with market expectations yield forecast errors that better capture the earnings surprises to the market. As a result, a stronger association between abnormal stock returns and forecast errors, or earnings response coefficient (ERC) (e.g., Brown et al., 1987b), is expected.

Previous studies find that the accuracy criterion and the market association criterion do not always produce consistent results. For example, when comparing analyst forecasts with mechanical forecasts from time-series models, most studies find that analysts are more accurate (Brown et al., 1987a; O’Brien, 1988). However, Brown et al. (1987b) find a stronger market association for analyst forecast errors, whereas O’Brien (1988) finds a stronger market association for time-series forecast errors.

In our context, it is similarly unclear whether the two criteria would lead to the same conclusions. Analysts with investment banking ties may expend more effort in information gathering or have better access to management’s private information that enhances accuracy. However, they may also be overly guided by management due to an interest in maintaining the banking relationship. It is not clear whether their information is available to, or regarded as credible or value-relevant by, the investors. Independent analysts may participate less in the guidance game and have less preferred information access. But the market may perceive them
to be more objective and stand by their beliefs. If forecasts by independent analysts are closer to *ex ante* market expectations, although less accurate *ex post*, the ERC for independent analysts will be higher than that for nonindependent analysts.

The influence on forecasts due to investment banking ties is precisely what the Global Settlement intends to reduce or eliminate. If enhanced analyst independence increases the forecast quality in terms of representing market expectations, we expect that the market association criterion will capture the superiority of independent analysts to nonindependent analysts that may not be captured by the accuracy and bias criterion. Similarly, for the disciplining effect on independent analysts, we expect a stronger market association for forecast errors by nonindependent analysts when independent analysts are following the same firms compared to when they are not.

### 3.2. Sample Selection, Research Design and Descriptive Statistics

#### 3.2.1. Sample selection

Following the first two steps of the sample selection process discussed in Chapter 2, we gather analyst forecasts of quarterly earnings from the First Call Historical Database and the types of analyst firms from Nelson’s Directory of Investment Research from 1993 to 2002, with 141,954 firm quarters with at least one forecast made by an analyst firm identifiable as independent or nonindependent.

We obtain stock prices and returns from CRSP. We measure abnormal returns for a firm quarter over two windows (*BHAR90* and *BHAR3*): the long window consists of 90 days (or roughly 63 trading days) up to one day after the earnings announcement; and the short window consists of three trading days around the earnings announcement. We use the size-adjusted buy-and-hold abnormal returns calculated as the difference between the buy-and-
hold return to a stock and the buy-and-hold return to the portfolio of firms in the same size decile over the relevant windows. Using daily cumulative (summed) abnormal returns produces the same qualitative results (not reported). From CRSP, we also obtain firm SIZE (market capitalization at the beginning of the quarter) and BETA (Scholes-Williams beta as provided by CRSP). Requirement of data availability from CRSP reduces our sample to 97,202 firm quarters.

Book value of equity from Compustat (item #60) is used in calculating two control variables: market-to-book ratio (MB), and growth in book value of equity (GROWTH) measured as the average percentage change in book value of equity over the prior four quarters. A total of 24,105 firm quarters are lost after merging with Compustat data. We also calculate two control variables based on the time series of actual earnings reported by First Call for each firm during the entire sample period: earnings volatility (STD ROE) calculated as the standard deviation of return-on-equity, and earnings persistence (PSST) estimated as the autoregressive coefficient from the Foster (1977) model. We require a minimum of 20 quarterly observations for a firm to calculate these two variables.

To allow for cross-firm comparability, all earnings and forecasts are scaled by the stock price at the beginning of the quarter, adjusted for stock splits and dividends. To mitigate the effect of outliers, we remove observations in the top and bottom extreme 1% of abnormal returns and price-deflated forecast errors based on the consensus (mean) of all forecasts. This leaves us a sample of 69,192 firm quarters, among which 882 are followed exclusively by independent analysts, 6,999 followed by both nonindependent and independent analysts (IND = 1), and 61,311 followed exclusively by nonindependent analysts (IND = 0).

---

12 In particular, PSST is the coefficient \( b \) estimate in \( \Delta x_t = a + b \Delta x_{t-1} + \epsilon_t \), where \( x_t \) is the earnings of quarter \( t \) and \( \Delta \) is the seasonal difference operator.
When testing the disciplining role, we use the same matching procedure as that of Chapter 2 to get the paired sample based on the new dataset. For each firm quarter $t$ in the 6,999 quarters ($\text{IND} = 1$), we select, if available, a quarter from the same fiscal quarters of the same firm within three years surrounding $t$ with no independent analyst following ($\text{IND} = 0$). The matched sample yields a total of 4,173 pairs, or 8,346 firm quarters. Relative to the total 6,999 firm quarters available for matching, the matched sample remains reasonably large.

When testing the superiority role, we base our analysis on the 6,999 firm quarters followed by both independent and nonindependent analysts.

Table 3-1 summarizes our sample selection process described above and Table 3-2 provides the time profile of our sample. Similar to Table 2-2, from Panel A of Table 3-2 we observe that although firms followed by independent analysts are relatively few (1.3% exclusively by independent analysts and 10.1% by both independent and nonindependent analysts), they gradually increase over the sample years (from 0.2% and 2.9% in 1993 to 1.8% and 15.8% in 2002). This may reflect the increased number of independent firms and/or expanded coverage of independent firms by First Call. On the other hand, firms followed only by nonindependent analysts in our final sample have been relatively stable over the years. Given the large number of firm quarters followed only by nonindependent analysts, their firm characteristics could be quite different from those followed by independent analysts and may not be fully controlled for. Our matched sample is intended to mitigate this problem.

In Panel B of Table 3-2, firm quarters are paired so that we have the same number of observations (4,173) for the two groups with and without independent analyst following. Although the number of observations with independent analysts gradually increases, that of the matched sample without independent analysts does not because the match is obtained from the surrounding years of the base sample. For example, the match for a firm quarter in
1995 could be in 1993 for the same firm. We also classify firm quarters into good news and bad news groups based on the consensus forecast errors. The number of good news firm quarters more than doubles that of bad news ones for both groups even though matching is not based on forecast errors.

### 3.2.2. Research design

The research design of the study is straightforward. Given two (consensus) forecasts, we expect a stronger association between abnormal returns ($BHAR$) and the forecast error ($FE$) in the forecast that is more aligned with market expectation of earnings. This would be captured by a higher ERC on the forecast error. To test if the presence of independent analysts helps better align the consensus forecasts with market expectations, we use the following model:

$$BHAR_{it} = \alpha_0 + \alpha_1 FE_{it} + \alpha_2 FE_{it} \times IND_{it} + \sum_j \beta_j FE_{it} \times Controls_{it} + \phi FE_{-1, it}$$

$$+ \sum_k \lambda_k Q_k + \sum_m \rho_m Yr_m + \sum_n \theta_n INDUSTRY_{it} + \epsilon_{it}$$

(3.1)

where subscripts $i$ and $t$ refer to firm $i$ in quarter $t$. This model is applied to the matched sample with firm quarters followed by both independent and nonindependent variables (IND = 1) and firm quarters followed only by nonindependent analysts (IND = 0). The coefficient $\alpha_1$ measures the ERC when there are no independent analysts and $\alpha_2$ measures the incremental ERC due to the presence of independent analysts. If independent analysts help improve the consensus forecasts, we expect $\alpha_2 > 0$. Otherwise we expect $\alpha_2$ to be zero or even negative. We use this model for consensus forecast errors by all analysts to determine whether independent analysts bring in an overall improvement. We also apply the model to consensus forecast errors by only nonindependent analysts to examine if the presence of independent analysts disciplines the nonindependent analysts to better align with market expectations. The model can be easily modified by separating forecast errors into good news ($FE \geq 0$) and bad
news ($FE < 0$) to evaluate the effects of independent analysts across the two types of news. Since nonindependent analysts are slower to update bad news than good news (O’Brien et al., 2005), we expect the effect of independent analysts to be stronger for bad news.

We use two windows for the dependent variable $BHAR$. Prior studies (e.g., Ball and Brown, 1968; Collins and Kothari, 1989) show that the long window often produces stronger associations between abnormal returns and earnings surprises or higher ERCs. Following the standard practice in the ERC literature, we control for a number of factors that are shown to be related to the ERC. In particular, we control for $SIZE$, $BETA$, $MB$ (market-to-book), $GROWTH$ (growth in book value of equity), $STD\_ROE$ (earnings volatility), and $PSSST$ (earnings persistence). Measurement of these variables is discussed earlier. In addition, we also control for total number of analysts following ($FOLLOW$) since it reflects the overall information environment and there is evidence (see below) that analyst following is higher with $IND = 1$ than with $IND = 0$. Because of the skewness of $SIZE$ and $FOLLOW$, we use the logarithm of these two variables $LGSIZE$ and $LGFOLLOW$ in the regressions. We separately include lagged forecast errors $FE_{-1}$ to control for post-earnings-announcement-drift. We also control for fixed fiscal quarter, year and industry effects with quarterly dummies $Q$, yearly dummies $Yr$ and industry dummies $INDUSTRY$.\[^{13}\]

For firm quarters that are followed simultaneously by independent and nonindependent analysts, we directly compare the relative superiority of their forecasts based on the following simpler model:

$$BHAR_{it} = \alpha_0 + \alpha_1 FE_{it} + \sum_k \lambda_k Q_k + \sum_m \rho_m Yr_m + \sum_n \theta_n INDUSTRY_n + \epsilon_{it}$$ (3.2)

\[^{13}\]Our classification of industries is based on Barth et al. (2001). Since some industries in Barth et al. (2001) have about one hundred or fewer observations in our sample, we form 12 industries: Mining & Construction (SIC 1000-1999, excluding 1300-1399), Textiles & Printing (2200-2780), Chemicals (2800-2824, 2840-2899), Pharmaceuticals (2830-2836), Extractive (2900-2000, 1300-1399), Durable Manufacturers (3000-3999, excluding 3570-3579 and 3670-3679), Computers (7370-7379, 3570-3579, 3670-3679), Transportation (4000-4899), Retail (5000-5999), Financial institutions (6000-6999), Services (7000-8999, excluding 7370-7379), and all remaining firms.
The model is applied separately to the forecast errors by independent analysts and by nonindependent analysts with the two ERCs compared. Since the set of firm quarters is held constant for the two groups of analysts, controlling for firm-specific characteristics related to the ERCs is not an issue. Because forecast errors for the same quarter usually differ between the two groups of analysts, an additional reason for not including the interacting control variables is that the two different forecast errors interacting with the control variables would differ in capturing the incremental ERCs associated with the control variables. Then comparing the left-over coefficients on \( FE \) itself would not be meaningful.

Finally, we use the following model to obtain a measure of the incremental contribution of forecasts by a group of analysts to the consensus forecasts by the remaining analysts:

\[
BHAR_{it} = \beta_0 + \beta_1 F1_{it} + \beta_2 (F1_{it} - F2_{it}) + \sum_{k} \lambda_k Q_k + \sum_{m} \rho_m Y_{im} + \sum_{n} \theta_n INDUSTRY_{in} + \epsilon_{it} \tag{3.3}
\]

where \( F2 \) is the consensus forecast by analysts whose incremental contribution is under study, and \( F1 \) and \( FE1 \) are the consensus forecast and forecast error by the remaining analysts. The coefficient \( \beta_2 \) captures the incremental contribution of forecast by a group of analysts when it differs from the forecast by the other analysts. To see this, note the two extreme cases: If the forecast by other analysts, \( F1 \), is perfectly aligned with market expectations, \( FE1 \) fully captures the earnings surprise to the market and any deviation of \( F2 \) from \( F1 \) would not be useful; then \( \beta_2 = 0 \). However, if the forecast by the group of analysts under study, \( F2 \), is perfectly aligned with market expectations, its deviation from \( F1 \) is crucial in adjusting the forecast to market expectations. In this case, \( \beta_2 = \beta_1 \), so that \( FE2 \), the forecast error by the group of analysts under study, fully captures the earnings surprise. That is, \( \beta_1 FE1 + \beta_2 (F1 - F2) = \beta_1 (Actual - F1) + \beta_2 (F1 - F2) = \beta_1 (Actual - F2) = \beta_1 FE2 \). In between 0 and \( \beta_1 \), the coefficient \( \beta_2 \) measures the incremental contribution of forecasts by the group of analysts.
under study to capturing market expectations.\textsuperscript{14} Model 3.3 allows us to compare the incremental contribution of forecasts made by independent analysts to those made by nonindependent analysts.

3.2.3. Descriptive statistics

Table 3-3 provides the descriptive statistics for the matched sample. Panel A gives the consensus (mean) forecast errors (\(FE\)) and the level of analyst following (\(FOLLOW\)). Both the mean and median \(FE\) for \(IND = 0\) are significantly higher than for \(IND = 1\).\textsuperscript{15} This suggests that the consensus forecasts are less pessimistic when independent analysts are present than when they are not, consistent with the results in Table 2-4. Within the group where both independent and nonindependent analysts follow the firms (\(IND = 1\)), we separate the forecasts of nonindependent analysts from those of independent analysts and calculate their separate forecast errors \(FE_{NI}\) and \(FE_{IND}\). Their paired differences (mean 0.00018 and median 0.00000) suggest that when both groups of analysts follow a firm, nonindependent analysts are more pessimistic/less optimistic about the firm than independent analysts, consistent with the findings in Table 2-4 and Jacob et al. (2005). Since \(FE\) for \(IND = 0\) and \(FE_{NI}\) for \(IND = 1\) are both forecast errors by nonindependent analysts, their paired differences indicate whether the presence of independent analysts has any effect on nonindependent analysts. We find that both the mean and median \(FE_{NI}\) for \(IND = 1\) are significantly smaller than \(FE\) for \(IND = 0\). Thus, nonindependent analysts become less

\textsuperscript{14} One can equivalently re-write Model 3.3 as \(BHAR = \beta_0 + \beta_1 FE1 + \beta_2 (FE1 - FE2) + Controls + \varepsilon = \beta_0 + (\beta_1 - \beta_2) FE1 + \beta_2 FE2 + Controls + \varepsilon\), i.e., a relative weighting of the two earnings surprises. If forecast error \(FE1\) perfectly captures the surprise to the market, we would have \(\beta_2 = 0\). If forecast error \(FE2\) does, then \(\beta_1 - \beta_2 = 0\), or \(\beta_2 = \beta_1\). Thus, in between 0 and \(\beta_1\), coefficient \(\beta_2\) measures the incremental information contained in \(FE2\).

\textsuperscript{15} Mean \(FE\) is positive due to our deletion of outliers. If outliers of \(FE\) were retained, mean \(FE\) would be negative, consistent with forecast optimism. The relative ordering of \(FE\) in the various comparisons is not affected by the outliers.
pessimistic when independent analysts also follow the firm than when they do not.\textsuperscript{16} With regard to analyst following, the mean (median) number of total analysts is 6.9 (5) when there are both independent and nonindependent analysts (IND = 1). This is significantly higher than the mean (median) of 5.2 (4) when there are only nonindependent analysts (IND = 0). Counting only nonindependent analysts, there are still more analysts for IND = 1 than for IND = 0. For firms followed by both groups of analysts, 97\% have only one independent analyst.

Panel B describes the other variables for the IND = 0 and IND = 1 groups. The two abnormal returns are positive on average, consistent with the results in Table 3-2 that there are more good news firms in our sample than bad news firms. Our sample firms tend to be slightly less risky than an average firm, with a mean $BETA$ of between 0.80 and 0.90. Since we have a matched sample, paired difference for most variables are insignificant, except some weakly significant difference for $SIZE$, $BETA$ and $GROWTH$. $STD\_ROE$ and $PSST$ are identical between the two groups because only one value is calculated for each firm using all the firm’s observations during the sample period.

Table 3-4 presents the correlation matrix for the variables used in our analysis. Pearson (Spearman) correlations are displayed in the lower (upper) diagonal. IND is negatively correlated with $FE$, consistent with earlier results that consensus forecasts with independent analysts are less pessimistic than those without. Consistent with Table 3-3, $LGSIZE$ and $LGFOLLOW$ are significantly correlated with IND, suggesting that our matched sample approach does not fully control away the differences between paired firm quarters. Therefore, including these variables in the regressions controls not only for cross-firm differences but also for within-firm cross-quarter differences. A positive correlation between $FE$ and its lag ($FE\_1$) is observed, suggesting autocorrelation of earnings surprises

\textsuperscript{16} Untabulated results indicate that nonindependent analysts indeed have better forecast accuracy than independent analysts, consistent with prior studies. The mean absolute forecast errors are 0.00198 and 0.00234 for independent and nonindependent analysts, respectively, and the difference is significant at the 0.01 level.
(Abarbanell and Bernard, 1992). Abnormal returns are positively correlated with $FE$ as expected. The positive correlation between abnormal returns and $FE_1$ is consistent with post earnings announcement drift. $MB$ and $GROWTH$ are positively correlated in Spearman correlations, but the small magnitude of the correlation coefficient (0.251) suggests that they capture different dimensions of firm growth. Similarly, each of $STD_ROE$ and $PSST$ appears to incrementally provide information about earning persistence.

3.3. Empirical Results

3.3.1. The overall effect of independent analysts

We first examine the overall effect of independent analysts on the association between abnormal returns and consensus forecast errors by all analysts. If independent analysts and nonindependent analysts are not different from each other, the presence of independent analysts should not have any effect on the ERC. If the presence of independent analysts better aligns the consensus forecast with market expectations, we expect to see an incremental ERC in the presence of independent analysts. The regression results based on Model 3.1 are reported in Table 3-5. For brevity, coefficients on quarterly, yearly and industry dummies are not reported. All statistical significance is based on two-tailed tests unless stated otherwise.

We consider the base case without the control variables in columns 1 and 3. For the long window in column 1 in Panel A, the coefficient on $FE$ is 7.636 and that on $FE \times IND$ is 2.933, both significant at the 0.01 level. This indicates that, for a given earnings surprise, the presence of independent analysts would increase the ERC by nearly 40%. For the short window in column 3, the coefficient on the interaction variable is insignificant. The economically and statistically significant effect of independent analysts on the long-window ERC is consistent with prior findings that the long window is likely to better capture the news
effect of earnings relative to market expectations (e.g., Collins and Kothari, 1989). In columns 2 and 4, we add other control variables. The incremental long-window ERC with independent analysts is reduced slightly with the control variables but is still a large and significant 2.064. Table 3-3 indicates that analyst following is larger when independent analysts also follow the firms. Although the coefficient on $FE \times LGFOLLOW$ is significantly positive, the incremental ERC on $FE \times IND$ suggests that not only the number of analysts matters, but the type of analysts also matters.

In Panel B, we further separate the earnings surprises into good news and bad news, with $GOOD$ and $BAD$ as dummies for $FE \geq 0$ and $FE < 0$. Column 1 indicates that the long-window ERC for good news ($FE \times GOOD$) is 11.372 when there are no independent analysts. The incremental ERC with independent analysts is 1.859 and only marginally significant (at the 0.10 level, one-tailed). The incremental effect is little changed with the control variables included in column 2. As expected, the ERC for bad news ($FE \times BAD$) is much smaller than for good news, consistent with the findings of Basu (1997). Without the control variables, the long-window ERC for bad news is 3.878 when there are no independent analysts. The incremental ERC for independent analysts is 4.714 and significant at the 0.01 level, that is, the presence of independent analysts more than doubles the ERC for bad news. With the control variables, the ERC for bad news per se becomes insignificant and appears captured by other variables. The incremental ERC for independent analysts, however, is little affected. For the short-window results in columns 3 and 4, independent analysts do not significantly affect the ERC for either news.

Overall, when both independent and nonindependent analysts follow a firm, the association between long-window abnormal returns and consensus forecast errors is significantly stronger than when only nonindependent analysts follow the same firms. The
incremental effect is especially high when earnings news is bad. We conclude that the presence of independent analysts significantly improves the alignment of consensus forecasts with market expectations, particularly when the consequence of misalignment is potentially more severe and the room for improvement is larger (i.e., in the face of bad news). The consensus forecast errors examined here are by all analysts, independent and nonindependent. The improvement in ERC could be either due to nonindependent analysts becoming more careful in aligning their forecasts with market expectations in the presence of independent analysts (disciplining effect), or due to the individual superiority of independent analysts to nonindependent analysts, or both. We examine these two sources of improvement in the following subsections.

3.3.2. The disciplining effect of independent analysts

To explore whether the presence of independent analysts has a disciplining effect on nonindependent analysts, for group IND = 1 (firms followed by both independent and nonindependent analysts) we use forecasts only by nonindependent analysts to calculate the consensus and re-run the regressions in Table 3-5. Since forecasts for group IND = 0 are all by nonindependent analysts, the regressions allow use to compare the ERCs for nonindependent analysts with and without the presence of independent analysts. If nonindependent analysts behave the same regardless, we expect no incremental ERC when independent analysts are present.

Regression results are reported in Table 3-6. Columns 1 and 2 in Panel A indicate that for the long window, the presence of independent analysts significantly increases the ERC for nonindependent analysts by 1.855 (24% increase) without the control variables. With the control variables, the incremental ERC is 0.897 and remains marginally significant (at the 0.06 level, one-tailed). As before, no incremental ERC is found for the short window in
columns 3 and 4. While the presence of independent analysts appears to have a weak effect on nonindependent analysts, it is possible that some nonindependent analysts in the matching quarters are not the same nonindependent analysts in the matched quarters. This itself does not go against our expectations on the general disciplining effect on nonindependent analysts. However, to make sure that the same nonindependent analysts would behave differently in the presence of independent analysts, we use the subset of forecasts by the same nonindependent analysts following both the matching and matched quarters and report the results in columns 5-8. The number of observations (6,372) is smaller because some quarters have no common nonindependent analysts. The results remain qualitatively the same. The incremental ERC of 1.904 represents a 26% increase and is significant at the 0.06 level (one-tailed).

Panel B reports the results with earnings surprises separated into good news and bad news based on the overall consensus forecast. Although the incremental coefficients for good news are mostly insignificant, we find significant incremental effect for bad news in the long window. While the baseline ERCs for bad news in columns 1 and 5 are 3.908 and 2.929 without and with nonindependent analysts constrained to be the same, the incremental ERCs due to the presence of independent analysts are 3.796 and 3.096, respectively, doubling the baseline ERCs. They remain at least marginally significant with the control variables included. Overall, results in Table 3-6 are consistent with the disciplining effect of independent analysts on nonindependent analysts documented in Chapter 2. The effect is most pronounced for bad news, likely consistent with what regulators hope independent analysts to have on nonindependent analysts.

---

\(17\) For over eighty percent of cases, consensus forecast errors by either independent analysts or nonindependent analysts point consistently to the same kind of earnings news. Results remain qualitatively the same if we only use forecast errors by nonindependent analysts to classify news, or if we exclude the few cases with inconsistent earnings news (one indicates good news and the other indicates bad news).
3.3.3. Individual superiority of independent analysts to nonindependent analysts

Independent analysts not only can discipline nonindependent analysts to be better, but also make forecasts by themselves superior to those by nonindependent analysts. To examine this issue, we focus on firm quarters that are simultaneously followed by both independent and nonindependent analysts. These firm quarters themselves constitute a matched sample with independent analysts matched with nonindependent analysts. To maximize the sample size, we use all firm quarters (6,999) followed by both groups of analysts rather than the subset of 4,173 firm quarters with a match followed by only nonindependent analysts, although the latter yields qualitatively similar results. For each firm quarter, we separately calculate the consensus forecast errors by independent analysts ($FE_{IND}$) and nonindependent analysts ($FE_{NI}$) and then examine their associations with abnormal returns based on Model 3.2.

The regression results are reported in columns 1-4 in Panel A of Table 3-7. For the long window the ERC for independent analysts is 6.625 and that for nonindependent analysts is 8.213. The ERCs for the short window are 1.772 and 2.375 respectively. On the surface, it appears that forecasts by nonindependent analysts are superior to those by independent analysts. It is, however, unfair to directly compare the ERCs across independent and nonindependent analysts in this way. Descriptive statistics in Table 3-3 indicate that on average there are six nonindependent analysts and only one independent analyst following a firm. An independent analyst may dominate any individual nonindependent analyst in representing market expectations but is inferior to the aggregation of all nonindependent analysts by the law of large numbers. It is well known that the mean of a sample has a lower variance (closer to the true population mean) than that of an individual observation.

To compare the ERCs on a level playing field, we control for the number of analysts
through the following randomization procedure. For each firm quarter, we first determine the smaller of the number of independent analysts and the number of nonindependent analysts. In nearly all cases (6,937 out of 6,999), this is the number of independent analysts. Then from each group of analysts we randomly draw this number of forecasts and calculate the consensus forecasts. Regressions are run separately for the two sets of forecast errors. The process is repeated 1,000 times and the mean coefficient estimates are reported in columns 5-8 of Table 3-7. In essence, this is the randomization testing strategy described in Noreen (1989). Not only are the ERCs comparable this way, but the distribution of the 1,000 ERCs from randomization can serve as the basis for testing the statistical significance of the difference in the ERCs for independent and nonindependent analysts.

Results in columns 5 and 7 for independent analysts are very close to those reported in columns 1 and 3, since the same forecast errors by independent analysts are used in nearly all the cases. The slight difference is due to the few cases (62 out of 6,999) where independent analysts outnumber nonindependent analysts and a drawing from forecasts by independent analysts has to be made. The marked difference by randomization is that the ERCs for nonindependent analysts is much reduced, from 8.213 in column 2 to 5.551 in column 6 for the long window, and from 2.375 in column 4 to 1.613 in column 8 for the short window. Most notably, the ERCs for independent analysts for both the long and short windows are now larger than the ERCs for nonindependent analysts. Using the distribution of the 1,000 ERCs for nonindependent analysts as the testing basis, the long-window ERC for independent analysts is higher than that by nonindependent analysts by 1.058, or a 20% increase, significant at the 0.01 level. The short-window ERC is higher by 10% and significant at the 0.10 level. Since the dependent variables are the same, we can also compare the $R^2$’s across the regressions. Unlike columns 1-4 where the $R^2$’s for nonindependent analysts are larger than
those for independent analysts, the $R^2$s for independent analysts are larger than those for nonindependent analysts in columns 5-8.

Panel B of Table 3-7 reports the results separately for good news and bad news with similar control for number of analysts. In columns 1-4 for good news, we find that the ERCs for independent analysts in the two windows (5.569 and 1.286) are higher than those for nonindependent firms (4.184 and 1.092) by 33% and 18% and significant at the 0.01 and 0.05 levels, respectively. In columns 5-8 for bad news, the ERC is higher by 24% and significant at 0.05 level for the long window. No significant improvement is observed for the short window. Overall, Table 3-7 suggests that once comparison is made on equal footing, independent analysts dominate nonindependent analysts on the individual basis in aligning their forecasts with market expectations.

Table 3-8 provides the test results on the incremental contribution by independent and nonindependent analysts based on Model 3.3. As discussed earlier, the coefficient on $(F1 – F2)$ captures the incremental contribution by analysts making forecast $F2$. Although any analyst is likely to bring in additional information when she makes a forecast, the question is, will she contribute more if she is independent than if she is not? To compare on equal footing, we again resort to the randomization testing strategy. For each firm quarter, we first determine the smaller of the number of independent analysts and the number of nonindependent analysts. Then we randomly draw this number of forecasts from each group of analysts and calculate the consensus forecasts ($F2$). For each drawing, we also calculate the consensus forecast ($F1$) and forecast error ($FE1$) by the remaining analysts. Regressions are run for Model 3.3 to separately estimate the incremental contribution by independent and nonindependent analysts. The process is repeated 1,000 times and the mean coefficient estimates are reported.
Columns 1 and 2 in Panel A for independent analysts show that their incremental contributions are 3.454 and 0.737 for the long window and short window, respectively, both highly significant. The incremental contributions by nonindependent analysts in columns 3 and 4 are 2.700 and 0.848. The difference in incremental contribution for the long window (0.754) is significant at the 0.05 level and represents a 30% improvement of independent analysts over nonindependent analysts. The difference is not significant for the short window. Results for good news firms and bad news firms are reported in Panel B. For good news, the incremental contributions are insignificantly different from each other. However, for bad news, the differential incremental contribution is highly significant for the long window (0.958). In fact, the incremental contribution by (mostly single) nonindependent analysts is insignificant (0.750), whereas the incremental contribution by independent analysts is more than twice as large (1.707) and is significant at the 0.01 level. Overall, independent analyst forecasts, when compared on an individual basis, are superior to forecasts by nonindependent analysts in capturing market expectations.

3.3.4. Sensitivity tests

3.3.4.1. The 12 investment banks targeted by the Global Settlement

The 12 largest investment banks (IBs) were specifically targeted by the Global Settlement for having the most severe conflict of interest problems. To examine how analysts from these firms are affected by independent analysts, we re-run the earlier tests and restrict nonindependent analysts to only those from these 12 firms. The results are reported in Table 3-9.

In Panel A, we examine the disciplining effect of independent analysts on analysts from the 12 IBs. Forecast errors are by only these IB analysts in quarters when independent analysts are also following (IND = 1) the same firms and in the matched quarters when they
are not (IND = 0). The number of observations is smaller (2,601 pairs) due to the additional constraint of the 12 IB status. For the long window, we find a marginally significant (at the 0.10 level, one-tailed) coefficient of 1.737 on $FE \times IND$ in column 1, representing an economically large 25% increase in ERC when there are independent analysts relative to when there are no independent analysts (7.075). When other control variables are included in column 2, the incremental ERC is still a large 1.167, although statistically not significant. For the short window (columns 3 and 4), we find no incremental ERC as before. In Panel B, we separate earnings surprises into good news and bad news. We again find that the incremental ERC is large and highly significant when earnings news is bad for the long window. The presence of independent analysts increases the ERC by more than 120%. Overall, the results suggest that the disciplining effect found earlier also applies to analysts from the 12 IBs.

In Panels C and D, we examine whether independent analysts are superior to analysts from the 12 IBs individually. Panel C is similar to Table 3-7. For each firm quarter followed by both groups of analysts, we first determine the smaller of the number of independent analysts and the number of analysts from the 12 IBs. Then from each group we randomly draw this number of forecasts and calculate the consensus forecast errors. Regressions are separately run for each group. The process is repeated 1,000 times and the mean coefficients are reported. The ERCs for independent analysts (6.400 for the long window and 1.946 for the short window) are higher than the ERCs for analysts from the 12 IBs (4.668 and 1.573) by more than 20%. The differences are significant at the 0.01 level.

Panel D is similar to Table 3-8 on the incremental contribution by independent analysts and analysts from the 12 IBs based on the same randomization strategy as above. We again find that the incremental contribution by independent analysts (4.899 and 1.208) is significantly higher than the incremental contribution by a comparable number of analysts.
from the 12 IBs (0.704 and 0.447). Note that the difference is now also significant for the short window. In addition, the incremental contribution by analysts from the 12 IBs also appears to be lower than that by the pooled nonindependent analysts in Table 3-8, though the two samples are not the same. Overall, our results confirm the individual superiority of independent analysts to analysts from the 12 IBs.\textsuperscript{18}

3.3.4.2. The relative timing of forecasts

When determining the presence of independent analysts, our criterion is whether there is at least one independent analyst following the firm. We find that the timing of forecasts is rather random and neither group of analysts makes forecasts systematically earlier or later than the other group.\textsuperscript{19} However, one might still be concerned that for some quarters nonindependent analysts make their forecasts earlier than the independent analysts and are thus not aware whether any independent analyst is following the same firm in the quarter. Although this would introduce noise into our measure and bias against our findings, we conduct two additional checks. First, we exclude all firm quarters where independent analysts make the last forecast. Second, to be conservative, we redefine the presence of independent analysts as any independent analyst following the firm in the previous quarter. The findings of the disciplining effect and the overall effect of independent analysts do not change qualitatively.

3.3.4.3. Forecast horizons

Forecasts made later in time may incorporate the information from forecasts which precede them. We also examine forecasts made in different horizons. Overall, we find that our results do not change qualitatively. For brevity, we do not report the results based on 1-year or

\textsuperscript{18} Unreported results indicate that the superiority is more pronounced when earnings news is bad, similar to the findings earlier.

\textsuperscript{19} For the 6,999 firm quarters followed by both independent and nonindependent analysts, a mean (median) of 52% (50%) of forecasts by nonindependent analysts are made later than forecasts by independent analysts.
180-day forecast horizons. In Table 3-10, we report the results based on the single last forecasts by nonindependent and independent analysts. Panels A and B indicate that the disciplining effect of independent analysts also holds for the last forecast by nonindependent analysts. Moreover, unlike Panel B of Table 3-6, the disciplining effect for bad news is also significant in the short window. When comparing the last forecast by independent analysts with the last forecast by nonindependent analysts in Panels C and D, independent analysts again are relatively superior to, and make larger incremental contribution than, nonindependent analysts for the long window. Note that in Panels C and D, only the single last forecast by each group is compared and no randomized drawing as in Tables 3-7 and 3-8 is needed.20

3.3.4.4. Alternative matched samples

To see if our results are sensitive to the particular matching criteria we choose, we examine several alternative matched samples. For example, we relax the seasonality constraint and do not require the matched quarters with only nonindependent analysts to be from the same fiscal quarter, but the quarter that is closest to the current quarter. This reduces the time-specificity of firm characteristics. To control for the magnitude of earnings surprises, we also match by the closest consensus forecast errors. Naturally, requiring certain matching criteria means loosening others in order to obtain a reasonably large sample. It is difficult to justify which matched sample is the best. Our main results remain qualitatively the same with the alternative matched samples.

---

20 Statistical significance of the difference in coefficients from two regressions in Panels C and D is based on the Chow test. If we use the 1000 ERCs from the randomization process in Table 7 as the comparison basis, the long-window ERC of 6.525 for FE_IND in Panel C is significantly different from the mean of 5.551 at the 0.01 level, whereas the ERC of 5.716 for FE_NI is insignificantly different. The Vuong (1989) test indicates that the difference in the R²’s for the long window (0.069 vs. 0.058) is significant at the 0.01 level and insignificant for the short window (0.022 vs. 0.024).
3.3.4.5. Holding periods for abnormal returns

While the 90-day and 3-day returns windows we choose to use for reporting our results are admittedly ad hoc, they are commonly used in prior research and illustrate the sensitivity of our results to the length of holding periods. We also examine other windows of varying lengths, including 60-day, 30-day, and 2-week windows; the period from the day after prior quarter’s earnings announcement to the day after current quarter’s earnings announcement; and the period from the last analyst forecast date to the day after the current quarter’s earnings announcement. Overall, our primary results on the effects of independent analysts become weaker as the window becomes shorter, as demonstrated by the results for the 90-day and 3-day windows. This trend is consistent with Ball and Brown (1968) and Collins and Kothari (1987), that the longer window tends to capture the market response to earnings news better.

3.3.4.6. The degree of independent analyst following

In the earlier tests of the association between abnormal returns and consensus forecast errors and the disciplining effect of independent analysts, we used an indicator variable for the presence of independent analysts. This can be justified by the fact that the majority of firms have only one independent analyst (Table 3-3). It is not clear whether the disciplining effect will be stronger when there are more independent analysts. One may also argue that if independent analysts are superior to nonindependent analysts when compared on a one-to-one basis, more independent analysts should lead to an overall stronger association between abnormal returns and consensus forecast errors. Note that the superiority tests (Tables 3-7 and 3-8) already control for the number of analysts. Thus, the number of analysts may only affect the overall effect (Table 3-5) and the disciplining effect (Table 3-6).

In the matched sample, we find that only 136 out of the 4,173 quarters followed by
both independent and nonindependent analysts have more than one independent analyst (2 analysts for 135 quarters and 3 analysts for 1 quarter). In our tests on the overall effect and the disciplining effect based on Model 3.1, we include an additional interaction variable of forecast errors interacted with a dummy variable for more than one independent analyst. Its coefficients are insignificant. Thus, additional independent analysts do not appear to add value. However, we hasten to emphasize that the tests lack power due to too small a number of observations with more than one independent analyst. We do not want to generalize our results to imply that investment banks only need to provide one independent research report, rather than three as required by the Global Settlement.

3.3.4.7. Analyst firms not identified in Nelson’s Directory

There are a total of 348 analyst firms in the First Call database, among which 49 cannot be found in Nelson’s Directory. In merging analyst forecasts from First Call with the analyst firm identities (independent and nonindependent) from Nelson’s Directory, we lose all forecasts made by analysts from these firms (3,378 out of 145,332 quarters are lost because they are exclusively followed by such analysts, see Table 3-1). To examine if our results are sensitive to such forecasts, we regard analysts from these firms as nonindependent and thus include all available forecasts. We repeat all our analyses and none of our results are qualitatively affected.

3.3.4.8. Managed actual earnings

Earnings response coefficients may be higher or lower because forecasts are more or less closely aligned with market expectations, or because actual earnings are more or less managed. One possibility for the higher ERC in quarters followed by both types of analysts than that in quarters followed only by nonindependent analysts is that actual earnings are managed less in those quarters. Note that the issue is irrelevant to our tests on the superiority
of independent analysts to nonindependent analysts because we compare them for the same quarters, thus actual earnings are held constant.

To examine whether earnings management is able to explain the overall effect and the disciplining effect of independent analysts for the matched sample, we calculate discretionary accruals from the Jones (1991) model and performance-matched discretionary accruals following Kothari, Leone and Wasley (2005). For firm quarters followed by both independent and nonindependent analysts, the mean (median) absolute values of the two discretionary accrual measures are 0.0614 and 0.0556 (0.0231 and 0.0245). For firm quarters followed by only nonindependent analysts, the corresponding measures are 0.0530 and 0.0463 (0.0236 and 0.0239). Thus, in quarters followed by both groups of analysts, discretionary accruals are actually higher (significant differences except the medians of the Jones measure) and would reduce the ERC. Thus, accrual-based earnings management cannot explain the higher ERC for these quarters. When we include absolute discretionary accruals as an additional control variable in Model 3.1 by interacting them with forecast errors, our results are qualitatively unchanged (not reported). Though the disciplining effect for the pooled news is weaker, the disciplining effect for bad news remains significant.

3.4. Chapter Summary

In this chapter, we examine the disciplining role of independent analysts and the superiority of their forecasts based on the market association criterion. By this criterion, forecasts better aligned with market expectations should yield forecast errors more strongly associated with abnormal stock returns, or ERCs. Over the quarter-long window, we show that the ERC on the consensus forecast errors by all analysts is higher by an economically and statistically significant 40% when the firms are followed by both independent and nonindependent analysts than by nonindependent analysts alone in nearby quarters. The ERC
improvement is about 100% when earnings news is bad. We then show that the improvement is likely due to two roles played by independent analysts. First, the presence of independent analysts disciplines the behavior of nonindependent analysts, and makes their forecasts better aligned with market expectations. The ERC for nonindependent analysts in the presence of independent analysts is higher by about 25% than in the absence of independent analysts and is higher by about 100% when earnings news is bad. Second, independent analysts themselves are superior to nonindependent analysts in that the market relies more on their forecasts in forming expectations. The ERC for independent analysts is nearly 20% higher than the ERC for nonindependent analysts. Incrementally, independent analysts contribute to the consensus forecast by 30% more than nonindependent analysts, mostly when earnings news is bad.
Chapter 4

Conclusions and Future Work

4.1. Conclusions

This dissertation examines the value of independent analysts based on both forecast accuracy and market association criteria. More specifically we study the disciplining role and superiority of independent analysts. We show that while independent analysts may not provide more accurate or less biased forecasts by themselves, they add value to the analyst forecasting process by disciplining the behavior of nonindependent analysts. Nonindependent analysts’ forecasts become more accurate and less biased when independent analysts are following the same firms than when they are not. Moreover, the increase in forecast accuracy does not appear to be attributable to independent analysts’ selective following of firms with more public information to make earnings more predictable. Rather, it is attributable to the higher quality of nonindependent analysts’ private information.

Using the market association as another forecast evaluation criterion, we show that the presence of independent analysts makes nonindependent analysts more prudent in aligning their forecasts with market expectations, further suggesting the disciplining role of independent analysts. In addition, their forecasts, when compared on an individual basis, are superior to forecasts by nonindependent analysts in representing market expectations. The two effects combined lead to a significant overall improvement in the association between abnormal returns and earnings surprises when independent analysts are following the same firms relative to when they are not.

When comparing the findings from the two forecast evaluation criteria (forecast accuracy and market association), we find that the disciplining role of independent analysts is
observed under both criteria. Forecasts by nonindependent analysts are more accurate, less biased, and closer to market expectations in the presence of independent analysts than in their absence. However, superiority of forecasts by the two groups of analysts is different under the two criteria. Although forecasts by independent analysts are \textit{ex post} less accurate and more biased than those by nonindependent ones, they represent \textit{ex ante} market expectations better. The difference is likely due to the two criteria capturing different aspects of analyst forecast quality. As discussed earlier, forecasts by nonindependent analysts may be \textit{ex post} more accurate or less biased because of their better access to management’s private information or greater effort in information gathering. However they may be also overly guided by management due to their business affiliation. The market may not believe their guided earnings and discount its value relevance. Rather, the market may perceive independent analysts to be more objective and put more weight on the forecasts of independent analysts. Therefore the market association criterion may capture an \textit{ex ante} belief in the superiority of forecasts by independent analysts that is not necessarily consistent with the superiority of \textit{ex post} accuracy and bias.

The results of this dissertation have important policy implications in light of the fact that prior studies have generally failed to find the value of analyst independence. The disciplining role of independent analysts has been little explored previously and provides support to the Global Settlement’s requirement that investment banks should acquire and provide independent research reports along with their own. The superiority of forecasts by independent analysts in terms of market association suggests that forecasts by nonindependent analysts may be \textit{ex post} more accurate but do not necessarily represent \textit{ex ante} market expectations better. This provides support to the various analyst reforms delineated in the
Global Settlement that aim to sever the ties between investment banking and research departments and promote analyst independence.

4.2. Unanswered Questions and Future Work

4.2.1. The following decision by independent and nonindependent analysts

One interesting question is what kind of firms independent analysts are likely to follow as opposed to those followed by nonindependent analysts. From Table 2-2 and Table 3-2, we observe that only about 10% firms are followed by independent analysts. It is possible that independent analysts are more likely to follow firms with specific characteristics. What are these characteristics? How are they different from those of firms followed by nonindependent analysts? Prior studies in the analyst following literature (Bhushan, 1989; O’Brien and Bhushan, 1990; Bushman, Piotroski and Smith, 2005) suggest several firm characteristics that are related to the analyst following decision: ownership structure, firm size, past performance, risk, number of lines of business of the firm and insider trading. Besides these factors, some specific factors may also affect independent analysts’ following decision, for example, whether the firm is under/over followed by other analysts and whether the firm has potential high growth rate. Some independent analysts claim that they follow firms ignored by other analysts and with potential high growth rate. We can also test whether independent analysts are more likely to follow some specific industries. More importantly, we want to examine to what extent the following decisions by independent and nonindependent analysts are differentially affected by firms’ investment banking business.

4.2.2. Herd behavior of nonindependent analysts

The only strategic interaction of analysts considered in this dissertation is between independent and nonindependent analysts. Other strategic interactions are ignored. For
example, forecasts by nonindependent analysts are assumed to be independent of each other. However, analysts interact in other ways such as herding. With changes of information environment due to the presence of independent analysts, herd behavior may also be changed. One possible extension of this study is to investigate whether herd behavior of nonindependent analysts is affected by the presence of independent analysts.

Several theories have been proposed on the herding behavior. The two most popular are information cascades and reputational herding. Under both theories, agents rationally ignore their own information and mimic the actions of other agents who have acted previously. Information cascades have been investigated by many studies, including Banerjee (1992), Bikhchandani et al. (1992, 1998), Welch (1992) and Chamley and Gale (1994). Hirshleifer and Teoh (2003) review the theory and evidence relating to herd behavior and cascading in capital markets. In their seminal work on information cascades and herd behavior, Bikhchandani et al. (1992) consider two action choices of agents: accept or reject a project. Each agent has an independent signal about the value of each choice and can observe the choices of all predecessor agents. Suppose that the first two agents receive “high” signals and choose to accept. It is possible that the information implicit in the first two agents’ actions overwhelms the private information that the third agent has, and then she will choose to accept the project too. All subsequent agents are in exactly the same situation as the third agent: they will ignore all their private information and choose to accept. This domino-like effect is often referred to as a cascade. Once a cascade starts, public information stops accumulating. This renders the informational inefficiency because some useful information is blocked.

Like cascades, reputational herding takes place when an agent chooses to ignore her private information and mimic the action of another agent who has acted previously. However,
reputational herding models have an additional layer of mimicking resulting from positive reputational externalities that can be obtained by acting as part of a group for choosing a certain project. In the typical model of reputational herding, each agent is one of two types, smart or dumb, although the type is unobservable to all. Smart agents receive informative private signals about the project’s expected return, while dumb ones receive uninformative signals (noise). The smart agents’ signals are positively cross-correlated, implying that smart agents following their private information have a tendency to act similarly. Consequently, in certain circumstances, an agent can “look smart” by herding.\(^{21}\) Research of reputational herding includes Clement and Tse (2005), Graham (1999), Hong, Kubik and Solomon (2000), Scharfstein and Stein (1990), Stickel (1990) and Trueman (1994).

For both theories above, agents with more precise private information are less likely to herd than others. Based on the theory of information cascades, the more precise information an agent holds, the less likely that the accumulated previous information overwhelms her private information, so she is more likely to deviate from prior actions using her own information. In the framework of reputational herding, several studies (Clement and Tse, 2005; Graham, 1999; Hong et al., 2000; Stickel, 1990; and Trueman, 1994) show that as an agent’s private information becomes more accurate, it becomes more likely that she will announce her private information because it becomes more likely that her revised belief about the value of the project will be consistent with her private information. In other words, it is less costly to sacrifice a poor signal than a good one.

In Chapter 2 of this dissertation, we find that the private information of nonindependent analysts is more precise in the presence of independent analysts than in their

---

\(^{21}\) There are two important assumptions for the theory of reputational herding. One is that agents care only about their reputations perceived by the market, not the actual profit of the project. As the weight on profit increases, the herd behavior shrinks. The other assumption is that the private signals received by smart agents are correlated, so there is an informational gain from comparing agents. If their signals are independent, evaluation will be just based on the actual value of the project.
absence. Then according to the theories of herding behavior mentioned above, we have the following hypothesis:

**Hypothesis 1:** Nonindependent analysts are less likely to herd in the presence of independent analysts than in their absence.

The herding behavior of independent analysts compared to nonindependent ones, however, is not clear. Independent analysts have less precise private information than nonindependent ones, so they should be more likely to herd with prior forecasts based on information cascades theory. However, independent and nonindependent analysts have different incentives. Due to their conflicts of interest, nonindependent analysts may provide overly guided earnings forecasts. If independent analysts care about how their reputation is perceived by the market, they should deviate from nonindependent analysts’ forecasts and herd less. It is difficult to tell which effect dominates the other and I do not provide any predictions about independent analysts’ herding behavior here.

Zhang (1997) offers a setting in which agents have private information not only about project quality, but about the precision of their signals. In the unique symmetric equilibrium, those whose signals are less precise delay longer than those with more precise signals. The intuition is straightforward. The higher an individual’s precision, the higher the expected return from investment; it is more costly for an individual with higher precision to wait. Also imprecise agents have greater need for corroborating information before investing. Therefore, in equilibrium agents with more precise information are more likely to act earlier than those with less precise information. Again combining the above argument with our result about the private information improvement of nonindependent analysts, we have the following hypothesis:

**Hypothesis 2:** Nonindependent analysts are more likely to disclose their forecasts
earlier in the presence of independent analysts than in their absence.

The last hypothesis about herding is a general one, not limited to this dissertation. The conclusions for information cascades hinge on the finiteness of the agents’ choice set. In equilibrium, agents with slightly different information do not have the opportunity to take slightly different actions. As a result, an agent’s action choice will not be different from the previous one. Once this happens, the action choice has no role in adding information to the history of signal draws. In general, as the set of alternatives becomes larger and richer, cascades tend to take longer to form and aggregate more information. If the set of action alternatives is continuous, then even an individual later in the sequence will still adjust his action at least slightly based on the private signal (Lee, 1993). Consequently, private signals can be perfectly inferred from actions, information aggregates efficiently, and cascades do not form. Analysts provide both EPS forecasts and stock recommendations. There are only five categories for analyst stock recommendations, while forecasts of EPS can be quite continuous. Thus we have a hypothesis as follows:

**Hypothesis 3:** The frequency of analysts’ herding behavior is higher for stock recommendations than for EPS forecasts.

**4.2.3. Compensatory relation between independent and nonindependent analysts**

Since the sample period of this study is before the implementation of the Global Settlement, independent analysts are more likely to be “independent” in the real sense in that they do not receive compensation from other analyst firms. The Global Settlement, however, requires the investment banks to purchase research reports from independent research firms. Although this will be done through an intermediary, how the compensation scheme among analysts will affect the independence of independent analysts is an interesting question.

When compensated by nonindependent analysts, independent analysts as agents
simultaneously serve two kinds of principals, investors and nonindependent analysts. Such a situation is a typical instance of the common agency problem, which is that several principals simultaneously and independently attempt to influence a common agent. Common agency games have been introduced and analyzed in a pioneering paper by Bernheim and Whinston (1986). They prove the existence of Nash equilibria but they also show by means of examples that some of these equilibria correspond to inefficient actions. They provide some ways to eliminate inefficiencies, one of which is to bring in a risk-neutral intermediary to proscribe principals from dealing with the agent directly. This is exactly what SEC did to remedy the potential impairment of independent analysts’ independence in reality. Whether the behavior of intermediaries will be affected by the pressure from nonindependent analysts is another question. If the independence of independent analysts is still impaired even with the presence of intermediaries, then both the disciplining effect and the superiority of independent analysts documented in this study will be reduced. However independent analysts may also improve their forecast quality with the money from these investment banks by recruiting analysts with higher capability, educating their current employees etc. And their disciplining effect on nonindependent analysts may be also stronger with their more accurate forecasts. Therefore whether the disciplining effect and superiority of independent analysts will be reduced after the Global Settlement is an empirical question.

4.2.4. The overall impact of the Global Settlement on nonindependent analysts

This dissertation only provides evidence for the potential positive effect of the Global Settlement: nonindependent analyst forecasts may be improved due to the monitoring of independent analysts or fewer connections with their investment banking departments. However, the settlement may also introduce some side-effects. Since research department can no longer obtain money from investment bank departments, analysts’ compensation decreases
dramatically and many star analysts have left Wall Street or been fired. According to Avital Louria Hahn from Thomson Media, “the number of top analysts is shrinking rapidly, as staffing shifts to more junior analysts” (*The Investment Dealers’ Digest*, March 22, 2004). If so, the forecast quality of analysts may be reduced because of the less capable analysts retained in the industry. Therefore it is interesting to examine whether the Global Settlement achieves its goal to improve analyst research report quality.

4.2.5. What kinds of independent analysts are more likely to be picked

The Global Settlement requires each investment bank to buy research reports from at least three independent research firms. One natural question is what kind of independent research firms are more likely to be picked. Do they have good reputation, large size, good historic performance, or other positive factors? Even though the independent research firms are picked by an independent intermediary, will the pressure from the investments banks to the intermediary cause him to pick firms with forecasts closer to the forecasts from investment banks? This question is left for future research.

4.2.6. The degree of independent analysts following

The Global Settlement requires the investment banks to obtain at least three research reports by independent analysts. This poses the question of whether more independent analysts have stronger disciplining effect. We partially consider this question in Chapter 3. However for our sample, the vast majority of firms with independent analyst following have only one independent analyst. The limitation of the variation in the number of independent analyst following prevents us from drawing a general conclusion. With more data available in a few years, we can study the effect of differing degrees of independent analyst following in the future.
References


### Tables

**Table 2-1. Sample selection**

<table>
<thead>
<tr>
<th>Description</th>
<th>Firm quarters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecasts, actual earnings and announcement dates available from First Call</td>
<td>145,332</td>
</tr>
<tr>
<td>Brokerage houses identifiable from Nelson's Directory of Investment Research</td>
<td>141,954</td>
</tr>
<tr>
<td>Price and size and available from CRSP (Full sample)</td>
<td>132,351</td>
</tr>
<tr>
<td>(Followed by independent analysts only/both/nonindependent analysts only)</td>
<td>(2,122/ 9,661/ 120,568)</td>
</tr>
</tbody>
</table>

**Matched Sample 1 with outliers**

- (top and bottom 1% of FE_ALL, FE_NI, FE_IND) removed
  - 12,298

**Matched Sample 2 with outliers (top and bottom 1% of FE_ALL, FE_NI, FE_IND and top 1% of H, S_NI, S_IND) removed**

- 8,208

Matched sample is obtained through the following process: for each of the 9,661 firm quarters that is followed by both independent and nonindependent analysts (t), we select a quarter from the same fiscal quarters of the same firm within three years surrounding the current quarter (t-12, t-8, t-4, t+4, t+8, t+12) with no independent analyst following. If more than one quarter is available, we select the one closest in time to the current quarter. FE_ALL, FE_NI and FE_IND are forecast errors (actual earnings minus the mean forecast) for all analysts, nonindependent analysts and independent analysts, respectively. H is the accuracy of public information. S_NI and S_IND are the accuracy of private information of nonindependent and independent analysts, respectively.
Table 2-2. Over-year distribution of the samples

Panel A: Overall sample

<table>
<thead>
<tr>
<th>Analyst following</th>
<th>Both independent &amp; nonindependent analysts (IND = 1)</th>
<th>Nonindependent analysts only (IND = 0)</th>
<th>Independent analysts only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>nob</td>
<td>%</td>
<td>nob</td>
</tr>
<tr>
<td>~1993</td>
<td>301</td>
<td>1.79</td>
<td>16,494</td>
</tr>
<tr>
<td>1994</td>
<td>466</td>
<td>5.04</td>
<td>8,709</td>
</tr>
<tr>
<td>1995</td>
<td>721</td>
<td>7.02</td>
<td>9,379</td>
</tr>
<tr>
<td>1996</td>
<td>869</td>
<td>6.99</td>
<td>11,414</td>
</tr>
<tr>
<td>1997</td>
<td>942</td>
<td>6.96</td>
<td>12,392</td>
</tr>
<tr>
<td>1998</td>
<td>1,091</td>
<td>7.56</td>
<td>13,130</td>
</tr>
<tr>
<td>1999</td>
<td>1,195</td>
<td>8.47</td>
<td>12,658</td>
</tr>
<tr>
<td>2000</td>
<td>1,132</td>
<td>8.21</td>
<td>12,187</td>
</tr>
<tr>
<td>2001</td>
<td>1,270</td>
<td>9.41</td>
<td>11,941</td>
</tr>
<tr>
<td>2002</td>
<td>1,674</td>
<td>11.80</td>
<td>12,187</td>
</tr>
<tr>
<td>All years</td>
<td>9,661</td>
<td>7.30</td>
<td>120,568</td>
</tr>
</tbody>
</table>

Panel B: Matched samples

<table>
<thead>
<tr>
<th>Analyst following</th>
<th>Matched Sample 1</th>
<th>Matched Sample 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Both independent &amp; nonindependent analysts (IND = 1)</td>
<td>Nonindependent analysts only (IND = 0)</td>
</tr>
<tr>
<td>Year</td>
<td>nob</td>
<td>%</td>
</tr>
<tr>
<td>~1993</td>
<td>273</td>
<td>4.44</td>
</tr>
<tr>
<td>1994</td>
<td>340</td>
<td>5.53</td>
</tr>
<tr>
<td>1995</td>
<td>538</td>
<td>8.75</td>
</tr>
<tr>
<td>1999</td>
<td>797</td>
<td>12.96</td>
</tr>
<tr>
<td>2000</td>
<td>682</td>
<td>11.09</td>
</tr>
<tr>
<td>2001</td>
<td>795</td>
<td>12.93</td>
</tr>
<tr>
<td>2002</td>
<td>897</td>
<td>14.59</td>
</tr>
<tr>
<td>All years</td>
<td>6,149</td>
<td>100.00</td>
</tr>
</tbody>
</table>

The full sample consists of all firm quarters with analyst forecasts from the March 2003 version of First Call Historical Database, analyst firms identifiable in Nelson’s Directory of Investment Research as independent or nonindependent, and stock prices from CRSP. $IND = 1$ indicates firm quarters followed by both independent and nonindependent analysts. $IND = 0$ indicates firm quarters followed only by nonindependent analysts. Matched Sample 1 is obtained by matching each of the quarters with $IND = 1$ with a quarter from the same fiscal quarters of the same firm within three years with $IND = 0$. Observations in the top and bottom 1% of forecast errors are not included. Matched Sample 2 is a subset of Matched Sample 1 consisting of observations for which measures of accuracies of analysts’ public and private information can be empirically estimated. Observations in the top 1% of the accuracy measures are not included.
### Table 2-3. Comparison of forecast bias and forecast accuracy between independent and nonindependent analysts

#### Panel A: Quarters with IND = 1 from Matched Sample 1 (6,149 pairs)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Nonindependent analysts (1)</th>
<th>Independent analysts (2)</th>
<th>Paired Differences (1 – 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>( FE_{NI} ) vs. ( FE_{IND} )</td>
<td>0.024***</td>
<td>0.030***</td>
<td>0.002</td>
</tr>
<tr>
<td>( ACCY1_{NI} ) vs. ( ACCY1_{IND} )</td>
<td>-0.235</td>
<td>-0.091</td>
<td>-0.269</td>
</tr>
<tr>
<td>( ACCY2_{NI} ) vs. ( ACCY2_{IND} )</td>
<td>15.855</td>
<td>10.339</td>
<td>15.175</td>
</tr>
<tr>
<td>( N )</td>
<td>5.440</td>
<td>4.000</td>
<td>1.034</td>
</tr>
</tbody>
</table>

#### Panel B: Quarters with IND = 1 from Matched Sample 2 (4,104 pairs)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Nonindependent analysts (1)</th>
<th>Independent analysts (2)</th>
<th>Paired Differences (1 – 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>( FE_{NI} ) vs. ( FE_{IND} )</td>
<td>0.046***</td>
<td>0.044***</td>
<td>0.025***</td>
</tr>
<tr>
<td>( ACCY1_{NI} ) vs. ( ACCY1_{IND} )</td>
<td>-0.241</td>
<td>-0.108</td>
<td>-0.272</td>
</tr>
<tr>
<td>( ACCY2_{NI} ) vs. ( ACCY2_{IND} )</td>
<td>14.521</td>
<td>10.241</td>
<td>13.634</td>
</tr>
<tr>
<td>( N )</td>
<td>6.431</td>
<td>5.000</td>
<td>1.029</td>
</tr>
</tbody>
</table>

\( FE_{NI} \) and \( FE_{IND} \) are forecast errors (actual earnings minus the mean forecast) for nonindependent and independent analysts, respectively. \( ACCY1_{NI} \) and \( ACCY1_{IND} \) are forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1, for nonindependent and independent analysts, respectively. \( ACCY2_{NI} \) and \( ACCY2_{IND} \) are forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for nonindependent and independent analysts, respectively. \( N \) is number of analysts.

Statistical significance of the means (medians) is based on the t-test (sign test). *** indicates significance at the 0.01 level.
Table 2-4. Comparison of forecast bias and forecast accuracy in the presence and in the absence of independent analysts

Panel A: Univariate Results: Matched Sample 1 (6,149 pairs)

<table>
<thead>
<tr>
<th></th>
<th>IND = 1 (1)</th>
<th></th>
<th>IND = 0 (2)</th>
<th></th>
<th>Paired Differences (1) – (2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>FE_ALL</td>
<td>0.019***</td>
<td>0.029***</td>
<td>0.046***</td>
<td>0.034***</td>
<td>-0.027***</td>
<td>-0.004***</td>
</tr>
<tr>
<td>FE_NI</td>
<td>0.024***</td>
<td>0.030***</td>
<td>0.046***</td>
<td>0.034***</td>
<td>-0.022***</td>
<td>-0.003***</td>
</tr>
<tr>
<td>ACCY1_ALL</td>
<td>-0.233</td>
<td>-0.091</td>
<td>-0.275</td>
<td>-0.098</td>
<td>0.042***</td>
<td>0.003***</td>
</tr>
<tr>
<td>ACCY2_ALL</td>
<td>15.735</td>
<td>10.391</td>
<td>14.482</td>
<td>8.854</td>
<td>1.261***</td>
<td>0.820***</td>
</tr>
<tr>
<td>ACCY1_NI</td>
<td>-0.235</td>
<td>-0.091</td>
<td>-0.275</td>
<td>-0.098</td>
<td>0.040***</td>
<td>0.002***</td>
</tr>
<tr>
<td>ACCY2_NI</td>
<td>15.855</td>
<td>10.339</td>
<td>14.482</td>
<td>8.854</td>
<td>1.388***</td>
<td>0.719***</td>
</tr>
<tr>
<td>SIZE</td>
<td>4038.8</td>
<td>742.3</td>
<td>4114.0</td>
<td>667.9</td>
<td>-75.2</td>
<td>29.3***</td>
</tr>
<tr>
<td>N</td>
<td>6.474</td>
<td>5.000</td>
<td>4.705</td>
<td>3.000</td>
<td>1.770***</td>
<td>1.000***</td>
</tr>
<tr>
<td>N_NI</td>
<td>5.440</td>
<td>4.000</td>
<td>4.705</td>
<td>3.000</td>
<td>0.735***</td>
<td>0.000***</td>
</tr>
<tr>
<td>HORIZON</td>
<td>49.748</td>
<td>49.500</td>
<td>51.553</td>
<td>51.000</td>
<td>-1.805***</td>
<td>-1.667***</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>50.808</td>
<td>50.000</td>
<td>51.553</td>
<td>51.000</td>
<td>-0.745**</td>
<td>-0.500</td>
</tr>
<tr>
<td>EXP</td>
<td>2.222</td>
<td>2.000</td>
<td>2.336</td>
<td>2.000</td>
<td>-0.114***</td>
<td>0.000</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>2.536</td>
<td>2.125</td>
<td>2.336</td>
<td>2.000</td>
<td>0.200***</td>
<td>0.250***</td>
</tr>
</tbody>
</table>

Panel B: Univariate Results: Matched Sample 2 (4,104 pairs)

<table>
<thead>
<tr>
<th></th>
<th>IND = 1 (1)</th>
<th></th>
<th>IND = 0 (2)</th>
<th></th>
<th>Paired Differences (1) – (2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>FE_ALL</td>
<td>0.043***</td>
<td>0.042***</td>
<td>0.060***</td>
<td>0.054***</td>
<td>-0.017*</td>
<td>-0.011***</td>
</tr>
<tr>
<td>FE_NI</td>
<td>0.046***</td>
<td>0.044***</td>
<td>0.060***</td>
<td>0.054***</td>
<td>-0.014</td>
<td>-0.009***</td>
</tr>
<tr>
<td>ACCY1_ALL</td>
<td>-0.236</td>
<td>-0.106</td>
<td>-0.272</td>
<td>-0.117</td>
<td>0.036***</td>
<td>0.009***</td>
</tr>
<tr>
<td>ACCY2_ALL</td>
<td>14.386</td>
<td>10.204</td>
<td>13.320</td>
<td>9.276</td>
<td>1.066***</td>
<td>0.482***</td>
</tr>
<tr>
<td>ACCY1_NI</td>
<td>-0.241</td>
<td>-0.108</td>
<td>-0.272</td>
<td>-0.117</td>
<td>0.031***</td>
<td>0.008***</td>
</tr>
<tr>
<td>ACCY2_NI</td>
<td>14.521</td>
<td>10.241</td>
<td>13.320</td>
<td>9.276</td>
<td>1.201***</td>
<td>0.460***</td>
</tr>
<tr>
<td>SIZE</td>
<td>4147.3</td>
<td>1012.5</td>
<td>4293.4</td>
<td>940.4</td>
<td>-146.1</td>
<td>26.5***</td>
</tr>
<tr>
<td>N</td>
<td>7.461</td>
<td>6.000</td>
<td>6.022</td>
<td>4.000</td>
<td>1.438***</td>
<td>1.000***</td>
</tr>
<tr>
<td>N_NI</td>
<td>6.431</td>
<td>5.000</td>
<td>6.022</td>
<td>4.000</td>
<td>0.409***</td>
<td>0.000</td>
</tr>
<tr>
<td>HORIZON</td>
<td>49.530</td>
<td>49.000</td>
<td>50.977</td>
<td>50.400</td>
<td>-1.448***</td>
<td>-1.015**</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>50.376</td>
<td>49.162</td>
<td>50.977</td>
<td>50.400</td>
<td>-0.601</td>
<td>-0.158</td>
</tr>
<tr>
<td>EXP</td>
<td>2.398</td>
<td>2.000</td>
<td>2.472</td>
<td>2.143</td>
<td>-0.074***</td>
<td>0.000</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>2.690</td>
<td>2.333</td>
<td>2.472</td>
<td>2.143</td>
<td>0.218***</td>
<td>0.286***</td>
</tr>
</tbody>
</table>
### Table 2-4. – Continued

#### Panel C: Regression Results: Matched Sample 1 (nob = 12,298)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE_ALL</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.032</td>
</tr>
<tr>
<td>IND</td>
<td>-0.025**</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>0.008**</td>
</tr>
<tr>
<td>LGN</td>
<td>-0.009</td>
</tr>
<tr>
<td>HORIZON(_NI)</td>
<td>0.001***</td>
</tr>
<tr>
<td>EXP(_NI)</td>
<td>-0.002</td>
</tr>
<tr>
<td>Q2</td>
<td>-0.027**</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.056***</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.047***</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.003</td>
</tr>
</tbody>
</table>

#### Panel D: Regression Results: Matched Sample 2 (nob = 8,208)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE_ALL</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.024</td>
</tr>
<tr>
<td>IND</td>
<td>-0.016</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.001</td>
</tr>
<tr>
<td>LGN</td>
<td>0.004</td>
</tr>
<tr>
<td>HORIZON(_NI)</td>
<td>0.001***</td>
</tr>
<tr>
<td>EXP(_NI)</td>
<td>0.000</td>
</tr>
<tr>
<td>Q2</td>
<td>-0.002</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.025*</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.015</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.004</td>
</tr>
</tbody>
</table>

FE_ALL and FE_NI are mean forecast errors of all and nonindependent analysts, respectively. ACCY1_ALL and ACCY1_NI are forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1, for all and nonindependent analysts, respectively. ACCY2_ALL and ACCY2_NI are forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for all and nonindependent analysts, respectively. IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. SIZE (LGSIZE) is (logarithm of) market capitalization of the firm at the beginning of the quarter; N and NI_NI (LGN and LGN_NI) are (logarithm of) number of all and nonindependent analysts; HORIZON and HORIZON_NI are forecast horizon measured as days from the forecast date to earnings announcement averaged across all and nonindependent analysts, respectively; EXP and EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across all and nonindependent analysts, respectively. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
Table 2-5. Comparison of accuracies of public and private information between nonindependent analysts in the presence and in the absence of independent analysts (Matched Sample 2)

Panel A: Univariate Results (4,104 pairs)

<table>
<thead>
<tr>
<th></th>
<th>IND = 1 (1)</th>
<th>IND = 0 (2)</th>
<th>Paired Differences (1) – (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>H</td>
<td>6.306</td>
<td>3.773</td>
<td>6.654</td>
</tr>
<tr>
<td>S_NI</td>
<td>8.749</td>
<td>5.084</td>
<td>7.322</td>
</tr>
<tr>
<td>S_IND</td>
<td>7.905</td>
<td>2.412</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Regression Results (nob = 8,208)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
<th>H</th>
<th>S_NI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-3.312***</td>
<td>-8.560***</td>
<td></td>
</tr>
<tr>
<td>IND</td>
<td>0.063</td>
<td>0.879***</td>
<td></td>
</tr>
<tr>
<td>LGSIZE</td>
<td>2.048***</td>
<td>1.788***</td>
<td></td>
</tr>
<tr>
<td>LGN</td>
<td>-2.287***</td>
<td>1.867***</td>
<td></td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.030***</td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td>EXP_NI</td>
<td>-0.355***</td>
<td>0.085</td>
<td></td>
</tr>
<tr>
<td>Q2</td>
<td>-0.092</td>
<td>0.442*</td>
<td></td>
</tr>
<tr>
<td>Q3</td>
<td>-0.201</td>
<td>0.736***</td>
<td></td>
</tr>
<tr>
<td>Q4</td>
<td>-0.702***</td>
<td>0.458</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.133</td>
<td>0.171</td>
<td></td>
</tr>
</tbody>
</table>

Accuracies of analysts’ public and private information are calculated based on

\[
h = \frac{N(N - 1)}{N^2 \left[(1 - 1/M) \text{DISP} + \text{Var}(FE)\right]^2 - \sum_{i=1}^{N} \text{Var}(FE_i)^2} \quad \text{and} \quad s_i = \frac{1}{\text{Var}(FE_i)} - h, \text{ for } i = 1, \ldots, N, \text{ where}
\]

\[
h = \frac{N(N - 1)}{N^2 \left[(1 - 1/M) \text{DISP} + \text{Var}(FE)\right]^2 - \sum_{i=1}^{N} \text{Var}(FE_i)^2} \quad \text{and} \quad s_i = \frac{1}{\text{Var}(FE_i)} - h, \text{ for } i = 1, \ldots, N, \text{ where}
\]

\[
\text{Var}(FE) \text{ is proxied by squared error in the mean forecast } (A - \Sigma F_i/N)^2; \text{ Var}(FE_i) \text{ is proxied by squared error in an individual forecast } (A - F_i)^2; \text{ DISP is proxied by sample variance of all available forecasts } \left[\Sigma (F_i - \Sigma F_i/N)^2\right]/(N-1); \text{ and } N \text{ is the total number of forecasts. } h \text{ is measured as the square root of } s; \text{ S_NI and S_IND are measured as the square root of } s_i \text{ average across nonindependent and independent analysts, respectively. } \text{ IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. * *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.}
Table 2-6. The disciplining effect of independent analysts on analysts from the 12 investment banks targeted in the Global Settlement (nob = 5,488)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>FE_NI</th>
<th>ACCY1_NI</th>
<th>ACCY2_NI</th>
<th>H</th>
<th>S_NI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.121**</td>
<td>-0.840***</td>
<td>22.719***</td>
<td>-3.452***</td>
<td>-9.922***</td>
</tr>
<tr>
<td>IND</td>
<td>-0.015</td>
<td>0.029***</td>
<td>2.955**</td>
<td>-0.113</td>
<td>1.385***</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.007</td>
<td>0.090***</td>
<td>4.073***</td>
<td>-2.133***</td>
<td>1.940***</td>
</tr>
<tr>
<td>LGN</td>
<td>0.010</td>
<td>-0.008</td>
<td>6.749***</td>
<td>-2.314***</td>
<td>1.692***</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.001*</td>
<td>-0.001**</td>
<td>0.007</td>
<td>0.027***</td>
<td>-0.012**</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>-0.002</td>
<td>-0.015***</td>
<td>-1.413***</td>
<td>-0.407***</td>
<td>0.104</td>
</tr>
<tr>
<td>Q2</td>
<td>0.004</td>
<td>0.016</td>
<td>4.068**</td>
<td>-0.091</td>
<td>0.277</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.017</td>
<td>0.002</td>
<td>1.525</td>
<td>-0.510**</td>
<td>0.732**</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.005</td>
<td>-0.032*</td>
<td>-3.327</td>
<td>-0.905***</td>
<td>0.163</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.002</td>
<td>0.093</td>
<td>0.039</td>
<td>0.135</td>
<td>0.123</td>
</tr>
</tbody>
</table>

All nonindependent analysts refer to those from the 12 investment banks targeted in the Global Settlement. FE_NI is the mean forecast error of nonindependent analysts. ACCY1_NI is forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1 for nonindependent analysts. ACCY2_NI is forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for nonindependent analysts. Accuracies of analysts’ public and private information are calculated based on

\[
h = \frac{N(N-1)[\text{Var}(FE) - \text{DISP}/N]}{N^2[(1-1/M)\text{DISP} + \text{Var}(FE)]^2 - \sum_{i=1}^{N}[\text{Var}(FE_i)]^2}
\]

and \( s_i = \frac{1}{\text{Var}(FE_i)} - h \), for i = 1, ..., N, where \( \text{Var}(FE) \) is proxied by squared error in the mean forecast (\( \sum F_i/N \)); \( \text{Var}(FE_i) \) is proxied by squared error in an individual forecast (\( \sum (F_i - \bar{F})^2 \)); \( \text{DISP} \) is proxied by sample variance of all available forecasts \( \left[ \sum (F_i - \bar{F})^2 \right]/(N-1) \); and N is the total number of forecasts. H is measured as the square root of h; S_NI is measured as the square root of s, average across nonindependent analysts. IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
Table 2-7. The disciplining effect of independent analysts on nonindependent analysts: Holding nonindependent analysts constant in the presence and absence of independent analysts (nob = 7,330)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE_NI</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.090**</td>
</tr>
<tr>
<td>IND</td>
<td>-0.007</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.003</td>
</tr>
<tr>
<td>LGN</td>
<td>-0.002</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.001***</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>-0.003</td>
</tr>
<tr>
<td>Q2</td>
<td>-0.003</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.023</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.018</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Nonindependent analysts are required to be the same in the presence and absence of independent analysts. FE_NI is the mean forecast error of nonindependent analysts. ACCY1_NI is forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1 for nonindependent analysts. ACCY2_NI is forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts for nonindependent analysts. Accuracies of analysts’ public and private information are calculated based on

\[
h = \frac{N(N-1)(\text{Var}(FE) - \text{DISP} / N)}{N^2[(1 - 1/M)\text{DISP} + \text{Var}(FE)]^2 - \sum_{i=1}^{N} \text{Var}(FE_i)^2}
\]

and

\[
s_i = \frac{1}{\text{Var}(FE_i)} - h, \text{ for } i = 1, \ldots, N, \text{ where}
\]

Var(FE) is proxied by squared error in the mean forecast \((A - \sum F_i/N)^2\); Var(FE_i) is proxied by squared error in an individual forecast \((A - F_i)^2\); DISP is proxied by sample variance of all available forecasts \(\Sigma(F_i - \sum F_i/N)^2) / (N-1)\); and N is the total number of forecasts. H is measured as the square root of h; S_NI is measured as the square root of s_i average across nonindependent analysts. IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
Table 2-8. The disciplining effect of independent analysts on nonindependent analysts: The impact of Regulation Fair Disclosure (Matched Sample 2, nob = 8,208)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>FE_NI</th>
<th>ACCY1_NI</th>
<th>ACCY2_NI</th>
<th>H</th>
<th>S_NI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.050</td>
<td>-0.798***</td>
<td>-13.103***</td>
<td>-3.600***</td>
<td>-9.112***</td>
</tr>
<tr>
<td>IND</td>
<td>-0.012</td>
<td>0.017*</td>
<td>0.575*</td>
<td>-0.074</td>
<td>0.617***</td>
</tr>
<tr>
<td>IND×Reg_FD</td>
<td>-0.016</td>
<td>0.033*</td>
<td>1.421**</td>
<td>0.567</td>
<td>1.086**</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.004</td>
<td>0.082***</td>
<td>3.598***</td>
<td>2.048***</td>
<td>1.788***</td>
</tr>
<tr>
<td>LGN</td>
<td>0.006</td>
<td>-0.008</td>
<td>0.354</td>
<td>-2.286***</td>
<td>1.869***</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.001***</td>
<td>0.000</td>
<td>0.017**</td>
<td>0.030***</td>
<td>-0.008</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>0.004</td>
<td>-0.011***</td>
<td>-0.236***</td>
<td>-0.355***</td>
<td>0.085</td>
</tr>
<tr>
<td>Q2</td>
<td>0.004</td>
<td>0.019</td>
<td>0.452</td>
<td>-0.093</td>
<td>0.441*</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.022</td>
<td>0.005</td>
<td>0.612*</td>
<td>-0.198</td>
<td>0.742***</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.013</td>
<td>-0.037***</td>
<td>-0.573</td>
<td>-0.721***</td>
<td>0.423</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.003</td>
<td>0.096</td>
<td>0.211</td>
<td>0.133</td>
<td>0.171</td>
</tr>
</tbody>
</table>

Reg_FD is an indicator variable for observations after Regulation Fair Disclosure (October 2000). FE_NI is the mean forecast error of nonindependent analysts. ACCY1_NI is forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1 for nonindependent analysts. ACCY2_NI is forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for nonindependent analysts. Accuracies of analysts’ public and private information are calculated based on

$$ h = \frac{N(N-1)[(\text{Var}(FE) - \text{DISP}/N]}{N^2[(1-1/M)\text{DISP} + \text{Var}(FE)]^2 - \sum_{i=1}^{N}[\text{Var}(FE_i)]^2} $$

and

$$ s_i = \frac{1}{\text{Var}(FE_i)} - h, \text{ for } i = 1, \ldots, N, $$

where $\text{Var}(FE)$ is proxied by squared error in the mean forecast ($A - \Sigma F/N)^2$; $\text{Var}(FE_i)$ is proxied by squared error in an individual forecast ($A - F_i)^2$; $\text{DISP}$ is proxied by sample variance of all available forecasts $[\Sigma(F_i - \Sigma F/N)^2]/(N-1)$; and $N$ is the total number of forecasts. $H$ is measured as the square root of $h$; $S_NI$ is measured as the square root of $s_i$, average across nonindependent analysts. IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
Table 2-9. The disciplining effect of independent analysts on nonindependent analysts: Forecasts of nonindependent analysts made after forecasts of independent analysts (nob = 6,390)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE_NI</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.057</td>
</tr>
<tr>
<td>IND</td>
<td>0.021</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.003</td>
</tr>
<tr>
<td>LGN</td>
<td>0.001</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.001***</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>-0.001</td>
</tr>
<tr>
<td>Q2</td>
<td>-0.005</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.009</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.009</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Forecasts of nonindependent analysts are required to be made after forecasts of independent analysts. FE_NI is the mean forecast error of nonindependent analysts. ACCY1_NI is forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1 for nonindependent analysts. ACCY2_NI is forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for nonindependent analysts. Accuracies of analysts’ public and private information are calculated based on:

\[ h = \frac{N(N-1)(\text{Var}(FE) - \text{DISP}/N)}{N^2[(1 - 1/M)\text{DISP} + \text{Var}(FE)]^2 - \sum_{i=1}^{N} [\text{Var}(FE_i)]^2} \]

\[ s_i = \frac{1}{\text{Var}(FE_i)} - h, \text{ for } i = 1,\ldots, N, \text{ where} \]

Var(FE) is proxied by squared error in the mean forecast \((A - \Sigma F_i/N)^2\); Var(FE_i) is proxied by squared error in an individual forecast \((A_i - F_i)^2\); DISP is proxied by sample variance of all available forecasts \((\Sigma_i(F_i - \Sigma F_i/N)^2)/(N-1)\); and N is the total number of forecasts. H is measured as the square root of h; S_NI is measured as the square root of s_i average across nonindependent analysts. IND = 1 if a firm quarter is followed by both independent and nonindependent analysts; IND = 0 if a firm quarter is followed only by nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
Table 2-10. Confirming the disciplining effect of independent analysts on nonindependent analysts: Matching quarters followed by only nonindependent analysts with other quarters followed by only nonindependent analysts (nob = 5,786)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE_NI</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.176***</td>
</tr>
<tr>
<td>IND</td>
<td>-0.005</td>
</tr>
<tr>
<td>LGSIZE</td>
<td>-0.022***</td>
</tr>
<tr>
<td>LGN</td>
<td>0.021*</td>
</tr>
<tr>
<td>HORIZON_NI</td>
<td>0.001***</td>
</tr>
<tr>
<td>EXP_NI</td>
<td>-0.001</td>
</tr>
<tr>
<td>Q2</td>
<td>0.024</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.006</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.002</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.011</td>
</tr>
</tbody>
</table>

For each quarter followed by only nonindependent analysts in matched sample 2, we designate IND = 1 to it and match it to another quarter from the same fiscal quarters of the same firm also followed by only nonindependent analysts, designated IND = 0. FE_NI is the mean forecast error of nonindependent analysts. ACCY1_NI is forecast accuracy, measured as the absolute error in the mean forecast multiplied by -1 for nonindependent analysts. ACCY2_NI is forecast accuracy, measured as the mean of the inverse of absolute errors in individual forecasts, for nonindependent analysts. Accuracies of analysts’ public and private information are calculated based on $h = \frac{N(N - 1)(\text{Var}(FE) - \text{DISP} / N)}{N^2 [(1 - 1 / M) \text{DISP} + \text{Var}(FE)]^2 - \sum_{i=1}^{N} [\text{Var}(FE_i)]^2}$ and $s_i = \frac{1}{\text{Var}(FE_i)} - h$, for i = 1, ..., N, where Var(FE) is proxied by squared error in the mean forecast $(A - \sum F_i / N)^2$; Var(FE_i) is proxied by squared error in an individual forecast $(A - F_i)^2$; DISP is proxied by sample variance of all available forecasts $(\sum (F_i - \sum F_i / N)^2) / (N-1)$; and N is the total number of forecasts. H is measured as the square root of h; S_NI is measured as the square root of $s_i$ average across nonindependent analysts. LGSIZE is logarithm of market capitalization of the firm at the beginning of the quarter; LGN_NI is logarithm of number of nonindependent analysts; HORIZON_NI is forecast horizon measured as days from the forecast date to earnings announcement averaged across nonindependent analysts; EXP_NI is experience measured as the number of years in which an analyst supplied at least one forecast for the firm before the current year, averaged across nonindependent analysts. Q2, Q3 and Q4 are dummy variables for fiscal quarters 2, 3, and 4. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels.
### Table 3-1. Sample selection

<table>
<thead>
<tr>
<th>Description</th>
<th>Firm quarters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecasts, actual earnings and announcement dates available from First Call</td>
<td>145,332</td>
</tr>
<tr>
<td>Brokerage houses identifiable from Nelson's Directory of Investment Research</td>
<td>141,954</td>
</tr>
<tr>
<td>Price, return, size and beta available from CRSP</td>
<td>97,202</td>
</tr>
<tr>
<td>Accounting data available from Compustat</td>
<td>73,097</td>
</tr>
<tr>
<td>Sample with outliers (top and bottom 1% of forecast errors and</td>
<td>69,192</td>
</tr>
<tr>
<td>abnormal returns) removed</td>
<td></td>
</tr>
<tr>
<td>(Followed by independent analysts only/both/nonindependent analysts only)</td>
<td>(882/ 6,999/ 61,311)</td>
</tr>
<tr>
<td>Matched sample</td>
<td>8,346</td>
</tr>
</tbody>
</table>

Matched sample is obtained through the following process: for each of the 6,999 firm quarters that is followed by both independent and nonindependent analysts (t), we select a quarter from the same fiscal quarters of the same firm within three years surrounding the current quarter (t-12, t-8, t-4, t+4, t+8, t+12) with no independent analyst following. If more than one quarter is available, we select the one closest in time to the current quarter.
## Table 3-2. Over-year distribution of the sample

**Panel A: Full Sample**

| Analyst following | | | | | |
|---|---|---|---|---|
| | Independent analysts only | Both independent and nonindependent analysts (IND=1) | Nonindependent analysts only (IND = 0) | |
| Year | N | % | N | % | N | % |
| ~1993 | 16 | 0.002 | 238 | 0.029 | 7,872 | 0.969 |
| 1994 | 21 | 0.004 | 362 | 0.075 | 4,417 | 0.920 |
| 1995 | 76 | 0.014 | 549 | 0.098 | 4,951 | 0.888 |
| 1996 | 69 | 0.010 | 640 | 0.093 | 6,156 | 0.897 |
| 1997 | 93 | 0.013 | 712 | 0.097 | 6,527 | 0.890 |
| 1998 | 83 | 0.011 | 794 | 0.101 | 6,961 | 0.888 |
| 1999 | 109 | 0.014 | 842 | 0.109 | 6,745 | 0.876 |
| 2000 | 157 | 0.023 | 773 | 0.112 | 5,957 | 0.865 |
| 2001 | 126 | 0.019 | 929 | 0.138 | 5,653 | 0.843 |
| 2002 | 132 | 0.018 | 1,160 | 0.158 | 6,072 | 0.825 |
| All years | 882 | 0.013 | 6,999 | 0.101 | 61,311 | 0.886 |

**Panel B: Matched sample**

<table>
<thead>
<tr>
<th>Analyst following</th>
<th>Both independent and nonindependent analysts (IND = 1)</th>
<th>Nonindependent analysts only (IND = 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Good News (FE ≥ 0)</td>
</tr>
<tr>
<td>~1993</td>
<td>204</td>
<td>119</td>
</tr>
<tr>
<td>1994</td>
<td>253</td>
<td>162</td>
</tr>
<tr>
<td>1995</td>
<td>399</td>
<td>233</td>
</tr>
<tr>
<td>1996</td>
<td>414</td>
<td>262</td>
</tr>
<tr>
<td>1997</td>
<td>403</td>
<td>272</td>
</tr>
<tr>
<td>1998</td>
<td>434</td>
<td>301</td>
</tr>
<tr>
<td>1999</td>
<td>524</td>
<td>385</td>
</tr>
<tr>
<td>2000</td>
<td>423</td>
<td>303</td>
</tr>
<tr>
<td>2001</td>
<td>550</td>
<td>370</td>
</tr>
<tr>
<td>2002</td>
<td>569</td>
<td>438</td>
</tr>
<tr>
<td>All years</td>
<td>4,173</td>
<td>2,845</td>
</tr>
</tbody>
</table>

See Table 3-1 for sample selection. IND = 1 indicates firm quarters followed by both independent and nonindependent analysts. IND = 0 indicates firm quarters followed only by nonindependent analysts. FE is the consensus forecast error measured as actual earnings minus consensus (mean) forecast deflated by the stock price at the beginning of the quarter.
Table 3-3. Descriptive statistics for the matched sample (n = 8,346)

Panel A: $FE$ and $FOLLOW$

<table>
<thead>
<tr>
<th></th>
<th>$IND = 0$ (1)</th>
<th>$IND = 1$ (2)</th>
<th>Paired Differences (1) – (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>$FE$</td>
<td>0.00059***</td>
<td>0.00032***</td>
<td>0.00037***</td>
</tr>
<tr>
<td>$FE_{NI}$</td>
<td>0.00059***</td>
<td>0.00032***</td>
<td>0.00041***</td>
</tr>
<tr>
<td>$FE_{IND}$</td>
<td>0.00023***</td>
<td>0.00025***</td>
<td></td>
</tr>
<tr>
<td>$FOLLOW$</td>
<td>5.19147</td>
<td>4.00000</td>
<td>6.94704</td>
</tr>
<tr>
<td>$FOLLOW_{NI}$</td>
<td>5.19147</td>
<td>4.00000</td>
<td>5.91421</td>
</tr>
<tr>
<td>$FOLLOW_{IND}$</td>
<td>1.03283</td>
<td>1.00000</td>
<td></td>
</tr>
<tr>
<td>$FOLLOW_{NI} – FOLLOW_{IND}$</td>
<td>4.88138***</td>
<td>3.00000***</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Other variables

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>$BHAR90$</td>
<td>0.01455</td>
<td>0.00374</td>
<td>0.00762</td>
<td>0.00243</td>
<td>0.00694</td>
<td>0.00304</td>
</tr>
<tr>
<td>$BHAR3$</td>
<td>0.00605</td>
<td>0.00283</td>
<td>0.00548</td>
<td>0.00349</td>
<td>0.00057</td>
<td>-0.00006</td>
</tr>
<tr>
<td>$SIZE$</td>
<td>5178.003</td>
<td>893.530</td>
<td>5049.251</td>
<td>964.246</td>
<td>128.751</td>
<td>-30.459***</td>
</tr>
<tr>
<td>$BETA$</td>
<td>0.86198</td>
<td>0.80184</td>
<td>0.84812</td>
<td>0.79456</td>
<td>0.01387*</td>
<td>0.01776**</td>
</tr>
<tr>
<td>$MB$</td>
<td>3.26293</td>
<td>2.35292</td>
<td>5.55897</td>
<td>2.38005</td>
<td>-2.29604</td>
<td>-0.02227</td>
</tr>
<tr>
<td>$GROWTH$</td>
<td>0.06997</td>
<td>0.03151</td>
<td>0.05293</td>
<td>0.03010</td>
<td>0.01704*</td>
<td>0.00000</td>
</tr>
<tr>
<td>$STD_ROE$</td>
<td>0.07194</td>
<td>0.01999</td>
<td>0.07194</td>
<td>0.01999</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>$PSST$</td>
<td>0.54219</td>
<td>0.61272</td>
<td>0.54219</td>
<td>0.61272</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>
| $FE\_1$              | 0.00046       | 0.00032       | 0.00044                     | 0.00031       | 0.00002                   | 0.00001*     

$IND = 1$ indicates firm quarters followed by both independent and nonindependent analysts. $IND = 0$ indicates firm quarters followed only by nonindependent analysts. Consensus forecast error $FE$ is measured as the difference between actual earnings and consensus (mean) forecast by all analysts deflated by the stock price at the beginning of the quarter. $FE_{NI}$ and $FE_{IND}$ are consensus forecast errors by nonindependent and independent analysts, respectively. All forecasts are made within 90 days of earnings announcements. $FOLLOW$ is the total number of analyst following the firm quarter. $FOLLOW_{NI}$ and $FOLLOW_{IND}$ are the number of nonindependent and independent analysts following the firm quarter respectively. $BHAR90$ and $BHAR3$ are the size-adjusted buy-and-hold abnormal returns over the 90-day and 3-day windows up to one day after the earnings announcement. $SIZE$ is the market capitalization (in $millions) at the beginning of the quarter. $BETA$ is the equity beta at the beginning of the year. $MB$ is the market-to-book ratio at the beginning of the quarter. $GROWTH$ is the average growth in book value of equity over the previous four quarters. $STD\_ROE$ is the firm-specific standard deviation of return-on-equity during the sample period. $PSST$ is the autoregressive coefficient estimate from the Foster (1977) model. $FE\_1$ is the consensus forecast error in the previous quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
<table>
<thead>
<tr>
<th></th>
<th>IND</th>
<th>FE</th>
<th>FE_1</th>
<th>BHAR90</th>
<th>BHAR3</th>
<th>LGSIZE</th>
<th>LGFOLLOW</th>
<th>BETA</th>
<th>MB</th>
<th>GROWTH</th>
<th>STD_ROE</th>
<th>PSST</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IND</strong></td>
<td>-0.030</td>
<td>-0.006</td>
<td>-0.013</td>
<td>-0.003</td>
<td>0.021</td>
<td>0.221</td>
<td>-0.012</td>
<td>0.007</td>
<td>-0.002</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td><strong>FE</strong></td>
<td>-0.027</td>
<td>0.291</td>
<td>0.248</td>
<td>0.244</td>
<td>-0.083</td>
<td>-0.044</td>
<td>-0.008</td>
<td>-0.086</td>
<td>0.007</td>
<td>0.048</td>
<td>0.042</td>
<td></td>
</tr>
<tr>
<td><strong>FE_1</strong></td>
<td>-0.005</td>
<td>0.130</td>
<td>0.107</td>
<td>0.034</td>
<td>-0.077</td>
<td>-0.037</td>
<td>-0.016</td>
<td>-0.039</td>
<td>0.051</td>
<td>0.066</td>
<td>0.044</td>
<td></td>
</tr>
<tr>
<td><strong>BHAR90</strong></td>
<td>-0.017</td>
<td>0.182</td>
<td>0.055</td>
<td>0.241</td>
<td>-0.033</td>
<td>-0.050</td>
<td>-0.079</td>
<td>-0.019</td>
<td>-0.024</td>
<td>-0.057</td>
<td>0.021</td>
<td></td>
</tr>
<tr>
<td><strong>BHAR3</strong></td>
<td>-0.004</td>
<td>0.185</td>
<td>0.018</td>
<td>0.255</td>
<td>-0.014</td>
<td>-0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.007</td>
<td>-0.005</td>
<td>0.021</td>
<td></td>
</tr>
<tr>
<td><strong>LGSIZE</strong></td>
<td>0.021</td>
<td>-0.023</td>
<td>-0.009</td>
<td>-0.055</td>
<td>-0.028</td>
<td>0.609</td>
<td>0.288</td>
<td>0.373</td>
<td>-0.035</td>
<td>-0.117</td>
<td>0.143</td>
<td></td>
</tr>
<tr>
<td><strong>LGFOLLOW</strong></td>
<td>0.246</td>
<td>-0.012</td>
<td>0.000</td>
<td>-0.057</td>
<td>-0.004</td>
<td>0.600</td>
<td>0.264</td>
<td>0.151</td>
<td>-0.007</td>
<td>0.024</td>
<td>0.135</td>
<td></td>
</tr>
<tr>
<td><strong>BETA</strong></td>
<td>-0.013</td>
<td>-0.002</td>
<td>0.011</td>
<td>-0.073</td>
<td>-0.002</td>
<td>0.244</td>
<td>0.247</td>
<td>0.136</td>
<td>0.086</td>
<td>0.177</td>
<td>0.118</td>
<td></td>
</tr>
<tr>
<td><strong>MB</strong></td>
<td>0.011</td>
<td>-0.015</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-0.031</td>
<td>0.003</td>
<td>0.002</td>
<td>0.011</td>
<td>0.251</td>
<td>0.142</td>
<td>0.123</td>
<td></td>
</tr>
<tr>
<td><strong>GROWTH</strong></td>
<td>-0.018</td>
<td>0.003</td>
<td>0.005</td>
<td>-0.008</td>
<td>-0.003</td>
<td>-0.011</td>
<td>-0.005</td>
<td>0.039</td>
<td>-0.012</td>
<td>0.069</td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td><strong>STD_ROE</strong></td>
<td>0.000</td>
<td>-0.014</td>
<td>-0.017</td>
<td>0.015</td>
<td>-0.024</td>
<td>-0.040</td>
<td>-0.027</td>
<td>-0.016</td>
<td>0.379</td>
<td>0.033</td>
<td>-0.124</td>
<td></td>
</tr>
<tr>
<td><strong>PSST</strong></td>
<td>0.000</td>
<td>0.047</td>
<td>0.054</td>
<td>0.014</td>
<td>0.020</td>
<td>0.091</td>
<td>0.096</td>
<td>0.098</td>
<td>0.003</td>
<td>-0.014</td>
<td>-0.006</td>
<td></td>
</tr>
</tbody>
</table>

See Table 3-3 for variable definitions. LGSIZE is the logarithm of SIZE and LGFOLLOW is the logarithm of FOLLOW. Pearson correlations are below the diagonal and Spearman correlations are above the diagonal.
Table 3-5. The overall effect of independent analysts on the association between abnormal returns and consensus forecast errors by all analysts (matched sample, n = 8,346)

Model:  
\[ BHAR_n = \alpha_0 + \alpha_1 FE_{it} + \alpha_2 FE_{it} \times IND_{it} + \sum_j \beta_j FE_{it} \times Controls_{it} + \phi FE_{-1it} \]
\[ + \sum_k \lambda_k Q_t + \sum_m \rho_m Y_{tm} + \sum_n \theta_n INDUSTRY_n + \epsilon_{it} \]  

(3.1)

Panel A: Pooled forecast errors

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Predicted Sign</th>
<th>Dependent Variable</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td></td>
<td>0.044***</td>
<td>0.043***</td>
</tr>
<tr>
<td>FE</td>
<td>+</td>
<td></td>
<td>7.636***</td>
<td>10.897***</td>
</tr>
<tr>
<td>FE×IND</td>
<td>+</td>
<td></td>
<td>2.933***</td>
<td>2.064*</td>
</tr>
<tr>
<td>FE×LGSIZE</td>
<td>–</td>
<td></td>
<td>-1.480***</td>
<td>-0.024</td>
</tr>
<tr>
<td>FE×LGFOLLOW</td>
<td>?</td>
<td></td>
<td>2.322***</td>
<td>0.071</td>
</tr>
<tr>
<td>FE×BETA</td>
<td>–</td>
<td></td>
<td>0.522</td>
<td>-0.355</td>
</tr>
<tr>
<td>FE×MB</td>
<td>+</td>
<td></td>
<td>0.000</td>
<td>0.004***</td>
</tr>
<tr>
<td>FE×GROWTH</td>
<td>+</td>
<td></td>
<td>1.019</td>
<td>1.205</td>
</tr>
<tr>
<td>FE×STD ROE</td>
<td>–</td>
<td></td>
<td>-0.165</td>
<td>-0.298*</td>
</tr>
<tr>
<td>FE×PSST</td>
<td>+</td>
<td></td>
<td>5.171***</td>
<td>2.295***</td>
</tr>
<tr>
<td>FE_1</td>
<td>+</td>
<td></td>
<td>0.734***</td>
<td>-0.043</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td></td>
<td>0.065</td>
<td>0.068</td>
</tr>
</tbody>
</table>
Table 3-5 – Continued

Panel B: Good news and bad news separated

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Predicted Sign</th>
<th>BHAR90 (1)</th>
<th>BHAR90 (2)</th>
<th>BHAR3 (3)</th>
<th>BHAR3 (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.036**</td>
<td>0.039**</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>FE×GOOD</td>
<td>+</td>
<td>11.372***</td>
<td>21.342***</td>
<td>3.628***</td>
<td>4.052***</td>
</tr>
<tr>
<td>FE×GOOD×IND</td>
<td>+</td>
<td>1.859</td>
<td>1.614</td>
<td>-0.309</td>
<td>-0.546</td>
</tr>
<tr>
<td>FE×BAD</td>
<td>+</td>
<td>3.878***</td>
<td>-1.414</td>
<td>2.102***</td>
<td>0.375</td>
</tr>
<tr>
<td>FE×BAD×IND</td>
<td>+</td>
<td>4.714***</td>
<td>4.783***</td>
<td>0.517</td>
<td>0.473</td>
</tr>
<tr>
<td>FE×GOOD×LGSIZE</td>
<td>–</td>
<td>-3.043***</td>
<td>-3.043***</td>
<td>-0.238</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×LGFOLLOW</td>
<td>?</td>
<td>3.527***</td>
<td>3.527***</td>
<td>0.390</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×BETA</td>
<td>–</td>
<td>-2.262</td>
<td>-2.262</td>
<td>-0.911*</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×MB</td>
<td>+</td>
<td>0.014</td>
<td>0.014</td>
<td>0.075***</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×GROWTH</td>
<td>+</td>
<td>-6.254</td>
<td>-6.254</td>
<td>-0.750</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×STD_ROE</td>
<td>–</td>
<td>0.176</td>
<td>0.176</td>
<td>-0.486**</td>
<td></td>
</tr>
<tr>
<td>FE×GOOD×PSST</td>
<td>+</td>
<td>11.263***</td>
<td>11.263***</td>
<td>2.465**</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×LGSIZE</td>
<td>–</td>
<td>0.183</td>
<td>0.183</td>
<td>0.153</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×LGFOLLOW</td>
<td>?</td>
<td>0.821</td>
<td>0.821</td>
<td>-0.169</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×BETA</td>
<td>–</td>
<td>3.535**</td>
<td>3.535**</td>
<td>0.204</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×MB</td>
<td>+</td>
<td>0.002</td>
<td>0.002</td>
<td>0.004***</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×GROWTH</td>
<td>+</td>
<td>19.679***</td>
<td>19.679***</td>
<td>7.729***</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×STD_ROE</td>
<td>–</td>
<td>-0.342</td>
<td>-0.342</td>
<td>-0.014</td>
<td></td>
</tr>
<tr>
<td>FE×BAD×PSST</td>
<td>+</td>
<td>-0.375</td>
<td>-0.375</td>
<td>1.811**</td>
<td></td>
</tr>
<tr>
<td>FE_1</td>
<td>+</td>
<td>0.706***</td>
<td>0.706***</td>
<td>-0.045</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.068</td>
<td>0.075</td>
<td>0.036</td>
<td>0.040</td>
</tr>
</tbody>
</table>

GOOD and BAD are the dummy variables for FE ≥ 0 and FE < 0. For definitions of other variables, see Tables 3-3 and 3-4. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
Table 3-6. The disciplining effect of independent analysts on the association between abnormal returns and consensus forecast errors by nonindependent analysts (matched sample)

Model: \( BHAR_{it} = \alpha_0 + \alpha_1 FE_{NI_{it}} + \alpha_2 FE_{NI_{it}} \times IND_{it} + \sum_j \beta_j FE_{NI_{it}} \times Controls_{it} + \psi FE_{NI_{it}} \times LGSIZE_{it} \times \theta IND_{it} + \sum_m \lambda_m Q_m + \sum_n \rho_n Y_n + \sum_{it} \theta_n \theta IND_{it} + \epsilon_{it} \)  \hspace{1cm} (3.1)

Panel A: Pooled forecast errors

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Predicted Sign</th>
<th>BHAR90</th>
<th>BHAR3</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.044***</td>
<td>0.043***</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>FE_NI</td>
<td>+</td>
<td>7.627***</td>
<td>9.654***</td>
<td>2.871***</td>
<td>2.182***</td>
</tr>
<tr>
<td>FE_NI×IND</td>
<td>+</td>
<td>1.855*</td>
<td>0.897</td>
<td>-0.092</td>
<td>-0.219</td>
</tr>
<tr>
<td>FE_NI×LGSIZE</td>
<td>-</td>
<td>-1.246***</td>
<td>-0.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×LGFOllw</td>
<td>?</td>
<td>2.341***</td>
<td>0.077</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BETA</td>
<td>+</td>
<td>0.279</td>
<td></td>
<td>-0.362</td>
<td></td>
</tr>
<tr>
<td>FE_NI×GROWTH</td>
<td>+</td>
<td>0.000</td>
<td></td>
<td>0.005***</td>
<td></td>
</tr>
<tr>
<td>FE_NI×STD_ROE</td>
<td>-</td>
<td>-0.163</td>
<td></td>
<td>-0.302*</td>
<td></td>
</tr>
<tr>
<td>FE_NI×PSST</td>
<td>+</td>
<td>5.382***</td>
<td></td>
<td>2.305***</td>
<td></td>
</tr>
<tr>
<td>FE_1</td>
<td>+</td>
<td>0.691***</td>
<td></td>
<td>-0.063</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.062</td>
<td></td>
<td>0.035</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Note: *** p < 0.01, ** p < 0.05, * p < 0.1.
Table 3.6. – Continued

Panel B: Good news and bad news separated

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Predicted Sign</th>
<th>BHAR90 (1)</th>
<th>BHAR90 (2)</th>
<th>BHAR90 (3)</th>
<th>BHAR90 (4)</th>
<th>BHAR90 (5)</th>
<th>BHAR90 (6)</th>
<th>BHAR90 (7)</th>
<th>BHAR90 (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.036**</td>
<td>0.038**</td>
<td>0.004</td>
<td>0.004</td>
<td>0.038**</td>
<td>0.040**</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>FE_NI×GOOD×IND</td>
<td>+</td>
<td>0.589</td>
<td>0.197</td>
<td>-0.415</td>
<td>-0.640</td>
<td>1.085</td>
<td>-1.335</td>
<td>-0.269</td>
<td>-0.692</td>
</tr>
<tr>
<td>FE_NI×BAD</td>
<td>+</td>
<td>3.908***</td>
<td>-2.028</td>
<td>2.096***</td>
<td>0.298</td>
<td>2.929**</td>
<td>-4.502</td>
<td>1.401***</td>
<td>-2.027</td>
</tr>
<tr>
<td>FE_NI×BAD×IND</td>
<td>+</td>
<td>3.796***</td>
<td>3.989***</td>
<td>0.365</td>
<td>0.441</td>
<td>3.096*</td>
<td>2.867</td>
<td>0.240</td>
<td>-0.135</td>
</tr>
<tr>
<td>FE_NI×GOOD×LGSIZE</td>
<td>–</td>
<td>-2.620***</td>
<td>-0.222</td>
<td></td>
<td></td>
<td>-4.216***</td>
<td>-0.514**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×LGFOllOW</td>
<td>?</td>
<td>3.313***</td>
<td>0.382</td>
<td></td>
<td></td>
<td>4.423***</td>
<td>0.476</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×BETA</td>
<td>–</td>
<td>-2.331</td>
<td>-0.829*</td>
<td></td>
<td></td>
<td>-1.812</td>
<td>-0.231</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×MB</td>
<td>+</td>
<td>0.014</td>
<td>0.072**</td>
<td></td>
<td></td>
<td>4.537***</td>
<td>0.892**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×GROWTH</td>
<td>+</td>
<td>-6.260</td>
<td>-0.703</td>
<td></td>
<td></td>
<td>-7.700*</td>
<td>-1.594</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×STD_ROE</td>
<td>–</td>
<td>0.202</td>
<td>-0.488**</td>
<td></td>
<td></td>
<td>-1.652**</td>
<td>-0.672***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×GOOD×PSST</td>
<td>+</td>
<td>11.203***</td>
<td>2.414**</td>
<td></td>
<td></td>
<td>9.635***</td>
<td>3.310***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×LGSIZE</td>
<td>–</td>
<td>0.350</td>
<td>0.192</td>
<td></td>
<td></td>
<td>0.731</td>
<td>0.337</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×LGFOllOW</td>
<td>?</td>
<td>0.736</td>
<td>-0.242</td>
<td></td>
<td></td>
<td>0.527</td>
<td>0.454</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×BETA</td>
<td>–</td>
<td>3.178**</td>
<td>0.162</td>
<td></td>
<td></td>
<td>3.088*</td>
<td>0.433</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×MB</td>
<td>+</td>
<td>0.001</td>
<td>0.004***</td>
<td></td>
<td></td>
<td>0.005</td>
<td>0.006***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×GROWTH</td>
<td>+</td>
<td>16.021**</td>
<td>5.427**</td>
<td></td>
<td></td>
<td>17.808*</td>
<td>5.216*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×STD_ROE</td>
<td>–</td>
<td>-0.198</td>
<td>-0.026</td>
<td></td>
<td></td>
<td>-1.515</td>
<td>-0.453</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE_NI×BAD×PSST</td>
<td>+</td>
<td>-0.006</td>
<td>1.841**</td>
<td></td>
<td></td>
<td>-2.077</td>
<td>1.105</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE</td>
<td>+</td>
<td>0.710***</td>
<td>-0.057</td>
<td></td>
<td></td>
<td>0.626**</td>
<td>-0.091</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.065</td>
<td>0.070</td>
<td>0.036</td>
<td>0.039</td>
<td>0.065</td>
<td>0.077</td>
<td>0.028</td>
<td>0.035</td>
</tr>
</tbody>
</table>

Forecasts errors FE_NI are by nonindependent analysts only. GOOD and BAD are the dummy variables for FE ≥ 0 and FE < 0. For definitions of other variables, see Tables 3-3 and 3-4. Forecast errors in columns 1–4 of each panel are based on forecasts by all nonindependent analysts following the IND = 1 and IND = 0 matched quarters. Forecast errors in columns 5–8 are based on the subset of forecasts by the same nonindependent analysts following both the IND = 1 and IND = 0 matched quarters. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
Table 3-7. The relative superiority of independent analyst forecasts to nonindependent analyst forecasts (IND = 1 sample)

Model: \( BHAR_t = \alpha_0 + \alpha_1 FE_{it} + \sum_k \lambda_k Q_k + \sum_m \rho_m Y_{im} + \sum_n \theta_n INDUSTRY_n + \epsilon_{it} \) (3.2)

Panel A: Pooled forecast errors (n = 6,999)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
<th>All analysts</th>
<th>Controlling for number of analysts through randomized drawing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BHAR90</td>
<td>BHAR3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.054***</td>
<td>0.050***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.054***</td>
<td>0.050***</td>
</tr>
<tr>
<td>( FE_{IND} )</td>
<td></td>
<td>6.625***</td>
<td>1.772***</td>
</tr>
<tr>
<td>( FE_{NI} )</td>
<td></td>
<td>8.213***</td>
<td>2.375***</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td></td>
<td>0.070</td>
<td>0.074</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.070</td>
<td>0.062</td>
</tr>
<tr>
<td>( FE_{IND} – FE_{NI} )</td>
<td></td>
<td>1.058***</td>
<td>0.152*</td>
</tr>
</tbody>
</table>

Panel B: Good news and bad news separated, with control for number of analysts through randomized drawing

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Dependent Variable</th>
<th>Good news (n = 4,735)</th>
<th>Bad news (n = 2,264)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BHAR90</td>
<td>BHAR3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.066***</td>
<td>0.065***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.034</td>
<td>0.033</td>
</tr>
<tr>
<td>( FE_{IND} )</td>
<td></td>
<td>5.569***</td>
<td>1.286***</td>
</tr>
<tr>
<td>( FE_{NI} )</td>
<td></td>
<td>4.184***</td>
<td>1.092***</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td></td>
<td>0.049</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.087</td>
<td>0.084</td>
</tr>
<tr>
<td>( FE_{IND} – FE_{NI} )</td>
<td></td>
<td>1.385***</td>
<td>0.195**</td>
</tr>
</tbody>
</table>

\( FE_{IND} \) and \( FE_{NI} \) are consensus forecast errors by independent and nonindependent analysts respectively. Good news and bad news are based on \( FE \geq 0 \) and \( FE < 0 \). For definitions of other variables, see Table 3-3. In Panel A, columns 1 to 4 are based on all available forecasts for each group of analysts. Columns 5 to 8 control for the number of analysts in the calculation of \( FE_{IND} \) and \( FE_{NI} \) through the following randomization procedure: For each firm quarter, we first determine the smaller of the number of independent analysts and the number of nonindependent analysts. Then we randomly draw this number of forecasts from each group of analysts and calculate the consensus forecasts. Regressions are separately run for the two sets of forecast errors. The procedure is repeated 1,000 times and the mean coefficient estimates are reported. The same procedure is applied in Panel B for good news and bad news quarters. The significance of \( FE_{IND} – FE_{NI} \) is based on the distribution of the 1,000 coefficients obtained in the randomization process. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
Table 3-8. Incremental contribution by independent analysts vs. incremental contribution by nonindependent analysts to consensus forecasts, with control for number of analysts through randomized drawing (IND = 1 sample)

Model: $$BHAR_{it} = \beta_0 + \beta_1 FE1_{it} + \beta_2 (F1_{it} - F2_{it}) + \sum_k \lambda_k Q_k + \sum_m \rho_m Y_{r_m} + \sum_n \theta_n INDUSTRY_{n} + \varepsilon_{it}$$ (3.3)

Panel A: Pooled forecast errors (n = 6,999)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Forecast F2 by independent analysts</th>
<th>Forecast F2 by nonindependent analysts</th>
</tr>
</thead>
<tbody>
<tr>
<td>BHAR90</td>
<td>0.052***</td>
<td>0.051***</td>
</tr>
<tr>
<td>BHAR3</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE1</td>
<td>8.969***</td>
<td>8.569***</td>
</tr>
<tr>
<td>(F1 – F2)</td>
<td>3.454***</td>
<td>2.700***</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.078</td>
<td>0.075</td>
</tr>
<tr>
<td>Difference of (F1 – F2) between independent and nonindependent analysts</td>
<td>0.754**</td>
<td>-0.111</td>
</tr>
</tbody>
</table>

Panel B: Good news and bad news separated

<table>
<thead>
<tr>
<th></th>
<th>Good news (n = 4,735)</th>
<th>Bad news (n = 2,264)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forecast F2 by independent analysts</td>
<td>Forecast F2 by nonindependent analysts</td>
</tr>
<tr>
<td>BHAR90</td>
<td>0.056***</td>
<td>0.058***</td>
</tr>
<tr>
<td>BHAR3</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE1</td>
<td>9.416***</td>
<td>8.377***</td>
</tr>
<tr>
<td>(F1 – F2)</td>
<td>2.841***</td>
<td>3.035***</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.055</td>
<td>0.053</td>
</tr>
<tr>
<td>Difference of (F1 – F2) between independent and nonindependent analysts</td>
<td>-0.194</td>
<td>-0.296</td>
</tr>
</tbody>
</table>

F2 is the consensus forecast by analysts whose incremental contribution is under study. F1 and FE1 are the consensus forecast and forecast error by the remaining analysts. For definitions of other variables, see Table 3-3. The number of analysts is controlled through the following randomization procedure: For each firm quarter, we first determine the smaller of the number of independent analysts and the number of nonindependent analysts. Then we randomly draw this number of forecasts from each group of analysts and calculate the consensus forecasts (F2). For each drawing, we also calculate the consensus forecast (F1) and forecast error (FE2) by the remaining analysts. Regressions are separately run for independent and nonindependent analysts. The procedure is repeated 1,000 times and the mean coefficient estimates are reported. The same procedure is applied in Panel B for good news and bad news quarters. The significance of the difference in (F1 – F2) between independent and nonindependent analysts is based on the distribution of the 1,000 coefficients obtained in the randomization process. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
Table 3.9. The effects of independent analysts on analysts from the 12 investment banks targeted in the Global Settlement

Panel A: The disciplining effect of independent analysts on analysts from the 12 IBs (n = 5,202)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Predicted Sign</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.049***</td>
<td>0.048***</td>
</tr>
<tr>
<td>FE_NI</td>
<td>+</td>
<td>7.075***</td>
<td>6.073</td>
</tr>
<tr>
<td>FE_NI×IND</td>
<td>+</td>
<td>1.737</td>
<td>0.157</td>
</tr>
<tr>
<td>FE_NI×GSIZE</td>
<td>–</td>
<td>-0.637</td>
<td>-0.004</td>
</tr>
<tr>
<td>FE_NI×LGFollow</td>
<td>?</td>
<td>1.770</td>
<td>0.121</td>
</tr>
<tr>
<td>FE_NI×BETA</td>
<td>–</td>
<td>0.605</td>
<td>0.611</td>
</tr>
<tr>
<td>FE_NI×MB</td>
<td>+</td>
<td>0.000</td>
<td>0.006***</td>
</tr>
<tr>
<td>FE_NI×Growth</td>
<td>+</td>
<td>-7.074**</td>
<td>-0.391</td>
</tr>
<tr>
<td>FE_NI×STD_RoE</td>
<td>–</td>
<td>-0.290</td>
<td>-0.401**</td>
</tr>
<tr>
<td>FE_NI×PSST</td>
<td>+</td>
<td>4.654*</td>
<td>1.448*</td>
</tr>
<tr>
<td>FE_1</td>
<td></td>
<td>0.232</td>
<td>-0.065</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.065</td>
<td>0.033</td>
</tr>
</tbody>
</table>

Panel B: The disciplining effect with good news and bad news separated (n = 5,202)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Predicted Sign</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.042**</td>
<td>0.040**</td>
</tr>
<tr>
<td>FE_NI×GOOD</td>
<td>+</td>
<td>10.276***</td>
<td>15.853***</td>
</tr>
<tr>
<td>FE_NI×GOOD×IND</td>
<td>+</td>
<td>-0.364</td>
<td>-0.842</td>
</tr>
<tr>
<td>FE_NI×BAD</td>
<td>+</td>
<td>3.517***</td>
<td>-8.184</td>
</tr>
<tr>
<td>FE_NI×BAD×IND</td>
<td>+</td>
<td>4.469**</td>
<td>5.291***</td>
</tr>
<tr>
<td>FE_NI×GOOD×LGSIZE</td>
<td>–</td>
<td>-1.248</td>
<td>0.039</td>
</tr>
<tr>
<td>FE_NI×GOOD×LGFollow</td>
<td>?</td>
<td>1.774</td>
<td>0.181</td>
</tr>
<tr>
<td>FE_NI×GOOD×BETA</td>
<td>–</td>
<td>-4.198**</td>
<td>-0.081</td>
</tr>
<tr>
<td>FE_NI×GOOD×MB</td>
<td>+</td>
<td>0.059</td>
<td>0.068**</td>
</tr>
<tr>
<td>FE_NI×GOOD×Growth</td>
<td>+</td>
<td>-9.519***</td>
<td>-0.627</td>
</tr>
<tr>
<td>FE_NI×GOOD×STD_RoE</td>
<td>–</td>
<td>0.132</td>
<td>-0.415*</td>
</tr>
<tr>
<td>FE_NI×GOOD×PSST</td>
<td>+</td>
<td>7.828**</td>
<td>0.673</td>
</tr>
<tr>
<td>FE_NI×BAD×LGSIZE</td>
<td>–</td>
<td>0.915</td>
<td>-0.041</td>
</tr>
<tr>
<td>FE_NI×BAD×LGFollow</td>
<td>?</td>
<td>-0.239</td>
<td>0.051</td>
</tr>
<tr>
<td>FE_NI×BAD×BETA</td>
<td>–</td>
<td>6.523***</td>
<td>1.294**</td>
</tr>
<tr>
<td>FE_NI×BAD×MB</td>
<td>+</td>
<td>0.003</td>
<td>0.006***</td>
</tr>
<tr>
<td>FE_NI×BAD×Growth</td>
<td>+</td>
<td>-0.495</td>
<td>1.177</td>
</tr>
<tr>
<td>FE_NI×BAD×STD_RoE</td>
<td>–</td>
<td>-1.565</td>
<td>-0.456</td>
</tr>
<tr>
<td>FE_NI×BAD×PSST</td>
<td>+</td>
<td>-1.204</td>
<td>1.692</td>
</tr>
<tr>
<td>FE_1</td>
<td></td>
<td>0.316</td>
<td>0.584</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.067</td>
<td>0.072</td>
</tr>
</tbody>
</table>

96
### Table 3-9. – Continued

Panel C: The relative superiority of independent analysts to analysts from the 12 IBs, with control for number of analysts through randomized drawing (n = 5,072)

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Dependent Variable</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.059***</td>
<td>0.056***</td>
</tr>
<tr>
<td>FE_IND</td>
<td></td>
<td>6.400***</td>
<td></td>
</tr>
<tr>
<td>FE_NI</td>
<td></td>
<td></td>
<td>4.668***</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td></td>
<td>0.077</td>
<td>0.068</td>
</tr>
<tr>
<td>FE_IND – FE_NI</td>
<td></td>
<td>1.732***</td>
<td></td>
</tr>
</tbody>
</table>

Panel D: Incremental contribution by independent analysts vs. incremental contribution by analysts from the 12 IBs, with control for number of analysts through randomized drawing (n = 5,072)

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Dependent Variable</th>
<th>Forecast F2 by independent analysts</th>
<th>Forecast F2 by analysts from the 12 IBs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BHAR90</td>
<td>BHAR3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.058***</td>
<td>0.004</td>
</tr>
<tr>
<td>FE1</td>
<td></td>
<td>6.988***</td>
<td>2.235***</td>
</tr>
<tr>
<td>(F1 – F2)</td>
<td></td>
<td>4.899***</td>
<td>1.208***</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td></td>
<td>0.078</td>
<td>0.026</td>
</tr>
<tr>
<td>Difference of (F1 – F2) between independent analysts and analysts from the 12 IBs</td>
<td>4.194***</td>
<td>0.761***</td>
<td></td>
</tr>
</tbody>
</table>

In Panels A and B, forecast errors FE_NI are by analysts from the 12 IBs. In Panels C and D, the randomization procedure is similar to that described in Tables 3-7 and 3-8, except that the random drawings from nonindependent analysts are now from forecasts by analysts from the 12 IBs. For other variable definitions, see Tables 3-3, 3-4, 3-7 and 3-8. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).
Table 3-10. The effects of independent analysts on the last forecasts by non-independent analysts

Panel A: The disciplining effect (n = 8,346)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Predicted Sign</th>
<th>Dependent Variable</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.043***</td>
<td>0.043***</td>
<td>0.005</td>
</tr>
<tr>
<td>FE_NI</td>
<td>+</td>
<td>4.990***</td>
<td>6.361***</td>
<td>2.318***</td>
</tr>
<tr>
<td>FE_NI×IND</td>
<td>+</td>
<td>2.617***</td>
<td>2.589**</td>
<td>0.380</td>
</tr>
<tr>
<td>FE_NI×LGSIZE</td>
<td>–</td>
<td>-0.599</td>
<td></td>
<td>0.080</td>
</tr>
<tr>
<td>FE_NI×LGFOLOW</td>
<td>?</td>
<td>-0.229</td>
<td></td>
<td>-0.291</td>
</tr>
<tr>
<td>FE_NI×BETA</td>
<td>–</td>
<td>0.417</td>
<td></td>
<td>-0.405</td>
</tr>
<tr>
<td>FE_NI×MB</td>
<td>+</td>
<td>0.000</td>
<td></td>
<td>0.005***</td>
</tr>
<tr>
<td>FE_NI×GROWTH</td>
<td>+</td>
<td>-0.164</td>
<td></td>
<td>0.509</td>
</tr>
<tr>
<td>FE_NI×STD_ROE</td>
<td>–</td>
<td>-0.048</td>
<td></td>
<td>-0.297*</td>
</tr>
<tr>
<td>FE_NI×PSST</td>
<td>+</td>
<td>4.080**</td>
<td></td>
<td>2.104***</td>
</tr>
<tr>
<td>FE_1</td>
<td></td>
<td>0.834***</td>
<td></td>
<td>-0.041</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.049</td>
<td>0.051</td>
<td>0.030</td>
</tr>
</tbody>
</table>

Panel B: The disciplining effect with good news and bad news separated (n = 8,346)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Predicted Sign</th>
<th>Dependent Variable</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Intercept</td>
<td>?</td>
<td>0.035**</td>
<td>0.038**</td>
<td>0.003</td>
</tr>
<tr>
<td>FE_NI×GOOD</td>
<td>+</td>
<td>8.315***</td>
<td>14.386***</td>
<td>3.170***</td>
</tr>
<tr>
<td>FE_NI×GOOD×IND</td>
<td>+</td>
<td>1.923</td>
<td>1.980</td>
<td>0.006</td>
</tr>
<tr>
<td>FE_NI×BAD</td>
<td>+</td>
<td>1.667*</td>
<td>-2.035</td>
<td>1.455***</td>
</tr>
<tr>
<td>FE_NI×BAD×IND</td>
<td>+</td>
<td>4.021***</td>
<td>4.750***</td>
<td>0.909**</td>
</tr>
<tr>
<td>FE_NI×GOOD×LGSIZE</td>
<td>–</td>
<td>-1.893***</td>
<td></td>
<td>-0.087</td>
</tr>
<tr>
<td>FE_NI×GOOD×LGFOLOW</td>
<td>?</td>
<td>1.613</td>
<td></td>
<td>-0.007</td>
</tr>
<tr>
<td>FE_NI×GOOD×BETA</td>
<td>–</td>
<td>-1.619</td>
<td></td>
<td>-0.733</td>
</tr>
<tr>
<td>FE_NI×GOOD×MB</td>
<td>+</td>
<td>-0.007</td>
<td></td>
<td>0.059**</td>
</tr>
<tr>
<td>FE_NI×GOOD×GROWTH</td>
<td>+</td>
<td>-5.629</td>
<td></td>
<td>-1.300</td>
</tr>
<tr>
<td>FE_NI×GOOD×STD_ROE</td>
<td>–</td>
<td>0.520</td>
<td></td>
<td>-0.471**</td>
</tr>
<tr>
<td>FE_NI×GOOD×PSST</td>
<td>+</td>
<td>8.961***</td>
<td></td>
<td>2.659***</td>
</tr>
<tr>
<td>FE_NI×BAD×LGSIZE</td>
<td>–</td>
<td>0.622</td>
<td></td>
<td>0.159</td>
</tr>
<tr>
<td>FE_NI×BAD×LGFOLOW</td>
<td>?</td>
<td>-1.974*</td>
<td></td>
<td>-0.485</td>
</tr>
<tr>
<td>FE_NI×BAD×BETA</td>
<td>–</td>
<td>2.598*</td>
<td></td>
<td>-0.008</td>
</tr>
<tr>
<td>FE_NI×BAD×MB</td>
<td>+</td>
<td>0.002</td>
<td></td>
<td>0.004***</td>
</tr>
<tr>
<td>FE_NI×BAD×GROWTH</td>
<td>+</td>
<td>9.731</td>
<td></td>
<td>5.757***</td>
</tr>
<tr>
<td>FE_NI×BAD×STD_ROE</td>
<td>–</td>
<td>-0.486</td>
<td></td>
<td>-0.004</td>
</tr>
<tr>
<td>FE_NI×BAD×PSST</td>
<td>+</td>
<td>-0.342</td>
<td></td>
<td>1.449**</td>
</tr>
<tr>
<td>FE_1</td>
<td></td>
<td>0.839***</td>
<td></td>
<td>-0.037</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.055</td>
<td>0.057</td>
<td>0.032</td>
</tr>
</tbody>
</table>

98
Table 3-10. – Continued

Panel C: The relative superiority of the last forecasts by independent analysts to the last forecasts by nonindependent analysts (n = 6,999)

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>BHAR90</th>
<th>BHAR3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.054***</td>
<td>0.051***</td>
</tr>
<tr>
<td>FE_IND</td>
<td>6.525***</td>
<td></td>
</tr>
<tr>
<td>FE_NI</td>
<td></td>
<td>5.716***</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.069</td>
<td>0.058</td>
</tr>
<tr>
<td>FE_IND – FE_NI</td>
<td></td>
<td>0.809</td>
</tr>
</tbody>
</table>

Panel D: Incremental contribution of the last forecasts by independent analysts vs. incremental contribution of the last forecasts by nonindependent analysts (n = 6,999)

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Forecast F2 by independent forecast</th>
<th>Forecast F2 by nonindependent forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BHAR90</td>
<td>BHAR3</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.052***</td>
<td>0.001</td>
</tr>
<tr>
<td>FE1</td>
<td>8.970***</td>
<td>2.533***</td>
</tr>
<tr>
<td>(F1 – F2)</td>
<td>3.193***</td>
<td>0.720***</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.078</td>
<td>0.030</td>
</tr>
</tbody>
</table>

Difference of (F1 – F2) between independent analysts and nonindependent analysts

2.126**  -0.475*

In Panels A and B, FE_NI is the error in the single last forecast by nonindependent analysts. In Panel C, forecast errors FE_IND and FE_NI are the errors in the single last forecasts by independent and nonindependent analysts, respectively. In Panel D, F2 is the single last forecast by the group of analysts whose incremental contribution is under study, and F1 and FE1 are the consensus forecast and forecast error by the remaining forecasts. For other variable definitions, see Tables 3-3 and 3-4. In Panels C and D, statistical significance of the difference in coefficients from two regressions is based on the Chow test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed).