Essays on Earnings Forecasting Accuracy

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Abstract

This dissertation comprises two essays on earnings forecasting accuracy. Chapter 2 focuses on how management forecasting accuracy is affected by managers' behavioral biases over time and Chapter 3 addresses how analyst portfolio design choices affect cross-sectional differences in analyst forecasting accuracy.

In particular, Chapter 2 examines how CEOs' overconfidence and their exhibited self-serving attribution biases affect how they adjust their future earnings forecasts when they receive feedback concerning their prior forecasts. I find that overconfident CEOs respond to feedback by improving their future forecasting accuracy, but they do so more slowly than their less confident peers. I also find that overconfident CEOs learn to improve their future forecasting accuracy only when feedback is less ambiguous in the form of forecasting errors. In contrast, managers who are less confident respond to both less ambiguous forecasting errors and more ambiguous market feedback concerning their prior forecasts.

Chapter 3 examines analysts' supply chain coverage portfolio design and their forecasting accuracy. I define the relation between a firm and one of the firm's major customer firms as a "supply chain relation". Further, I define an analyst who issues forecasts for both the firm and one or more of the firm's major customers in the same year as a "supply chain analyst". I classify all firms followed by the supply chain analyst into one of the three categories in a given year: “focal firms”, i.e., firms for which the analyst also covers one or more of the firm’s major customers, “major customers” of a focal firm for the analyst, and “other” firms which include all remaining firms in the analyst’s portfolio.

I find that analysts who follow both a focal firm and one or more of the firm’s major customers issue significantly more accurate earnings forecasts for both the focal firm and the firm’s major customers than the same analysts issue for “other” firms in the same analyst portfolio. I also find that these analysts are more accurate in their forecasts for the focal firm and the firm’s major customers than other non-supply chain analysts following the same firm, but not the firm’s supply chain. I show that the superior forecasting accuracy for supply chain analysts for both the focal firm and the firm’s major customers is achieved at the cost of reduced forecasting accuracy for “other” firms in the analyst portfolio. In explaining the relative importance of forecasting accuracy for the firms in the analyst portfolio, I find that focal firms and the firms’ major customers are more likely to generate more profitable trading commissions and operate in an industry segment that has a greater number of other peer firms than “other” firms in the same analyst portfolio. This evidence is consistent with earlier studies and suggests when analysts have stronger incentives to generate trading commissions from the stock of a firm, the analysts are more likely to spend effort to acquire more precise information about the firm (Hayes, 1998). When covering the firm’s supply chains helps analysts produce more precise information about the firm, analyst forecasting accuracy improves accordingly.

Key Words: Management forecast, CEO overconfidence, analyst forecast, supply chain, supply chain analyst, analyst portfolio design

Preface

I owe my sincere gratitude to many people who help and support me during my five years toward this degree. First, I would like to thank my advisor, Harry Evans, and my co-advisor Nandu Nagarajan for their intellectual guidance, patience, encouragement, and their kindness over the last five years. I am especially fortunate to have Harry as my mentor. I have benefited tremendously from each meeting and discussion I had with him, as well as the project we worked on. His behavior and attitude influence me substantially, and help me to become a better scholar, an enthusiastic teacher, and perhaps a better person. I am also very thankful to Nandu, who has continuously provided me with helpful advice and insightful comments since I have been in the program. I am also grateful to other members in my committee, Vicky Hoffman, Mei Feng, and Kyonghee Kim, for their comments and suggestions on each draft of this dissertation.

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Table of contents

List of appendices

List of tables

Figures

Chapter 1: Introduction

Earnings forecasts are regarded as providing valuable information to the investment community. They are important to investors for determining the underlying value of a firm, evaluating a firm's potential investment opportunities, and for boards of directors in effectively designing managers' compensation contracts (e.g., Givoly and Lakonishok, 1984; Brown, Hagerman, Griffin, and Zmijewski, 1987). Prior studies have examined three types of earnings forecasts: forecasts issued by managers, by analysts, and forecasts estimated using time series earnings models (see, for example, Beyer, Cohen, Lys, and Walther, 2010). These studies suggest that managers and analysts incorporate general economic news and firm-specific information into their forecasts in a particularly timely fashion, and their forecasts are more accurate than forecasts produced by time series models (e.g., Brown and Rozeff, 1978; Brown, Richardson, and Schwager, 1987; Fried and Givoly, 1982). Therefore, more recent studies, including this dissertation, focus on forecasts issued by managers and analysts.

For earnings forecasts to be valuable prior to the release of earnings reports, they need to be informative. Accurate and informative earnings forecasts build managers' and analysts' credibility and reputation in financial markets, and help analysts enjoy higher annual compensation and better career prospects (Williams, 1996; Frankel and Lee, 1998; Mikhail, Walther, and Willis, 1999; Hong, Kubik, and Solomon, 2000; Clement and Tse, 2003; Graham, Harvey, and Rajgopal, 2005; Jackson, 2005).

Forecasting accuracy is affected by a variety of different factors. These factors are mostly related to the quantity or the quality of information used as input to the forecasting task (Beyer et al., 2010). Prior studies suggest that managers have private information about their own firms and they are better informed about their firms than analysts; therefore, management forecasts concerning the firm's prospects are more accurate than forecasts issued by analysts (Beyer et al., 2010). Likewise, when analysts have better information about a firm, their forecasts for the firm are more accurate (Jacob, Lys, and Neale, 1999).

Factors that have been documented to affect forecasting accuracy can be broadly categorized into three categories: (a) characteristics of the forecast itself, (b) the information environment of the firm or the characteristics of the firm for which a forecast is issued, and (c) characteristics of individuals who issue the forecast. An example of the characteristics of a forecast that affects the forecast accuracy is forecast horizon. Studies have suggested that forecasts with longer horizons are generally less accurate than those with shorter horizons because of the greater uncertainty associated with longer earnings realization processes (e.g., Clement and Tse, 2003).

Second, characteristics of a firm's information environment affect forecasting accuracy. For example, firms operating in a common-law environment generally have stronger investor protection laws and higher-quality financial reporting systems in place than do firms in a civil-law environment. As a result, the market demand for analyst forecasting accuracy is higher and forecasts are generally more accurate in a common-law environment than forecasts in a civil-law environment (Barniv et al., 2005). Characteristics of a firm are also important in affecting forecasting accuracy. For example, forecasts for a firm are less accurate when the firm is riskier, operating at a loss, experiencing information asymmetry, having more complicated operations, higher litigation risk, or operating in a more volatile or a less informative environment (e.g., Lang and Lundholm, 1996; Duru and Reeb, 2002; Rogers and Stocken, 2005).

Finally, forecasting accuracy is also affected by the characteristics of the individuals who issue the forecast. These characteristics are related to either individual forecaster's behavioral biases or her economic rationality in her forecasting decision. For example, prior studies have generally suggested that forecasters' abilities, experiences, and resources available for application to the forecasting task affect their forecasting accuracy (e.g., Trueman, 1986; Clement, 1999; Clement and Tse, 2003). Moreover, the psychology literature has extensively documented that when individuals make judgments or decisions in an uncertain environment, their cognitive biases affect their information processing and decision-making processes (Kahneman and Tversky, 1973). This argument suggests that behavioral biases also affect individuals' forecasting accuracy. For example, Hribar and Yang (2009) show that CEOs who are subject to overconfidence biases are more likely to subjectively overestimate (underestimate) the favorable (unfavorable) effects of their actions or decisions on positive (negative) earnings realizations, and they are overly optimistic about the firm's future earnings prospects. Hilary and Menzly (2006) document that analysts become overconfident in their abilities to predict future earnings after a series of good predictions, and their subsequent forecasting accuracy is reduced.

Managers and analysts are distinctly different decision makers, and characteristics specific to these individuals also can affect their forecasting accuracy. Unlike managers who only issue forecasts for their own firms, analysts provide periodic earnings forecasts for perhaps 10 to 20 firms based on their analyses of the firms' financial, operational, and strategic plans. Therefore, how analysts organize the firms in their portfolios and how analysts allocate their level of effort to different firms in the portfolio would affect the quantity and the quality of information they have about each firm in their portfolios and their overall forecasting accuracy (Kini, Mian, Rebello, and Venkateswaran, 2009).

This dissertation examines the accuracy of earnings forecasts issued by managers and analysts. I focus on factors related to individuals' characteristics, including individuals' behavioral biases and their economic rationality, which are associated with forecasting accuracy for two reasons. First, prior studies have documented the effects of managers' biases on their forecasting accuracy (e.g., Hribar and Yang, 2007; Schrand and Zechman, 2010). These studies consider such biases as a fixed parameter that varies cross-sectionally but not over time. However, earnings forecasts require multi-period decisions. Individual forecasters will receive and process feedback information concerning their prior forecasts when they make their forecasting decisions for the next period.[1] The literature in economics, psychology, and management has documented the general efficacy of feedback concerning individuals' prior decisions in facilitating their learning and adaption when they perform the task again (Postman and Brown, 1952; Anderson and Berdahl, 2002). This line of research suggests that while individuals' behavioral biases affect how they process feedback information when they make subsequent decisions, their behavioral biases are also adjusted as a result of feedback (Camerer, 1995). Therefore, it is possible that managers' behavioral biases and their forecasting accuracy would vary over time.

Second, while one stream of the literature focuses on the effect of managers' and analysts' behavioral biases on their forecasting behaviors, the dominant academic paradigm is that managers and analysts are economically rational in their forecasting decisions. For example, prior studies suggest that analysts are economically rational in deciding the set of firms they follow in their portfolios (e.g., Barth et al., 2001; Kini et al., 2009). These studies generally

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[1] For example, Feng and Koch (2010) examine how managers' decisions to issue quarterly earnings guidance in the current period are affected by outcomes from their previous earnings guidance. They find that managers are less likely to provide guidance in the subsequent year when their past forecasts have been overly optimistic, have resulted in earnings disappointments, and were accompanied by high levels of stock price volatility.

suggest that when analysts specialize in an industry by including firms from the same industry in their portfolios, they gain synergy in information gathering and processing for these firms, and their overall forecasting accuracy improves (Kini et al., 2009; De Franco, Kothari, and Verdi, 2009). At the same time, an examination of analyst portfolio decisions shows that fewer than 40% of all analysts in the Institutional Brokers Estimates System (I/B/E/S) from January 1991 to December 2008 followed only firms from a single industry at the one-digit standard industrial classification (SIC) code level. It is thus puzzling why a vast proportion of analysts cover more than one industry "when less breadth is related to improved forecast accuracy" (Ramnath, Rock, and Shane, 2008, p.10). This dissertation seeks to provide some insight to this question.

Chapter 2 and Chapter 3 of this dissertation examine the effect of managers' behavioral biases on their forecasting accuracy over time and cross-sectional variations in analysts' economic rationality in their portfolio choice on their forecasting accuracy, respectively. In particular, Chapter 2 focuses on a combination of managers' overconfidence biases and self-serving attribution biases that affect management forecasting accuracy over time. I consider overconfidence biases as individuals' tendency to over-estimate the likelihood of the effect of their actions or decisions on positive outcomes and under-estimate the likelihood of the effect of their actions or decisions on negative outcomes (Kahneman and Tevesky, 1973). Further, a self-serving attribution bias occurs when people attribute their successes to internal or personal factors but attribute their failures to situational factors beyond their control (Kahneman and Tevesky, 1973; Einhorn and Hogarth, 1978). I expect that overconfident managers adjust their overconfidence biases in their abilities to predict future earnings after receiving negative feedback concerning their prior inaccurate predictions. I also expect that the improvement in their subsequent forecasting accuracy is influenced by their overconfidence and self-serving attribution biases.

Using a large sample of management forecasts from the First Call database, I show in Chapter 2 that the attribution biases exhibited by overconfident managers affect how they respond to feedback information concerning their prior inaccurate forecasts and their subsequent forecasting accuracy. I also show that the extent of feedback ambiguity affects how these managers respond to feedback. Specifically, overconfident CEOs adjust their initially biased forecasts when feedback is less ambiguous in the form of forecasting errors. In contrast, managers who are less confident respond to both less ambiguous feedback in the form of forecasting errors and more ambiguous market feedback concerning their prior forecasts.

Chapter 3 proposes a new approach to understanding how some analysts organize their coverage portfolios by including both a firm and one or more of the firm's major customer firms in their portfolios in the same year. I term these analysts as "supply chain analysts". I examine the economic consequences for analysts taking such a portfolio approach in terms of costs and benefits in analyst forecasting accuracy for the firms in their portfolios. For this purpose, I classify all firms followed by a supply chain analyst in a given year into one of the following three categories: "focal firms," i.e., firms for which the analyst also covers one or more major customer firms, "major customers" of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. I then provide an economically rational explanation for analysts' choice of the focal firms and the major customer firms.

Using a comprehensive analyst forecast data from the Institutional Brokers Estimates System (I/B/E/S) database, I show in Chapter 3 that an analyst who takes a supply chain portfolio approach by covering both a focal firm and one or more of the firm's major customer firms issue significantly more accurate earnings forecasts for the focal firm than (1) the same analyst issues for “other” firms in the analyst portfolio, and (2) than other analysts issue who only follow the same focal firm but not the focal firm’s major customers. Likewise, I also expect that the supply chain analyst issues more accurate earnings forecasts for the focal firm’s major customers than (1) the same analyst issues for “other” firms in the analyst portfolio, and (2) other analysts who only follow the same major customer firms but none of the major customers’ suppliers (focal firms). I find analysts’ choice of the focal firms and the major customer firms reflects analysts’ economic rationality in generating revenue for their brokerage firms.

Both Chapter 2 and 3 assume that forecasting accuracy is an important objective that managers and analysts are concerned about when they issue earnings forecasts. However, other studies in the literature suggest that managers and analysts often consider other objectives besides forecasting accurately (e.g., Frost, 1997; Lin and McNichols, 1998; Ke and Yu, 2006; Kini et al., 2009). These studies suggest that managers and analysts may sacrifice their earnings forecasting accuracy in order to achieve other conflicting objectives (e.g., Lin and McNichols, 1998). For example, managers may intentionally overstate their firms’ earnings forecasts to exaggerate the profitability of their firms’ investment opportunities in order to attract the limited available capital. Analysts, on the other hand, may intentionally forecast optimistically for a firm in order to curry favor with the firm’s management and gain the firm’s future investment banking business (e.g., Frost, 1997; Lin and McNichols, 1998). Despite these conflicting incentives that may induce managers and analysts to distort their earnings forecasting accuracy, prior studies also suggest that managers’ and analysts’ reputation in financial markets serve as a disciplinary mechanism to curb their forecasting biases (Williams, 1996; Graham et al., 2005; Jackson, 2005; Fang and Yasuda, 2009).

In sum, Chapter 2 and Chapter 3 contribute to our understanding of management and analyst forecasting accuracy. Specifically, Chapter 2 adds to the management forecasting literature by documenting that individuals' behavioral biases affect their earnings forecasting accuracy over time. Findings from Chapter 2 suggest that such biases are not fixed attributes, but are adjusted when individuals receive feedback concerning their prior decisions.

Chapter 3 adds to the analyst forecasting literature by proposing a new approach to understanding analyst portfolio design decisions. I show that some analysts may organize the firms in their portfolios through a firm's supply chain relations by covering both a focal firm and one or more of the focal firm's major customer firms. I document that analysts who take such a supply chain portfolio approach gain insights concerning future revenue realizations of focal firms by also preparing forecasts for the focal firms' major customers. At the same time, these analysts also gain insights concerning the costs to be incurred by the major customers by preparing forecasts for the major customers' suppliers. I document that analysts'choice of focal firms and major customer firms is driven by their economic incentives related to their earnings forecasts. Specifically, when the stock of a firm has a higher potential to generate more trading commissions to the analysts' brokerage firms, analysts have stronger incentive to acquire more precise information about the firm by following the firm's supply chain. As a result, their earnings forecasts for the firm are more accurate.

The remainder of the dissertation is organized as follows. Chapter 2 examines management forecasting accuracy. More specifically, I examine how CEOs' behavioral biases, namely, a combination of CEO overconfidence and self-serving attribution biases, affect how CEOs respond to feedback concerning their prior forecasts in improving their future forecasting accuracy over time. Section 2.2 first reviews the related literature on CEO overconfidence and management forecasting accuracy, and then develops the related hypotheses. Section 2.3 describes the research data. Section 2.4 reports empirical results of hypothesis tests, as well as results for various robustness tests. Section 2.5 concludes Chapter 2. Chapter 3 examines analyst forecasting accuracy. I particularly focus on how analyst portfolio design choices affect their forecasting accuracy, and examine the characteristics, antecedents, and consequences of analyst portfolio design by including both a focal firm and one or more of the focal firm's major customers in the portfolio. Section 3.2 reviews the related literature on the economic determinants of analyst forecasting accuracy and the effect of analyst economic objectives in their earnings forecasting accuracy. Section 3.3 develops the hypotheses. Sections 3.4 and 3.5 describe the research design and the data for the empirical tests. Empirical results and various robustness tests are presented in section 3.6. Section 3.7 concludes Chapter 3. The overall conclusion of the dissertation is presented in Chapter 4.

Chapter 2: CEO Overconfidence, Managerial Earnings Forecasts, and Feedback

This chapter examines management forecasting accuracy. It focuses on how managers' behavioral biases, in particular, a combination of managers' overconfidence and attribution biases, affect how managers respond to feedback concerning their prior forecasts in improving their future forecasting accuracy.

2.1 Introduction

Management earnings forecasts are one of the most important components of earnings forecasts in financial markets. Forecasting accuracy is an important mechanism by which managers build positive reputations in capital markets (Graham, Harvey, and Rajgopal, 2005). Managers make errors in forecasting earnings for a variety of reasons. While they may have some incentives to misrepresent earnings expectations (Noe, 1999; Aboody and Kasznik, 2000; Rogers and Stocken, 2005), forecasting errors can also reflect the uncertainty underlying the earnings generation process. When issuing earnings forecasts, managers subjectively evaluate how their own actions or decisions are likely to influence the realization of actual earnings. Forecasting errors may thus be due, at least in part, to their overestimation (underestimation) of the favorable (unfavorable) effects of their actions or decisions on earnings. Managers who are overly optimistic about the firm's future earnings are referred to as "overconfident." The degree of managers' optimism concerning the future consequences of their actions will directly affect their forecasting decisions. Indeed, prior research suggests that overconfident managers are more likely to issue optimistic earnings forecasts (Hribar and Yang, 2007).

This study examines the dynamics of the process whereby managers with varying degrees of confidence issue earnings forecasts, receive feedback concerning those forecasts, and make subsequent forecasts. I posit that managers' forecasting decisions are shaped by the feedback they receive concerning their prior forecasts. The general corrective effect of feedback on individuals' future behavior is well established in the psychology literature, but managers' confidence levels also exert an influence on the way they interpret feedback on their prior forecasts. In particular, overconfident managers who receive positive feedback concerning their prior forecasting decisions are more likely to attribute this positive feedback to their own ability or acumen, while attributing negative feedback to external factors (Einhorn and Hogarth, 1978; Hoch and Loewenstein, 1989).[2] This attribution bias is more pronounced when the causal link between outcome feedback and prior decisions is more ambiguous. As a result, overconfident managers are less likely to respond to noisier negative feedback, and slower to adjust their forecasting behavior compared with their less confident counterparts.[3]

I examine two prominent forms of feedback following earnings forecasts: forecast errors and market reactions.[4] I use these two forms of feedback to test how the attribution biases of overconfident managers affect their responses to feedback concerning their prior forecasts. Forecast errors and market reactions differ in terms of the information complexity and the ambiguity associated with the causal link between feedback and managers' prior forecasting

[2] Earlier research has documented managers' biased causal attribution with respect to their earnings forecasts. For example, Baginski, Hassell, and Hillison (2000), Baginski, Hassell, and Kimbrough (2004) show that when managers voluntarily disclose causal attributions in their forecasts, they are more likely to attribute forecasts of bad news to observable external factors, and attribute forecasts of good news to their internal actions.

[3] Prior research suggests that the direction of feedback can have a different effect on an individual's subsequent behavior. In particular, positive feedback reinforces individuals' prior decisions, and negative feedback has a corrective effect on individuals' future decisions (Annett, 1969; Ilgen et al., 1979). In this chapter, I mainly focus on the negative feedback which has a corrective effect on managers' subsequent forecasting behaviors because these managers start by issuing forecasts containing larger errors, and they have incentives to reduce such errors.

[4] Analysts forecast revision is another form of feedback managers receive concerning their prior forecasts. Baginski and Hassell (1990) indicate that security price reactions to management forecasts are useful in predicting subsequent analyst forecast revisions. Thus, I would expect that market feedback is a good surrogate for the feedback provided by analysts when they revise their forecasts after managers issued their forecasts.

decisions. The magnitude of forecasting error, hereafter termed "error feedback," is the difference between forecasted earnings and actual earnings. It is generally more precise and verifiable, with a relatively clear causal relation between this feedback and the manager's prior decisions. The market reaction to the forecast's release, hereafter termed "market feedback," reflects investors' immediate perception of the credibility of the forecast (e.g., Healy and Palepu, 2001; Hutton and Stocken, 2009).[5] Market feedback is relatively noisy because it reflects a more complex set of factors which may simultaneously affect stock prices.[6]

Prior research has shown that when the causal link between feedback and managers' prior decisions is noisier, the corrective effect of feedback on individuals' learning is weaker (Hoch and Loewenstein, 1989) and managers' attribution bias is not mitigated. This suggests that overconfident managers are less likely to respond significantly to market feedback, and that market feedback has a weaker effect on the improvement of managers' forecasting accuracy. However, when the causal link between feedback and managers' prior decisions is clearer, the corrective effect of feedback can mitigate managers' attribution bias. As a result, overconfident managers are more likely to respond to error feedback by improving their future forecasting accuracy. By contrast, less confident managers, who are less subject to attribution bias, are less

[5] McNichols (1989) provides evidence that the market is efficient in incorporating the ex-post credibility of management forecasts. McNichols (1989) shows that the short-window stock return surrounding a management forecast release provides a good prediction of the forecasting error. This association is consistent with investors' responding differently to forecasts that are ex post optimistic or pessimistic. This evidence suggests that management earnings forecasts contain information not previously reflected in the stock prices. At the same time, stock prices also reflect information about earnings beyond that in management forecasts. Consistent with this, Jennings (1987) proposes that forecast credibility is as important as news in the forecasts in measuring the information content of management forecasts. Based on this argument, stock returns following the release of management forecasts provide managers with immediate market feedback concerning investors' perceptions of the credibility of the forecasts.

[6] Forecasting errors may be noisy feedback to managers concerning their prior forecasting behavior because of the uncertainty involved in the earnings generation process. However, forecasting errors and market reactions to the forecasts provide useful but different information to managers concerning their prior forecasts. In particular, forecasting errors provide managers with a signal about the magnitude of their prior forecasting errors, and market reaction to the forecasts provide a signal on the market preferences with respect to the direction of managers' forecasting errors. For example, market reaction following a forecast may suggest that the market rewards managers for issuing pessimistic rather than optimistic forecasts.

likely to attribute feedback to external factors. I expect these managers to respond to both error feedback and market feedback by improving their subsequent forecasting accuracy.

To examine the effect of managers' confidence levels on the dynamics of the managerial learning process, I used a sample of 2,482 quarterly management earnings forecasts from the First Call's Company Issued Guidance ("CIG") database from January 1, 1994 to December 31, 2008. This sample represents the forecasting history for 568 managers, of which 283 were classified as overconfident based on their initial overly optimistic forecasts. The remaining 285 were classified as a benchmark group of less confident managers; while they made forecasting errors of the same absolute magnitude as the overconfident managers, their forecasts underestimated actual earnings. I then compared the learning rates, i.e., the pattern of forecasting errors over time, for the two groups of managers.

My results indicated that over time both groups of managers appeared to learn and to adjust their initial forecasting errors; that is, forecasts issued by overconfident managers became less optimistic (more accurate), while forecasts issued by less confident managers became less pessimistic (more accurate). However, overconfident managers improved their subsequent forecasting accuracy more slowly than less confident managers. The rate of improvement of forecasting accuracy is measured by the amount of experience (time) required by a manager to react to prior feedback by issuing his or her first more accurate forecast. I found that, on average, overconfident managers learnt more slowly, requiring 0.3 additional forecasts, or 0.5 additional quarters, to issue their first more accurate forecast than their less confident counterparts. The slower learning rate is consistent with the notion of managers' overconfidence biases which inhibit their learning and the improvements of their subsequent forecasting accuracy.

I also found that, consistent with overconfident managers' attribution bias weakened the corrective effect of feedback on their learning behavior, when the causal relationship between feedback and the managers' prior decision was more ambiguous, overconfident managers did not respond significantly to the noisier market feedback when making subsequent forecasts. This result held after controlling for potential self-selection in managers' voluntary earnings forecasting decisions using a two-stage procedure. This is in contrast to less confident managers who did respond significantly to market feedback. However, when the causal link was less ambiguous, as in the case of error feedback, both overconfident and less confident managers responded to the feedback by improving their subsequent forecasting accuracy.

These findings have two implications. First, they suggest that feedback can effectively mitigate managers' cognitive overconfidence bias, but only when the feedback mechanism is verifiable and unambiguous in the causal link between the feedback outcome and managers' prior decisions.[7] Second, they suggest that managers' attribution biases affect the way they respond to feedback in their subsequent forecasting behavior. To test the robustness of this analysis, I also used alternative CEO overconfidence measures developed by Malmendier and Tate (2005, 2008), and classify CEOs as overconfident if, in addition to their initial overly optimistic forecasting behavior, they also either overinvest in their own firms or are portrayed by the press as overconfident. The results of the analyses using these two alternative CEO overconfidence measures were consistent with those using the measure based on initial forecasting decisions alone, as described above.

[7] An alternative explanation for the improvement of forecasting accuracy documented above is the effect of regression to the mean. To the extent that the improvement of forecasting accuracy for both overconfident and less confident managers is purely a mean reversion effect, we would expect this effect to work equally in either direction for overconfident and less confident managers. This is obviously not the case based on the evidence I will present in the chapter.

This chapter contributes to both the management forecasting literature and to the emerging research on the effect of managers' overconfidence on corporate disclosure decisions. While much of the existing literature on management forecasts has focused primarily on cross-sectional causes and the consequences of management forecasting errors, less attention has been paid to the dynamics of management forecasts (Hirst et al., 2008). This study adds to the multi-period dimension of the literature by documenting the dynamics of the management forecasting process whereby overconfident managers respond, albeit slowly, to feedback by adjusting their behavioral bias. In addition, I find that overconfident managers' future forecasting behavior is affected by their attribution biases and I describe how they respond to feedback. I also find that the extent of feedback's ambiguity and verifiability affects the rate of learning for managers with different confidence levels. The chapter also contributes to the emerging literature on how managers' overconfidence bias affects firms' decision making. The findings of the study suggest that managers' overconfidence bias is not a fixed attribute, but is conditioned by the feedback they receive. This conclusion sheds light on how firms can mitigate the negative effect of managers' overconfidence on corporate decision making by effectively evaluating managers' prior decisions.

The rest of the chapter is organized as follows. Section 2.2 reviews the background literature used for the development of my hypotheses. Section 2.3 describes the sampling procedures and provides empirical results. I then provide various robustness tests and additional tests in Section 2.4. Section 2.5 presents conclusions.

2.2 Background literature and hypotheses development

Earnings forecasts are an important disclosure mechanism by which managers may seek to establish or alter market earnings expectations, preempt litigation concerns, discourage entry into their industry, or influence their reputation for transparent and accurate reporting (e.g., Jennings, 1987; Skinner, 1994; Kasznik and Lev, 1995; Skinner, 1997; Frost, 1997; Bamber and Cheon, 1998; Graham et al., 2005; Hutton and Stocken, 2009). However, to leverage the potential benefits associated with management forecasts, they need to be credible. Credible forecasts help managers build a positive forecasting reputation, which ultimately affects firm value (Graham et al., 2005).

While managers may introduce bias in their forecasts in response to incentives, such as to avoid a negative earnings surprise (Matsumoto, 2002), to increase their stock-based compensation, and/or to gain from insider trading (Noe, 1999; Aboody and Kasznik, 2000; Rogers and Stocken, 2005), forecasting errors also arise because of the uncertainty involved in the forecasting process. In an uncertain environment, managers' personal judgment biases will influence their assessment of the effectiveness of their decisions or actions on the probability of high (or low) future earnings outcomes.

One such bias documented in the existing literature is CEO overconfidence (Roll, 1986; Malmendier and Tate, 2005, 2008). Management overconfidence has been offered as an explanation for various economic phenomena, including merger and acquisition decisions (Roll, 1986), premiums paid for acquisitions (Hayward and Hambrick, 1997), corporate financing decisions, and dividend payout decisions (Ben-David et al., 2007). In many cases, overconfident CEOs overestimate their own acumen relative to that of others (Larwood and Whittaker, 1977; Svenson, 1981). Thus, when presented with information comprising both favorable signals associated with a greater likelihood of good news (for instance, higher earnings) and unfavorable signals associated with a greater likelihood of bad news (for instance, lower earnings), overconfident CEOs are more likely to overestimate the probability that their own decisions or actions will yield higher earnings for the firm and underestimate the corresponding probability of yielding lower earnings. This suggests that overconfident managers are more likely to issue optimistic earnings forecasts (Hribar and Yang, 2007).

Prior research has focused primarily on demonstrating that managerial overconfidence can significantly affect managerial decisions, yet few studies examine the evolution of individual managers' overconfidence bias, with the exception of Billett and Qian (2008).[8] The related literature in economics, psychology and management has documented the general efficacy of feedback for individuals' learning (e.g. Arrow, 1962; Anderson, 1983; Einhorn and Hogarth, 1978; Huber, 1991; Bonner, Libby, and Nelson, 1997). This line of research has shown that feedback on the outcome of individuals' prior decisions affects their confidence in their ability to assess future performance when they perform the task again (Postman and Brown, 1952; Anderson and Berdahl, 2002). Studies have demonstrated that when tasks are clearly specified and when feedback is negative, many individuals display learning patterns generally consistent with Bayesian updating (Camerer, 1995). This is because, unlike positive feedback that reinforces individuals' prior decisions, negative feedback has a corrective effect on individuals' future decisions (Annett, 1969; Ilgen et al., 1979). To the extent that overconfident managers respond to feedback and adjust their confidence level in their forecasting behavior, their subsequent forecasting accuracy is improved.

However, managers' overconfidence bias affects the way they interpret the causality of the feedback and their subsequent response to it.[9] Research has found that overconfident individuals

[8] Billett and Qian (2008) examine the history of mergers and acquisitions made by individual CEOs. They find CEOs are more likely to engage in value destructive mergers and acquisitions following positive experiences from past acquisitions. They also find an CEO's net purchase of stock is greater preceding subsequent deals than it is for the first deals. Taken together, this evidence suggests that CEOs become overconfident as a result of their self-attribution biases.

[9] Both the psychology and behavioral economics literatures document that the source of overconfidence comes from the self-attribution bias. Hirshleifer (2001, p.1549) explains the link between overconfidence and self-attribution

are often strongly influenced by their own attribution bias, i.e., they are inclined to attribute favorable outcomes to their own decisions or actions, but unfavorable outcomes to external factors or bad luck (Kahneman and Tversky, 2000; Bettman and Weitz, 1983). This attribution bias means that overconfident managers pay less attention to negative feedback than to positive feedback. As a result, the corrective effect of negative feedback on managers' future forecasting behavior is mitigated. This is in contrast to less confident managers who are less subject to attribution biases, more responsive to negative feedback, and therefore more likely to correct their prior behavior. Hence, the attribution bias slows down the rate at which overconfident managers improve their forecasting accuracy. Thus, I propose that:

H1: Overconfident managers improve their forecasting accuracy more slowly than less confident managers.

Although the psychology literature has generally established the effectiveness of feedback in facilitating individuals' learning and the adaptability of their future behavior, Annett (1969), Ilgen et al. (1979), and Hogarth et al. (1991) argue that the effectiveness of the relationship between feedback and learning is contingent on feedback characteristics. That is, if feedback is ambiguous, and the relationship between prior decisions and the feedback received is open to different explanations, individuals assign less weight to this feedback when they perform the task again. Thus noisier feedback would weaken the effect of feedback on individuals' learning. By contrast, if feedback is relatively straightforward and less ambiguous, or if there is a direct causal link between prior decisions and feedback, individuals will give more weight on such feedback when they perform the task again.

To explore the effect of ambiguity of feedback in the management forecasting setting, I examine two prominent forms of feedback: market feedback and error feedback, each of which

bias as: "overconfidence and biased self-attribution are static and dynamic counterparts; self-attribution causes individuals to learn to be overconfident rather than converging to an accurate self-assessment."

have distinctive characteristics with respect to the information complexity involved and the strength of the association between the feedback and individuals' prior decisions. Specifically, error feedback provided by actual earnings realization is generally more precise and verifiable, with a clearer relationship between feedback and managers' prior decisions; market feedback reflects a combination of both the market's perception of the credibility of management forecasts and other positive/negative signals which may simultaneously affect stock prices. [10] Therefore, relative to error feedback, market feedback on management forecasts is relatively noisy and seldom shows a clear causality.

I expect managers' responses to feedback concerning how they attribute the feedback to internal or external factors to affect how managers improve their subsequent forecasting accuracy. In particular, less confident managers will be more likely to improve their forecasting accuracy when they respond to the feedback by taking corrective adjustments, even if feedback is noisy. By contrast, overconfident managers will respond to feedback and take corrective adjustments when the feedback has clear causality, but they would ignore ambiguous feedback (Kahneman and Tversky, 1973; Einhorn and Hogarth, 1978; Hogarth et al., 1991). Therefore, I expect overconfident managers will be more likely to ignore market feedback and to respond to error feedback, because the latter provides clearer information concerning their prior forecasting accuracy. Consistent with this, I propose:

H2: Overconfident managers will respond to error feedback, but not to market feedback.

[10] The actual earnings realization process is also subject to uncertainty and exogenous shock, which makes the causal link between error feedback and managers' prior forecasts nosier. Here I assume that error feedback is less ambiguous relative to market feedback. This is because, unlike market feedback that is subject to a lot of other economy-wide and industry-wide forces that managers have no control over, error feedback is dependent on both the earnings realization and the reported earnings that are controllable by managers.

2.3 Data and empirical results

2.3.1 Data screening

Table 2.1 presents the sample screening procedures. The initial sample includes all quarterly management forecasts from the First Call database from the first quarter of 1994 to the last quarter of 2008. I chose January 1, 1994 as the starting point because the First Call data is reasonably complete from 1994 onward (Anilowski et al., 2007). I restricted my sample to point and close range forecasts because only these provide the numerical estimates required to get the quantitative measures of management forecasts. Consistent with prior studies (e.g., Anilowski et al., 2007), the following were excluded from my sample: forecasts with confounding events that could lead to discontinuity in EPS, such as mergers and acquisition announcements; forecasts with missing CUSIPs; duplicate forecasts; forecasts with apparent data errors; and “stale” forecasts that occur more than 90 days prior to the actual quarterly earnings announcement. For firms that issued multiple forecasts for the same quarter, I retained the first valid management forecast after the actual earnings announcement for the previous quarter. Actual earnings and analysts’ consensus forecasts for the quarter were also obtained from the First Call. These procedures yielded a total of 12,827 firm-quarter management forecasts with the Compustat quarterly financial information.

[Insert Table 2.1]

I combined the above quarterly management forecasts with the identity of individual managers based on CEO tenure information from the Execucomp database. I assumed that all forecasts issued after each individual CEO took up his or her position in the firm (variable “becameceo”) and before leaving the position (variable “leftotc”) were issued by that CEO. 3,659 forecasts without corresponding CEO information were deleted. I deleted 1,116 forecasts when there was more than one CEO in the same firm quarter, due to either dual CEO appointments or CEO turnover in the firm quarter. Of the total 8,052 forecasts retained that were issued by 1,681 CEOs, 65.19% were pessimistic, 27.02% were optimistic, and the remaining 7.79% were neutral forecasts.

I defined CEOs as overconfident (or less confident) based on the first forecast they issued for the firm. Specifically, a manager is classified as "overconfident" if the first forecast puts her in the top 50% of all optimistic forecasts (defined as forecasted earnings greater than the actual earnings) issued in the same quarter. A manager was classified as "less confident" if she made the same magnitude of initial forecasting error as the overconfident manager but the forecast puts her in the top 25% of all pessimistic forecasts (defined as forecasted earnings smaller than the actual earnings) in the same quarter. From this classification, a total of 283 overconfident managers and 285 less confident managers were identified. These two groups of managers together issued a total of 2,482 forecasts during the sample period. Each forecast was classified as either less accurate or more accurate relative to the average forecasting errors using all forecasts issued in the same quarter. A forecast was classified as "less accurate" if the error was in the top 50% of all optimistic forecasts or in the top 25% of all pessimistic forecasts in the same quarter. Forecasts that fell in the remaining range of errors were defined as "more accurate".[11]

[11] I classify managers as less confident if the managers' first one or first two forecasts are pessimistic with the forecasting errors in the bottom 25% of all pessimistic forecasts. I choose these asymmetric cut-off points to classify overconfident managers and their less confident peers because quarterly management forecasts are predominantly skewed toward being pessimistic (e.g. Gong et al., 2009; Cotter et al., 2008) with around 65% (27%) of forecasts as pessimistic (optimistic) in my sample. I also use an alternative cut-off point and define managers as overconfident if the first one or two forecasts they issue during their tenure puts them in the top 25% of all optimistic forecasts issued in the same quarter. The results remained unchanged.

2.3.2 Justifications for CEO overconfidence measurement

I conducted various tests to justify the use of my primary overconfidence measure that is based on the forecasting biases contained in the first forecasts managers issued. I first applied alternative CEO overconfidence measures used in prior studies to examine the consistency of these measures with my primary measure. I then used my CEO overconfidence measure to replicate the effect of CEO overconfidence on management corporate decisions documented in prior studies (e.g., Ben-David et al., 2007).

Two alternative measures of CEO overconfidence were adapted from prior research (e.g., Malmendier and Tate, 2005, 2008; Jin and Kothari, 2006; Hirbar and Yang, 2007). The first is based on a CEO's decision to overinvest in the idiosyncratic risk of the firm.[12] Using Thomson Financials TFN Insiders' Trading data, I defined a CEO as overconfident if, prior to issuing her first forecast, the total value of her purchase of the firm's stock was greater than the total value of her sales of the stock, and coded *OC_PUR* as 1, and 0 otherwise. The second measure uses media perceptions of the manager's confidence level (Malmendier and Tate, 2005; 2008; Jin and Kothari, 2006; Hribar and Yang, 2007). I classify a CEO as overconfident if, prior to issuing her first forecast, the number of times she was described by the press in "confident" and "optimistic" terms exceeded the number of times she was described in less confident terms, such as "frugal", "conservative", "cautious", "practical", "reliable", and "steady", and coded *OC_MEDIA1* as 1, 0 otherwise.[13] CEOs without press mentions were assigned a value of 0. I also used the continuous

[12] The rationale for this measure is as follows: CEOs typically receive large grants of stock and options as compensation. They cannot trade their options or hedge the risk by short-selling company stock, and the value of their human capital is intimately linked to the firm's performance. Because of this under-diversification, risk-averse CEOs should limit their additional investment in equity of their firms. Malmendier and Tate (2005, 2008) translate this logic to a measure to classify CEO overconfidence based on whether CEOs consistently increase their holdings of company stock.

[13] More specifically, I collect all articles that characterize the sample CEOs within the measurement window that describe the CEO in "confident" terms (including "confident", "confidence", "optimistic", "optimism") and in "cautious" or negative "confident" terms (including "cautious", "reliable", "practical", "conservative", "frugal",

measure of media perceptions of the CEO based on the frequency with which a CEO was described as confident or optimistic (relative to more conservative terms), and computed *OC_MEDIA2* = [(confident mention-conservative mention)/total mention].

In Appendix 2.2, Panel A shows the descriptive statistics of overconfident CEOs based on the two alternative measures. It suggests that managers who were classified as overconfident when their first forecasts were overly optimistic were significantly more likely (p=0.015) to overexpose their personal wealth to the idiosyncratic risk of the firm by purchasing their own company's stock (*OC_PUR*), and were significantly more likely (p=0.035 for *OC_MEDIA1* and p=0.039 for *OC_MEDIA2*) to be described by the press in confident terms than in less confident terms This suggests that using the biases contained in managers' first forecasts is a reasonable approach to identify overconfident CEOs.

I then used my classification of CEO overconfidence to examine the relationship between CEO overconfidence and corporate policies, including corporate dividend payout policy and financing policy, as documented in prior studies. Results are presented in Appendix 2.2 Panel B. Consistent with prior studies (Ben-David et al., 2007), I found that when using managers' first forecasts to classify CEOs confidence levels, firms with overconfident CEOs performed worse in future periods after the forecasts were issued (*ROA*), were less likely to pay out dividends (*DIV*), used more long-term debt (*LONG_TERM_DEBT*), invested more in research and

"steady"). Major publications used include The New York Times, Business Week, the Financial Times, The Economist, and the Wall Street Journal. A CEO is defined as being overconfident if the cumulative number of articles in which the CEO is described in "confident" terms is greater than the number of articles that refers to the CEO in less confident terms. I then code *OC_MEDIA1* equals 1 for this CEO. The continuous variable of CEO overconfidence (*OC_MEDIA2*) is based on the difference in the number of times a CEO is described in "confident" terms and in "conservative" terms. Based on this definition, the *OC_MEDIA2* measure ranges from -1 to 1. To be consistent with prior research, I use the term "overconfidence" to describe the construct of interest, although the measure is actually a relative measure of confidence, and I cannot calibrate an optimal level of confidence to differentiate "overconfident" from "confident."

development (*RD_RATIO*), and were more likely to repurchase their own stock (*REPURCHASE*) than firms with less confident CEOs.

I also validated the evidence in Hribar and Yang (2007) that overconfident managers are more likely to issue optimistically biased forecasts. Results shown in Panel C of Appendix 2.2 generally support this premise. The dependent variable for the regression in Panel C is $OPTIMISTIC_t$, which as an indicator variable equals 1 if a forecasted earning is greater than the actual earnings (i.e., optimistic forecasts), and 0 otherwise. The independent variable of interest is *OC_MF*, which is an indicator variable equals 1 if the manager who issues the forecast is classified as overconfident and 0 otherwise. The regression analyses in examining whether overconfident managers are more likely to issue optimistically biased forecasts in Panel C is based on all subsequent forecasts issued by each manager after excluding the first forecast she issued for the firm. This is because by construction, a CEO is classified as overconfident if their first forecast is overly optimistic. The results in both column (1) and column (2) show a positive and significant coefficient on *OC_MF* (coefficient=0.225 and 0.144, P<0.01 and <0.10, respectively), which suggests that overconfident managers are more likely to issue optimistic subsequent forecasts than other managers, consistent with earlier studies (Hribar and Yang, 2007). In addition, column (2) shows that firms with good news (*NEWS*), higher book-to-market ratio (*BM*) are also more likely to issue optimistic forecasts; conversely, firms that are smaller (*LOG_ASSETS*), experience a lower sales growth rate (*SALE_GROWTH*), and have a lower level of working capital accruals (|*WACC*|) are less likely to issue optimistic forecasts. Overall, the above evidence provides empirical support for using managers' initial forecasting bias to measure their overconfidence bias.

2.3.3 Univariate results

Panel A of Table 2.2 provides descriptive statistics for the first forecast issued by each manager, which I used to categorize managers' confidence levels. By construction, except for the direction of the forecasting error (*$BIAS_t$*), I should not expect any significant difference in the characteristics of the first forecast managers issued. The results in Panel A of Table 2.2 are consistent with this. As shown in Panel A, forecasts issued by overconfident managers and by less confident managers are not significantly different in terms of the magnitude of forecasting error (*$ERROR_t$*) (p=0.211), news in the forecasts (*$NEWS_t$*) (p=0.241), and forecasting horizon (*$HORIZON_t$*) (p=0.315).

[Insert Table 2.2 Panels A and B]

Panel A also shows that overconfident and less confident managers work in firms that have similar earnings volatility (*STD_EPS_t*) (p=0.365), size (*$ASSETS_t$*) (p=0.584), and in industries with similar levels of competition (*HH_INDEX_t*) (p=0.131). However, overconfident managers are more likely to be employed in firms with lower growth opportunities (*$SALEGROWTH_t$*) (p=0.001), lower valuations (*BM_t*) (p=0.008), less liquidity (*$ALTMAN_t$*) (p=0.009) and lower discretionary working capital ($|WACC_t|$) (p=0.032).

Panel B of Table 2.2 presents descriptive statistics for forecasts issued by the 168 overconfident managers and 201 less confident managers.[14] It shows that overconfident managers issued a mean (median) of 5.3 (5) forecasts versus 5.08 (4) forecasts by less confident managers during their tenure.

[14] Of the 283 managers I initially categorized as overconfident and the 285 managers I initially categorized as less confident, 115 overconfident and 84 less confident managers are dropped because these managers never issued subsequent forecasts. My analysis focuses on the forecasts issued by the remaining 168 overconfident managers and 201 less confident managers who continued providing management forecasts.

Results in Panel B suggest that for their subsequent forecasts, overconfident managers are more optimistic (*$BIAS_t$*, p=0.010), less accurate (*$ERROR_t$*, p=0.05), and issue forecasts with longer horizons (*$HORIZON_t$*, p=0.020) than less confident managers.

[Insert Table 2.2]

To show that both overconfident and less confident managers improve their subsequent forecasting accuracy, Table 2.3 reports forecasting errors based on the sequence of the forecasts issued by each CEO during their tenure with the firm. The results show that, in general, as managers issue more forecasts for their firms, their forecasting accuracy improves. Panel A of Table 2.3 shows that overconfident managers reduce their forecasting error from the initial error of 0.010 (S=1) to an average of 0.0037 in subsequent forecasts (S≥2). This difference is statistically significant at p=0.000 level. The corresponding forecasting errors for less confident managers, shown in Panel B of Table 2.3, reduce from the initial 0.0149 (S=1) to 0.0046 in subsequent forecasts (S≥2). The difference is also statistically significant at p=0.000 level. When I combined forecasting errors by both overconfident and less confident managers, as shown in Panel C, a similar pattern of improvement of forecasting accuracy was observed.

[Insert Table 2.3]

2.3.4 Empirical results for H1

To test H1 that overconfident managers are slower than less confident managers to adjust their subsequent forecasts, I examined the length of time that managers' initial forecasting behaviors survived in their subsequent forecasts. To do so, I examined the number of forecasting experiences that were needed before overconfident managers changed from their first overly optimistic forecast to issue a more accurate forecast, or before less confident managers changed their initial pessimistic forecast to issue a more accurate forecast. The results were robust to using the number of cumulative quarters until these managers issued their first more accurate forecast as an alternative measure.

As indicated earlier, I defined a forecast as "more accurate" if the absolute value of forecasting error was smaller than 50% of the forecasting error for all optimistic forecasts, but greater than 25% of the forecasting error for all pessimistic forecasts in the same quarter. Therefore, if during the entire tenure with the firm, overconfident managers consistently issued forecasts containing errors that were greater than 50% of all optimistic forecasts issued in the quarter, and less confident managers consistently issued forecasts containing errors that were greater than 25% of all pessimistic forecasts, the time measure before these managers issued a more accurate forecast was missing because they never issued a “more accurate” forecast.

A total of 31 overconfident managers consistently issued overly optimistic subsequent forecasts, while 22 less confident managers consistently issued pessimistic forecasts containing larger errors. The remaining 316 managers (including 137 overconfident and 179 less confident managers) adjusted by issuing a more accurate subsequent forecast during the sample period.[15]

Panel A of Table 2.4 presents univariate comparisons of the cumulative number of forecasts and quarters that elapsed before these 316 managers issued a more accurate forecast. Consistent with H1, I found that overconfident managers issued an average of 2.55 forecasts (5.84 quarters) before their first more accurate forecasts. This compares to 2.23 forecasts (5.36 quarters) for the less confident managers. The statistics in Panel A of Table 2.4 show that the difference is significant at conventional levels.

[Insert Table 2.4]

[15]The final sample of 316 managers does not include 199 managers who stop providing subsequent forecasts after their first forecasts, and 53 managers who never change their subsequent forecasting behavior.

To control for other variables that may change managers' forecasting behavior, I also used a multivariate regression model to examine, among the 316 managers who adjusted by issuing a more accurate subsequent forecast, whether it took overconfident managers longer time than less confident managers to issue their first more accurate forecasts. The regression model is specified in the following equation:

$$TIME_t = \beta_0 + \beta_1\ OC\_MF + Control\ variables + \varepsilon_t \qquad (1)$$

In the equation, a positive coefficient on the indicator variable, *OC_MF*, would be consistent with the hypothesis that overconfident managers are slower to adjust by issuing their first more accurate forecasts than less confident managers.

Results presented in Panel B of Table 2.4 are generally consistent with H1. Panel B shows a positive and significant coefficient on *OC_MF*, after controlling for other factors that may affect managers' forecasting behaviors. In addition, the coefficients on $MF\_FREQUENCY_t$, $CH\_SALESGROWTH_t$ and $CH\_HHINDEX_t$ are negative and significant, suggesting managers are slower to adjust (by issuing a more accurate forecast) when they revise their forecasts more frequently in the quarter ($MF\_FREQUENCY_t$), when firms experience a smaller change in sales growth rate ($CH\_SALESGROWTH_t$) and face less changes in industry competition intensity ($CH\_HHINDEX_t$).

The preceding analyses exclude those managers who have consistently issue forecasts with larger errors, i.e., they never improve their forecasting accuracy over their entire tenure with the firm during the sample period, because the dependent variable for the time before these managers adjust by issuing a more accurate forecast was missing for these managers. However, these managers represent the ones who are the slowest to improve. In other words, this suggest the data for H1 hypothesis testing is right censored. I then used a survival analysis technique that deals with the right censored data and include these managers in the analysis. Figure 1 compares the survival rate of the overly optimistic forecasting behavior of overconfident managers with the survival rate of the initial pessimistic forecasting behavior of less confident managers. It shows that the survival rate of the initial forecasting bias is significantly higher for the optimistic forecasting behavior by overconfident managers than the pessimistic forecasting behavior for less confident managers (p=0.09).

I also used a Cox multivariate regression model to repeat the analysis. The dependent variable of the Cox regression model is two dimensional, reflecting both whether managers ever changed their initial forecasting behavior by issuing a more accurate subsequent forecast and the cumulative experiences or time elapsed until the change.[16] Untabulated results using this model specification indicate that the conclusions drawn from OLS regression shown in Panel B of Table 2.4 remain unchanged.

2.3.5 Measurement of error feedback and market feedback

To examine H2 on managers' differential responses to feedback with varying degree of ambiguity of the causality link between feedback and managers' prior decisions, I used error feedback and market feedback, the two prominent forms of feedback concerning managers' prior forecasting decisions, to proxy less ambiguous and more ambiguous feedback, respectively. I estimated error feedback, which is the forecasting error of prior forecasts, as the absolute difference between forecasted and actual earnings for the quarter, deflated by the stock price at the beginning of the quarter.

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[16] In the Cox model specification, I define an overconfident manager who consistently issues overly optimistic subsequent forecasts as continuing his initial forecasting behavior, and code "continue" as 1; an overconfident manager who issues a more accurate subsequent forecast as "discontinue" his initial forecasting behavior and "continue" is coded as 0; a less confident manager who consistently issues subsequent forecasts in the bottom 25% of pessimistic forecasts for the quarter as "continue" his initial forecasting behavior, and code "continue" as 1; a less confident manager who issues a more accurate subsequent forecast does not continue his initial forecasting behavior and code "continue" as 0.

Measuring market feedback is more complex because it should capture the magnitude of market discounting of the forecast upon its release by an overconfident manager conditional on other factors that simultaneously affect stock price. To get a cleaner measure of market feedback, I used a benchmark model to estimate the expected three-day cumulative abnormal stock return following a forecast release in which all managers were assumed to be homogeneously confident. I then estimated the expected cumulative abnormal return in the same window following a forecast issued by managers with varying degrees of confidence. The difference in the predicted market return from the two regressions is my measure of the market feedback to forecasts issued by overconfident and less confident managers.

Model (1) in Panel D of Appendix 2.2 shows the benchmark expected market return model when all managers are assumed to be homogeneously confident. Here the predicted value of the market return following a managerial forecast is conditional on contemporaneous factors, such as forecast characteristics variables and firm characteristics variables that affect stock prices. Consistent with prior studies (Ajinkya and Gift, 1984; Waymire, 1984; McNichols, 1989; Williams, 1996; Hutton and Stocken, 2009), stock returns following a forecast release are higher when the firm issues a forecast of good news ($GOOD\_NEWS_{i,t}$), when the forecast is more accurate ($ERROR_{i,t}$), and when the forecasted earnings are positive ($PREDICT\_LOSS_{i,t}$ and $NEWS_{i,t} * PREDICT\_LOSS_{i,t}$). Firms operating in less competitive industries ($NEWS_{i,t} * HH\_INDEX_{i,t-1}$), with higher liquidity ($NEWS_{i,t} * ALTMAN_{i,t-1}$) and smaller size ($LOG\_ASSETS_{i,t-1}$) also enjoy higher stock returns following a forecast release.

Model (2) in Panel D of Appendix 2.2 shows the expected market return model where managers are heterogeneous in their confidence levels. In this model, I added in the indicator variables for managers' differential confidence level, *OC _MF* and *UC_MF*, besides all the other control variables included in model (1). *OC_MF* is an indicator variable equals 1 if a manager is classified as overconfident; 0 otherwise; *UC_MF* is an indicator variable equals 1 if a manager is classified as less confident but made the same magnitude of initial forecasting errors as overconfident managers; 0 otherwise.

The results from Model (2) suggest that the coefficient on good news forecasts by overconfident managers ($OC\_MF * GOOD\_NEWS_{i,t}$) is negatively and significantly associated with the firm's 3-day stock return upon the forecast release, consistent with earlier evidence that the market filters out biases by overconfident managers and the more general evidence that, conditional on forecasting accuracy, the market punishes managers for failing to meet or beat their own forecasts (e.g., Bartov et al., 2002; Matsumoto, 2002; etc.). The coefficient on good news forecasts by less confident managers ($UC\_MF*GOOD\_NEWS_{i,t}$) is also negative and significant, indicating that, conditional on the news, the market punishes managers for issuing highly inaccurate yet pessimistic forecasts. The difference between the predicted market return from Model (2) and the predicted market return from the benchmark expected return Model (1) is the measure of the market feedback to managers, reflecting the magnitude of investors' discounting the credibility of forecasts issued by overconfident or less confident managers. The magnitudes and the significance levels of the coefficients on the other variables are similar to what were reported in model (1).

2.3.6   Empirical results for H2

Hypothesis 2 relates to whether overconfident CEOs respond to error feedback and market feedback differently in their subsequent forecasts. The analysis is based on all subsequent forecasts managers issued after their first forecasts. This means that managers need to first make a decision on whether or not they would continue providing forecasts after their initial forecasts containing larger errors. Feng and Koch (2010) show that after receiving an adverse reaction to prior forecasts, managers are more likely to stop providing forecasts in the future periods.

To deal with this potential self-selection bias in examining managers' subsequent forecasting behaviors, I used a two-stage Heckman procedure. In the first stage, I model managers' decisions to continue or stop providing subsequent forecasts as a function of their confidence levels and other factors associated with managers' voluntary forecast decisions (Ajinkya and Gift, 1984; Lang and Lundholm, 1993; Feng and Koch, 2010). The first stage model is as follows:

$$Pr(FORECAST) = \beta_0 + \beta_1 OC\_MF + \beta_2\, OPTIMISTIC_{t-1} + \beta_3\, ASSETS_{t-1} + \beta_4 N\_ANALYST_{t-1} + \beta_5 BM_{\,t-1} + \beta_6 BETA_{t-1} + \beta_7 STE\_EPS_{t-1} + \beta_8 LITIGATION_{t-1} + \varepsilon_t \qquad (2)$$

In the equation, I include the measure of CEO overconfidence (*OC_MF*), as Ben-David et al. (2007) find that overconfident CEOs are more likely to voluntarily provide earnings forecasts. Lang and Lundholm (1993) suggest that mangers are more likely to disclose firm-specific information when there is a higher demand for firm information. They suggest using the total number of analysts following the firm to proxy such information demand. The demand for firm information is higher when the firm is more heavily followed by analysts. Consistent with this, I include the total number of analysts following the firm ($N\_ANALYST_t$) in the model. Bartov et al. (2002) and Matsumoto (2002) suggest that managers have a high incentive to issue forecasts in order to walk down analysts so that actual earnings realization can beat analyst forecasts. I include the expectation gap (EXP_GAP_t), which is an indicator variable equals one if actual earnings are lower than analysts' consensus forecasts prior to the actual earnings announcements, and 0 otherwise. Skinner (1994), Rogers and Stocken (2005) suggest that firms voluntarily disclose in order to preempt the risk of litigation. Consistent with these studies, I include an indicator variable for high litigation industries ($LITIGATION_t$). It equals 1 if the industry of the firm is in one of the following “high litigation” industries: biotech (SIC 2833-2836), computer (SIC 3570-3577, 7370-7374), electronics (SIC 3600-3674), and retail industry (SIC 5200-5961), and 0 otherwise.

The results presented in Panel A of Table 2.5 suggest that when firms are not heavily followed by analysts ($N\_ANALYST_{t-1}$), are under-valued by the market (BM_{t-1}), and when the earnings expectation gap (EPS_GAP_{t-1}) is low, managers are more likely to stop providing forecasts.

[Insert Table 2.5 Panels A and B]

Based on this forecast prediction model, in the second stage of the Heckman two-step procedure, I constructed an inverse Mills ratio to control for the self-selection problem in the second stage regression analysis for H2 (Heckman, 1979). I used the following equation to model the current forecasting error ($ERROR_{i,t}$) as a function of the two forms of feedback, market feedback ($MKT\_FB_{i,t-1}$) and error feedback ($ERROR\_FB_{i,t-1}$) from the earlier period, and run the analyses for overconfident and less confident managers separately.

$$ERROR_{i,t}=\beta_0+\beta_1 ERROR\_FB_{i,t-1}+\beta_2\, MKT\_FB_{i,t-1}+Control\ Variables+MILLS_{\,i,t}+x_i+\varepsilon_{i,t} \quad (3)$$

In Equation (3), the dependent variable is management forecasting errors ($ERROR_{i,t}$), defined as the absolute difference between the forecasted earnings and actual earnings, deflated by the stock price at the beginning of the quarter. The greater the value of the forecasting error, the less accurate the forecast is.[17] Detailed definitions of other control variables in the equation are presented in Appendix 2.1.

[17] Because this model specification requires that managers issue at least two forecasts, all managers who discontinue issuing forecasts after their initial forecasts are dropped in the analysis.

The main independent variables are the error feedback ($ERROR\_FB_{i,t-1}$) and market feedback ($MKT\_FB_{i,t-1}$). With regard to market feedback, prior studies suggest that, depending on the direction of the feedback, its effect on an individual's learning will vary. Annett (1969) and Ilgen et al. (1979) show that positive feedback reinforces individuals' prior decisions when they perform the task again, while negative feedback has a corrective effect on individuals' future decisions. Thus I divide the market feedback into positive ($POS*MKT\_FB_{i,t-1}$) and negative ($NEG*MKT\_FB_{i,t-1}$) based on the direction of the market feedback measure.[18] The discussion mainly focuses on negative market feedback which has a corrective effect on managers' prior forecasting behavior.

Hypothesis 2 predicts that overconfident managers are more likely to respond to error feedback than market feedback concerning their prior forecasts. Thus, I expect a positive and significant coefficient on the error feedback ($ERROR\_FB_{i,t-1}$) with the magnitude of the coefficient less than 1.[19] With regard to the market feedback, I expect overconfident managers not to respond to the noisier negative market feedback, but to respond to positive market feedback because of their attribution bias, Therefore, I expect an insignificant coefficient on the negative market feedback ($NEG*MKT\_FB_{i,t-1}$), and a significant positive coefficient on the positive market feedback ($POS*MKT\_FB_{i,t-1}$).

The results in column (1) of Table 2.5 Panel B generally support H2. More specifically, the coefficient on $ERROR\_FB_{i,t-1}$ is positive, significant and less than 1. This is consistent with the general efficacy of error feedback in correcting individuals' prior decisions. However, the coefficient on negative market feedback ($NEG*MKT\_FB_{i,t-1}$) is insignificant after controlling for

[18] I did not divide error feedback into positive or negative feedback because the variable is measured in absolute terms; in addition, forecasts that contained signed errors that are either positive or negative are inaccurate forecasts.
[19] A coefficient that is equal to one suggests that current forecasting error is equal to prior forecasting error. A beta coefficient on prior forecasting error less than one indicates that compared with prior forecasting error, current forecasting error is reduced by (1-beta).

firm characteristics variables and managers' monetary incentives to issue biased forecasts. This suggests that the corrective effect of negative market feedback is moderated by managers' overconfidence bias and their imbedded attrition bias in attributing noisier negative outcomes to environmental factors rather than their own forecasting acumen. As a result, overconfident managers do not respond to negative market feedback by correcting their forecasting behavior. The coefficient on positive market feedback ($POS*MKT\_FB_{i,t-1}$) is positive but insignificant.

Column (1) of Panel B also shows that the control for self-selection ($MILLS_{i,t}$) is highly significant, indicating a significant effect of self-selection bias on managers' subsequent forecasting accuracy. Column (1) also shows that forecast errors are larger when the forecasting horizon ($LOG\_HORIZON_{i,t-1}$) is longer, and when firms are more closely followed by analysts ($N\_ANALYST_{i,t-1}$), consistent with earlier studies that suggest managers are less accurate in their forecasts when the earnings forecasting task is more difficult. Moreover, forecasting errors are larger when the news conveyed in the forecasts ($NEWS_{i,t}$) is good, when earnings are more volatile ($STD\_EPS_{i,t-1}$), when the firm is over-valued ($BM_{i,t-1}$), less liquid ($ALTMAN_{i,t-1}$), and when earnings forecasts reflect more of managers' discretionary judgments ($|WACC_{i,t-1}|$). The two variables, which measure the effects of CEO compensation incentives ($INCENTIVE\_RATIO_{i,t-1}$), and their incentives to gain abnormal gain from insider trading ($PUR\_PCT_{i,t-1}$) to issue biased forecasts on current forecasting accuracy are insignificant.

To complement the analyses, I next investigated the extent to which less confident managers respond to market and error feedback. The results in column (2) of Table 2.5 Panel B indicate that, in contrast with the results shown for overconfident managers, less confident managers are responsive to negative market feedback and error feedback in improving their subsequent forecasting accuracy, as shown by the positive and significant coefficient on both error feedback ($ERROR\_FB_{i,t-1}$) and negative market feedback ($NEG*MKT\_FB_{i,t-1}$).[20] In addition, the significance level for error feedback (as shown by the t-statistics of the coefficient) is much higher than for market feedback, consistent with the general notion of Bayesian learning that individuals are more responsive to feedback in correcting their prior behavior when feedback is less ambiguous (error feedback) than when it is ambiguous (market feedback).

Other variables that are significantly associated with subsequent forecasting errors mostly hold as discussed earlier for overconfident managers, except for the number of analysts following ($N\_ANALYST_{t-1}$), the news conveyed in the forecast ($NEWS_{i,t}$) and the liquidity of the firm ($ALTMAN_{i,t-1}$).

I also conducted the Chow tests to examine whether the slopes of coefficients on the two feedback variables in column (1) and (2) are different for overconfident and less confident mangers. The test showed that the coefficient on negative market feedback ($NEG*MKT\_FB_{i,t-1}$) for overconfident managers is -0.010, which is significantly smaller at $p<0.10$ level than the corresponding coefficient of 0.045 for less confident managers. Similarly, the coefficient on error feedback for overconfident managers is 0.384, which is statistically the same at $p=0.607$ level as the coefficient of 0.206 for less confident managers. These results together provide further support for H2 that although overconfident managers respond to error feedback, their attribution biases and the neglect of negative market feedback inhibit their learning and the rate at which they improve their subsequent forecasting accuracy.

2.4 Robustness analyses

This section reports the results of a variety of untabulated robustness tests of the empirical results. First, I repeated the analyses for H2 in Table 2.5 using the intersections of

[20] Note that negative market feedback carries a negative value. So a positive coefficient on this variable suggests that the more negative the feedback, the more accurate the subsequent forecast will be.

different CEO overconfidence measures. I defined CEOs as overconfident if, in addition to issuing their first overly optimistic forecasts, they also overinvested in their own firms, or were described by the press more in confident terms than in less confident terms. The untabulated results for H2 were robust using these alternative CEO overconfidence measures.

Second, I repeated the analyses for H1 and H2 by re-defining CEOs as overconfident if their first two forecasts issued for the firms were consistently overly optimistic, and classified managers as less confident managers if their initial forecasting errors for the first two forecasts were of a similar magnitude but erred towards pessimism. This resulted in a smaller number of total forecasts issued by these two groups of managers, but the main results remained quantitatively the same.[21]

Third, I arbitrarily chose the third rather than the first forecast managers issued during their tenure and defined them as overconfident if this forecast put them in the top 50% of all optimistic forecasts, and less confident if this put them in the bottom 25% of all pessimistic forecasts. I then examined forecasting behavior after this forecast for both overconfident and less confident managers. The untabulated results using this alternative definition of CEO overconfidence suggested that overconfident managers were significantly slower than less confident managers to adjust their subsequent forecasting behaviors. When I substituted with the second or the fourth forecasts and repeated the analysis, the conclusion remained unchanged.

[21] More specifically, the number of managers who are classified as overconfident reduced from 283 to 84 when the series of forecasts used to classify overconfident managers changed from the first one to the first two forecasts that are consistently in the top 50% of all optimistic forecasts in the quarter. This represents a 70.3% dropout rate (from 283 to 84 managers). This dropout rate is significantly lower than the corresponding 84.9% dropout rate (from 285 to 43) for less confident managers, when the series of the forecasts used to classify less confident managers changed from the first one to the first two forecasts that are consistently in the top 25% of all pessimistic forecasts issued in the quarter.

2.5 Conclusion

In this chapter, I argue that although feedback facilitates managers' learning in general, its effectiveness is conditional on individuals' attribution biases and the extent of ambiguity of the causal link between feedback and individuals' prior decisions. When managers are overconfident, they typically attribute positive feedback to their own input and negative feedback to external factors. Such attribution biases would mitigate the effectiveness of corrective effect of feedback in adjusting mangers' future forecasting behavior, which reduces the rates at which managers improve their subsequent forecasting accuracy. Consistent with this, I find that overconfident managers are slower than their less confident counterparts to improve their future forecasting accuracy. I also find that unlike their less confident counterparts who would respond to both forms of feedback, overconfident managers would only respond to less ambiguous error feedback, but not to more ambiguous market feedback.

Like any empirical work, this chapter has some limitations. Most notably, the use of the first set of forecasts issued by managers to measure CEO overconfidence is clearly an imprecise measure of CEOs' confidence tendencies. To operationalize managers' overconfidence, I focus on the role of CEOs in firms' forecasting decisions. This is not meant to imply that CEOs make their earnings forecasting decisions independently – not only are they constrained by environmental and institutional forces (Lieberson and O'Connor, 1972), but their forecasting decisions may also be significantly influenced by the CFOs (Jiang et al., 2010; Yang, 2009). However, CEOs clearly play a significant role in forecasting decisions and their levels of confidence thus affect the way they perceive the firm's future performance under uncertainty.

Chapter 3: Supply Chain Analysts

Chapter 2 examined the effect of managers' behavioral biases on their forecasting accuracy over time. In this chapter, I examine how analysts' economic rationality concerning their portfolio design choices affects the cross-sectional differences in their forecasting accuracy.

3.1 Introduction

Analysts' earnings forecasts are the most common earnings forecasts in financial markets. Analyst forecasting accuracy is important for analysts to build their reputation and to improve their career prospects (Hong et al., 2003; Jackson, 2005), and it is affected by a variety of firm-specific and analyst-specific factors. The first important factor that affects analyst forecasting accuracy is analysts' decisions on the firms to cover ("coverage portfolio") and characteristics of firms they include in their portfolios (e.g., Beyer, Cohen, Lys, and Walther, 2010).[22] Prior analyses of analysts' portfolio coverage decisions have primarily focused on the role of industry specialization.[23] Kini, Mian, Rebello, and Venkateswaran (2009) and De Franco, Kothari, and Verdi (2009) suggest that when firms in an analyst's portfolio are subject to common economic forces, such as when firms operate in the same industry, the analyst can draw inferences concerning one firm from the performance of the other firms in the portfolio. This process should improve the analyst's information acquisition and processing efficiency and her overall forecasting accuracy.

[22] Analysts' choice of the firms to cover and the characteristics of the firms analysts include in their portfolios are a combined result of choices made by analysts and their employing brokerage firms. Kini et al. (2009) suggest that the extent of analysts' discretions in their research portfolio choices is likely to reflect the organizational culture of analyst brokerage firms, the resources available from the brokerage firms, as well as individual analysts' decisions based on their own preferences, skills, and experience. Therefore, throughout this chapter, when I use the wording "analysts' decisions of their coverage portfolios" and alike, I do not mean that analysts have full discretion in their coverage choices. Rather, these choices are jointly determined by individual analysts and analysts' brokerage firms.

[23] For example, *Nelson's Directory of Investment Research* lists analysts by industry groups; the *Institutional Investor* and the *Wall Street Journal* provide annual rankings of analysts by industry.

However, an examination of analyst industry portfolio shows that fewer than 40% of all analyst-years in the Institutional Brokers Estimates System (*I/B/E/S*) from January 1991 to December 2008 followed only firms from a single industry at the one-digit standard industrial classification (SIC) code level.[24] For the remaining 60% of analyst-years who cover firms in multiple industries, an average of 33% of the firms these analyst-years follow operate outside the industry that an analyst has primary expertise in the year. I define an industry as the one in which an analyst has primary expertise in the year if the industry has the largest representation among all industries the analyst follows in the same year. I term this industry as the analyst's primary industry in the year.

These descriptive statistics raise the following related questions. Why do certain brokerage firms assign their analysts to cover firms in multiple industries "when decreased breadth is related to improved forecast accuracy" (Ramnath, Rock, and Shane, 2008, p. 45)[25] and why would analysts include firms outside their primary industry in their coverage portfolios?

This chapter proposes a new approach to understanding analyst portfolio design decisions. I hypothesize that some analysts extend their coverage portfolios beyond their primary industry by including not only a firm, but also one or more of the firm's major customer firms in their portfolios. I define the relation between a firm and one of the firm's major customers as a "supply chain relation". Further, I define an analyst who issues a forecast for both a firm and one or more of the firm's major customers in the same year as a "supply chain analyst". Note that I define the "supply chain analyst" at the analyst-year level. That is, a supply chain analyst may follow a major customer of one or more firms in her portfolio in one year, but may not

[24] During this period, all analysts in the I/B/E/S database on average followed 2.27 industries at the one-digit SIC code level and 3.48 industries at the two-digit SIC code level.
[25] Ramnath et al. (2008) suggest brokerage firm size as one potential explanation for why analysts working in smaller brokerage firms are more likely to experience broader industry coverage. However, they conclude that size alone does not explain analyst portfolio decisions.

cover any major customer of any of the firms in her portfolio in the next year. My approach treats this analyst as a supply chain analyst in the first year but not in the second year.[26]

The phenomenon of analysts extending their coverage portfolios to include both a firm and one or more of the firm's major customer firms in the same year in their portfolios is not uncommon. For example, of all the 83,414 analyst-years covered in *I/B/E/S* during the sample period from 2001-2008, 8.2% are supply chain analyst-years. During the sample period, each supply chain analyst covers an average of 19 firms, 15.8% of which are in supply chain relations. Of these supply chain relations in analyst portfolio, 22.2% (i.e., 3.6% of 15.8%) involve one party in the supply chain relation operating in the analyst primary industry while the other party operating outside the analyst primary industry. This evidence suggests that analysts may include firms that operate outside their primary industry to build their supply chain coverage portfolio. Recall earlier that for all analyst-years in *I/B/E/S* who cover firms in multiple industries, an average of 33% of firms they follow operate outside the analyst industry of primary expertise. 1.6% of these firms are either a focal firm or a major customer of a focal firm for an analyst in the same year.[27]

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[26] For example, suppose analyst A covers firms C1, C2 and C3 in year t, and C3 is a major customer of C2. In this case, analyst A is a supply chain analyst in year t because of the coverage of the supply chain involving firms C2 and C3. If analyst A drops the coverage of C3 and only covers firms C1 and C2 in year t+1, this analyst is no longer a supply chain analyst in year t+1.

[27] While 1.6% looks small, I should note that this percentage can be significantly understated because of the limitation in identifying whether a firm is in a supply chain relation for an analyst in the same year. As I will discuss in more detail later in Section 3.5, the identification of whether a firm is a focal firm or a major customer firm (i.e., firms in supply chain relations) for an analyst relies on whether the firm reported with the Securities and Exchange Commission (SEC) as having major customer relations or whether the firm was reported as a major customer of a reporting firm. However, only 9.5% of the firms in I/B/E/S reported having such relations. The remaining 90.5% firms in I/B/E/S that did not report having any major customer relation are assumed to be the firms that are not in any supply chain relation for any analyst, and are coded as zero in the percentage calculation. The number of firms that reported having major customer relations could be further reduced by the anonymity of the names of the reported major customers. Ellis, Thomas, and Fee (2010) document that a significant number of reporting firms did not disclose the real names of the major customers with the SEC. If I limit the population firms to firms that are outside analyst primary industry, but were either reported having major customer relations or were reported as a major customer firm (in other words, the total possible number of firms that can be identified as a firm in a supply chain relation and operate outside analyst primary industry, then the percentage of firms that are either a focal firm or a major customer firm among all firms that are outside analyst primary industry is 12%.

In this chapter, I first describe the process by which analysts may design their coverage portfolio by including a firm's supply chain relations in their portfolios in the same year. For this purpose, I classify all firms followed by a supply chain analyst in a given year into one of the following three categories: "focal firms," i.e., firms for which the analyst also covers one or more major customer firms, "major customers" of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. I then analyze the implications of the supply chain portfolio approach in terms of both the benefits and the costs with respect to forecast accuracy for the firms in the analyst portfolio. Finally, I examine the economic determinants of an analyst's choice of the focal firms and the major customer firms.

In terms of the benefits in forecasting accuracy of analysts' supply chain portfolio approach, I expect supply chain analysts to issue more accurate earnings forecasts for the focal firms and for the major customers of the focal firms than for all remaining "other" firms in the analyst portfolio. I also expect forecasts for the focal firms issued by the supply chain analysts (analysts who also cover the firms' major customers) to be more accurate than forecasts for the same focal firms issued by other non-supply chain analysts who do not cover any of the focal firms' major customers. Likewise, I expect the supply chain analysts to issue more accurate earnings forecasts for the major customers of the focal firms than non-supply chain analysts following the same major customer firms, i.e., other analysts following the same major customers but none of the major customers' suppliers (focal firms).

I expect this hypothesized superior forecasting accuracy for the focal firms of supply chain analysts to stem from the insights that these analysts gain concerning future revenue realizations of focal firms by also preparing forecasts for the focal firms' major customers. Prior literature suggests that analysts typically begin their earnings forecasting process by forecasting revenue (Lundholm and Sloan, 2007). The revenue realization of a focal firm, in turn, will typically be significantly influenced by the volume of its business with its major customers. These major customers' operations, competitive positions, and organizational health will affect their suppliers' earnings performance. For example, when a major customer of a focal firm experiences financial distress, this major customer firm often takes actions, such as delaying or stopping payment or cancelling orders, which can have direct negative consequences for the earnings performance of the major customer's supplier (Hertzel, Li, Officer, and Rodgers, 2008). Therefore, when an analyst includes both a focal firm and one or more of the focal firm's major customers in her portfolio, the analyst is likely to have better information concerning the possible impact of the major customers on the focal firm's future sales. Such insights will help the analyst generate more accurate aggregated revenue and earnings forecasts for the focal firm than the same analyst generates for "other" firms for which the analyst does not enjoy such insights from the firm's supply chain.

At the same time, the nature of the supply chain relation also suggests that the information the analyst acquires concerning the focal firm will also provide the analyst with additional insights for preparing forecasts for the focal firm's major customers. This is because purchases from the suppliers can be important expenses that influence the major customers' earnings profitability (Banker and Chen, 2006). Therefore, I expect that analysts whose portfolios include both a major customer firm and one or more of the major customer's suppliers will gain insights with regard to the likelihood of favorable or unfavorable events concerning the suppliers that may have implication on the operational performance of the suppliers' major customers, such as new technology that improves the suppliers' operational efficiency, strikes, or raw material shortages that disrupt the suppliers' operations. As a result, I expect these analysts will issue more accurate earnings forecasts for the major customers than the same analysts will issue for “other” firms for which the analysts do not cover any of the firms’ suppliers in the analyst portfolio.

I use a comprehensive dataset by merging two sources of data from 1991 to 2008 to test these hypotheses. These two sources include the Compustat customer segment file, which includes all the firms that reported with the Securities and Exchange Commission (SEC) as having major customer relations, and the I/B/E/S detailed analyst earnings forecast file. Consistent with my hypotheses, I find that when an analyst includes both a focal firm and one or more of the focal firm’s major customers in the analyst portfolio, the analyst issues significantly more accurate earnings forecasts for the focal firm than (1) the same analyst issues for “other” firms in the analyst portfolio (within-analyst), and (2) other analysts issue who only follow the same focal firm but none of the focal firm’s major customers (cross-analyst). At the same time, I also find that this supply chain analyst issues more accurate earnings forecasts for the major customer of the focal firm than (1) the same analyst issues for “other” firms in the analyst portfolio (within-analyst), and (2) other analysts who only follow the same major customer but none of the major customer’s suppliers (cross-analyst). These differences in forecasting accuracy are both economically and statistically significant. For example, as shown later in Panel D of Table 3.4, forecasts for the focal firms by a given supply chain analyst are on average around 3.0% more accurate than forecasts issued for “other” firms by the same analyst. This improvement in forecasting accuracy is approximately four times greater than the improved forecasting accuracy associated with an analyst issuing forecasts for firms for which the analyst has industry expertise versus for other firms the analyst does not have such expertise.

At the same time, I also argue that supply chain analysts' superior forecasting accuracy for the focal firms and the firms' major customers, as described above, is generally achieved at the cost of reduced forecasting accuracy for "other" firms in the analyst portfolio. Assuming that a fixed amount of resources are available for each individual analyst, by spending more time gathering information for the firms in supply chain relations, the analyst reduces the amount of time she can commit to "other" firms in her portfolio.[28] As a result, her forecasting accuracy for "other" firms in the portfolio is likely to be negatively affected. [29] Again, I find empirical support for this hypothesis in both within-analyst and cross-analyst analyses. First, earlier I documented that for a given supply chain analyst, forecasts for the focal firms and for the focal firms' major customers were more accurate than the same analyst issues for "other" firms in the analyst portfolio. These findings imply that for a given supply chain analyst, her forecasts for "other" firms in her portfolio are significantly less accurate than her forecasts for either the focal firms or the focal firms' major customers (i.e., within-analyst comparison). Second, I find that the supply chain analyst is significantly less accurate in her forecasts for "other" firms in her portfolio than other non-supply chain analysts who follow these same "other" firms (i.e., cross-analyst comparison).

I then examine the overall average forecasting accuracy for all firms in a supply chain analyst portfolio. I find that supply chain analysts on average are significantly less accurate at

[28]As I cannot observe the amount of time analysts spend on researching the firms in supply chain relations, I assume the amount of time analysts spend on each individual firm is positively associated with analyst forecasting accuracy. This assumption seems reasonable, and is consistent with earlier evidence in the literature that analyst forecasting accuracy for a firm is positively associated with the level of effort the analyst expends on the firm (Jacob et al., 1999).

[29] One limitation in examining the effect of analysts' supply chain portfolio approach on analyst forecasting accuracy in this chapter is that I did not disentangle the effect of analysts' skills on their forecasting accuracy. It is possible supply chain analysts are less accurate for "other" firms in their portfolios because they are less skilled than other non-supply chain analysts following the same "other" firm. If, instead, supply chain analysts are more skilled than other non-supply chain analysts following the same "other" firms, I would expect that supply chain analysts are more accurate for "other" firms in their portfolios than other non-supply chain analysts following the same "other" firms. That alternative explanation will work against my findings.

the portfolio level than other non-supply chain analysts whose portfolios include no supply chain relation. Further analyses indicate that on average, supply chain analysts follow 39% more firms and 13% more industries than non-supply chain analysts. In addition, 51% of the focal firms and the firms' major customers followed by supply chain analysts are from the same industry. This evidence suggests that it is likely that covering a firm's supply chain relations is costly for an analyst because of the additional time the analyst must devote to covering more firms that operate outside the analyst's industry expertise, which results in a more diversified coverage portfolio. When the amount of resources supply chain analysts can allocate to each firm in their portfolios is significantly less than that for non-supply chain analysts, it is not surprising that the level of overall forecasting accuracy at analyst portfolio level for supply chain analysts is lower than the level of overall forecasting accuracy for non-supply chain analysts.

In sum, evidence presented in this chapter indicates that supply chain analysts allocate greater resources and more effort to the focal firms and the firms' major customers than to "other" firms in analyst portfolio. As a result, supply chain analysts achieve superior forecasting accuracy for these firms. I then examine the economic rationale for the relative importance of the focal firms and major customer firms in these analysts' portfolios.

Prior studies suggest that analysts achieve multiple objectives in their earnings forecasts. On the one hand, analysts seek to issue more accurate earnings forecasts to build their reputation and to improve their career prospects in financial markets (Hong et al., 2003; Jackson, 2005). On the other hand, analysts also need to generate revenue for their brokerage firms either by generating trading commissions or bringing in investment banking businesses from the stock of the firms they cover. These objectives may be complementary or conflicting with each other. For example, Hayes (1998) models how analyst incentive to generate trading commissions affects analyst decisions in gathering information on a firm. She predicts that analysts choose to expend more effort in gathering information for a firm when the expected trading commissions generated from the firm are high. As analysts produce more precise information about the firm, their earnings forecasts for the firm are more accurate.[30] Conversely, analysts may sacrifice their forecasting accuracy by strategically issuing optimistically biased forecasts to build their relations with firm management in order to gain future underwriting business from the firm (Lin and McNichols, 1998; Hong and Kubik, 2003). Therefore, it is possible that analysts' choice of a focal firm and the major customer firm in the portfolio will depend on the level of potential revenue these firms can generate for the analysts' brokerage firms.

My empirical evidence is consistent with the preceding expectation. In particular, I find that an analyst is more likely to choose a firm as a focal firm or a major customer, when the potential trading commission generated from the firm is higher than "other" firms in the analyst portfolio. In other words, analysts selectively choose the firms in supply chain relations to maximize the economic benefits from the efforts they expend on information acquisition for these firms.

By analyzing the determinants and consequences (in the form of benefits and costs) of analysts' supply chain coverage portfolio design, this chapter has important implications for the literature on financial analysts. First, this chapter contributes to the literature on analyst portfolio design. I propose and test a new approach in which some analysts consider not only

[30] Bradshaw (2004), Loh and Mian (2006), and Fang and Yasuda (2009) document that when analysts are more accurate in their earnings forecasts for a firm, they are also more likely to use their own forecasts to issue more profitable stock recommendations for the firm. It is possible that investors are more likely to trade on an analyst's stock recommendations when the analyst's stock recommendations are more profitable. As a result, the trading commissions the analyst can generate for her brokerage firm would be higher.

industry membership, but also a firm's supply chain relations in designing analyst coverage portfolios. I show that by including both a focal firm and one or more of the focal firm's major customers in the analyst portfolio, an analyst can improve her earnings forecast accuracy for both the focal firm and the firm's major customers.

Second, this study provides comprehensive analyses on how analyst portfolio organization affects forecasting accuracy for *all* firms in an analyst's portfolio. While prior studies provide extensive empirical evidence on how firm characteristics and analyst individual characteristics may affect analyst earnings forecasting accuracy for individual firms, little research has investigated how analyst forecasting accuracy for one firm in an analyst's portfolio may be related to the forecasting accuracy for the other firms in the same analyst portfolio. In addition, few studies have examined analyst forecasting accuracy for all firms at the analyst portfolio level. I show that analyst forecasting accuracy for the firms in the same portfolio varies according to whether or not these firms are in supply chain relations, confirming the importance of studying analyst portfolio design.

The rest of this chapter is organized as follows. In section 3.2, I first review related literature on economic determinants on analyst forecasting accuracy at the firm level. I then review related papers on analysts' economic objectives and the effect of these objectives on analyst portfolio choice and their forecasting accuracy. Section 3.3 develops my hypotheses. I then describe the methodology and model specifications for hypotheses testing in section 3.4. Section 3.5 presents sample construction and descriptions. I report the empirical results in section 3.6 and 3.7. Section 3.8 presents result on robustness tests. Section 3.9 concludes the chapter.

3.2 Related literature

In this section, I review two streams of literature related to this chapter. The first stream addresses economic determinants of analyst earnings forecasting accuracy. These economic determinants are mostly examined at the firm level in the literature. The second stream is related to analysts' economic objectives in their earnings forecasts and the effect of these objectives on analyst coverage portfolio choices and their forecasting accuracy.

3.2.1 Economic determinants of analyst forecasting accuracy

Accounting literature provides extensive evidence on the economic determinants that affect the quality of information analysts acquire about a firm as input for the forecasting task and analyst forecasting accuracy. Prior studies mostly focus on the effect of these economic determinants on analyst forecasting accuracy for individual firms. These determinants can be broadly classified into three categories, which include characteristics of a forecast itself, characteristics of a firm's information environment or the firm a forecast is issued for, and characteristics of individuals who issue the forecasts.

First, characteristics of the forecast itself affect the precision of the information analysts acquire about the firm for the forecasting task and analyst forecasting accuracy. One example of characteristics of a forecast is forecasting horizon. Prior studies suggest that forecasts with longer horizons are less accurate than those with shorter horizons because of higher uncertainty associated with earnings realization processes (e.g., Clement and Tse, 2003).

Second, characteristics of the information environment about a firm affect analyst forecasting accuracy. For example, Barniv et al. (2005) examines how a firm's legal and financial reporting environment affects analyst forecasting accuracy. They argue that firms operating in a common-law country have stronger investor protection laws and higher-quality financial reporting systems in place than firms operating in a civil-law country. As the market-based incentives for analysts to produce more informative earnings forecasts for a firm is stronger in a common-law country than those in a civil-law country, analysts in the former country are more accurate than those in the latter country.

Characteristics of the firm a forecast is issued for also affect the quality of information analysts acquire about the firm and analyst forecasting accuracy. When more analysts follow a firm, more pre-disclosure information will be available about the firm, and analysts are more accurate in their earnings forecasts for the firm (Waymire, 1985). Using data from the Financial Accounting Foundation (FAF) reports to proxy for the informativeness of a firm's disclosure, Lang and Lundholm (1996) document that when firms provide more informative disclosures, analyst forecasts tend to be more accurate.

Analyst forecasting accuracy is also affected by the uncertainty and the complexity of the operation of the firm for which a forecast is issued (e.g., Duru and Reeb, 2002; Clement, 1999; Jacob et al., 1999). When information about a firm is more uncertain, analysts tend to be more dispersed in their forecasts, and their forecasts are less accurate (Barron et al., 2002). Duru and Reeb (2002) investigate analyst forecasting accuracy for firms with international diversification. They suggest that international diversification increases a firm's earnings volatility and the complexity of analyst forecasting tasks. As a result, analysts are less accurate in their forecasts for these firms.

Third, characteristics of individual forecasters also affect forecasting accuracy. For example, analysts who are more skilled, have more experience, expend more effort gathering information about the firm, and have more resources from their brokerage firms are more accurate (for example, Clement, 1999; Jacob et al., 1999). Clement (1999) examines the joint impact of an analyst's experience, the complexity of the forecasting task, and available analyst resources on analyst forecasting accuracy. He argues that analyst forecasting accuracy is affected by the level of effort an analyst devotes to gathering and processing information for the firm. The more effort the analyst expends on the forecasting task for a firm, the more accurate her earnings forecasts are for the firm. Clement uses the total number of firms and industries followed by an analyst to measure the complexity of an analyst's forecasting task. He argues that as the total number of firms and industries an analyst follows increases, the effort the analyst can expend on each firm or industry is less, holding the total level of effort constant. As a result, the analyst becomes less accurate in her forecasts. Clement also argues that larger brokerage firms provide more opportunities for analyst training, have more advanced distribution networks for disseminating analyst research reports, have more resources available to their analysts, and are able to hire more capable analysts; therefore, analysts in larger brokerage firms produce more accurate earnings forecasts than those in smaller brokerage firms. The empirical evidence in Clement (1999) supports these arguments. In particular, Clement (1999) finds that analyst forecasting accuracy is positively associated with analyst forecasting experience and the size of the analyst's employing brokerage firm. Conversely, analyst forecasting accuracy is negatively associated with the total number of firms and industries the analyst follows.

Analyst forecasting accuracy is also affected by analysts' individual behavioral biases. Hilary and Menzly (2006) argue that analysts are subject to attribution biases. They document that attribution biases lead analysts who have experienced a short-lived success to become overconfident in their ability to forecast future earnings. They find that analysts who have predicted earnings more accurately than the median analysts in the previous periods are less accurate in their subsequent forecasts.

Despite all the documented economic or behavioral factors that affect analyst forecasting accuracy, the first and fundamental factor that affects analyst forecasting accuracy is analysts' choice of the firms they follow and their decisions on the amount of effort they allocate to each firm in their portfolios. These decisions are significantly affected by analysts' economic objectives in their earnings forecasts.

3.2.2 Analysts' objectives in their earnings forecasts and their portfolio coverage

Analysts face different and often competing objectives in their earnings forecasts. On the one hand, analysts have incentives to issue accurate earnings forecasts, because more accurate analysts are considered more highly skilled, and they are more likely to build up their reputation in financial markets and to be hired by larger and higher-status brokerage firms than less accurate analysts (Jackson, 2005; Hong and Kubik, 2003). On the other hand, analysts also have incentive to bring revenue to their brokerage firms in the form of underwriting business and/or trading commissions generated from the stocks of the firms they follow (Hayes, 1998; Lin and McNichols, 1998). Prior studies suggest that analysts' compensation is also positively associated with the amount of revenue they generate for their brokerage firms (Groysberg et al., 2008).

These two objectives (i.e., to issue accurate earnings forecasts and to bring revenue to their brokerage firms) are both likely to affect how analysts organize their coverage portfolio, their choice of the firms to follow, and their overall forecasting accuracy. Prior studies suggest that analysts' research coverage is a combined result of choices made by individual analysts and their employing brokerages to fulfill analysts' personal objectives and the objectives of their organizations; overall, however, analysts' coverage portfolios are geared toward the overall improvement of information acquisition and processing efficiency and forecasting accuracy (Kini et al., 2009).

At the same time, these studies also suggest that because analysts are constrained in their resources, the more firms (industries) an analyst follows, the less time the analyst can spend on each individual firm (industry), consequently, the less accurate analysts are in their earnings forecasts (Clement, 1999; Jacob et al., 1999). Therefore, it is important that analysts organize the firms in their portfolios to gain synergies in information acquisition and processing. Such synergy is generally known as industry effects. Prior studies suggest that when the set of firms in an analyst's portfolio are subject to common industry forces, the analyst can develop an in-depth understanding of the industry, and enjoy economies of scale in making inferences concerning one firm in their portfolios based on the performance information of the other firms in the same portfolio, and improve their overall forecasting accuracy (Kini et al., 2009; De Franco et al., 2009). Gilson, Healy, Noe, and Palepu (2001) provide empirical evidence showing that analysts who have industry expertise are significantly more accurate in their earnings forecasts than those who do not.

Analysts may organize their portfolios using other alternative portfolio designs to improve their overall forecasting accuracy. For example, Sonney (2007) suggests that some analysts follow firms whose headquarters are geographically close to the analysts. Using international forecasts for 15 major European markets, Sonney (2007) compares forecasting accuracy between analysts who follow firms about which they have more local knowledge (country specialist) versus those who follow firms from a global industry sector (sector specialist). He argues that country specialists are able to produce more accurate earnings forecasts for firms in their portfolios than their sector-specialist peers, because country specialists have advantages in their local knowledge about the firms they follow.[31]

Analysts' incentives to generate trading commissions from the stock of a firm may also help analysts produce more accurate earnings forecasts (e.g., Hayes, 1998; Barth et al., 2001). For example, Hayes (1998) suggests that when an analyst is interested in maximizing the trading volume generated from her earnings forecasts, the analyst will look for more precise information about the firm that induces trading. This is because investors always prefer more precise information about the firm, and they are more likely to trade on the more precise information analysts produce. As investors increase the volume of their trading based on the information produced by the analysts, the amount of trading commissions generated from this information will increase. As the information analysts produce is more precise, analyst earnings forecasts are more accurate. Barth et al. (2001) focus on analyst coverage of firms with substantial intangible assets, most of which are not recognized in the firms' financial statements. They argue that analysts have stronger incentives to expend effort following these firms because these analysts are able to generate more informative forecasts for these firms, and their forecasts are more likely to generate profitable trading opportunities. As analysts improve the quality of the information they produce about the firm, their earnings forecasts are more accurate (Clement, 1999).

Other studies suggest that analysts' objective to be accurate in their earnings forecasts and their objective to bring revenue to their brokerage firms are in conflict with each other. These

[31] Despite the superior forecasting performance of country specialists, Sonney (2007) notes that a general tendency over the last decade has been for European brokerage firms to switch from country-based to more sector-oriented structures. He suggests that the reorganization of financial analysis departments towards more sector-oriented structures may have been driven by other objectives than the desire to boost the accuracy of earnings forecasts. He also suggests other alternative explanations for the trend. For example, when brokerage firms organize analyst research by industry, it is easier for them to market analyst research to portfolio managers, who seem to care more about industry considerations than international diversification.

studies suggest that analysts may sacrifice their objective to issue accurate earnings forecasts to their objective to generate revenue for their brokerage firms (Lin and McNichols, 1998; Feng and McVay, 2009). For example, analysts may strategically issue optimistically biased forecasts so that they can build their relations with firm management to gain future investment banking business (Lin and McNichols, 1998).[32]

In sum, while analysts have incentives to be accurate in their earnings forecasts, their organizational objectives may not be wholly geared toward promoting forecasting accuracy. Therefore, ultimately analyst portfolio coverage decisions and the decisions on the level of effort allocated to each individual firm are driven by analysts' trading-off different objectives in their earnings forecasts.

3.3 Hypotheses development

In this section, I develop hypotheses concerning the benefits and the costs in terms of forecasting accuracy for all firms in the portfolio for analysts taking a supply chain portfolio approach by covering both a firm and one or more of the firm's major customers in the same year. For this purpose, I classify all firms followed by a supply chain analyst in a given year into one of the following three categories: "focal firms," i.e., firms for which the analyst also covers one or more of the firm's major customer firms, "major customers" of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. In terms of benefits in analyst forecasting accuracy, I hypothesize that an analyst who follows both a focal firm and one or more of the focal firm's major customers issue more accurate earnings

[32] Nevertheless, there is some evidence that analysts who are affiliated with brokerage firms that have been underwriters of the firms (affiliated analysts) are more accurate in their earnings forecasts than non-affiliated analysts. This is because the analyst's association with investment banking activities helps the analyst generate more precise information about the firm. For instance, Clarke, Khorana, Patel, and Rau (2007) find that analysts from larger investment banks tend to be more accurate and less biased in their earnings forecasts. Using forecasts from the period 1998–2001, Jacob, Rock, and Weber (2008) find that investment bank analysts are on average more accurate than independent analysts.

forecasts for the focal firm than (1) the same analyst issues for "other" firms in the analyst portfolios and (2) other non-supply chain analysts issue who follow the same focal firm but none of the focal firm's major customers. Further, I also hypothesize that a supply chain analyst issues more accurate earnings forecasts for the major customers of the focal firm than (1) the same analyst issues for "other" firms in the analyst portfolio and (2) other non-supply chain analysts issue who follow the same major customers but none of the customers' suppliers. In terms of costs in forecasting accuracy, I expect a supply chain analyst to issue less accurate earnings forecasts for "other" firms than other non-supply chain analysts following the same "other" firms. I then examine the underlying economic factors that affect analysts' choices of the focal firms and the major customer firms.

3.3.1 Benefits of supply chain coverage in forecasting accuracy

Analyst earnings forecasts start with an overall sales growth forecast at the industry level, followed by firm-specific adjustments (Lundholm and Sloan, 2007). This forecasting sequence suggests that accurate revenue forecasts at the industry and the firm level are important in affecting analyst earnings forecasting accuracy.

The importance of major customers in a focal firm's revenue and earnings realization has been widely suggested in prior studies (e.g., Baiman and Rajan, 2002a, 2002b; Kulp et al., 2004; Hertzel et al., 2008). When a major customer of a focal firm expects greater growth, the major customer's future demand for products and services from the focal firm is also likely to be greater. By contrast, when the major customer experiences financial distress, the potential disruption of the major customer's operations will negatively affect the future sales and profits of the major customer's focal firm (Hertzel et al., 2008).

Major customers also significantly affect their suppliers' operational strategy and financial performance. For example, when a major customer demands more frequent delivery of products and services from its focal firm, the focal firm will incur additional costs in serving this major customer, which may reduce the focal firm's profitability (Kaplan and Narayanan, 2001). Balakrishnan et al. (1996) suggest that when a major customer implements just-in-time inventory management, the focal firm may also need to implement just-in-time production in order to meet the customer's needs. Major customers may also leverage their significant bargaining power to demand a lower price and to restrict the focal firm's total output, in order to enhance their own financial performance at the expense of the focal firm (Cooper and Slagmulder, 1999; Matsumura and Schloetzer, 2009).[33] Therefore, when an analyst issues forecasts for both a focal firm and one or more of the focal firm's major customers, the analyst is able to make better judgments on how well the production process of the focal firm is aligned with that of the major customers, and how much the focal firm can benefit from the improved operational efficiency of the focal firm's major customers. In addition, the analyst can also judge the extent to which the major customers may exercise their bargaining power at the expense of the other parties in the supply chain, including, in particular, the suppliers.

Therefore, I expect that when an analyst includes both a focal firm and one or more of the focal firm's major customers in the analyst portfolio, the analyst can better gauge the impact of the major customers on the focal firm's future revenue growth, and produce more accurate earnings forecasts for the focal firm. For instance, an analyst who issues forecasts for an apparel manufacturer may be in a better position to assess the level of the manufacturer's sales if she

[33] The presence of a major customer may also benefit a focal firm via cost reduction. For example, focal firms may leverage the demand information from major customers and improve their operating efficiency through more effective inventory and production management (Kulp et al., 2004; Lee et al., 2000; Baiman and Rajan, 2002a, 2002b).

also issues forecasts for the retail stores that are the major customers of the manufacturer. Similarly, an analyst may be able to produce more accurate demand forecasts for a firm in the coal mining industry if she also issues forecasts for the firm's major customers in the utility industry. I expect that such a superior forecasting accuracy will be reflected in both within-analyst and cross-analyst comparisons. With regard to the within-analyst comparison, I expect that, for a given supply chain analyst, her forecasts for the focal firms will be more accurate than her forecasts for "other" firms in the analyst portfolio. This leads to my first hypothesis:

H1a (within-analyst comparison): A given analyst who follows both a focal firm and one or more of the focal firm's major customers will issue more accurate earnings forecasts for the focal firm than she will for "other" firms in the same analyst portfolio.

I also expect cross-analyst variations of forecasting accuracy for a given focal firm. Such a cross-analyst analysis complements the within-analyst comparison of forecasting accuracy for a given supply chain analyst. In particular, while the within-analyst comparison controls for unobservable individual *analyst* characteristics that may affect analyst forecasting accuracy, the cross-analyst comparison controls for unobservable individual *firm* characteristics that may affect analyst forecasting accuracy.

H1b (cross-analyst comparison): Analysts who follow both a focal firm and one or more of the focal firm's major customers will issue more accurate earnings forecasts for the focal firm than will other analysts who only follow the same focal firm but none of the focal firm's major customers.

H1a and H1b assume that forecasting accuracy for revenue is a key component in determining analyst earnings forecasting accuracy. My H2 hypothesizes that supply chain analysts also issue more accurate forecasts for the focal firms' major customers because these analysts have better information on the costs to be incurred by the major customers that are related to input from the major customers' suppliers.

Expenses are a critical component of a firm's earning realization. Analyst forecasting accuracy for the expenses to be incurred for the firm would significantly affect the analyst's overall earnings forecasting accuracy for the firm (Lundholm and Sloan, 2007; Banker and Chen, 2006). In a supply chain relation, the focal firm is the supplier of the major customer firm. This focal firm may play an important role in determining the earnings performance of the firm's major customers. For example, a major customer firm with an established relationship with its suppliers would benefit from a dependable source of supplies, as well as the assurance of the availability and the quality of the supplies (Fee and Thomas, 2004). Therefore, this major customer may take advantage of its relationship with the suppliers by improving the effectiveness of its inventory management and operational efficiency, thereby reducing its inventory costs and improving its overall earnings performance (Gavirneni et al., 1999; Lee et al., 2000). By contrast, when a major customer firm has poor relations with its suppliers, the suppliers can impose costs on the major customer firm by failing to supply trade credit, backing away from entering into long-term contracts, or delaying shipments. Similarly, when the suppliers experience a raw material shortage or raw material price increase, such adverse events would affect the major customer firm's production efficiency, inventory management, final product delivery, which would ultimately affect the major customer's overall costs and earnings realizations. Therefore, analysts who issue forecasts for both a major customer firm and one or more of the major customer's suppliers are more likely to have better insights concerning the potential impact of suppliers on the major customers' future costs, and will issue more accurate earnings forecasts for the major customers than they will issue for "other" firms in the portfolio for which the analysts do not have such supply chain insights. Similar to H1, I expect that the superior forecasting accuracy for the major customer firms is reflected in both within-analyst and cross-analyst comparisons. The two resulting parallel hypotheses are as follows:

H2a (within-analyst comparison): A given analyst who follows both a focal firm and one or more of the focal firm's major customers will issue more accurate earnings forecasts for the major customer(s) than she will for "other" firms in the analyst portfolio.

H2b (cross-analyst comparison): Analysts who follow both a focal firm and one or more of the firm's major customers will issue more accurate earnings forecasts for the major customer(s) than will other analysts who only follow the same major customer(s) but not the major customer's focal firm.

3.3.2 Cost of supply chain coverage in forecasting accuracy

Hypotheses H1 and H2 suggest that an analysts issues more accurate earnings forecasts for both the focal firm and the focal firm's major customer by following both parties in the supply chain than (a) the same analyst issues for "other" firms in the analyst portfolio, and (b) other non-supply chain analysts following the same firm issue. I expect that this analyst will also incur costs for taking such a portfolio approach. Prior research suggests that analyst forecasting accuracy is a function of the level of effort analysts devote to the forecasting task (e.g., Clement, 1999; Barth et al., 2001). This means that to achieve the superior forecasting accuracy for the focal firm and the firm's major customer(s), supply chain analysts must have spent significant time and resources on information acquisition for these firms. The inclusion of a firm's supply chain may result in additional firms in the analyst portfolio. Assuming a fixed level of total effort analysts expend on forecasting tasks, this means that the average amount of effort the analysts can expend on collecting and analyzing information for "other" firms in the analyst portfolio will be accordingly reduced.[34] As the amount of time and effort an analyst

[34] One limitation of this assumption is that it does not discriminate differences in analyst forecasting abilities and the effect of analyst ability on analyst forecasting accuracy. An alternative assumption to hold the total level of effort and the total number of firms analysts follow constant by taking a supply chain portfolio will lead to the same hypothesis. In particular, when an analyst replaces a non-supply chain firm in her portfolio with a supply chain firm in a year and spend a lot more time and resources on the firms in the supply chain, the amount of time and resources this analyst can spend on other non-supply chain firms in the portfolio will be less on average less,

spends on a firm reduces, her forecasts for the firm would be less accurate (Jacob et al., 1999). Therefore, I expect that the superior forecasting accuracy for the focal firm and the firm's major customers for supply chain analysts is achieved at the expense of reduced forecasting accuracy for "other" firms in the analyst portfolio. Again, this hypothesis has two implications. First, I expect that for a given supply chain analyst, her forecasts for "other" firms in the portfolio will be less accurate than her forecasts for the focal firm or the focal firm's major customer (i.e., within-analyst comparison). These are examined in hypotheses H1a and H2a, where I expect that a supply chain analyst issues more accurate earnings forecasts for the focal firm or for the focal firm's major customer than the same analyst issues for "other" firms in the analyst portfolio. Second, I also expect cross-analyst differences in forecasting accuracy for a given "other" firm, stated as follows:

H3: (cross-analyst comparison): Analysts who follow both a focal firm and one or more of the focal firm's major customers will issue less accurate earnings forecasts for "other" firm(s) in the analyst portfolio than will other non-supply chain analysts who only follow the same "other" firm(s).

3.3.3 Determinants of analysts' choice of the focal firms and the major customer firms

To the extent that supply chain analysts achieve superior forecasting accuracy for both a focal firm and the focal firm's major customer firms at the expense of reduced forecasting accuracy for "other" firms in the analyst portfolio, the focal firm and the firm's major customers must be relatively more important than "other" firms in the same portfolio. My next hypothesis examines how analysts select a firm as the focal firm or the major customer in the portfolio.[35]

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holding the total number of firms and the amount of available resources the same. As a result, her forecasts for "other" firms in the portfolio will be less accurate. The implication of this assumption on the overall forecasting accuracy at the analyst portfolio level is unclear.

[35] An analyst may cover a focal firm first and then choose to follow the focal firm's major customer to establish a supply chain portfolio. Alternatively, the analyst may follow the major customer firm first and then extend to include the firm's supplier (i.e., the focal firm), or initiate the coverage of both the focal firm and the firm's major customer firm at the same time. This chapter does not differentiate the analyst's decision sequence of the firms in the supply chain relation.

Prior research suggests that analysts' incentive to acquire information on a firm is significantly affected by their economic objectives in their earnings forecasts (e.g., O'Brien and Bhushan, 1990; Hayes, 1998; Mikhail et al., 1999; Jackson, 2005). For example, Hayes (1998) suggests that the precision of the information analysts produce about a firm and their earnings forecasting accuracy is significantly affected by analysts' economic objectives in their earnings forecasts. Hayes suggests that when analysts have higher incentives to generate trading commissions for their brokerage firms from the stock of the firm the analysts follow, these analysts will allocate more effort to acquire more precise information about the firm. This is because investors will make their trading decisions based on the precision of the information analysts produce. As analysts improve the precision of the information they produce about a firm, analyst earnings forecasts for the firm are more accurate.[36]

Following Hayes (1998), I expect that when a firm has higher potential to generate revenue for the analysts' brokerage firms in the form of trading commissions, analysts are more likely to spend more effort acquiring information on the firm and produce more precise information about the firm by choosing the firm as a focal firm or as a major customer firm, and cover the other parties in the firm's supply chain. This leads to the following hypothesis:

H4: (within-analyst comparison): A given analyst is more likely to choose a firm as a focal firm or as a major customer firm and follow one or more of the other parties in the firm's supply chain, when the firm has greater potential to bring in more trading commissions to the analyst's brokerage firm.

3.4 Estimation equations and variable definitions

In this section, I first discuss the model used for testing H1-H3. These three hypotheses examine the effect of analysts' supply chain portfolio coverage on analyst forecasting accuracy.

[36] By contrast, Lin and McNichols (1998) suggest that when analysts have higher incentives to establish an investment banking relation with a firm, analysts are less accurate in their earnings forecasts because these analysts may intentionally issue more favorable earnings forecasts for the firm to curry favor with firm management and build "management relation".

I then discuss the model for testing H4, which estimates the economic determinants of analysts' choice of the focal firms and the major customer firms.

3.4.1 Model specifications for testing H1-H3 concerning analyst forecasting accuracy

H1a tests the within-analyst differences in forecasting accuracy for a given supply chain analyst between the focal firms and "other" firms in the analyst portfolio. I used the regression model shown below to test this hypothesis. The data used for the model include all annual and quarterly forecasts issued by supply chain analysts for the focal firms and "other" firms in the analyst portfolio over the sample period from 1991 to 2008.[37] The panel dataset includes earnings forecasts issued for different firms by the same analysts, which implies that correlations related to individual analyst characteristics are present in the data. Overlooking such correlations could result in underestimation of the standard errors, which, in turn, could cause spurious inflation of the corresponding t-statistics (Petersen, 2009).

To address this concern, I used the two-step approach of Fama and MacBeth (1973), a method that is widely used in empirical analyses of financial panel datasets, to control for the effect of individual analyst characteristics on analyst forecasting accuracy. In the first step of the method, I ran a cross-sectional regression for each analyst-year to obtain estimates of the coefficients on the independent variables. In the second step, I used the series of the coefficient estimates to calculate the mean estimates for the independent variables and standard errors of these estimates. To deal with heteroscedasticity and autocorrelation among the coefficient estimates, I used the adjusted Newey-West (1987) standard errors of the estimates to calculate the t-statistics for the significance level of the independent variables. The regression model is specified as follows:

[37] In the robustness test section discussed later, the results still hold when I examined annual forecasts or quarterly forecasts separately.

$$FORECAST\_ERROR_{i,j,t} = \beta_0 + \beta_1 FOCAL\_SUPPLY\_CHAIN_{i,j,t} + CONTROL\_VARIABLES + \varepsilon_{i,j,t} \quad (1)$$

In equation (1) the dependent variable is analyst earnings forecasting error, *FORECAST_ERROR*. Following prior studies, I measure analyst forecasting accuracy using the following formula:

$$FORECAST\_ERROR_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE}_{j,t}}{\overline{AFE}_{j,t}}, \quad (2)$$

where $\overline{AFE}_{j,t}$ is the mean of absolute earnings forecasting errors ($AFE_{i,j,t}$) using all forecasts issued for firm *j* in year t for quarterly forecasts and annual forecasts separately. I calculated the absolute earnings forecasting error, $AFE_{i,j,t}$ as $AFE_{i,j,t} = |F_{i,j,t} - EPS_{i,j,t}|$, where $F_{i,j,t}$ is the forecasted quarterly or annual earnings issued by analyst *i* for firm *j* in year *t*, and $EPS_{i,j,t}$ is the corresponding actual earnings per share announced by firm *j* in year *t*. This measurement controls for firm effects and year effects that may cause systematic differences in forecasting accuracy (Clement, 1999). It represents a proportional forecast error for each individual forecast relative to the average forecast error for a firm in a fiscal year. The smaller the value of this measure, the more accurate is a forecast.[38] A negative value of this measure represents above-average forecasting performance, while a positive value of this measure represents below-average forecasting performance.

The primary independent variable in equation (1) is *FOCAL_SUPPLY_CHAIN*, which is an indicator variable that equals 1 for forecasts issued for a focal firm and 0 for forecasts issued by the same analyst for "other" firms in the analyst portfolio. A negative coefficient on *FOCAL_SUPPLY_CHAIN* would support H1a, suggesting that for a given supply chain analyst,

[38] I also used the ranked forecast error and the absolute forecast error scaled by assets per share at the beginning of the year as alternative measures for earnings forecasting error. Regression analyses using these two alternative measures yielded similar results. The robustness test section in section 3.6.9 presents the details.

her average forecasting error is smaller for focal firms than her average forecasting error for "other" firms in the analyst portfolio.[39]

The remaining independent variables in equation (1) are controls on individual forecast characteristics, analysts' firm-specific characteristics, and firm characteristics that may affect analyst forecasting accuracy. These variables are discussed below.

O'Brien (1988) suggests that earnings are more difficult to forecast when the forecasting horizon is longer because there is more uncertainty in the earnings realization process. To control for this effect, I included *HORIZON* in the model, which is the number of lag days between the date a forecast is issued and the date on which the actual earnings per share (EPS) is announced.

Jacob et al. (1999) and Gilson et al. (2001) document that analysts with industry expertise in a particular industry issue more accurate earnings forecasts for the firms in the industry than the analysts issue for other firms without such industry expertise. I used an indicator variable *PRIMARY_INDUSTRY* that equals 1 if a forecast is issued for a firm that is in an industry that has the largest representation among all the firms the analyst follows in the same year. I termed this industry as the analyst's primary industry as a measure for the analyst's industry

[39] To the extent that following both a focal firm and the focal firm's major customers gives analysts information advantage with regard to the focal firm's future revenue growth, it is possible that for a given analyst, the greater the number of major customers of a focal firm that an analyst covers, or the more important the major customers are in contributing to the annual sales of the focal firm, the more precise the analyst's information about the focal firm's future revenue realization will be, and the more accurate the analyst is in her forecasts for the focal firm. To test this conjecture, I replaced the indicator variable *FOCAL_SUPPLY_CHAIN* with two different variables to measure the extent to which an analyst follows the major customers of a focal firm. *NUMBER_CUSTOMER* was the total number of customers of a focal firm that an analyst followed; if the analyst followed none of the firm's major customers, *NUMBER_CUSTOMER* was coded as zero. *PCT_SALES* proxied the importance of the major customers in contributing to the focal firm's annual total sales. It was the aggregate total sales made to the major customers of the focal firm divided by the total sales of the focal firm in the year. If the analyst followed none of the firm's major customers, it was coded as 0. Untabulated results show a negative and significant coefficient on *NUMBER_CUSTOMER* and *PCT_SALES*, respectively, suggesting that the more major customers of a focal firm an analyst follows, or the more the major customers contribute to the total sales of the focal firm, the more accurate the analyst is in her earnings forecasts for the focal firm.

expertise.[40] Adding this variable in the model helps examine the additional contribution of an analyst's supply chain coverage in explaining variations on analyst forecasting accuracy that is beyond the explanatory power of the analyst's industry expertise. I also added an interaction term *FOCAL_SUPPLY_CHAIN * PRIMARY_INDUSTRY* in the model to examine whether an analyst issues more accurate earnings forecasts for the focal firms for which the analyst has both industry expertise and supply chain knowledge than she issues for firms for which she does not have both expertise.

Mikhail, Walther, and Willis (1997) document a "learning by doing" effect. They show that analyst earnings forecasts become more accurate as the analyst's firm-specific forecasting experience increases. I used *YEAR_EXP* to measure an analyst's firm-specific forecasting experience. It indicates the number of years an analyst has been following the firm.

Lang and Lundholm (1996) and Bamber and Cheon (1998) suggest that analysts are less accurate in their earnings forecasts for firms that face greater uncertainty concerning earnings realization. These authors suggest that analyst earnings forecasting dispersion (*DISPERSION*), which represents the extent of disagreement among analysts concerning their expectations of the possible effects of future events on a firm's earnings realization, captures the extent of a firm's earnings uncertainty. *DISPERSION* is measured as the standard deviation of analyst forecasting errors for fiscal year *t*, calculated for quarterly forecasts and annual forecasts separately. The greater the value is, the greater is the uncertainty concerning a firm's earnings realization.

[40] In comparison, Gilson et al. (2001) define an analyst as an industry specialist if the analyst follows at least five firms in the same industry. Jacob et al. (1999) measure the extent of an analyst's industry specializations based on the percentage of companies followed by the analyst with the same two-digit SIC code. Considering an average of 67% of firms each analyst follows in I/B/E/S is from the same industry, I assumed that each analyst has a primary industry in which she is specialized. I also replaced the indicator variable, *PRIMARY_INDUSTRY* with the percentage of the total number of firms that are in the same industry at the one-digit SIC relative to the total number of firms an analyst follows in the same year, as in Jacob et al. (1999), to measure an analyst's industry specialization in the regression analyses. The results are quantitatively the same.

Analyst forecasting accuracy is also dependent on the amount of information available to an analyst about the firms she follows (Atiase, 1985; King, Pownall, and Waymire, 1990). Prior studies have documented that analysts are more accurate in their earnings forecasts for a firm when the firm is also followed by a greater number of other analysts because of the additional information other analysts will generate about the firm. I used *NUMBER_ANALYST_FOLLOW* to measure the total number of analysts following a firm during fiscal year t. I expect forecasts to be more accurate for firms that are covered by a greater number of other analysts.

The same model specification was used to test H2a on the within-analyst differences in forecasting accuracy for major customer firms versus for "other" firms the same supply chain analyst follows in a year. In the model, I replaced the indicator variable *FOCAL_SUPPLY_CHAIN* with *CUSTOMER_SUPPLY_CHAIN*, where *CUSTOMER_SUPPLY_CHAIN* equals 1 if a forecast is issued for a focal firm's major customer firm, and 0 for forecasts issued for "other" firms in the same analyst portfolio.

I used a modified model specification to test H1b, H2b, and H3 concerning the cross-analyst differences in forecasting accuracy between supply chain analysts and other non-supply chain analysts following the same firm. In the model, I used an indicator variable *SUPPLY_CHAIN_ANALYST* that equals 1 if a forecast is issued by a supply chain analyst and 0 if a forecast is issued by a non-supply chain analyst. In addition, because the model estimates cross-analyst forecasting accuracy for a given firm, I ran a Fama-MacBeth regression for each individual firm-year rather than for each analyst-year and adjusted the standard errors of the coefficient estimates using Newey-West's (1987) method. I also excluded firm characteristics variables, but included analyst and brokerage firm characteristics in the model. These included variables are the total number of industries at the one-digit SIC code level that an analyst follows in a given year (*NUMBER_SIC1*) and the log value of the total number of analysts hired by the analyst's employing brokerage firm (*LOG_BROKER_SIZE*). These two variables control for the effect of the complexity of an analyst's portfolio and the extent of support an analyst receives from her brokerage firm (Clement, 1999).

3.4.2 Model specification for testing H4 concerning analysts' choice of the focal firms and the major customer firms

Hypothesis H4 predicts that an analyst is more likely to choose a firm as the focal firm or as the major customer firm, and follow one or more of the other parties in the firm's supply chain when the firm can generate more profitable trading commissions for the analyst's brokerage firm.

To test H4, I pooled all the firms each supply chain analyst follows in the same year over the sample period and used a conditional logit model to estimate equation (3). The model is estimated conditional on that one or more of the firms in an analyst portfolio are in a supply chain relation as a focal firm or as the focal firm's major customer firm. Based on Johnson, Ryan, and Tian (2009), the conditional logistic regression model provides consistent parameter estimates for factors that affect the probability that a firm will be chosen as a focal firm or a major customer firm.

$$\begin{aligned} FIRMS\_SUPPLY\_CHAIN_{i,j,t} = {} & \beta_1 INVESTMENT\_BANKING_{j,t} + \beta_2 LOG\_TRADINGVALUE_{j,t-1} \\ & + \beta_3 LOG\_NUMBER\_FIRM\_SIC1_{i,t-1} + \beta_4 PRIMARY\_INDUSTRY_{i,j,t} \\ & + CONTROL\_VARIABLES + \gamma_t + \varepsilon_{i,j,t} \end{aligned} \quad (3)$$

In the regression equation (3), the dependent variable, *FIRMS_SUPPLY_CHAIN*, is an indicator variable that equals 1 if for analyst *i*, firm *j* is a focal firm in year *t*, with one or more of the firm's major customers also followed by the same analyst during the same year. *FIRMS_SUPPLY_CHAIN* also equals 1 if firm *j* is a major customer firm for analyst *i* in year t, with one or more of the major customer's suppliers also followed by the same analyst during the year. *FIRMS_SUPPLY_CHAIN* equals 0 for the remaining "other" firms followed by analyst *i* in year *t.*

The right-hand side of equation (3) includes economic factors based on prior literature that may affect an analyst's choice of firms to follow and the amount of effort the analyst would expend on gathering information for the firm. Hayes (1998), Michaely and Womack (1999), Barth et al. (2001) and Ljungqvist et al. (2006) suggest that analysts are more likely to follow a firm when the potential revenue a firm may bring to the analyst's brokerage firm is high. Following these studies, I used an indicator variable *INVESTMENT_BANKING* that equals 1 if an analyst's brokerage firm has been an underwriter for issuance of equity for the firm during the three years before and after the forecast year and 0 otherwise.[41] This variable measures the likelihood that the firm may bring in underwriting fees for the analyst's brokerage firm. I also used *LOG_TRADINGVALUE*, which is the log value of the total trading value of the firm (in thousands of dollars) during the prior year. This variable captures the potential trading commissions that the firm could potentially bring to the analyst brokerage firm. The greater the value of *LOG_TRADINGVALUE,* the higher the potential trading commissions that the firm could generate.

Equation (3) also includes other firm characteristics that prior research suggests may affect analysts' incentives to follow a firm. For example, O'Brien and Bhushan (1990) argue that if there are economies of scale in learning about firms' operations in the same industry (for example, because information about technologies or productions is common across firms), then

[41] Alternatively, I defined *INVESTMENT_BANKING* equals 1 if during the three years before the forecast year, the analyst's brokerage firm has been an underwriter for the issuance of equity for the firm and 0 otherwise. The results remain statistically the same. The results also hold when I define whether a brokerage firm has an investment banking relationship with the firm using the three years after the forecast year as an alternative window.

the return for analysts' effort in information acquisition on the firm will increase with the total number of other firms in the industry. Therefore, I included *LOG_ NUMBER_FIRM_SIC1*, which is the log value of the total number of other firms in the firm's industry at the one-digit SIC code level. I expect *LOG_ NUMBER_FIRM_SIC1* to be positively associated with the likelihood of a firm being chosen as a focal firm or a major customer firm.

I also included an indicator variable, *PRIMARY_INDUSTRY*, to measure whether or not a firm is in an industry in which the analyst has expertise. I expect an analyst is more likely to choose a firm as a focal firm or a major customer firm when the analyst already has expertise in the firm's industry, because the analyst can make the best use of her industry knowledge about the firm and the cost to follow the firm's supply chain is lower.

Barth et al. (2001) suggest that analysts are more likely to follow firms with higher growth and greater information asymmetry. They suggest that analysts are more likely to produce more informative earnings forecasts for these firms and investors are more likely to trade on the information analysts produce for these firms. Therefore, I included *SALE_GROWTH* to capture the firm's total sales growth in the current year relative to the prior year, and used the market-to-book ratio (*MARKET_TO_BOOK*) to proxy for a firm's growth opportunity. Following Barth et al. (2001), I also included *AD_RATIO* and *RD_RATIO* to capture a firm's technology and brand name as the proxies for the amount of the firm's intangible assets. These two measures are the ratios of advertising expenses (*AD_RATIO*) and research and development expenses (*RD_RATIO*) to the total sales in the year, respectively. In addition, Lang and Lunhdolm (1996) suggest that analysts are likely to cover more profitable firms. Therefore, I also included return on assets (*ROA*) as an additional control variable in the model.

3.5 Sample construction and summary statistics

I constructed the sample by merging two sources of data. The first source was the Compustat customer segment file, which identified the firms that reported having major customer relations. The second was the analysts' detailed earnings forecast data from *I/B/E/S*. Data construction for each source is discussed in the following two sub-sections.

3.5.1 Major customer data and identification of firms' supply chains

I obtained data on supplier-customer relationships from the Compustat customer segment file, a subset of the Compustat segment database that records the identity of, and sales to, a firm's major customers based on the firm's original annual filing with the SEC. SFAS No. 14 (FASB 1975) requires firms to report financial information for any industry segment that comprises more than 10% of the reporting firm's consolidated yearly sales, assets, or profit. In addition, the name of any customer representing more than 10% of the total sales of the reporting firm must be disclosed.

However, the Compustat customer segment file only reports a permanent firm identifier code (*GVKEY*) for each reporting firm, but not for the reported major customer firm. In addition, the names of the major customer firms in this file are not reported in a standard format. For example, the name of the same customer company is often not reported consistently by different reporting firms or even by the same reporting firm in different years.[42] Some firms may even report a subsidiary or division as a major customer rather than its parent company.

To link each name of the reported major customer firm with a unique permanent firm identifier, and to merge with analyst forecast data for the reported customer, I used an algorithm

[42] For example, some firms may report its major customer as "GE" in one year and as "General Electric" in another year. This major customer may also be reported by some firms as "General Electric Company." Some other firms may report the subsidiary "GE Health" as its major customer, rather than its parent company of "GE" In such cases, discretion is required in judging whether "GE", "General Electric", "General Electric Company" or "GE health" all refer to the same company.

similar to that in Fee and Thomas (2004) and Ellis, Fee, and Thomas (2009). This algorithm compares the number and the order of the letters for the name of each major customer firm reported in the customer segment file with the company names listed in the historical Center for Research in Security Price (*CRSP*) company name database. Based on the output from the algorithm, I retained the first three most closely matched historical company names from *CRSP* for each reported major customer firm. I then visually inspected the reported name of the major customer firm from Compustat and the three matched names from *CRSP*, and determined a distinct permanent firm identifier for the reported major customer firm. For those reported major customer firms whose names were not well matched with the names from *CRSP*, I first searched the reported names of the major customer firms in Google[43] or the Directory of Corporate Affiliations, and determined if the reported major customer was a subsidiary of a public parent company. If the reported major customer firm was confirmed to be a valid subsidiary of a public company, I then used the permanent identifier of the parent company as the identification code for the disclosed major customer firm; otherwise, I assumed the reported major customer did not have a valid firm identifier and discarded the focal firm – major customer pair.[44] The above procedures yielded a total of 50,678 focal firm-major customer firm paired relations during the sample period from 1991-2008. 26,330 of these pairs had firm identification codes for both the focal firm and the paired major customer firm, representing a total of 19,068 reporting firm-years for 4,736 distinct reporting firms.

[43] When using Google to search the parent company of a subsidiary, I used the subsidiary's name as shown in the Compustat customer segment file, together with other key words such as "parent," "subsidiary," "division," etc. to identify the name of the parent company and the corresponding CRSP firm identification code.
[44] In making these judgments, I have attempted to be conservative. For example, for firms with uncertain abbreviations, the customer is not matched with any firm identifier. These firms are excluded from later analyses. This conservative approach implies that the number of reporting firm-customer pairs with valid permanent firm identifiers for both the focal firm and the reported major customer may be understated.

3.5.2 Analyst forecast data and identification of supply chain analysts

The sample of analyst earnings forecasts comes from the *I/B/E/S* detailed analyst forecast file for the period from January 1, 1991 to December 31, 2008. Following prior studies (e.g., Ke and Yu, 2006; Sonney, 2007), I retained only those forecasts that were issued for firms in the U.S., and had values for the actual earnings as well as the reported earnings announcement date, I*/B/E/S* ticker, analyst code, and broker code. I excluded forecasts issued for those firms that are followed by fewer than three analysts in a fiscal year because comparisons of forecasting performance among different analysts are not reliable for thinly covered firms (e.g., Ke and Yu, 2006; Sonney, 2007). To reduce possible outlier effects, I also deleted forecasts for which the absolute forecasting errors were greater than three times the standard deviation of the absolute forecast error of the forecast calculated using all forecasts issued for the firm in the same fiscal year (e.g., Clement, 1999; Ke and Yu, 2006; Sonney, 2007).

I then used the identification codes for both the focal firms and their major customers discussed at the end of section 3.5.1 to merge with the analyst forecast data from *I/B/E/S*. Of the total 26,330 pairs of supply chain relations that had firm identification codes for both a focal firm and the firm's reported major customer firm, only 13,047 pairs of supply chain relations had analyst forecast data from *I/B/E/S* for both the focal firm and the reported major customer firm. These 13,047 pairs of supply chain relations represent 9,372 distinct reporting firm-years. 44.0% of the pairs have both the focal firm and the firm's reported major customer in the same industry at the one-digit SIC level.

Among the 9,372 distinct reporting firm-years that have analyst forecast data for both the reporting firm and its reported major customer firm, I identified 1,176 reporting firm-years that are followed by 2,696 analysts who issued forecasts for both the reporting firm and one or more of the focal firm's reported major customer firms in the same year. I labeled these analysts as "supply chain analysts" for the year.

Based on the individual analyst identity code (i.e., "*ANALYS*" in *I/B/E/S*) for these supply chain analysts, I retrieved all forecasts issued by these analysts in the same year over the sample period. I classified all forecasts each supply chain analyst issued in the fiscal year into one of the three categories: forecasts for the focal firms, for the major customers of the focal firms, and for all "other" firms in the analyst portfolio in the same year. I then kept the firm identification code ("*TICKER*") for each focal firm, the major customer firm, and "other" firms in the analyst portfolio, and retrieved all forecasts issued for these firms in separate files.

3.5.3 Descriptive statistics on supply chain analysts and firms in their portfolios

Table 3.1 reports year-by-year distribution of the number of firms for two samples. Column (1) reports the distribution of the total number of the reporting firms that reported having major customer relations, and have analyst forecast data available for both the reporting firms and the reported major customer firms in *I/B/E/S*. Firms reported in this sample represent the maximum possible number of firms that could be identified as the focal firms. Column (1) shows that the number of firms that reported having major customer relations first increased from 672 in 1991 to 868 in 1996, and then declined steadily from 766 in 1997 to 72 in 2008. One potential explanation for the decline is that an increasing number of firms since the late 1990s have chosen to keep real names of their major customers anonymous when these firms filed with the SEC (Ellis et al., 2009).[45]

[45] Ellis et al. (2010) show that firms systematically choose not to disclose the names of their major customers to discourage competition when the proprietary costs associated with disclosure are high and when firms operate in less competitive industries where strategic interactions among rivals are more prevalent. Ellis et al. (2010) also indicate that based on their conversations with the SEC, although firms are required to comply with SFAS No. 14 to disclose the names of their major customers, the SEC is unlikely to take enforcement action against the firms that fail to comply with such disclosure requirements. However, the SEC may request that firms remedy this reporting deficiency.

[Insert Table 3.1]

Columns (2)-(5) report the distribution of the number of focal firms, major customer firms, and "other" firms followed by supply chain analysts.[46] Column (2) of Table 3.1 shows that the number of focal firms followed by supply chain analysts was relatively stable between 89 and 119 from 1991 to 1998, and then steadily decreased after 1998 – a pattern that is similar to the pattern for the reporting firms in column (1). Column (2) also shows that of the maximum possible number of firm-years that could be identified as focal firms in column (1), 12.5% (1,176 of the 9,372 total firms in column (1)) of these firms are followed by supply chain analysts. Columns (3) and (4) report the year-by-year distribution of the total number of the major customers of the focal firms, and "other" firms in supply chain analysts' portfolios, respectively. They show a similar pattern as for the focal firms.

Next, Table 3.2 reports the corresponding industry distribution (at the one-digit SIC code level) for the firms reported in Table 3.1. Column (1) of Table 3.2 shows that of the firms that reported having major customer relations and also have analyst forecast data for both the focal firm and the paired firm's major customer, the durable manufacturing industry has the largest representation and the agriculture production industry has the least representation. The remaining columns of Table 3.2 report the industry distribution of the firms followed by supply chain analysts, including the focal firms in column (2), the major customers of the focal firms in column (3), and "other" firms in column (4). The numbers in parentheses in column (2) report the percentage of the focal firms in each industry. The figures show that the industry distribution of the focal firms followed by supply chain analysts is similar to what was reported in column (1) but with a much smaller total number of firms in each industry. The industry

[46] The three groups in the classification were not mutually exclusive. For example, a firm that was classified as a focal firm may also be classified as a major customer firm. A total of 42 firms were categorized as both a focal firm and a major customer. Excluding these 42 firms in the empirical analyses does not change the results.

distribution for the major customer firms and all other firms in columns (3) and (4) shows a similar pattern as in column (2).

[Insert Table 3.2]

3.5.4 Descriptive statistics on supply chain analysts' portfolios

To describe the portfolio characteristics of supply chain analysts, I used all the other non-supply chain analysts who follow the same focal firms but do not follow the firms' major customers as a benchmark. Table 3.3 shows that of a total of 9,235 analyst-years following 1,176 focal firm-years, 29.2% (2,696 of the total 9,235 analyst-years) of these analysts are supply chain analysts.

[Insert Table 3.3]

Column (1) of Table 3.3 shows that for all analysts (including both supply chain analysts and non-supply chain analysts) following the focal firms, the mean number of supply chain relations (i.e., the mean number of focal firm-major customer pairs) in the analyst's portfolio is 0.77. This means that for the analysts following the focal firms, on average, each analyst has 0.77 pair of focal firm-major customer relations in the portfolio. A significant percentage (72.1%) of the firms these analysts follow is in the analysts' primary industry. However, only 16% of analysts exclusively follow firms from a single industry at the one-digit SIC code level, with the remaining 84% of analysts following firms from more than one industry. This percentage is much higher than the corresponding 60% for all analysts in *I/B/E/S*. This evidence seems to suggest that on average, analysts following firms that have major customer relations tend to have a more diversified industry portfolio than the population analysts covered in *I/B/E/S*. Table 3.3 also shows that on average, analysts following the focal firms cover a mean of 15.35 firms in 2.96 (4.74) industries at the one- (two-) digit SIC code level. The analysts' employing brokerage firms hire a mean number of 54.98 analysts, covering 8.74 industries at the one-digit SIC code level.[47]

Columns (2) and (3) of Table 3.3 compare portfolio characteristics for supply chain analysts versus the other analysts following only the same focal firms but none of the firms' major customers. The descriptive statistics show that supply chain analysts follow a mean of 2.63 supply chain relations, versus 0 for the other analysts (by definition). 68.7% of the firms supply chain analysts follow are in the analyst's primary industry; this is in contrast with 73.6% for other non-supply chain analysts following the same focal firms. This difference is statistically significant at $p<0.01$ level. In addition, only 10.3% of the supply chain analysts follow firms from a single industry at the one-digit SIC code level. This percentage is significantly lower (at the $p<0.01$ level) than the corresponding 18.4% for other non-supply chain analysts. These statistics provide preliminary evidence that supply chain analysts are more diversified in their industry coverage than non-supply chain analysts. Moreover, supply chain analysts follow a mean of 19.14 firms from 3.22 industries at the one-digit SIC level, which is 39% and 13% more than the corresponding 13.78 firms and 2.85 industries for other non-supply chain analysts. Both of the differences are statistically significant at the $p<0.01$ level. This result seems to suggest that supply chain analysts increase the total number of firms and industries in their portfolios in order to maintain their supply chain coverage. Table 3.3 also shows that the brokerage houses employing supply chain analysts hire a significantly greater number of analysts and have more comprehensive industry coverage than the brokerage houses that employ the other non-supply chain analysts.

[47] Note that column (2) and column (3) in the last row of Table 3.3 report a total number of 973 distinct supply chain analysts and 2,536 distinct other analysts. These two numbers do not add up to the total number of 2,857 distinct analysts following the focal firms in column (1) because I have defined supply chain analyst at the analyst-year level. An analyst may be a supply chain analyst in one year, but may not be a supply chain analyst in another year.

More detailed analyses on how analysts may organize supply chain relations in their portfolios and how different supply chain portfolio organization affects analyst forecasting accuracy for the focal firms and the focal firms' major customers are presented in Appendix 3.2. In this Appendix, I further classified each supply chain analyst into one of the four groups. I based the classification on the distinct number of major customers each analyst follows for a focal firm and the distinct number of focal firms each analyst follows for a major customer firm in the same analyst portfolio. The first category includes "analysts with one (focal firm) to one (major customer) relation," indicating that for every focal firm in the analyst portfolio, the analyst follows only one major customer for each focal firm. The other three categories include analysts with "one-to-many relation," "many-to-one relation," and "hybrid relation." These three categories refer to those analysts if the analyst follows more than one major customer for at least one focal firm in the analyst portfolio ("one-to-many relation"), more than one focal firm for at least one focal firm's major customer ("many-to-one relation"), or a combination of the above two categories ("hybrid relation").

Appendix 3.2 Panel A shows that 1,746 of the 2,696 (64.8%) supply chain analysts are classified into the "one-to-one relation" category, with the remaining 950 analysts (35.2%) distributed in the other three categories. Panel B of Appendix 3.2 shows that as a supply chain analyst increases the total number of major customers of a focal firm in her portfolio, her forecasting accuracy for the focal firm marginally improves. Panel C of Appendix 3.2 shows that as a supply chain analyst increases the number of suppliers of the major customer in her portfolio, her forecasting accuracy for the major customer also marginally improves. Overall, the evidence presented in Appendix 3.2 is generally consistent with the argument that as supply chain analysts acquire more information about the focal firm's major customers, their forecasts for the focal firms become more accurate. Similarly, the more information these analysts acquire about the suppliers of the major customer, their earnings forecasts for the major customer firm are more accurate.

3.6 Empirical results

In this section, I present the univariate and the multivariate regression analyses used for hypotheses testing. I first present the results on the benefits to analysts taking a supply chain portfolio approach in terms of their forecasting accuracy for the focal firms and the firms' major customers in subsection 3.6.1 to 3.6.4. I then present the corresponding empirical results on the costs to these analysts of taking a supply chain portfolio approach by examining their forecasting accuracy for "other" firms in the portfolio in subsection 3.6.5. Subsection 3.6.6 discusses the empirical results on analyst forecasting accuracy at the portfolio level. Subsection 3.6.7 presents the results for testing H4 on the economic determinants of analysts' choice of the focal firms and the major customer firms. Subsection 3.6.8 and 3.6.9 present results for additional analyses and robustness tests.

3.6.1 Tests of H1a: within-analyst analyses of forecasting accuracy for the focal firms

To conduct within-analyst analyses of forecasting accuracy for a given supply chain analyst, I retrieved all 449,171 forecasts issued by supply chain analysts over the sample period. The sample included 44,377 forecasts for the 1,176 focal firm-years, 44,036 forecasts for the 742 major customer-years, and 360,758 forecasts for the 15,066 "other" firm-years.

H1a examines the within-analyst comparison of forecasting accuracy for a given supply chain analyst between the focal firms and "other" firms in the analyst portfolio. It predicts that supply chain analysts will issue more accurate earnings forecasts for the focal firms than they will for "other" firms in the analyst portfolio. To test this hypothesis, I stacked all forecasts supply chain analysts issued for the focal firms and “other” firms in their portfolios. The sample included a total of 405,135 forecasts (i.e., 44,377+360,758), with 49.75% (201,557 of 405,135) being annual forecasts and the other 50.25% (203,578 of 405,135) being quarterly forecasts.[48]

Panel A of Table 3.4 presents the descriptive statistics for the variables used in the multivariate regression analyses for H1a. Panel A shows that forecasts issued for the focal firms (*FOCAL_SUPPLY_CHAIN*) represent 11% of this sample. The remaining 89% of the forecasts are issued for “other” firms in supply chain analysts’ portfolios. In addition, 74% of the forecasts are issued for firms in which analysts have primary industry expertise.

Panel B of Table 3.4 presents the Pearson correlations for the variables used in the multivariate analyses. Recall that I measured forecasting accuracy (*FORECAST_ERROR*) as the percentage of the absolute forecasting error for each individual forecast relative to the average absolute forecast error that is calculated using all forecasts issued for the firm in the same fiscal year. The smaller the value of the forecasting error, the more accurate is the forecast. As expected, the indicator variable *FOCAL_SUPPLY_CHAIN* is negatively and significantly correlated with *FORECAST_ERROR*. The correlations of the other variables are generally consistent with prior studies (e.g., Clement, 1999; Jacob et al., 1999). For example, forecasts are more accurate when analysts have industry expertise in the firm (*PRIMARY_INDUSTRY*) and have greater forecasting experience with the firm (*YEAR_EXP*). Conversely, forecasts are less accurate when the forecasting horizon (*HORIZON*) is longer and when analysts are more dispersed in their expectations of the firm’s future earnings prospects (*DISPERSION*).

Panel B also shows a negatively significant correlation coefficient between *FOCAL_SUPPLY_CHAIN* and *PRIMARY_INDUSTRY*, suggesting that firms that are in an

[48] As I will discuss in the robustness section, testing the hypotheses using the quarterly and annual forecasts separately yields quantitatively the same results.

analyst's primary industry are less likely to be a focal firm; in addition, the correlation coefficient between *FOCAL_SUPPLY_CHAIN* and *YEAR_EXP* is positive and significant, suggesting that analysts with more firm-specific experience are more likely to include the focal firm's major customer firms in their portfolios. *FOCAL_SUPPLY_CHAIN* is negatively and significantly correlated with *NUMBER_ANALYST_FOLLOW*, suggesting that analysts are more likely to follow a focal firm's customer firms when the focal firm is followed by fewer other analysts. Because these correlations are pair-wise, the coefficient sign may differ in the multivariate analyses. Overall, the results in the correlation table seems to suggest that analysts are more likely to follow a firm's supply chain when the analyst has more experience with the firm and when the information produced by the analyst is likely to be more informative because of the information asymmetry for the firm.

Panel C of Table 3.4 presents the descriptive statistics on the forecasting accuracy for all firms included in supply chain analysts' portfolios. The first row of Panel A of Table 3.4 shows that the mean (median) forecasting error for all forecasts issued by supply chain analysts is 0.0003 (-0.0289). The second row shows that when forecasts are issued for firms that are in an analyst's primary industry, the mean (median) forecasting error is -0.0011 (-0.0309), which is significantly smaller than the corresponding mean (median) forecasting error of 0.0045 (-0.0220) for firms in which the analyst does not primary industry expertise.

I then partitioned all the forecasts issued by supply chain analysts in the same year into three groups: forecasts issued for focal firms, for major customer firms, and for all remaining "other" firms in the analyst portfolio. Row (4) shows that the mean (median) forecasting error for the focal firms is -0.0189 (-0.0484), which is statistically smaller (at the $p<0.01$ level) than the corresponding mean (median) forecasting error of 0.0033 (-0.0250) for "other" firms shown in Row (6). This result provides preliminary evidence that forecasts are more accurate for the focal firms than for “other” firms in the analyst portfolio. The comparison between the forecasting errors for the major customers and for “other” firms in the portfolio will be discussed in Section 3.6.4, which examines H2b concerning the within-analyst differences in forecasting accuracy for the major customers versus “other” firms in the analyst portfolio.

Panel D of Table 3.4 presents the Fama-MacBeth multivariate regression results for testing H1a. As discussed in the model specification section, to generate the Fama-MacBeth regression estimates, I ran a cross-sectional regression analysis for each of the 2,696 supply chain analyst-years. I then reported the average value of the coefficient estimates from the 2,696 cross-sectional regressions. The t-statistics reported in the table are based on the Newey-West (1987) adjusted standard errors of the series of the coefficient estimates.

Consistent with H1a, both columns (1) and (2) report a significantly negative coefficient on the indicator variable, *FOCAL_SUPPLY_CHAIN*, with a mean coefficient of -3.357 and -3.020, respectively. This suggests that for a given supply chain analyst, forecasts for the focal firms are on average around 3% more accurate than forecasts the same analyst issues for “other” firms in the portfolio. The mean coefficient on the indicator variable *PRIMARY_INDUSTRY* is negative and marginally significant. This result is consistent with earlier studies that analysts are on average more accurate for firms that are in an industry that the analysts have industry expertise than for those that the analysts do not have industry expertise. For the other control variables, the coefficients on analyst forecasting horizon (*HORIZON*) and forecast dispersion (*DISPERSION*) are both significant with the predicted signs. However, analysts’ prior forecasting experiences (*YEAR_EXP*) and the number of analysts following the firm (*NUMBER_ANALYST_FOLLOW*) are insignificant. Column (2) also shows a significant coefficient on the interactive term of analysts' supply chain coverage and analyst industry expertise (*FOCAL_SUPPLY_CHAIN * PRIMARY_INDUSTRY*), suggesting that analysts who have both industry expertise and supply chain knowledge for the focal firm are significantly more accurate than other firms in which the analyst does not have such dual expertise.

3.6.2 Tests of H1b: cross-analyst analyses of forecasting accuracy for the focal firms

H1b examines the cross-analyst differences in forecasting accuracy for a given focal firm. The hypothesis predicts that for a given focal firm, analysts who follow both a focal firm and at least one of the firm's major customers will issue more accurate earnings forecasts for the focal firm than will other non-supply chain analysts who follow the same focal firm but none of the focal firm's major customers.

To test H1b, I retrieved all forecasts issued for the 1,176 focal firm-years over the sample period. The sample included a total of 134,956 forecasts issued by all analysts following the same focal firms. 46.78% (63,136 of 134,956) of these forecasts were annual forecasts and the remaining 53.22% (71,820 of 134,956) were quarterly forecasts.

The descriptive statistics for the variables used in the multivariate regression analyses for H1b are presented in Panel A of Table 3.5. Panel A shows that of all the forecasts issued for the focal firms, 33% are by supply chain analysts. The remaining 67% are issued by other non-supply chain analysts. In addition, the majority (75%) of the forecasts for the focal firms are issued by analysts who have primary industry expertise in the focal firms.

[Insert Table 3.5]

The Pearson correlations for the variables used in the multivariate analyses are presented in Panel B of Table 3.5. As expected, the indicator variable *SUPPLY_CHAIN_ANALYST* is negatively and significantly correlated with *FORECAST_ERROR*. Forecasts are more accurate when an analyst has a less diversified portfolio in terms of the number of industries the analyst follows (*NUMBER_SIC1*), and when the analyst receives more resources from her employing brokerage firm (*LOG_BROKER_SIZE*). The correlations of the other variables are consistent with those presented earlier.

In addition, Panel B also shows positive correlation coefficients between *SUPPLY_CHAIN_ANALYST* and *YEAR_EXP*, *NO_SIC1*, and *LOG_BROKER_SIZE*. These correlation coefficients are consistent with the descriptive statistics reported in Table 3.3. They suggest that supply chain analysts may have more firm-specific experience, be employed by larger brokerage firms, and have more diversified industry coverage in their portfolios than non-supply chain analysts.

Panel C of Table 3.5 shows the univariate test results for analyst forecasting errors for the focal firms. Row (1) shows that the mean (median) forecasting error for the focal firms is -0.0017 (-0.0342). When the focal firm is in an analyst's primary industry, the mean (median) forecasting error is -0.0034 (-0.0313), which is statistically indifferent from the corresponding forecasting error of -0.0012 (-0.0348) when the focal firm is not in the analyst's primary industry.

The remainder of the table compares the forecasting errors for the focal firms of supply chain analysts versus those of other non-supply chain analysts who follow the same focal firms but not the firms' major customers. Row (2) shows that the mean (median) forecasting error for supply chain analysts is -0.0189 (-0.0484), which is statistically smaller at the $p<0.01$ level than the corresponding forecasting error of 0.0066 (-0.0264) shown in Row (3) for the other non-supply chain analysts. The outperformance in forecasting accuracy by supply chain analysts for the focal firms is significant whether or not the firm is in the analyst's primary industry.

Panel D of Table 3.5 presents the Fama-MacBeth multivariate regression results for testing H1b. Consistent with H1b, column (1) shows a negative and significant coefficient of -3.861 on the indicator variable *SUPPLY_CHAIN_ANALYST*. This suggests that for a given focal firm, supply chain analysts are on average 3.861% more accurate than non-supply chain analysts who only follow the same focal firm but none of the focal firm's major customers. When I added an interactive term of *SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY* in column (2), the coefficient on *SUPPLY_CHAIN_ANALYST* remains negative and marginally significant. In addition, the coefficient on the interaction term, *SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY*, is negative, but insignificant.

For the other control variables, Panel D shows a positive and significant coefficient on *HORIZON*, suggesting that forecasts with a longer horizon are less accurate as a result of more uncertainty in firms' earnings realization. The coefficients on *YEAR_EXP* and *LOG_BROKER_SIZE* are both negative and significant, consistent with earlier studies that suggest that analysts with more firm-specific forecasting experience and receive more resources from their employing brokerage firms are significantly more accurate. The coefficients on *NUMBER_SIC1* is positive and significant, consistent with earlier studies that analysts are less accurate when they are more diversified in their industry converge portfolio (Clement, 1999).

Overall, the results shown in Table 3.5 supports H1b, which suggests that for a given focal firm, analysts who follow both a focal firm and one or more of the firm's major customers issue significantly more accurate earnings forecasts than other non-supply chain analysts issue who follow only the same focal firm but none of the focal firm's major customers.

3.6.3 Tests of H2a: within-analyst analyses of forecasting accuracy for the major customer firms

H2a examines the within-analyst differences in forecasting accuracy between major customer firms and “other” firms in a given supply chain analyst’s portfolio. The hypothesis predicts that supply chain analysts will issue more accurate earnings forecasts for the major customers of the focal firms than they will for “other” firms in the analyst portfolio.

The sample included all the 404,794 forecasts issued for the major and “other” firms by each of the 2,696 supply chain analyst-years. 49.60% (200,795 of 404,794) of these forecasts are annual forecasts and the other 50.40% (203,999 of 404,794) are quarterly forecasts. In addition, 10.8% of these forecasts were issued for the major customer firms, with the remaining 89.2% being issued by the same analysts for “other” firms in the analyst portfolio.

Earlier in Table 3.4 Panel C, I showed that the mean (median) forecasting error for the major customer firms (Row 5) was -0.0061 (-0.0386), compared with the mean (median) forecasting error of 0.0033 (-0.0250) for “other” firms in the analyst portfolio. The differences are statistically significant for both the mean and median forecasting error at the conventional p-values.[49]

Table 3.6 provides the Fama-MacBeth multivariate regression results for testing H2b based on 2,696 cross-sectional regressions for each analyst-year. Consistent with H2b, both columns (1) and (2) report a negative and marginally significant coefficient on the indicator variable *CUSTOMER_SUPPLY_CHAIN*, with an estimated coefficient of -1.193 and -1.273, respectively. This indicates that for a given supply chain analyst, her earnings forecasts for the major customers of the focal firms are on average around 1.2% more accurate than her forecasts for “other” firms in the same portfolio. The interactive term of *SUPPLY_CHAIN_ANALYST* *

[49] The descriptive statistics and the correlation coefficients on the variables used in H2a testing are similar to those presented in Table 3.4 Panel B. Therefore, they are not tabulated.

PRIMARY_INDUSTRY in column (2) is insignificant. The effects of the control variables on analyst forecasting accuracy are generally consistent with those presented for H1a hypothesis testing.

[Insert Table 3.6]

3.6.4 Tests of H2b: cross-analyst analyses of forecasting accuracy for the major customer firms

H2b examines the cross-analyst differences in forecasting accuracy for a given major customer of a focal firm. It predicts that supply chain analysts will issue more accurate earnings forecasts for the major customer than will other analysts who follow the same major customer firm but none of the major customer firm's suppliers.

To test this hypothesis, I retrieved all the 182,330 forecasts issued for the 742 major customer firm-years. 87,546 (48.02%) of these forecasts are annual forecasts and the remaining 94,784 (51.98%) are quarterly forecasts. In addition, 24.1% of these forecasts were issued by supply chain analysts.

Panel A of Table 3.7 shows the univariate analyses of analyst forecasting accuracy for the major customers. Row (1) of Panel A shows that the mean (median) forecasting error for the major customer firms is -0.0006 (-0.0360). Row 1.1 shows that when the major customer is in an analyst's primary industry, the mean (median) forecasting error is -0.0017 (-0.0370). Row 1.2 shows that when the major customer is not in the analyst's primary industry, the mean (median) forecasting error is 0.0025 (-0.0330). The differences are statistically insignificant at the conventional p-values for either the mean or the median value of the forecasting error.

[Insert Table 3.7]

I also compared the forecasting errors for the major customers of supply chain analysts versus those of other analysts who follow the same major customers but none of the major customers' suppliers. In particular, Row (2) shows that the mean (median) forecasting error for the major customer firms of supply chain analysts is -0.0061 (-0.0386); in contrast, Row (3) shows the corresponding mean (median) forecasting error of the other analysts is 0.0010 (-0.0353). The difference is statistically significant for both the mean and the median value at the conventional p-values. Panel A of Table 3.7 also shows that the superior forecasting performance for the major customers by supply chain analysts holds whether or not the major customer is in the analyst's primary industry.

The descriptive statistics and the correlation coefficients of the variables used in the multivariate analyses are very similar to what were presented in Table 3.5, and are not presented. As expected, the indicator variable *SUPPLY_CHAIN_ANALYST* and *FORECAST_ERROR* are negatively and significantly correlated.

Panel B of Table 3.7 presents the Fama-MacBeth regression results for H2b testing. Consistent with H2a, column (1) of Panel B shows that the coefficient on *SUPPLY_CHAIN_ANALYST* is -1.180, which is significant at the p<0.10 level. When I introduced the interaction term of *SUPPLY_CHAIN_ANLAYST * PRIMARY_INDUSTRY*, the coefficient on *SUPPLY_CHAIN_ANALYST* remains negative and marginally significant. The sign and the statistical significance level of the other variables are generally consistent with those reported in Table 3.5 Panel D.

In sum, my results in general support H2b, which predicts that for a given major customer, supply chain analysts issue more accurate in their earnings forecasts than other non-supply chain analysts issue who follow only the same major customer but none of the major customer's suppliers.

3.6.5 Tests of H3: cross-analyst analyses of forecasting accuracy for "other" firms

The results for H1 and H2 suggest that supply chain analysts achieve superior forecasting accuracy for both the focal firms and the focal firms' major customers. This implies that these analysts must have spent a lot of their time gathering information for the firms in the supply chain. Assuming a fixed total amount of effort analysts would expend on the forecasting tasks and that the number of firms these analysts follow increases as a result of including additional firms in the firm's supply chain, it is expected that the average amount of time these analysts can spend on "other" firms in their portfolios is less. As a result, their forecasting accuracy for "other" firms will suffer. H3 hypothesizes that for a given "other" firm, supply chain analysts will issue significantly less accurate earnings forecasts than will other non-supply chain analysts following the same "other" firms.

To test H3, I pooled all 2,154,615 forecasts issued for the 15,066 "other" firm-years over the sample period, including 996,943 (46.27%) annual forecasts and 1,157,672 (53.73%) quarterly forecasts. Forecasts issued by supply chain analysts represented 16.7% of this sample.

Panel A of Table 3.8 shows the univariate analyses of the difference in forecasting accuracy for "other" firms of supply chain analysts versus of other non-supply chain analysts. Row (1) shows that the mean (median) forecasting error for "other" firms is -0.0088 (-0.0402). When these firms are in the analyst's primary industry, the mean (median) forecasting error is -0.0098 (-0.0419). When these firms are not in the analyst's primary industry, the corresponding mean (median) forecasting error is -0.0056 (-0.0347). The difference is statistically significant for both the mean and the median value at the conventional levels.

[Insert Table 3.8]

I then compared the forecasting errors for these firms of supply chain analysts versus those of the other non-supply chain analysts. Row (2) shows that the mean (median) forecasting error for "other" firms of supply chain analysts is 0.0033 (-0.0250), which is significantly larger than the corresponding error of -0.0113 (-0.0432) of the other analysts shown in Row (3) at the $p<0.01$ level. The inferior forecasting performance for these "other" firms by supply chain analysts holds whether or not these firms are in the analyst's primary industry.

Panel B of Table 3.8 presents the Fama-MacBeth multivariate regression analyses for testing H3. Consistent with H3, Panel B shows a positive and marginally significant coefficient of 1.419 and 1.428 on *SUPPLY_CHAIN_ANALYST* in columns (1) and (2) respectively. This result suggests that supply chain analysts issue significantly less accurate earnings forecasts for "other" firms than other non-supply chain analysts following the same "other" firms issue. Results for all the other control variables are generally consistent with those reported in the earlier sections.

3.6.6 Additional analyses on forecasting accuracy at the analyst portfolio level

The above analyses suggest that analysts benefit in their forecasting accuracy for both the focal firms and the firms' major customers by taking a supply chain portfolio approach. However, supply chain analysts issue significantly less accurate earnings forecasts for "other" firms in their portfolios than other non-supply chain analysts following the same "other" firms issue. This section examines whether analysts benefit in their forecasting accuracy at the portfolio level by taking a supply chain portfolio approach.

To examine the overall forecasting accuracy at the portfolio level for supply chain analysts, I stacked all forecasts used in the cross-analyst analyses for the focal firms, the major customers of the focal firms, and "other" firms. I ran the Fama-MacBeth regression analyses based on a cross-sectional regression for each firm-year. My main variable of interests is the indicator variable, *SUPPLY_CHAIN_ANALYST* that equals 1 if a forecast is issued by a supply chain analyst for a focal firm, a major customer firm, or an “other” firm in the analyst portfolio in the same year, and 0 if a forecast is issued by all other non-supply chain analysts.

Untabulated results suggest the coefficient on *SUPPLY_CHAIN_ANALYST* is positive and significant, suggesting that supply chain analysts are significantly less accurate at the portfolio level than other non-supply chain analysts. This result is consistent with earlier descriptive statistics shown in Table 3.3 that supply chain analysts follow significantly more firms from a more diversified industry at the one-digit SIC level than other non-supply chain analysts follow. This implies that when the amount of attention supply chain analysts can allocate to each firm in their portfolios is significantly less than the corresponding amount of attention devoted by other non-supply chain analysts, supply chain analysts will issue significantly less accurate earnings forecasts for all firms in the portfolio than will non-supply chain analysts.

However, despite an average lower level of attention to each firm in the portfolio, the findings that supply chain analysts are significantly more accurate for both the focal firms and the firms’ major customers than other non-supply chain analysts following the same firms implies the relative importance of the focal firms and the major customer firms in supply chain analysts’ portfolios.

3.6.7 Tests of H4: analysts’ choice of the focal firms and the major customer firms

H4 examines the economic factors that affect analysts’ choice of the focal firms and the major customer firms in the portfolio. The hypothesis predicts that when a firm has higher potential to bring more profitable trading commissions to an analyst’s brokerage firm, the analyst is more likely to expend effort on acquiring more precise information for the firm by covering the other parties in the firm's supply chain. The improvement of the information quality about the firm helps the analyst improve her forecasting accuracy for the firm.

To test this hypothesis, I started with 50,059 analyst-firm-year observations, which represent all firm-years followed by supply chain analysts over the sample period. The requirement for the financial and trading data from *COMPUSTAT* and *CRSP* reduced the number of observations to 31,616 analyst-firm-years.

Panel A of Table 3.9 provides descriptive statistics on the variables used in the regression model for H4 testing. I used *INVESTMENT_BANKING* and *LOG_TRADINGVALUE* to measure the potential revenue a firm may bring to an analyst's brokerage firm. Column (1) shows that the frequency that the analyst's brokerage firm is the underwriter for equity issuance for the focal firms and the major customers is 0.0032, which is statistically higher than the corresponding frequency of 0.0013 for "other" firms in the analyst portfolio ($t=3.56$, $p=0.004$). *LOG_TRADINGVALUE*, a proxy for the potential trading commission fees that the focal firms and the major customer firms are likely to generate is 17.225, which is significantly greater ($t = 14.52$, $p<0.01$) than the corresponding value of 16.824 for "other" firms in the analyst portfolio.

[Insert Table 3.9]

Panel A also shows that the log value of the number of firms in the industry of the focal firms and the major customer firms (*LOG_NUMBER_FIRM_SIC1)* is 6.876, which is significantly larger at the $p<0.01$ than the corresponding value of 6.715 for "other" firms in the analyst portfolio. The percentage of the focal firms and the major customer firms that are both in the analyst's primary industry is 73.0%, which is significantly lower at the p-value<0.01 level than 75.6% for "other" firms in the portfolio. Surprisingly, focal firms and the major customer firms experience a lower growth rate (*SALE_GROWTH*), have a smaller market-to-book ratio (*MARKET_TO_BOOK*), are less profitable (*ROA*), and have lower levels of intangible assets (*RD_RATIO* and *AD_RATIO*) than “other” firms in the analyst portfolio.

Panel B of Table 3.9 shows the Pearson correlation for the variables used in the regression analyses. *SUPPLY_CHAIN_FIRMS* is an indicator variable that equals 1 if a firm is a focal firm, or a major customer firm, 0 for “other” firms in the analyst portfolio. As expected, *SUPPLY_CHAIN_FIRMS* is positively significantly correlated with *LOG_TRADINGVALUE* and *LOG_NUMBER_FIRM_SIC1*. *SUPPLY_CHAIN_FIRMS* is insignificantly correlated with *INVESTMENT_BANKING*.

Panel C of Table 3.9 present the conditional logit multivariate regression results and the marginal effects of one unit change of each independent variable in the full model in column (3) on the probability that a firm is chosen to be a focal firm or a major customer firm.

Column (1) shows that the coefficient on analysts’ economic incentives to generate investment banking business (*INVESTMENT_BANKING*) is positive, but insignificant. Column (2) shows that the coefficient on *LOG_TRADINGVALUE* is positive and significant. Column (3) included both of the analysts’ incentive measures, *INVESTMENT_BANKING* and *LOG_TRADINGVALUE*, as well as other firm characteristics as additional explanatory variables of analysts’ choice of the focal firms and major customer firms. Column (3) shows that the coefficient on *INVESTMENT_BANKING* remains insignificant, and the coefficient on *LOG_TRADINGVALUE* remains positive and significant. The analysis on the marginal effect suggests that a one percent increase of the total trading volume for the stock of a firm increases the probability that the firm is chosen to be a focal firm or a major customer firm by approximately 0.01%, holding all other variables at the mean value.

Column (3) also shows that the coefficient on the total number of other firms in the firm's industry (*LOG_ NUMBER_FIRM_SIC1*) is still positively significant. The insignificant coefficient on *INVESTMENT_BANKING* is consistent with Hayes (1998) and Lin and McNichols (1998) that when a firm is more likely to bring in underwriting business to the analysts' brokerage firms, the analysts may sacrifice their forecasting accuracy for the firm and issue optimistically biased earnings forecasts to build their relations with firm management. Therefore, these analysts are less likely to expend the effort to get more precise firm-specific information by covering the other parties in the firm's supply chain.

The negative and significant coefficient on *PRIMARY_INDUSTRY* is surprising at first, however, the sign of this coefficient is consistent with earlier evidence that supply chain portfolio diversifies the analyst's industry coverage. Surprisingly, firms that are over-valued (*MARKET_TO_BOOK*), more profitable (*ROA*), experiencing a higher growth (*SALE_GROWTH*), and having higher levels of intangible assets (*AD_RATIO* and *RD_RATIO*) are less likely to be chosen as the focal firms or the major customer firms. These characteristics, however, are consistent with the industry clustering of the focal firms and the major customers in the manufacturing industry as shown in Table 3.2. It is possible that these firms tend to be more established firms, with lower growth opportunities, lower profitability, and invest less heavily in intangible assets.

Overall, analysts' incentive to generate trading commission for their brokerage firms is one of the key drivers of the analysts' choice of the focal firms and the major customer firms. This is consistent with earlier studies that suggest that analysts have higher incentives to acquire more precise firm-specific information when the potential trading commissions generated from the firm is high (Hayes, 1998). By covering the other parties in the firm's supply chain, analysts are able to generate more precise information about the firm; as a result, their forecasts for the firm are more accurate than in the absence of such supply chain information.

3.6.8 Additional analyses on market reaction to supply chain analysts' forecasts releases

The above evidence suggests that an analyst's supply chain portfolio design helps explain variations of her forecasting accuracy for the firms in her portfolio. Such a portfolio design is driven by the analyst's economic incentive to generate trading commissions for her brokerage firm. My next question examined the extent to which supply chain analysts build their forecasting reputation on the firms in supply chain relations in their portfolios. Specifically, I examined the extent to which investors incorporate the implication of analysts' supply chain portfolio approach on their forecasting accuracy for different firms within the same portfolio. I expect that if investors were to use all information concerning analyst forecast accuracy when reacting to a forecast release, investors would incorporate the effect of analyst's portfolio choice in their response to the forecast release based on the expected analyst forecast accuracy for the firm.

I used a valuation model similar to Bonner et al. (2003) and investigated the return response to all forecasts issued by supply chain analysts, controlling for the magnitude of the forecast revision relative to prior analysts' consensus forecasts. I expect if the market reacts to a forecast release issued by a supply chain analyst as if the analyst's supply chain portfolio approach matters on the expected forecasting accuracy for the firms in the analyst portfolio, then stock return upon the forecast release would be greater for the focal firm and the focal firm's major customers because of greater expected forecasting accuracy for these firms than for "other" firms.

Untabulated results suggest that, after controlling for the sign and the magnitude of forecast revisions relative to prior analysts' consensus forecasts, investors' reaction in the short window (-1, +1) surrounding a forecast release by supply chain analysts is not significantly different between focal firms, major customers of the focal firms, and "other" firms in the analyst portfolio. In other words, the finding seems to indicate that investors' reaction to the forecasts issued by supply chain analysts is not fixated on the expected analyst forecasting accuracy for different firms in the same portfolio.

3.6.9 Robustness tests

This section reports a variety of untabulated robustness tests of the empirical results. First, as discussed earlier, the sample contains multiple observations for each analyst or each firm. In this chapter, when I test the hypotheses, my main analyses used the Fama-MacBeth regression approach to estimate a cross-sectional regression for each analyst-year or firm-year separately. An alternative approach is to use all observations in a grand regression estimation, but use the generalized method-of-moments (*GMM*) estimator developed by Keane and Runkle (1998) to adjust the standard errors for both aggregate individual-specific or firm-specific effects (e.g., Bonner et al., 2003). Untabulated results suggest the statistical power for the outperformance in forecasting accuracy for the focal firms and the focal firms' major customers for analysts taking a supply chain portfolio approach is much stronger in both within-analyst and cross-analyst analyses than the results reported using the Fama and MacBeth's approach.

Second, I used two alternative measures of forecasting accuracy and repeated the regression analyses for H1 to H3. One measure follows Hong et al. (2000) and Hong and Kubik (2003). It is an adjusted ranked score of the absolute forecast error using all forecasts issued for a firm in the same fiscal year based on the following formula:

$$PCT\_ERROR\_RANK_{i,j,t} = (\frac{RANK\_ERROR_{i,j,t} - 1}{NUMBER\_FORECAST_{j,t} - 1} * 100),$$

where *RANK_ERROR* is the rank of the absolute value of the forecast error for each forecast. *RANK_ERROR* receives the lowest rank value of 1 if the absolute forecast error is the smallest among all forecasts issued for a firm in the same fiscal year. *NUMBER_FORECAST* is the total number of forecasts issued for the firm over the fiscal year. The value of *PCT_ERROR_RANK* ranges from zero to 100, with the most accurate forecast receiving a value of zero, and the least accurate forecast receiving the highest value of 100.

The other measure of forecasting error is the absolute forecast error scaled by assets per share at the beginning of the fiscal year (Cheong and Thomas, 2010). Untabulated results show that when I used both of these two alternative forecasting accuracy measures, the results for H1-H3 hypotheses testing remain unchanged.

Third, I used a continuous variable to measure analysts' supply chain coverage. In particular, I replaced the indicator variable that represents whether or not an analyst follows both a focal firm and one or more of the firm's major customers with the total number of major customers of a focal firm the analyst follows in the regression analyses for the forecasting accuracy for the focal firms. Similarly, I also replaced the indicator variable with the total number of suppliers of a major customer that the analyst follows in the regression analyses for the forecasting accuracy for the major customer firms. The results are robust to these alternative measures.

Fourth, following Ke and Yu (2006), I ruled out an alternative explanation that the superior forecasting accuracy for the focal firms for supply chain analysts was driven by analysts' being strategic in their forecasts to gain more favorable access to management. I included three additional indicator variables in equation (1) to represent analysts' being strategic in their forecasts.[50] Untabulated results show that even after controlling for analysts' potentially biased pattern in their forecasts, my main results still hold. The three indicator variables for analyst forecast bias pattern are all positive and significant, which is consistent with Ke and Yu's (2006) finding that when analysts follow initial optimism and later pessimism, they can gain better access to management so that their future forecasts are more accurate.

Fifth, as the majority (75%) of the focal firms and major customer firms in the sample that supply chain analysts followed are from the same industry at the one digit SIC level, it is possible that these analysts may gain additional benefit in their forecasting accuracy for both the focal firms and the firms' major customers by having both supply chain expertise and industry expertise for these firms. To test whether supply chain analysts are more accurate for the focal firms and the major customer firms when these firms are in the same industry, I added an indicator variable *SAME_SIC1* that equals 1 if at least one of major customer is in the same industry at the one-digit SIC level as the major customer's focal firm, 0 otherwise. I also added an interaction term between the indicator variable *FOCAL_SUPPLY_CHAIN* and *SAME_SIC1* (*FOCAL_SUPPLY_CHAIN * SAME_SIC1*) in the cross-analyst analyses of forecasting accuracy for the focal firms using the Fama-MacBeth approach. I followed the same approach when analyzing whether supply chain analysts are more accurate for the major customers firms if the major customers firms and at least one of the major customer's focal firms are in the same industry. Specifically, I defined *SAME_SIC1* as 1 if at least one of the major customer's focal firms is in the same industry at the one-digit SIC level as major customer firm, 0 otherwise. I also added the interaction term between the two indicator variables, *SAME_SIC1* and

[50] I followed Ke and Yu (2006) and classified an analyst's forecasting bias into four categories. I coded *OO* as 1 if the analyst's first and last forecast issued for the fiscal period were both optimistic (i.e., the forecasted earning was greater than the realized earning), and 0 otherwise. *OP* equaled 1 if the analyst's earnings forecast changed from initial optimism to later pessimism within the fiscal year and 0 otherwise. *PO* represented analysts' bias pattern in their earnings forecasts by switching from initial pessimism to later optimism. Finally, *PP* denoted the analysts whose first and last earnings forecasts were always pessimistic.

CUSTOMER_SUPPLY_CHAIN (*CUSTOMER_SUPPLY_CHAIN* * *SAME_SIC1*), to analyze the forecasting accuracy for the major customer firms. The results suggest that the signs of these terms are negative, but the coefficients are not significant.

Sixth, I partitioned the sample into pre- and post-Regulation Fair Disclosure (FD) and repeated the regression analyses on analyst forecasting accuracy for H1 to H3. Untabulated results suggest that while the results hold in both periods, the magnitude of the outperformance in forecasting accuracy for supply chain analysts for both the focal firms and the firms' major customers is greater in the post-Regulation FD period than in the pre-Regulation FD period, confirming that covering both a focal firm and the focal firm's major customers gives analysts insights in producing more accurate earning s forecasts for both the focal firm and the firm's major customer firms, and such information advantage is more salient after fair disclosure regulation was imposed.

Seventh, I also performed the tests by separating analyst forecasts based on the forecast horizon, and re-examined whether the results would be different between quarterly and annual forecasts. I find consistent evidence in both annual and quarterly forecasts.

Lastly, I built a two-stage Heckman model to address the selection bias of analysts' choice of the focal firms or their major customers (Heckman, 1979). Specifically, in the first step, I first computed an inverse Mills ratio from a probit regression model based on Equation (3) and estimated the probability that a firm was chosen to be a focal firm or the firm's major customer firm. I then included the computed inverse Mills ratio as an additional explanatory variable to re-estimate equation (1). My main results remain unchanged.

3.7 Conclusion

This chapter examines the relationship between analysts' supply chain coverage portfolio and their forecasting accuracy. Specifically, I focus on the impact of analyst decisions to include one or more of the major customers of a focal firm in their portfolios on analyst forecasting accuracy. I find that an analyst who follows both a focal firm and one or more of the focal firm's major customers issues significantly more accurate earnings forecasts for the focal firm and for the firm's major customer than (1) the same analyst issues for "other" firms in the analyst portfolio, and (2) other analysts issue who only follow the same firm but not the other parties in the firm's supply chain. These results are robust after controlling for known determinants that affect analyst forecasting accuracy and after correcting for potential self-selection bias using the inverse Mills ratio approach. I also find that supply chain analysts issue significantly less accurate earnings forecasts for "other" firms in their portfolios than all other non-supply chain analysts following the same "other" firms issue. When I examine the overall forecasting accuracy for supply chain analysts at the portfolio level, I find that supply chain analysts are on average less accurate than other non-supply chain analysts. This result is consistent with the finding that supply chain analysts cover significant more firms in a more diversified industry than all other analysts cover. It is possible analysts expend more effort to cover additional firms from a more diversified industry in order to maintain their supply chain coverage portfolio. This finding echoes the conclusion drawn from H1 to H3 concerning the relative importance of the focal firms and the major customers in supply chain analysts' portfolios.

To examine the economic factors that influence an analyst's choice of the focal firms and the major customer firms, I find that the focal firms and the firms' major customers are more likely to generate a high level of trading commission fees for the analyst's brokerage firm, are larger, and operate in industries with a greater number of peer firms, than "other" firms in the analyst portfolio. Overall, the evidence in this chapter suggests that analysts organize their coverage portfolios to achieve both their personal objective to be accurate in their earnings forecasts and their objective to generate revenue for their brokerage firms.

Some caveats are in place. First, in this chapter, I did not disentangle the effect of analyst skills on analyst forecasting accuracy. It is possible that analysts who are more skilled and have more experience self select to be a supply chain analyst, as well as self determine the number of firms and industries they follow. Indeed, the Fama and MacBeth's approach was used in this chapter to mitigate the concern on the effect of individual analyst differences on analyst forecasting accuracy. Nevertheless, the potential effect of self-selection (skills, ability, and individual knowledge etc.) warrants further investigation.

Second, in examining analyst forecasting accuracy for the major customers, I assume that purchase from suppliers can be important costs for the major customers and analysts benefit in their earnings forecasts for the suppliers' major customers by also preparing issuing forecasts for the suppliers. However, as I have discussed in section 4.1, SFAS No. 14 (FASB 1975) requires firms to disclose the names of their major customer firms, but not their suppliers. As a result, I determined major customer firms' suppliers by inverting the reporting firm–major customer relations based on the information provided in the Compustat customer segment file. In other words, the suppliers of the major customers are not identified from a universe of the suppliers of the major customers, and the identified suppliers may not be the major suppliers for the major customer firms. This implies that the influence of the identified supplier firms on the costs incurred by the major customers may not be significant, and the insights analysts gain from issuing forecasts for the supplier firms may not be significant in their earnings forecasting task for the suppliers' major customers. This limitation would work against finding empirical support for H2.

Third, in examining analysts' choice of the focal firms and the major customer firms, I assume that investors' more active trading on the stock of the firm can be attributed to analysts' producing more informative and more precise earnings information for the firm. I also assume that more active investors' trading will generate more trading commission fees for the analyst's brokerage firms. While prior studies provided empirical evidence that analysts who produce more precise and accurate earnings forecasts also produce more profitable stock recommendations (e.g., Ertimur et al., 2007), the direct empirical evidence is lacking concerning whether supply chain analysts also generate more trading commissions from their more accurate earnings forecasts for the focal firms and the major customer firms. These and others are left for future research.

Chapter 4: Conclusion

This dissertation includes two essays that examine earnings forecasting accuracy. These two essays, presented in Chapter 2 and Chapter 3, focus on the effects of individual forecasters' behavioral biases and their economic rationality on their forecasting accuracy.

In particular, Chapter 2 examines the effect of managers' behavioral biases on their forecasting accuracy over time. I examine how managers' overconfidence and attribution biases affect the way they process feedback information concerning their prior forecasts. I find that overconfident managers improve their forecasting accuracy over time in response to feedback concerning their prior forecasts, but they do so more slowly than their less confident peers. I also find that overconfident managers only respond to less ambiguous feedback in the form of forecasting errors, but they do not respond to more ambiguous market feedback. Their less confident counterparts, on the other hand, respond both to less ambiguous error feedback and also to more ambiguous market feedback. Overall, the evidence from Chapter 2 is consistent with the combined effect of managers' overconfidence and attribution biases inhibiting the improvement of management forecasting accuracy over time.

Chapter 3 examines analysts' portfolio organization design and the effect of such portfolio design on analyst forecasting accuracy. In Chapter 3, I propose that some analysts organize their coverage portfolios through a firm's supply chain relations by including both a focal firm and one or more of the focal firm's major customer firms in the portfolio. I argue that when analysts issue forecasts for both a focal firm and the focal firm's major customers, the insights they have about both parties in the firm's supply chain provide the analysts with the information advantages to produce more accurate earnings forecasts for both the focal firm and the focal firm's major customers.

My empirical evidence supports my expectations. In particular, I find that an analyst who follows both a focal firm and one more of the focal firm's major customers issues significantly more accurate earnings forecasts for the focal firm and the firm's major customers than the same analyst issues for "other" firms in the analyst portfolio. In addition, this analyst also issue significantly more accurate earnings forecasts for the focal firms and the focal firms' major customers than other non-supply chain analysts issue who only follow the same firms but not the other parties in the firms' supply chains. At the same time, I also find that the supply chain analyst issues significantly less accurate earnings forecasts for "other" firms in the analyst portfolio than other non-supply chain analysts following the same "other" firms. This evidence suggests the relative importance of the focal firms and the major customer firms in the supply chain analyst's portfolio. It is possible that the supply chain analyst may have sacrificed her forecasting accuracy for "other" firms in the portfolio to achieve her superior forecasting accuracy for the focal firms and the major customer firms.

I next provide a rational explanation for an analyst's choice of the focal firms and the firms' major customers in the portfolio. I find that an analyst is more likely to choose a firm as the focal firm and follow one or more of the focal firm's major customers, or as a major customer and follow one or more of the major customer's suppliers, when the potential to generate trading commissions from the stock of the firm is higher, and when the firm operates in an industry segment that has a larger number of other peer firms. This result suggests that supply chain analysts rationally make their portfolio design choices to achieve their economic objective to bring revenue to their brokerage firms.

Taken together, Chapters 2 and 3 provide empirical support for the perspective that earnings forecasting accuracy is affected by both individuals' behavioral biases as well as their economic rationality. Such effects are reflected in both cross-sectional and time-series analyses of earnings forecasting accuracy.

As Chapter 3 is the first study that connects the concept of analysts' supply chain portfolio approach with cross-sectional variations of analyst earnings forecasting accuracy, a number of interesting yet unanswered questions in this area remain for future research. For example, recent studies have suggested that analysts issuing more accurate earnings forecasts also issue more profitable stock recommendations (e.g., Loh and Mian, 2006). Considering the evidence shown in Chapter 3 that supply chain analysts issue more accurate earnings forecasts for the focal firms and the focal firms' major customers than other non-supply chain analysts following the same firms issue, it would be interesting to examine whether supply chain analysts will generate more profitable stock recommendations for the firms in supply chain relations than they will generate for "other" firms in the analyst portfolio. Another issue concerns analyst reputations. Do analysts build their reputation for issuing profitable stock recommendation for a selective number of firms in their portfolios or for the overall profitability of the recommendations for all the firms in the analyst portfolio? Moreover, given some analysts choose to be specialized in a firm's supply chain relations, while other analysts choose to be specialized in a particular industry, do we observe analysts switching from one specialization to another specialization? If so, why do some analysts switch their portfolio designs and what is the effect of such switching on analyst forecasting performance? Broader questions such as factors that drive analyst portfolio design decisions and the extent to which analyst expertise in one specialization (e.g., industry specialization, country specialization, or supply chain specialization) is portable to another specialization are also intriguing. These and other issues are left to future research.

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Appendix 2.1: Definition of variables

VARIABLE NAME	*DEFINITIONS*
OVERCONFIDENCE MEASURES	
OC_MF_t	An indicator variable for overconfident managers. It equals 1 if the first forecast places the CEO in the top 50% of all optimistic forecasts issued in the same quarter, and 0 otherwise.
UC_MF_t	An indicator variable for less confident managers. It equals 1 if the first forecast places the CEO in the top 25% of all pessimistic forecasts issued in the same quarter, and 0 otherwise.
OC_MEDIA1_t	An indicator variable for overconfident managers. It equals 1 if prior to issuing his first forecast for the firm in his tenure, the CEO is more often described by major presses such as The New York Times, Business Week, Financial Times, and The Economist in “confident” terms than in “less confident” terms. CEOs without press mentions are assigned a value of 0.
OC_MEDIA2_t	The continuous measure for OC_MEDIA1_t, measured as the difference between the number of times a CEO is described by major presses such as The New York Times, Business Week, Financial Times, and The Economist in “confident” terms and in “less confident” terms. CEOs without press mentions are assigned a value of 0.
OC_PUR_t	An indicator variable for CEO overconfidence. It equals 1 if a CEO whose cumulative net purchase of the stock of his own firm is positive before he issued his first forecast for the form in his tenure, 0 otherwise. CEOs without any insider trading data are assigned a value of 0.
FEEDBACK VARIABLES	
MKT_FB_{t-1}	The difference of the expected buy-and-hold stock return during the three day (-1,1) window following the prior management forecast between a model assuming that managers are different in the degrees of confidence, and another model assuming that all managers are homogenously confident. Details are described in the chapter.
$ERROR\_FB_{t-1}$	Feedback via prior management forecasting error, calculated as the absolute difference between the forecasted earnings and the actual earnings, deflated by the stock price at the beginning of the quarter.
$CAR_{-1,1}$	Market buy-and-hold stock return during the three day window (-1, 1) following a management forecast release.
$MF\_FREQUENCY_t$	Forecasting frequency, defined as the total number of quarterly forecasts managers issued for the fiscal quarter t.
$DIS\_CONTINUE_t$	An indicator variable equals 1 if the manager continues providing subsequent forecasts, 0 if the manager no longer provides any subsequent quarterly management forecast.
FORECASTS CHARACTERISTICS VARIABLES	
$OPTIMISTIC_t$	An indicator variable equals 1 if the forecasted earnings for the quarter is greater than actual earnings for the quarter, 0 otherwise.
$ERROR_t$	Management forecast error, calculated as the unsigned difference between forecasted earnings and the actual earning, scaled by the stock price at the beginning of the quarter.
$BIAS_t$	Management forecast bias, calculated as the signed difference between forecasted earnings and the actual earning, scaled by the stock price at the beginning of the quarter.
$PREDICT\_LOSS_t$	An indicator variable equals 1 if the forecasted earnings for quarter t are less than zero; and 0 otherwise.

NEWS$_t$	News conveyed in management forecasts, calculated as the difference between forecasted earnings and the preceding analyst consensus forecasts, scaled by the stock price at the beginning of the quarter.
GOOD_NEWS$_t$	Equal to the news conveyed in the forecast if the forecasted earnings is greater than the preceding analyst consensus forecasts, scaled by stock price at the beginning of the quarter, 0 otherwise.
BAD_NEWS$_t$	Equal to the news conveyed in the forecast if the forecasted earnings is smaller than the preceding analyst consensus forecasts, scaled by stock price at the beginning of the quarter, 0 otherwise.
HORIZON$_t$	Forecasting horizon is equal to the number of lag days between the forecast release date and the earnings announcement date.
EXP$_t$	The number of forecasts a manager issued prior to the current forecast.
FIRM CHARACTERISTICS VARIABLE	
DIV $_{t-1}$	An indicator equals 1 if declared dividends, and 0 otherwise.
LONG_TERM_DEBT $_{t-1}$	Portion of long-term debt out of total debt.
RD_RATIO $_{t-1}$	Research and development expense over the total sales.
REPURCHASE $_{t-1}$	An indicator equals 1 if purchase of common and preferred stock is greater than 1% of equity, 0 otherwise.
ROA $_{t-1}$	Return on assets, measured as earnings before extraordinary items divided by average total assets at quarter t-1.
CH_ROA$_t$	Change of return on assets, calculated as return on assets at quarter t minus return on assets at quarter t-1.
BM $_{t-1}$	Book to market ratio, measured as the book value of equity, divided by the market value of equity.
CH_BM$_t$	Change of the book to market ratio, calculated as the book to market ratio at quarter t minus market to book ratio at quarter t-1.
HH_INDEX $_{t-1}$	The Herfindahl index, calculated as the sum of the squares of the market shares of the firms' sales in the two-digit SIC industry.
CH_HHINDEX$_t$	Change in the Herfindahl index, calculated as the index at quarter t minus the index at quarter. t-1.
LOG_ASSETS $_{t-1}$	Log of one plus total assets.
CH_LOG ASSETS$_t$	Change of log assets, calculated as the log of total sale at quarter t minus log of total assets at quarter t-1.
SALES_GROWTH $_{t-1}$	Sales growth, calculated as total sales at time quarter t minus the total sales at quarter t-1, scaled by total sales at quarter t-1.
CH_SALEGROWTH$_t$	Change of sale growth, calculated as the sale growth at quarter t minus sale growth at quarter t-1.
ALTMAN $_{t-1}$	The Altman Z score (1968), computed as [1.2*working capital /total assets – 1.4*retained earnings/total assets + 3.3 * operating income/total assets + 0.6*market value of equity/total liability + sales/total assets] at the beginning of quarter t.
CH_ALTMAN$_t$	Change of the Altman score, calculated as the Altman Z at quarter t minus the Altman Z score at quarter t-1.

$\|WACC_{t-1}\|$	Working capital accruals, measured as the absolute value of [increase in account receivable + increase in inventory + decrease in account payable + decrease in income tax payable + net change in other accrued liabilities / lag total assets] at the beginning of quarter t.
$LITIGATION_{t-1}$	An indicator variable set to 1 for litigious industries, including Biotechnology (SIC 2833 - 2836), Computer Hardware (SIC 3570 - 3577), Electronics (SIC 3600 - 3674), Retailing (SIC 5200 - 5961), and Computer Software (SIC 7371 to 7379), and 0 otherwise.
$N\_ANALYST_{t-1}$	Number of individual analysts issuing forecasts for the firm in quarter t-1.
STD_EPS_{t-1}	Standard deviation of earnings per share over the past 16 quarters ending one quarter before the end of quarter t, scaled by the assets per share at the beginning of quarter t.
$BETA_{t-1}$	Firm risk, measured by the Dimson (1979) beta estimates. It is obtained by summing the slope coefficients on the two lagged and contemporaneous returns based on the CAPM model.
$INCENTIVE\_RATIO_{t-1}$	Following Bergstresser and Philippon (2006), incentive ratio measures pay-for-performance sensitivity for CEOs for the period when they issue forecasts. I calculate *ONEPCT* as the total change in value of the CEO's stock and stock option portfolio in response to a 1% change in the stock price using the method described by Core and Guay (2002), and then calculate pay-for-performance sensitivity as ONEPCT/(ONEPCT+ Salary + Bonus).
PUR_PCT_{t-1}	The cumulative percentage of stock purchased by the CEO in the year prior to issuing the forecasts relative to the market value at the beginning of the quarter.

Appendix 2.2:

Panel A: Descriptive statistics for overconfident CEOs using alternative CEO overconfidence measures

Variables	Overconfident CEO (N=283)	Less confident CEOs (N=285)	t-test statistics *(one-tailed P-value)*
	Mean	Mean	
OC_PUR	0.063	0.025	2.22** *(0.015)*
OC_MEDIA1	0.111	0.067	1.81** *(0.035)*
OC_MEDIA2	0.217	0.089	1.76** *(0.039)*

This table presents descriptive statistics for the proportion of overconfident and less confident CEOs using the alternative CEO overconfidence measures. All other variables are defined in Appendix 2.1. The t-test of mean of the variable uses the pooled method when the underlying variances are equal and the satterthwaite method when they are unequal. Absolute values of the t-test statistics are reported. One-tailed p-values are reported in parentheses.

* Significant at 10%; ** significant at 5%; *** significant at 1%

Panel B: Descriptive statistics on firm policies for overconfident CEOs

Variables	Overconfident CEOs	Less confident CEOs	t-test statistics *(two-tailed P-value)*
	Mean	Mean	
ROA	0.021	0.031	-2.12** *(0.03)*
DIV	0.404	0.430	-1.95* *(0.054)*
LONG_TERM_DEBT	0.777	0.744	4.02*** *(0.001)*
RD_RATIO	0.014	0.012	2.67*** *(0.008)*
REPURCHASE	0.3370	0.313	1.86* *(0.062)*

This table presents descriptive statistics on different dimensions of corporate policies between firms with overconfident CEOs and firms with less confident CEOs. All other variables are defined in Appendix 2.1. The t-test of mean of the variable uses the pooled method when the underlying variances are equal and the satterthwaite method when they are unequal. Absolute values of the t-test statistics are reported. Two-tailed p-values are reported in parentheses.

* Significant at 10%; ** significant at 5%; *** significant at 1%

Panel C: Logit regression - Are overconfident CEOs more likely to issue optimistic subsequent forecasts?

Independent Variables	Dependent variable: OPTIMISTIC$_t$ (1,0)	
	(1)	(2)
INTERCEPT	-0.754***	-0.956***
	(-25.98)	*(-3.21)*
OC_MF	0.225***	0.144*
	(2.99)	*(1.70)*
NEWS$_t$	0.146	3.515**
	(0.30)	*(2.28)*
BIAS$_{t-1}$		16.703
		(1.15)
EXP$_t$		-0.007
		(-1.02)
CEO_AGE$_t$		0.006*
		(1.89)
LOG_HORIZON$_t$		-0.014
		(-0.30)
SALE_GROWTH$_{t-1}$		-0.379**
		(-2.33)
BM$_{t-1}$		0.532***
		(5.21)
HHINDEX $_{t-1}$		0.000
		(0.11)
LOG_ASSETS$_{t-1}$		-0.052**
		(-2.20)
ALTMAN$_{t-1}$		0.040
		(0.58)
$\lvert$WACC$_{t-1}\rvert$		-1.616*
		(-1.92)
Observations	6357	5681
Psudo R-squared	0.011	0.0236

This table reports regression results on the probability that overconfident CEOs issue optimistically biased subsequent forecasts. Variable definitions are presented in Appendix 2.1. The sample starts with a total number of 8,052 quarterly management forecasts issued from January 1, 1994 to December 31, 2008 by 1,695 CEOs. A total of 6,357 forecasts are retained after excluding 1,695 observations that are the first forecast managers issued for their firms. The standard errors are clustered by firm to reduce heteroscedasticity.

t statistics in parentheses
* Significant at 10%; ** significant at 5%; *** significant at 1%

Panel D: Does the market recognize the forecasting biases by overconfident CEOs?
(Model Specifications for Market Feedback Measurement)

Independent Variables	Dependent variable: $CAR_{-1,+1}$			
	coefficients	*t-statistics*	coefficients	*t-statistics*
	Model (1)		Model (2)	
CONSTATNT	-0.006	*(-0.22)*	-0.004	*(-0.15)*
OC_MF			-0.014*	*(-1.76)*
OC_MF * $GOOD\_NEWS_{i,t}$			-0.334**	*(-2.17)*
OC_MF * $BAD\_NEWS_{i,t}$			0.103	*(0.19)*
UC_MF			-0.003	*(-0.38)*
UC_MF *$GOOD\_NEWS_{i,t}$			-1.620**	*(-2.47)*
UC_MF * BAD_NEWS_{t}			-0.880*	*(1.64)*
$GOOD\_NEWS_{i,t}$	3.608***	*(9.49)*	4.687***	*(8.61)*
$BAD\_NEWS_{i,t}$	5.678***	*(17.91)*	5.807***	*(14.51)*
$ERROR_{i,t}$	-0.317***	*(-2.82)*	-0.312***	*(-2.74)*
$MF\_FREQUENCY_{i,t}$	0.002	*(1.52)*	0.002	*(1.52)*
$NEWS_{i,t}$ * $PREDICT\_LOSS_{i,t}$	-4.983***	*(-14.31)*	-4.378***	*(-10.36)*
$NEWS_{i,t}$ * $LOG\_HORIZON_{i,t}$	-0.016***	*(-2.71)*	-0.016**	*(-2.48)*
$NEWS_{i,t}$* $ROA_{i,t-1}$	-0.410	*(-0.24)*	0.541	*(0.31)*
$NEWS_{i,t}$* SALE_GROWTH	-0.416	*(-0.53)*	-0.725	*(-0.78)*
$NEWS_{i,t}$ * $BM_{i,t-1}$	0.073	*(0.83)*	-0.168	*(-1.09)*
$NEWS_{i,t}$ * $HH\_INDEX_{i,t-1}$	0.093***	*(3.47)*	0.085***	*(3.12)*
$NEWS_{i,t}$* $LOG\_ASSETS_{i,t-1}$	-0.116	*(-1.06)*	0.083	*(0.62)*
$NEWS_{i,t}$* $ALTMAN_{i,t-1}$	0.105***	*(3.15)*	0.120***	*(3.55)*
$NEWS_{i,t}$* $BETA_{i,t-1}$	-0.073	*(-0.79)*	-0.036	*(-0.32)*
$PREDICT\_LOSS_{i,t}$	-0.023***	*(-3.45)*	-0.020***	*(-3.02)*
$LOG\_HORIZON_{i,t}$	0.015***	*(6.67)*	0.015***	*(6.63)*
$ROA_{i,t-1}$	-0.002	*(-0.05)*	-0.002	*(-0.03)*
$SALE\_GROWTH_{i,t-1}$	0.010	*(1.55)*	0.011	*(1.62)*
$BM_{i,t-1}$	0.040***	*(6.18)*	0.039***	*(6.03)*
$HH\_INDEX_{i,t-1}$	-0.000	*(-1.33)*	-0.000	*(-1.34)*
$LOG\_ASSETS_{i,t-1}$	-0.009**	*(-2.51)*	-0.009**	*(-2.47)*
$ALTMAN_{i,t-1}$	-0.001	*(-1.58)*	-0.001*	*(-1.67)*
$BETA_{i,t-1}$	0.001	*(0.96)*	0.002	*(1.10)*
Observations	5921		5921	
Firm fixed effects	yes		yes	
Adjusted R-square	0.1397		0.1408	

This table presents fixed-firm effects model to generate the market feedback measure for overconfident and less confident CEOs. All variables are defined in Appendix 2.1. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers. Variables with interaction terms are demeaned to reduce multicollinearity among the variables. The sample includes all 8,052 quarterly forecasts observations from January 1, 1994 till December 31, 2008.

t-statistics is in parentheses; * Significant at 10%; ** significant at 5%; *** significant at 1%

Appendix 3.1: Definition of variables

Variable Name	Definition
Dependent variable	
FORECAST_ERROR	Proportional absolute earnings forecasting accuracy, measured by the absolute earnings forecast error scaled by the mean earnings forecast error using all earnings forecasts issued for a firm during the same fiscal year. Annual forecasts and quarterly forecasts are calculated separately.
PCT_ERROR_RANK	A ranked score based on the absolute forecast error using all forecasts issued for a firm during the same fiscal year. The most accurate forecast receives a ranked score of 0, and the least accurate forecast receives a ranked score of 100. Annual forecasts and quarterly forecasts are calculated separately.
FIRMS _SUPPLY_CHAIN	An indicator variable that equals 1 if a firm is a focal firm or the focal firm's major customer in the same year, and 0 for other firms in the same analyst's portfolio.
ANALYSTS' SUPPLY CHAIN COVERAGE VARIABLES	
SUPPLY_CHAIN_ANALYST	An indicator variable that equals 1 if a forecast is issued by a supply chain analyst who issues forecasts for both a focal firm and at least one of the firm's major customer, and 0 for forecasts issued for the same firm by other analysts, who do not issue forecasts for the firm's supply chain.
FOCAL_SUPPLY_CHAIN	An indicator variable that equals 1 if for a given supply chain analyst, a forecast is issued for a focal firm, with at least one of the firm's major customers also followed by the same analyst, and 0 for forecasts issued for other firms followed by the same analyst.
CUSTOMER_SUPPLY_CHAIN	An indicator variable that equals 1 if for a given supply chain analyst, a forecast is issued for a focal firm's major customer, with at least one of the firm's suppliers also followed by the same analyst, and 0 for forecasts issued for other firms followed by the same analyst.
NUMBER_CUSTOMER	For the focal firm followed by a supply chain analyst, the total number of the major customers of the focal firm that the analyst follows. If an analyst follows none of the major customers of the focal firm, the variable is coded as 0.
PCT_SALES	For the focal firm followed by a supply chain analyst, the aggregated total sales made to the focal firm's major customers, deflated by the total sales of the focal firm in the fiscal year. If an analyst does not follow any of the major customers of the focal firm, the variable is coded as 0.
FORECASTS AND ANALYST CHARACTERISTICS VARIABLES	
PRIMARY_INDUSTRY	An indicator that equals 1 if the industry has the largest representation among all firms in an analyst's coverage portfolio in a given year, and 0 for all the other industries the analyst follows in the year.

DISPERSION	Analyst forecasting dispersion. It is calculated as the standard deviation of the proportional forecasting errors using all forecasts issued for a firm in the same fiscal year.
NUMBER_ANALYST_FOLLOW	The number of analysts who have issued forecasts for a firm during the same fiscal year.
HORIZON	Log value of forecasting horizon, calculated as the number of lag days between the date a forecast is issued and the date at which the corresponding actual earning is announced.
NUMBER_FORECAST	Number of forecast issued for the fiscal year, calculated for the annual forecast and quarterly forecast separately.
YEAR_EXP	Number of years' experience with the firm, calculated as the number of years an analyst has been issuing forecasts for a firm.
NUMBER_SIC1	The total number of industries at the one-digit SIC code level for which an analyst issues forecasts during a fiscal year.
LOG_BROKER_SIZE	The log value of the total number of analysts that the brokerage firm employs during a fiscal year.
FIRM CHARACTERISTICS VARIABLES	
INVESTMENT_BANKING	An indicator variable that equals 1 if a firm has appointed the brokerage firm as an underwriter for the firm's equity issuance during the three years before or three years after the year in which an analyst follows the firm.
LOG_TRADINGVALUE	Log of total trading value in the year, calculated as the cumulative trading volume * trading price.
LOG_MV	Log value of the total market value of the firm.
LOG_ NUMBER_FIRM_SIC1	Log of the total number of firms in the industry at the one-digit SIC code level.
SALE_GROWTH	Sales growth rate, measured as total sales at year t minus total sales at year t-1, scaled by the total sales at year t-1.
MARKET_TO_BOOK	Market to book ratio at the beginning of the year t.
ROA	Return on assets for year t-1.
AD_RATIO	The ratio of advertising expense to total sales at year t-1. Missing value of advertising expense is replaced with zero.
RD_RATIO	The ratio of research and development expense to total sales at year t-1. Missing value of research and development expense is replaced with zero.

Appendix 3.2

This appendix describes in more details how analysts may organize their supply chain relations in different ways in their portfolios. I classified supply chain analysts into four groups, based on the number of major customers of a focal firm they cover and the complexity of the supply chain relations in their portfolios.

The first group of supply chain analysts is labeled as "Analysts with one (focal firm)-to-one (major customer) relation." For this group of analysts, each supply relation in their portfolios has one distinct focal firm paired with one distinct major customer. In other words, for each of the focal firm the analyst follows, she only covers one major customer of the focal firm.

The second group of supply chain analysts is labeled as "Analysts with one (focal firm)-to-many (major customers) relations." In the one-to-many group, one single focal firm may be paired with two or more than two major customers. As long as analysts have one-to-many relation(s) in their supply chain portfolio, but not many-to-one relation(s) as I discuss below, they are classified in the second group.

The third group of supply chain analysts is labeled as "Analysts with many (focal firms)-to-one (major customer) relations." In the many-to-one group, multiple focal firms share the same major customer. As long as analysts have many-to-one relation(s) in their supply chain portfolio, but not one-to-many relations(s) as I discuss above, they are classified in the third group.

The last group of supply chain analysts is labeled as "Analysts with one-to-many and many-to-one relations." In this group, analysts' supply chain portfolio includes both one-to-many relation(s) and many-to-one relation(s).

Panel (A) of Appendix 3.2 compares these four groups of analysts along a number of dimensions. Column (1) reports the descriptive statistics for analysts with the one-to-one relation. This group of analysts has 1,746 observations, representing 64.8% of all analyst-year observations (1,746 of 2,696) in my sample period. The average number of supply chain relations covered by these analysts is 1.11. These analysts follow an average of 18.52 firms from 2.85 industries at the one- digit SIC code level. The employers (the brokerage firms) of these analysts hire an average of 61.64 analysts, and cover 9.02 industries.

Column (2) of Panel A includes analysts with the one-to-many relation. This group of analysts represents 12.4% of all observations (335 of 2,696). The average number of supply chain relations covered by these analysts is 3.80,[51] which is higher than the corresponding 1.1 supply chain relations followed by analysts who take the "one-to-one" approach (column 1). These analysts follow an average of 19.62 firms from 3.41 industries at the one-digit SIC code level. The employers of these analysts hire an average of 54.7 analysts, and cover 9.07 industries.

Column (3) includes those analysts with the many-to-one relation. It shows that this group

[51] Here, each focal-customer pair is counted as one supply chain relation. For instance, if Firm A has two major customers, Firms B and C, and if an analyst follows Firms A, B, and C, this analyst has two supply chain relations in her portfolio (one is Firm A-Firm B relation, and the other is Firm B-Firm C relation).

of analysts represents 6.5% of all observations (176 of 2,696). The average number of supply chains followed by these analysts is 2.08. The average number of firms these analysts follow and the number of analysts their employers hire is similar to the analysts with the "one-to-many relation" reported in column (2).

Column (4) includes those analysts with a combination of one-to-many and many-to-one relations. These analysts cover the most complicated supply chain relations. Not surprisingly, column (4) shows that these analysts cover 7.71 supply chain relations, which is the greatest among all supply chain analysts. In addition, they also cover more firms (20.91 firms) from more industries (3.32 industries at the one-digit SIC code level).

To the extent that analysts get better information about the future sales growth for the focal firms by following the focal firms' major customers, I expect that the more major customers of a focal firm that analysts follow, the more accurate their earnings forecasts for the focal firm will be. Panel B of Appendix 3.2 provides evidence on the implications of different supply chain portfolio designs on forecasting accuracy for the focal firms. Row 1 suggests that, on average, the forecasting errors for all focal firms are -0.0189. Forecasts for focal firms are most accurate at -0.0299 (Row 3) when analysts follow more than one of the focal firm's major customers (i.e., the one-to-many relation), although the difference is not statistically significant at conventional levels, except when I compare the forecasting accuracy for the focal firms between analysts "with one-to-many relation" and analysts "within both one-to-many and many-to-one relation".

Panel C of Appendix 3.2 provides evidence on the difference in corresponding forecasting accuracy for the major customers of the focal firms. Row 1 suggests that the average forecasting error for the major customers is -0.0061. The average forecasting error for the major customers is most accurate at -0.0153 in Row 4 when analysts follow more than one supplier (focal firm) of the major customer. But the difference of the forecasting accuracy for the major customer firms between group 3 in Row 4 and other analysts in the other three groups is not statistically significant at conventional levels.

Overall, the evidence is generally consistent with my argument that analysts issue more accurate earnings forecasts if they have more information about the parties in the supply chain, either by covering more major customers of a focal firm, or by covering more focal firms of a major customer.

Panel A: Descriptive statistics on different ways analysts organize their supply chain portfolios

This table describes the four different ways analysts organize supply chain relations in their portfolios. The statistics are analyzed at the individual analyst portfolio level. The columns below define four categories that analysts organize their supply chain relations based on the number of major customers of a focal firm they cover and the complexity of the supply chain relations in the their portfolios.

1. One(focal firm)-to-One(customer) Relation	Each supply relation in analyst portfolios has one distinct focal firm paired with one distinct major customer. In other words, for each of the focal firm the analysts follow, they only covers one major customer of the focal firm.
2. One-to-Many Relation	One single focal firm may be paired with two or more than two major customers. As long as analysts have one-to-many relation(s) in their supply chain portfolio, but not many-to-one relation(s) as I discussed below, they are classified in this group.
3. Many-to-One Relation	In the many-to-one relation, multiple focal firms share the same major customer. As long as analysts have many-to-one relation(s) in their supply chain portfolio, but not one-to-many relations(s) as I discussed above, they are classified in this group.
4. Hybrid Relation	In this group, analysts' supply chain portfolio includes both one-to-many relation(s) and many-to-one relation(s).

Descriptive Items	Analysts with one-to-one relation (1)	Analysts with one-to-many relation (2)	Analysts many-to-one relation (3)	Analysts with hybrid relation (4)	All (5)
Number of observations (analyst-year)	1,746	335	176	439	2,696
Mean number of supply chain relation followed in each analyst's portfolio (each focal firm-customer pair is counted as one)	1.11	3.80	2.08	7.71	2.63
Mean number of firms followed in each analyst's portfolio	18.52	19.62	19.95	20.91	19.14
Mean number of industries followed in each analyst's portfolio (the one-digit SIC code level)	2.85	3.41	3.10	3.32	3.22
Mean number of analysts employed by the brokerage firm	61.64	54.70	53.45	56.11	59.35
Number of industries followed by the brokerage firm (the one-digit SIC code level)	9.02	9.07	8.80	9.15	9.03

Panel B: Forecasting accuracy for the focal firms with different supply chain portfolio designs

This table provides descriptive statistics on the forecasting accuracy for the focal firms followed by supply chain analysts. The table provides detailed analyses of the forecasting error for the focal firms based on the four ways that supply chain analysts organize their supply chain portfolios.

Row	Organization category	FORECAST_ERROR (focal firms)
1	All focal firms	-0.0189
2	Focal firms with one-to-one relation	-0.0228
3	**Focal firms with one-to-many relation**	-0.0299
4	Focal firms with many-to-one relation	-0.0190
5	hybrid relation	-0.0124
	T-test for (3)-(2)	0.47
	T-test for (3)-(4)	-0.73
	T-test for (3)-(5)	-1.71*
	Distinct number of focal firms	428
	Number of observations	44,377

Panel C: Forecasting accuracy for the major customer firms with different supply chain portfolio designs

This table provides descriptive statistics on the forecasting accuracy for the major customers of the focal firms by supply chain analysts. The table provides detailed analyses of the forecasting error for the major customers firms based on the four ways that supply chain analysts organize their supply chain portfolios.

Row	Organization category	FORECAST_ERROR (major customer)
1	All major customer firms	-0.0061
2	Focal firms with one-to-one relation	-0.0035
3	Focal firms with one-to-many relation	-0.0013
4	**Hybrid relation**	-0.0153
5	Focal firms with one-to-many and many-to-one relation	-0.0085
	T-test for (4)-(2)	-1.06
	T-test for (4)-(3)	-0.91
	T-test for (4)-(5)	-0.58
	Distinct number of major customers	221
	Number of observations	44,036

Table 2.1: Sample screening procedures

Procedures		Number of observations	
(1)	Initial quarterly forecasts from the First Call CIG database (January 1, 1994 to December 2008) after excluding: a. Currency not in USD b. Duplicate observations c. Forecasts unrelated to EPS d. Multiple guidance per quarter (keep the first forecast in the quarter) e. Forecasts made after the fiscal quarter f. Stale forecasts longer than 90 days prior to the quarter end g. Forecasts with missing actual quarterly earnings to calculate forecasting error h. Forecasts issued before the actual earnings announcement for the last quarter		22,954
(2)	Forecasts without the return data to calculate the market reaction surrounding the issuance of the forecasts	(945)	
(3)	Forecasts without prior analysts' consensus forecasts	(8,705)	
(4)	Forecasts with mergers and acquisitions announcements after the analysts' consensus forecasts	(261)	
(5)	Firm quarters without the Compustat financial data	(169)	12,827
(6)	Firms without CEO information from the Execucomp	(3,659)	
(7)	Firm-quarters with dual CEO and CEO turnover in the quarter	(1,116)	8,052
(8)	Observations used in Appendix 2.1 Panels C and D, representing a total of 1,681 distinct CEOs in 1,246 firms.		8,052
(9)	Delete forecasts issued by managers whose initial forecasts are more accurate, and keep all forecasts issued by the total 568 overconfident and less confident CEOs (observations used in Table 2.2, Table 2.3, Table 2.5, including 1,176 forecasts issued by 283 overconfident managers, 1,306 forecasts for 285 less confident managers).	(5,570)	2,482
(10)	For 2,482 forecasts issued by 568 managers, 369 CEOs continue issuing forecasts after their first forecasts. 316 CEOs have adjusted and issue more accurate subsequent forecasts (observations used in Table 2.4).		316

Table 2.2: Descriptive statistics

Panel A: Descriptive statistics for the first forecasts issued by overconfident CEOs and less confident CEOs

Variables	Forecasts by overconfident CEOs (N=283)		Forecasts by less confident CEOs (N=285)		t-test statistics *(two-tailed P-value)*
	Mean	median	Mean	median	
$BIAS_t$	0.010	0.004	-0.015	-0.003	6.562*** *(0.000)*
$ERROR_t$	0.0101	0.0046	0.0149	0.0033	-1.252 *(0.211)*
$NEWS_t$	-0.005	-0.001	-0.0105	-0.0007	1.172 *(0.241)*
$HORIZON_t$	45.0601	52	42.9754	52	1.004 *(0.315)*
$CAR_{-1,+1}$	-0.0539	-0.0356	-0.003	0.0032	-5.493*** *(0.000)*
STD_EPS_t	0.7767	0.5862	0.4427	0.5609	-0.905 *(0.365)*
$SALE\_GROWTH_t$	-0.010	-0.024	0.057	0.030	-3.420*** *(0.001)*
BM_t	0.676	0.594	0.569	0.492	2.648*** *(0.008)*
HH_INDEX_t	4.064	0.183	2.781	0.065	1.514 *(0.131)*
$ASSETS_t$	7704.69	1384.17	7226.26	1337.52	0.546 *(0.584)*
$ALTMAN_t$	2.348	2.277	3.108	1.517	-2.612*** *(0.009)*
$BETA_t$	1.396	1.160	1.591	1.378	-1.76* *(0.080)*
$\|WACC_t\|$	0.0239	0.0144	0.0303	0.0156	-2.147** *(0.032)*

This table presents descriptive statistics for the first forecasts issued by overconfident and less confident CEOs. The t-test for the mean of the variables uses the pooled method when the underlying variances are equal and the satterthwaite method when they are unequal. The values of the t-test statistics are reported with the corresponding p-value in the parentheses. All variables are defined in Appendix 2.1. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers. The sample includes all quarterly management forecasts from January 1994 - December 2008.

P-values of the t-statistics are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Panel B: Descriptive statistics for all forecasts after the first forecasts by overconfident and less confident CEOs

Variables	Overconfident CEOs (N=893 firm quarter forecasts)		Less confident CEOs (N=1021 firm quarter forecasts)		t-test statistics *(two-tailed P-value)*
	Mean	median	Mean	Median	
$BIAS_t$	0.0002	-0.0006	-0.002	-0.0009	2.573*** *(0.010)*
$ERROR_t$	0.0046	0.0017	0.0037	0.0016	1.928** *(0.054)*
$CAR_{-1,+1}$	-0.003	-0.0006	-0.004	0.0001	0.089 *(0.929)*
$NEWS_t$	-0.0028	-0.0006	-0.0045	-0.0004	0.471 *(0.637)*
STD_EPS_t	0.7804	0.635	0.5807	0.5809	1.077 *(0.281)*
$HORIZON_t$	56.4244	64	54.2772	62	2.315** *(0.020)*
$SALE\_GROWTH_t$	0.0345	0.0231	0.0315	0.0242	0.335 *(0.737)*
BM_t	0.5245	0.4415	0.499	0.4262	1.559 *(0.119)*
$HHINDEX_t$	5.0652	0.2928	3.1868	0.0729	3.803*** *(0.000)*
$ASSETS_t$	6953.92	1429.47	7001.38	1435.00	-0.043 *(0.965)*
$ALTMAN_t$	2.7801	1.6751	3.768	2.1351	-0.188*** *(0.000)*
$\lvert WACC_t \rvert$	0.0207	0.013	0.0223	0.0141	-1.316 *(0.188)*

This table presents descriptive statistics for all subsequent forecasts after excluding the first forecasts issued by overconfident and the less confident CEOs. The t-test of the mean value of the variables uses the pooled method when the underlying variances are equal and the satterthwaite method when they are unequal. The values of the t-test statistics are reported with the corresponding p-value in the parentheses. All variables are defined in Appendix 2.1. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers. Two-tail p-values are reported. The sample period is from January 1994 - December 2008.

P-value of the t-statistics are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.3: Forecasting errors by overconfident CEOs and less confident CEOs

Forecast Sequence (S)	S=1	S=2	S=3	S=4	S=5	S=6	S>=7	S>=2	Test of the difference of forecast error between the first (S=1) and the subsequent forecasts (S>=2)
Panel A: Overconfident CEOs									
Variable: Forecasting errors ($ERROR_t$)									
Mean Error	0.0101	0.0064	0.0056	0.0039	0.0058	0.0036	0.0034	0.0037	6.798***
(Median Error)	(0.0046)	(0.0019)	(0.0016)	(0.0013)	(0.0018)	(0.0017)	(0.0017)	(0.0017)	*(0.000)*
N	283	168	127	100	81	66	351	1914	
Panel B: Less confident CEOs									
Mean Error	0.0149	0.0056	0.0033	0.0035	0.0042	0.0051	0.0026	0.0046	5.082***
(Median Error)	(0.0033)	(0.0018)	(0.0017)	(0.0013)	(0.0017)	(0.0018)	(0.0019)	(0.0016)	*(0.000)*
N	285	201	145	121	96	79	379	1914	
Panel C: All CEOs									
Mean Error	0.0125	0.006	0.0045	0.0037	0.0051	0.0047	0.0032	0.0042	7.283***
(Median Error)	(0.0038)	(0.0018)	(0.0016)	(0.0013)	(0.0017)	(0.0017)	(0.0015)	(0.0016)	*(0.000)*
N	568	369	272	221	177	145	730	1914	

This table presents descriptive statistics of forecasting errors using all forecasts issued by overconfident and less confident CEOs based on the sequence of each forecast by each manager during their tenure. The t-test of the mean value of the variables uses the pooled method when the underlying variances are equal and the satterthwaite method when they are unequal. Variables are defined in Appendix 2.1. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers. The sample period is from January 1994 - December 2008.

p-values of the t-statistics are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.4: Is learning speed symmetric between overconfident and less confident CEOs?

Panel A: Descriptive comparison of the time needed by overconfident and less confident CEOs to issue their first more accurate forecasts

Variables	Overconfident CEOs			Less confident CEOs			t-test statistics *(two-tailed P-value)*
	N	Mean	median	N	Mean	Median	
Number of forecasts	137	2.547	2	179	2.226	2	2.99*** *(0.003)*
Number of quarters	137	5.84	4	179	5.36	3.5	2.12** *(0.035)*

This table reports the number of forecasts (quarters) elapsed for overconfident CEOs and less confident CEOs from their first overly optimistic or pessimistic forecasts to their first more accurate forecasts. Managers need to issue at least one subsequent accurate forecast to be included in the analysis. Of the total original number of 283 (285) overconfident (less confident) CEOs, 115 (84) overconfident (less confident) CEOs are deleted because they stop providing subsequent forecasts. Another 31 (22) overconfident (less confident) CEOs are also excluded because these CEOs have consistently issued overly optimistic (overly pessimistic) forecasts during their entire tenure as the CEO of the firm. The resulting 137 (179) overconfident (less confident) CEOs represent those CEOs who have issued at least one "more accurate" forecast. The values of the t-test statistics are reported with the corresponding two tailed p-value in the parentheses.

* Significant at 10%; ** significant at 5%; *** significant at 1%

Panel B: Are overconfident CEOs slower to learn and issue more accurate subsequent forecasts?

Independent Variables	Dependent variable: Number of forecasts
CONSTANT	2.243*** *(16.55)*
OC_MF	0.214** *(2.20)*
$NEWS_t$	-0.582 *(-0.71)*
$MF\_FREQUENCY_t$	0.126** *(2.17)*
CH_ROA_t	-1.183 *(-0.81)*
$CH\_SALEGROWTH_t$	-0.413** *(-2.00)*
CH_BM_t	0.018 *(0.09)*
$CH\_HHINDEX_t$	0.046** *(2.09)*
CH_ASSETS_t	-0.148 *(-0.84)*
CH_ALTMAN_t	-0.009 *(-0.35)*
N of observations	262
Adjusted R-square	0.082

The table present OLS regression for the time elapsed for overconfident CEOs and less confident CEOs to issue their first more accurate subsequent forecasts. Variable definitions are as shown in Appendix 2.1. The reduced sample from 316 observations to 262 observations reflects missing variables for some of independent variables used in the model.

T-statistics are reported in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.5: Heckman two-stage regression on the effect of feedback on subsequent forecasting accuracy

Panel A: First stage estimation of the probability that CEOs discontinue providing subsequent forecasts

Variables	Dependent variable: Discontinue issuing forecast at quarter t ($DISCONTINUE_t$)
Constant	-1.0390*** *(-5.51)*
OC_MF	0.0113 (0.16)
$OPTIMISTIC_{t-1}$	0.0836 *(1.11)*
LOG_ASSETS_{t-1}	0.0168 *(0.70)*
$N\_ANALYST_{t-1}$	-0.0293*** *(-3.92)*
BM_{t-1}	0.3861*** (4.00)
$BETA_{t-1}$	0.0305 *(1.17)*
STD_EPS_{t-1}	0.0078 *(0.96)*
EPS_GAP_{t-1}	-4.4167*** *(-3.99)*
$LITIGATION_{t-1}$	-0.0665 *(-0.86)*
Observations	2047

This table reports the probability that managers discontinue providing subsequent forecasts after their initial forecasts. The sample consists of 2,486 forecasting observations from January 1, 1994 until December 31, 2008. The dependent variable is an indicator variable equal to 1 if a manager discontinue providing subsequent forecasts after the first forecast. Other variables definitions are shown in Appendix 2.1.

Z-statistics are in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Panel B: Second stage regression on the effect of feedback on subsequent forecasting accuracy

Independent Variables	Dependent variable: forecasting error ($ERROR_t$)	
	Overconfident CEO	Less confident CEO
	(1)	(2)
$INTERCEPT_{i,t-1}$	0.032*** *(3.02)*	-0.016 *(-1.17)*
POS * $MKT\_FB_{i,t-1}$	0.001 *(0.12)*	0.006 *(0.41)*
NEG * $MKT\_FB_{i,t-1}$	-0.010 *(-1.21)*	0.047*** *(3.17)*
$ERROR\_FB_{i,t-1}$	0.284* *(1.70)*	0.205*** *(14.47)*
$INCENTIVE\_RATIO_{i,t-1}$	-0.001 *(-0.40)*	-0.180 *(-1.51)*
$PUR\_PCT_{i,t-1}$	0.041 *(0.67)*	0.031 *(0.40)*
$LOG\_HORIZON_{i,t}$	0.001*** *(2.95)*	0.001* *(1.76)*
$N\_ANALYST_{i,t-1}$	0.000** *(2.32)*	-0.000 *(-1.00)*
$EXP_{i,t}$	0.000 *(1.07)*	0.000** *(2.43)*
$CEO\_AGE_{i,t}$	0.000 *(0.06)*	-0.000 *(-1.29)*
$NEWS_{i,t}$	0.074*** *(2.88)*	0.005 *(0.93)*
$STD\_EPS_{i,t-1}$	-0.000* *(-1.81)*	0.000*** *(2.68)*
$SALE\_GROWTH_{i,t-1}$	0.001 *(1.35)*	-0.001 *(-0.77)*
BM_{t-1}	-0.004*** *(-3.19)*	0.009*** *(4.79)*
$HHINDEX_{i,t-1}$	-0.000 *(0.58)*	-0.000 *(-0.35)*
$LOG\_ASSETS_{i,t-1}$	-0.000 *(-0.56)*	-0.001 *(-0.83)*
$ALTMAN_{i,t-1}$	-0.000** *(-2.01)*	-0.000 *(1.39)*
$\lvert WACC_{i,t-1}\rvert$	0.021*** *(3.00)*	0.021* *(1.82)*
$MILLS_{i,t}$	-0.019*** *(-7.25)*	0.018*** *(5.66)*
Observations	772	871
Clustered by industry	Yes	Yes
Individual fixed effects included	Yes	Yes
Adjusted R-squared	0.117	0.559

Joint chow test: F test statistics = 0.50, p =0.607
column1: _beta[$ERROR\_FB_{i,t-1}$] = column2: _beta[$ERROR\_FB_{i,t-1}$]
Joint chow test: F test statistics = 3.07, p =0.047
column1: _beta[NEG * $MKT\_FB_{i,t-1}$] = column2: _beta[NEG * $MKT\_FB_{i,t-1}$]

This table reports individual fixed effects regression on management forecast errors and the two sources of feedback concerning their prior forecasts using all quarterly forecasts issued by overconfident and less confident CEOs from January 1, 1994 till December 31, 2008. Variable definitions are presented in Appendix 2.1. T-statistics are in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.1: Year-by-year sample distribution at the firm level

This table reports the year-by-year distribution of the total number of distinct firms in two samples. Column (1) reports the number of firms that reported having major customer relations and have analyst forecast data for both the focal firms and the reported major customers. Column (2) to (4) report the total number of firms followed by supply chain analysts. These firms are classified into one of the three groups for each supply chain analyst: focal firms, i.e., for firms for which an analyst also covers one or more major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. The sample is derived from a merged sample using the Compustat customer segment file and the I/B/E/S analyst detailed forecast data from January 1, 1991 to December 31, 2008.

Year	Base Sample (firms that report having major customer relations and have analyst forecast data)	Firms followed by supply chain analysts		
	Number of reporting firms	Total number of focal firms	Total number of major customer firms	Total number of "other" firms
	(1)	(2)	(3)	(4)
1991	672	89	57	1206
1992	724	92	60	1037
1993	791	110	71	1266
1994	781	119	71	1374
1995	873	101	56	1153
1996	868	119	69	1317
1997	766	112	65	1267
1998	698	91	50	1080
1999	526	74	39	976
2000	541	46	36	713
2001	488	48	37	716
2002	438	47	35	612
2003	360	34	23	541
2004	288	33	24	522
2005	221	28	21	478
2006	151	16	15	359
2007	114	11	7	270
2008	72	6	6	179
Total	9,372	1,176	742	15,066
Number of Distinct firms	2,492	428	221	3,961

Table 3.2: Industry distribution at the firm level

This table reports the industry distribution (at the one-digit SIC code level) for two samples. Column (1) reports the industry distribution of the total number of reporting firm-years that reported having major customer relations and have analyst forecast data for both the focal firm and the reported major customer firm from January 1, 1991 to December 31, 2008. Column (2)-(4) report the industry distribution for all firm-years followed by supply chain analysts during the same sample period, and these firms are classified into three groups: focal firms, i.e., for firms for which the analysts also cover one or more of the firms' major customers, major customers of the focal firms for the analyst, and "other" firms which include all remaining firms in the analysts' portfolios.

One-digit SIC code	Industry classification	Firms that reported having major customer relations and are covered in I/B/E/S	Firms followed by supply chain analysts		
		Reporting firms	Focal firms	Major customers	"Other" firms
		(1)	(2)	(3)	(4)
0	Agricultural production	11	0 (0.00%)	3	39
1	Mining, building and construction products	692	80 (6.80%)	16	1120
2	Non durable manufacturing	1,526	147 (12.50%)	133	2323
3	Durable manufacturing	3,664	585 (49.74%)	221	4434
4	Transportation and communication	844	166 (14.12%)	161	2740
5	Wholesale, retail	392	47 (4.00%)	106	1287
6	Finance	316	28 (2.38%)	41	995
7	Business services	1,529	72 (6.12%)	43	1415
8	Other services	290	38 (3.23%)	15	672
9	Non operating establishments	108	13 (1.11%)	3	41
	Total number of firm-year observations	9,372	1,176 (100%)	742	15,066
	Total number of distinct firms	2,492	428	221	3,961

Table 3.3: Descriptive statistics on characteristics of analysts' portfolios

This table provides descriptive statistics on characteristic of analysts' portfolios. The statistics are reported at the analyst-year level for supply chain analysts and other non-supply chain analysts who follow the same focal firms but none of the firms' major customers. Portfolio descriptive statistics are reported in column (1) for all analysts who issue forecasts for the focal firms. Portfolio descriptive statistics for supply chain analysts are reported in column (2). Column (3) reports the portfolio characteristics for the analysts following the same focal firms but none of the focal firms' major customers. Column (4) reports the t-test statistics for the difference in portfolio characteristics between the two groups of analysts in column (2) and column (3). Two tailed t statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Descriptive Items	All analysts (who follow the focal firms)	Supply chain analysts (who follow a focal firm and its major customer)	Other analysts (who follow only the same focal firm but not its major customer)	t-test statistics [(2) - (3)]
	(1)	(2)	(3)	(4)
Mean number of supply chain relations included in the portfolio	0.77	2.63	0	42.27 ***
Mean percentage of firms from the analyst' primary industry	72.1%	68.7%	73.6%	-4.75 ***
Mean percentage of analysts who follow exclusively firms in one industry (the one-digit SIC code level)	16.0%	10.3%	18.4%	-10.70 ***
Mean number of firms followed in the portfolio	15.35	19.14	13.78	16.98 ***
Mean number of industries followed in the portfolio (the one-digit SIC code level)	2.96	3.22	2.85	11.38 ***
Mean number of industries followed in the portfolio (the two-digit SIC code level)	4.74	5.38	4.48	12.15 ***
Mean number of analysts employed by the brokerage firm	54.98	59.35	53.18	5.32 ***
Mean number of industries followed by the analyst's brokerage firm (the one-digit SIC code level)	8.74	9.03	8.62	12.24 ***
Number of analyst-year observations	9,235	2,696	6,539	
Number of distinct analysts	2,857	973	2,536	

Table 3.4: Within-analyst comparison of earnings forecasting accuracy between the focal firms and "other" firms

This table provides related descriptive statistics, Pearson correlation coefficients, and the Fama-MacBeth regression results for the within-analyst analyses of analyst forecasting accuracy of a given supply chain analyst for the focal firms and the same analyst issues for "other" firms. Firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers one or more major customers, major customers of a focal firm for the analyst, and "other" firms the same analyst follows in the portfolio. Forecasts for the focal firms and "other" firms are used in Panel A, B, and D for the analyses of forecasting accuracy between focal firms and "other" firms in the same analyst's portfolio. Panel C provides comprehensive forecasting accuracy analyses for all the three groups of firms. A firm is in an analyst's primary industry if the firm is in the industry that the analyst is primarily specialized in, i.e., the industry that has the largest representation among all the industries the analyst follows in the same year.

Panel A: Descriptive statistics of variables used in multivariate analyses on within-analyst comparison of forecasting accuracy between the focal firms and "other" firms (N=405,135)

Variables	Mean	Median	Q1	Q3	STD
FOCAL_SUPPLY_CHAIN	0.11	0	0	0	0.31
PRIMARY_INDUSTRY	0.74	1	1	1	0.44
DISPERSION	0.58	0.58	0.44	0.70	0.23
NUMBER_ANALYST_FOLLOW	19.96	18	11	27	11.29
HORIZON	246	187	74	346	208
YEAR_EXP	3.21	3	2	4	2.42

Panel B: Pearson correlation table for the variables used in multivariate analyses (N= 405,135)

	FORECAST _ERROR	FOCAL _SUPPLY _CHAIN	HORIZON	PRIMARY_ INDUSRY	YEAR_EXP	DISPERSION	NUMBER _ANALYS_ FOLLOW
FORECAST_ERROR	1.000						
FOCAL_SUPPLY_ CHAIN	-0.009 (<0.001)	1.000					
HORIZON	0.054 (<0.001)	0.061 (<0.001)	1.000				
PRIMARY_INDUSTRY	-0.002 (0.046)	-0.008 (<0.001)	-0.011 (<0.001)	1.000			
YEAR_EXP	-0.053 (<0.001)	0.021 (<0.001)	0.143 (<0.001)	-0.007 (<0.001)	1.000		
DISPERSION	0.020 (<0.001)	0.010 (<0.001)	0.055 (<0.001)	-0.003 0.037	0.014 (<0.001)	1.000	
NUMBER_ANALYST_ FOLLOW	-0.056 (<0.001)	-0.298 (<0.001)	-0.006 (<0.001)	0.004 (0.007)	0.092 (<0.001)	-0.005 (0.002)	1.000

Two tailed p-values are reported in the parentheses.

Panel C: Descriptive statistics on within-analyst comparison of forecasting accuracy for a given supply chain analyst

Row	Descriptive items	N	Mean	Median	Q1	Q3	STD
(1)	All forecasts for firms in the portfolio	449,171	0.0003	-0.0289	-0.5113	0.4071	0.6588
(2)	Forecasts for firms in analysts' primary industry	336,876	-0.0011	-0.0309	-0.5135	0.4059	0.6580
(3)	Forecasts for firms not in analysts' primary industry	112,295	0.0045	-0.0220	-0.5050	0.4117	0.6611
(4)	Forecasts for focal firms	44,377	-0.0189	-0.0484	-0.5284	0.3855	0.6455
(5)	Forecasts for major customer firms	44,036	-0.0061	-0.0386	-0.5221	0.4000	0.6539
(6)	Forecasts for all "other" firms	360,758	0.0033	-0.0250	-0.5077	0.4107	0.6610
T-test statistics for mean forecast error:							
(2)-(3)			-2.53***				
(4)-(6)			-6.72***				
(5)-(6)			-2.86***				
Z-test (Wilcoxon-test) statistics for median forecast accuracy:							
(1)-(2)			-2.29**				
(4)-(6)			-6.30***				
(5)-(6)			-2.60***				

Two tailed t-statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Panel D: Fama-MacBeth regression analyses for within-analyst comparison of forecasting accuracy between the focal firms and “other” firms

This table presents the summary results for the Fama-MacBeth regression analyses. The dependent variable is forecasting accuracy, measured as a proportional absolute forecast error for a forecast relative to the average absolute forecast error using all forecasts issued for a firm in a fiscal year. *FOCAL_SUPPLY_CHAIN* is an indicator variable that equals 1 if a forecast is issued for a focal firm, with one or more of the focal firm’s major customer followed by the same analyst in the same year, and 0 for “other” firms in the analyst portfolio. The sample comprises all forecasts issued by supply chain analysts for the focal firms and “other” firms. The column reports the mean coefficients based on 2,696 regression estimates for each analyst-year using equation (1). All coefficients have been multiplied by 100. The Fama-MacBeth t-statistics are computed based on the adjusted Newey-West (1987) standard errors to control for the heteroscedasticity and autocorrelation among the coefficient estimators. Two tailed t-statistics are in the parentheses. ***, **, and * are marked at the 1%, 5%, and 10% significance level respectively based on one-tailed p-value. Definitions of all the other variables are in Appendix 3.1.

Independent variables	Predicted sign	Dependent variable: FORECAST_ERROR	
		(1)	(2)
INTERCEPT	(+/-)	-35.636*** (-7.83)	-36.584*** (-8.04)
FOCAL_SUPPLY_CHAIN	-	-3.357** (-1.81)	-3.020* (-1.58)
PRIMARY_INDUSTRY	-	-0.765* (-1.22)	-0.799* (-1.46)
FOCAL_SUPPLY_CHAIN * PRIMARY_INDUSTRY	-		-1.342** (-2.26)
HORIZON	+	0.161*** (46.91)	0.161*** (45.52)
YEAR_EXP	-	-0.674 (-1.25)	-0.676 (-1.23)
DISPERSION	+	3.934** (1.74)	4.519** (1.97)
NUMBER_ANALYST_FOLLOW	-	-0.004 (-0.02)	-0.053 (-0.32)
Number of observations		2,696	2,696

Table 3.5: Cross-analyst analyses of forecasting accuracy for the focal firms

This table provides related descriptive statistics, Pearson correlation coefficients, and the Fama-MacBeth regression results for the cross-analyst comparison of forecasting accuracy for a given focal firm between supply chain analysts and other non-supply chain analysts who follow the same focal firms but none of the focal firms' major customers. The sample includes all forecasts issued for the focal firms over the sample period by both supply chain analysts and other analysts. Forecasting accuracy is measured as the proportional absolute forecast error for a forecast relative to the average absolute value of forecast error using all forecasts issued for a firm in a fiscal year. A focal firm is in an analyst's primary industry if the firm is in the industry that the analyst is primarily specialized in, i.e., the industry that has the largest percentage of firms in the analyst portfolio.

Panel A: Descriptive statistics of variables in multivariate analyses on cross-analyst comparison of forecasting accuracy for the focal firms (N= 134,956)

Variables	Mean	Median	Q1	Q3	STD
SUPPLY_CHAIN_ANALYST	0.33	0.00	1.00	1.00	0.47
PRIMARY_INDUSTRY	0.75	1.00	1.00	1.00	0.43
HORIZON	238.22	178	73	336	202.49
YEAR_EXP	2.67	2.00	1.00	3.00	1.85
NUMBER_SIC1	2.96	3.00	2.00	4.00	1.33
NUMBER_ANALYST_BROKER	57.41	46.00	20.00	76.00	49.30

Panel B: Pearson correlation for the variables in multivariate analyses on forecasting accuracy for the focal firms (N= 134,956)

	FORECAST_ ERROR	SUPPLY_ CHAIN_ ANALYST	PRIMARY_ INDUSTRY	HORIZON	YEAR_EXP	NUMBER_ SIC1	LOG _BROKER _SIZE
FORECAST_ERROR	1.000						
SUPPLY_CHAIN_ANALYST	-0.010 (<0.001)	1.000					
PRIMARY_INDUSTRY	-0.001 (0.851)	-0.028 (<0.001)	1.000				
HORIZON	0.328 (<.0001)	-0.015 (<0.001)	0.007 (0.014)	1.000			
YEAR_EXP	-0.005 (0.050)	0.068 (<0.001)	0.006 (<0.001)	0.015 (<0.001)	1.000		
NUMBER_SIC1	0.006 (0.007)	0.128 (<0.001)	-0.253 (<0.001)	-0.022 (<0.001)	0.119 (<0.001)	1.000	
LOG_BROKER_SIZE	-0.007 (0.006)	0.120 (<0.001)	-0.010 (<0.001)	-0.004 (0.061)	0.111 (<0.001)	0.071 (<0.001)	1

Two tailed p-values are reported in the parentheses.

Panel C: Descriptive statistics on cross-analyst comparison of forecasting accuracy for the focal firms

Row	Descriptive items	Mean	Median	Q1	Q3	STD
(1)	All forecasts for the focal firms	-0.0017	-0.0342	-0.5165	0.4071	0.6604
(1.1)	*When in analysts' primary industries*	-0.0034	-0.0313	-0.5109	0.4080	0.6541
(1.2)	*When not in analysts' primary industries*	-0.0012	-0.0348	-0.5183	0.4068	0.6625
(2)	Forecasts by supply chain analyst	-0.0189	-0.0484	-0.5284	0.3855	0.6455
(2.1)	*When in analysts' primary industries*	-0.0197	-0.0484	-0.5300	0.3814	0.6431
(2.2)	*When not in analysts' primary industries*	-0.0166	-0.0486	-0.5260	0.3964	0.6519
(3)	Forecasts by all the other analysts	0.0066	-0.0264	-0.5105	0.4176	0.6674
(3.1)	*When in analysts' primary industries*	0.0075	-0.0292	-0.5128	0.4180	0.6713
(3.2)	*When not in analysts' primary industries*	0.0036	-0.0185	-0.5021	0.4158	0.6552
T-test statistics for mean forecast error:						
(1.1)-(1.2)		-0.53				
(2)-(3)		-6.67***				
(2.1)-(3.1)		-6.11***				
(2.2)-(3.2)		-2.75***				
Z-test (Wilcoxon-test) statistics for median forecast accuracy:						
(1.1)-(1.2)		0.78				
(2)-(3)		-5.80***				
(2.1)-(3.1)		-4.94***				
(2.2)-(3.2)		-3.04***				
Number of observations		134,956				

Two tailed t-statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Panel D: Fama-MacBeth regression analyses on cross-analyst comparison of earnings forecasting accuracy for the focal firms

This table presents a summary of the Fama-MacBeth regression results. The dependent variable is forecasting accuracy, measured as a proportional absolute forecast error relative to the average absolute forecast error for a firm in a fiscal year. *SUPPLY_CHAIN_ANALYST* is an indicator variable that equals 1 if a forecast is issued by an analyst who issues a forecast for both a focal firm and one or more of the focal firm's reported major customers in the same year, and 0 for forecasts issued by analysts who only follow the same focal firm, but none of the firm's major customers. The sample comprises all forecasts issued for the focal firms, including forecasts issued by supply chain analysts and other non-supply chain analysts. The column reports the mean coefficients based on 1,176 regression estimates for each focal firm-years using equation (1). The Fama-MacBeth t-statistics are computed based on the adjusted Newey-West (1987) standard errors to control for the heteroscedasticity and autocorrelation among the coefficient estimators. All coefficients have been multiplied by 100. Two tailed t-statistics are in the parentheses. ***, **, and * are marked at the 1%, 5%, and 10% significance level respectively based on the one-tailed p-value. Definitions of all the other variables are in Appendix 3.1.

Independent variables	Predicted sign	Dependent variable: FORECAST_ERROR	
		(1)	(2)
INTERCEPT	(+/-)	-12.860** (-1.99)	-9.292 (-1.47)
SUPPLY_CHAIN_ANALYST	-	-3.861** (-1.71)	-3.829* (-1.65)
SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY	-		-3.459 (-0.89)
PRIMARY_INDUSTRY	-	-0.903 (-0.51)	-0.182 (-0.12)
HORIZON	+	0.105*** (20.88)	0.105*** (19.07)
YEAR_EXP		-1.245* (-1.37)	-1.574** (-1.66)
NUMBER_SIC1	+	0.857 (1.08)	2.130* (1.48)
LOG_BROKER_SIZE	-	-1.091* (-1.63)	-2.344** (-2.09)
Number of observations		1,176	1,176

Table 3.6: Fama-MacBeth regression analyses for within-analyst comparison of forecasting accuracy between the major customers and “other” firms

This table presents a summary of the Fama-MacBeth regression results. The dependent variable is the forecasting accuracy, measured as a proportional absolute forecast error for a forecast relative to the average value of absolute forecast error using all forecasts issued for a firm in a fiscal year. *CUSTOMER_SUPPLY_CHAIN* is an indicator variable that equals 1 if a forecast is issued for a major customer with one or more of the customer’s focal firms also followed by the same analyst and 0 for “other” firms in the analyst portfolio. Note all firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers one or more major customers, major customers of a focal firm for the analyst, and “other” firms which include all remaining firms in the analyst portfolio. The sample comprises all forecasts issued by supply chain analysts for the major customers of the focal firms and “other” firms in the same analyst portfolio. The column reports the mean coefficients based on 2,696 regression estimates for each of the analyst-year using the equation (1). The Fama-MacBeth t-statistics are computed based on the adjusted Newey-West (1987) standard errors to control for the heteroscedasticity and autocorrelation among the coefficient estimators. All coefficients have been multiplied by 100. Two tailed t-statistics are in the parentheses. ***, **, and * are marked at the 1%, 5%, and 10% significance level respectively based on one-tailed p-value. Definitions of all the other variables are in Appendix 3.1.

Independent variables	Predicted sign	Dependent variable: FORECAST_ERROR	
		(1)	(2)
INTERCEPT	(+/-)	-13.674 (-1.28)	-12.945 (-1.21)
CUSTOMER_SUPPLY_CHAIN	-	-1.193* (-1.61)	-1.273** (-1.73)
SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY	-		0.352 (0.49)
PRIMARY_INDUSTRY	-	0.123 (0.03)	-0.693 (-0.15)
HORIZON	+	0.164*** (48.47)	0.164*** (48.49)
YEAR_EXP	-	-1.449* (-1.60)	-1.421* (-1.55)
DISPERSION	+	0.663*** (8.94)	0.664*** (8.95)
NUMBER_ANALYST_FOLLOW	-	-0.821* (-1.59)	-0.835* (-1.61)
Number of observations		2,696	2,696

Table 3.7: Cross-analyst analyses of forecasting accuracy for the major customer firms

Panel A: Descriptive statistics on forecasting accuracy for the major customers

This table provides descriptive statistics on the variables used for analyses of forecasting accuracy for the major customers between supply chain analysts and the other analysts who only follow the same major customers but none of the customers' focal firms. The sample comprises all forecasts issued for the major customers of the focal firms. Note all firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers one or more of the major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. Forecasting accuracy is measured as the proportional absolute forecasting error for a forecast relative to the average absolute forecast error using all forecasts issued for a firm in a fiscal year. A major customer is in an analyst's primary industry if the firm is in the industry that the analyst is primarily specialized in, i.e., the industry that has the largest percentage of firms in the analyst portfolio.

Row	Descriptive items	Mean	Median	Q1	Q3	STD
(1)	All forecasts for the major customer firms	-0.0006	-0.0360	-0.5097	0.4038	0.6597
(1.1)	*When in analysts' primary industries*	-0.0017	-0.0370	-0.5112	0.4030	0.6593
(1.2)	*When not in analysts' primary industries*	0.0025	-0.0330	-0.5035	0.4062	0.6608
(2)	Forecasts by supply chain analyst	-0.0061	-0.0386	-0.5221	0.4000	0.6539
(2.1)	*When in analysts' primary industries*	-0.0074	-0.0399	-0.5256	0.3972	0.6542
(2.2)	*When not in analysts' primary industries*	-0.0004	-0.0322	-0.5066	0.4157	0.6524
(3)	Forecasts by all the other analysts	0.0010	-0.0353	-0.5056	0.4046	0.6615
(3.1)	*When in analysts' primary industries*	0.0003	-0.0361	-0.5064	0.4046	0.6611
(3.2)	*When not in analysts' primary industries*	0.0031	-0.0330	-0.5021	0.4042	0.6627
T-test statistics for mean forecast error:						
(1.1)-(1.2)		1.18				
(2)-(3)		-1.99 **				
(2.1)-(3.1)		-1.90 *				
(2.2)-(3.2)		-1.75 *				
Z-test (Wilcoxon-test) statistics for median forecast error:						
(1.1)-(1.2)		-0.99				
(2)-(3)		-1.74 *				
(2.1)-(3.1)		-1.88 *				
(2.2)-(3.2)		-1.91 *				
Number of observations		182,330				

Two tailed t-statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Panel B: Fama-MacBeth regression analyses for cross-analyst comparisons of earnings forecasting accuracy for the major customer firms

This table presents a summary of the Fama-MacBeth regression for each major customer firm to test H2b on the cross-analyst forecasting accuracy for a given major customer between supply chain analysts and other analysts who only follow the major customer but none of the firm's suppliers. The dependent variable is forecasting accuracy, measured as a proportional absolute forecast error for a forecast relative to the average absolute forecast error using all forecasts issued for a firm in a fiscal period. *CUSTOMER_SUPPLY_CHAIN* is an indicator variable that equals 1 if a forecast is issued for the major customers by an analyst who issues forecasts for both the major customers and one or more of the firm's suppliers in the same year, and 0 otherwise. The sample comprises all forecasts issued for the major customers of the focal firms by supply chain analysts and other analysts who only follow the major customer but none of the firm's focal firms. The column reports the mean coefficients estimated from 742 customer firm-years regression estimates based on the equation as shown in Equation (1). All coefficients have been multiplied by 100. The Fama-MacBeth t-statistics are computed based on the adjusted Newey-West (1987) standard errors to control for the heteroscedasticity and autocorrelation among the coefficient estimators. Two tailed t-statistics are in the parentheses. ***, **, and * are marked at the 1%, 5%, and 10% significance level respectively based on the one-tailed p-value. Definitions of all the other variables are in Appendix 3.1.

Independent variables	Predicted sign	Dependent variable: FORECAST_ERROR	
		(1)	(2)
INTERCEPT	(+/-)	-8.052** (-1.95)	-7.872** (-1.89)
SUPPLY_CHAIN_ANALYST	-	-1.180* (-1.63)	-1.386** (-1.71)
SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY	-		-0.006 (-0.01)
PRIMARY_INDUSTRY	-	0.557 (0.32)	0.414 (0.25)
HORIZON	+	0.064*** (19.07)	0.064*** (15.67)
YEAR_EXP	-	-0.394 (0.55)	-0.432 (-0.66)
NUMBER_SIC1	+	0.463 (0.64)	0.479 (0.49)
LOG_BROKER_SIZE	-	-0.116 (-0.30)	-0.103 (-0.27)
Number of observations		742	742

Table 3.8: Cross-analyst analyses of forecasting accuracy for "other" firms

Panel A: Descriptive statistics on forecasting accuracy for "other" firms

This table provides descriptive statistics to test the cross-analyst differences in forecasting accuracy for a given "other" firm between supply chain analysts and other non-supply chain analysts following the same "other" firm. The sample includes forecasts issued for "other" firms. Note all firms followed by each supply chain analyst are classified into three groups: focal firms, i.e., for firms for which an analyst also covers one or more of major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. A firm is in an analyst's primary industry if the firm is in the industry that the analyst is primarily specialized in, i.e., the industry that has the largest percentage of firms in the analyst portfolio. Two tailed t-statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Row	Descriptive items	Mean	Median	Q1	Q3	STD
(1)	All forecasts for "other" firms	-0.0088	-0.0402	-0.5160	0.3961	0.6582
(1.1)	*When in analysts' primary industries*	-0.0098	-0.0419	-0.5165	0.3948	0.6573
(1.2)	*When not in analysts' primary industries*	-0.0056	-0.0347	-0.5136	0.3999	0.6612
(2)	Forecasts by supply chain analyst	0.0033	-0.0250	-0.5077	0.4107	0.6610
(2.1)	*When in analysts' primary industries*	0.0018	-0.0274	-0.5097	0.4098	0.6603
(2.2)	*When not in analysts' primary industries*	0.0077	-0.0166	-0.5005	0.4126	0.6629
(3)	Forecasts by all the other analysts	-0.0113	-0.0432	-0.5173	0.3924	0.6576
(3.1)	*When in analysts' primary industries*	-0.0120	-0.0443	-0.5179	0.3913	0.6567
(3.2)	*When not in analysts' primary industries*	-0.0087	-0.0384	-0.5161	0.3964	0.6607
T-test statistics for mean forecast error:						
(1.1)-(1.2)		-3.89***				
(2)-(3)		12.20***				
(2.1)-(3.1)		10.04***				
(2.2)-(3.2)		6.82***				
Wilcoxon-test z-statistics for median forecast error:						
(1.1)-(1.2)		-3.38***				
(2)-(3)		12.56***				
(2.1)-(3.1)		10.33***				
(2.2)-(3.2)		7.05***				
Number of observations		2,154,615				

Panel B: Fama-MacBeth regression analyses on cross-analyst comparison of earnings forecasting accuracy for "other" firms

This table presents a summary of the Fama-MacBeth regression for each other firm, which tests H3 on the cross-analyst variations of earnings forecasting accuracy for "other" firms between supply chain analysts and other non-supply chain analysts who follow the same "other" firm. The sample includes all forecasts issued for "other" firms. Note all firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers one or more of major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst portfolio. The dependent variable is forecasting accuracy, measured as a proportional absolute forecast error for a forecast relative to the average absolute forecast error using all forecasts issued for a firm in a fiscal period. *SUPPLY_CHAIN_ANALYST* is an indicator variable that equals 1 if a forecast is issued by a supply chain analyst, and 0 for forecasts issued by the other analysts. The column reports the mean coefficients based on 15,066 regression estimates for each of other firm-years using Equation (1). All coefficients have been multiplied by 100. The Fama-MacBeth t-statistics are computed based on the adjusted Newey-West (1987) standard errors to control for the heteroscedasticity and autocorrelation among the coefficient estimators. Two tailed t-statistics are in the parentheses. ***, **, and * are marked at the 1%, 5%, and 10% significance level respectively based on the one-tailed p-value. Definitions of all the other variables are in Appendix 3.1.

Independent variables	Predicted sign	Dependent variable: FORECAST_ERROR	
		(1)	(2)
INTERCEPT	(+/-)	-14.352*** (-7.61)	-14.664*** (-7.54)
SUPPLY_CHAIN_ANALYST	-	1.419** (1.71)	1.428** (1.70)
SUPPLY_CHAIN_ANALYST * PRIMARY_INDUSTRY	-		-0.117 (-0.43)
PRIMARY_INDUSTRY	-	-0.629* (-1.47)	-0.642* (-1.47)
HORIZON	+	0.083 *** (33.39)	0.076*** (30.41)
YEAR_EXP	-	-1.869*** (-8.19)	-1.869** (-8.19)
NUMBER_SIC1	+	0.667*** (3.23)	0.573*** (2.97)
LOG_BROKER_SIZE	-	-0.746*** (-4.10)	-0.735*** (-3.93)
Number of observations		15,066	15,066

Table 3.9: Determinants of analysts' choice of the focal firms and the major customer firms

Panel A: Descriptive statistics of the variables used in analysts' choice of the focal firms and the major customer firms

This table provides descriptive statistics for the variables used in the regression analyses for analysts' choice of the focal firms and the firms' major customers. Firm characteristics of the focal firms and their major customers are reported in column (1). The corresponding firm characteristics for the other firms in the analyst coverage portfolio are reported in column (2). Note all firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers one or more of the major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst's portfolio. All variables are defined in Appendix 3.1. Two tailed t-statistics are marked ***, **, and *, respectively, at the 1%, 5%, and 10% significance levels.

Variables	Focal firms and the major customer firms (1)	Other firms in the portfolio (2)	T-statistics (p-value) (1)-(2)
INVESTMENT_BANKING	0.0032	0.0013	3.56*** (<0.01)
LOG_TRADINGVALUE	17.225	16.824	14.52*** (<0.01)
LOG_NO_FIRM_SIC1	6.876	6.715	19.29*** (<0.01)
PRIMARY_INDUSTRY	0.730	0.756	-4.86*** (<0.01)
SALE_GROWTH	0.197	0.358	-2.02** (<0.01)
MARKET_TO_BOOK	2.815	3.265	-3.33*** (<0.01)
ROA	0.036	0.042	-2.74** (0.01)
AD_RATIO	0.008	0.012	-1.87* (0.09)
RD_RATIO	0.088	0.361	-3.12*** (<0.01)
Number of observations	5,542	26,104	

Panel B: Pearson correlation for the variables in multivariate analyses on analysts' choice of the focal firms and the major customer firms (N= 31,616)

VARIABLES	SUPPLY_ CHAIN_ FIRMS	INVEST MENT_ BUSINESS	LOG_ TRADING _VALUE	LOG_ NUMBER_ FIRM_SIC1	PRIMARY_ INDUSTRY	SALE_ GROWTH	MB	ROA	AD_ RATIO	RD_ RATIO
SUPPLY_CHAIN_FIRMS	1.000									
INVESTMENT_BUSINESS	0.001 (0.813)	1.000								
LOG_TRADING_VALUE	0.090 (<0.001)	0.030 (<0.001)	1.000							
LOG_NUMBER_FIRM_SIC1	0.111 (<0.001)	-0.008 (0.164)	0.077 (<0.001)	1.000						
PRIMARY_INDUSTRY	0.001 (0.888)	0.011 (0.058)	0.035 (<0.001)	0.151 (<0.001)	1.000					
SALE_GROWTH	-0.006 (0.350)	-0.001 (0.913)	-0.012 (0.051)	0.008 (0.159)	0.004 (0.457)	1.000				
MB	-0.010 (0.084)	-0.001 (0.875)	0.053 (<0.001)	0.012 (0.042)	0.002 (0.711)	0.003 (0.580)	1.000			
ROA	-0.016 (0.006)	-0.002 (0.730)	0.115 (<0.001)	0.042 (<0.001)	-0.017 (0.003)	-0.013 (0.024)	0.012 (0.050)	1.000		
AD_RATIO	-0.010 (0.096)	-0.002 (0.737)	0.015 (0.012)	-0.008 (0.172)	0.007 (0.214)	0.001 (0.879)	0.029 (<0.001)	-0.034 (<0.001)	1.000	
RD_RATIO	-0.009 (0.146)	-0.001 (0.870)	-0.021 (<0.001)	0.001 (0.926)	0.006 (0.296)	-0.001 (0.913)	0.003 (0.662)	-0.148 (<0.001)	0.025 (<0.001)	1.000

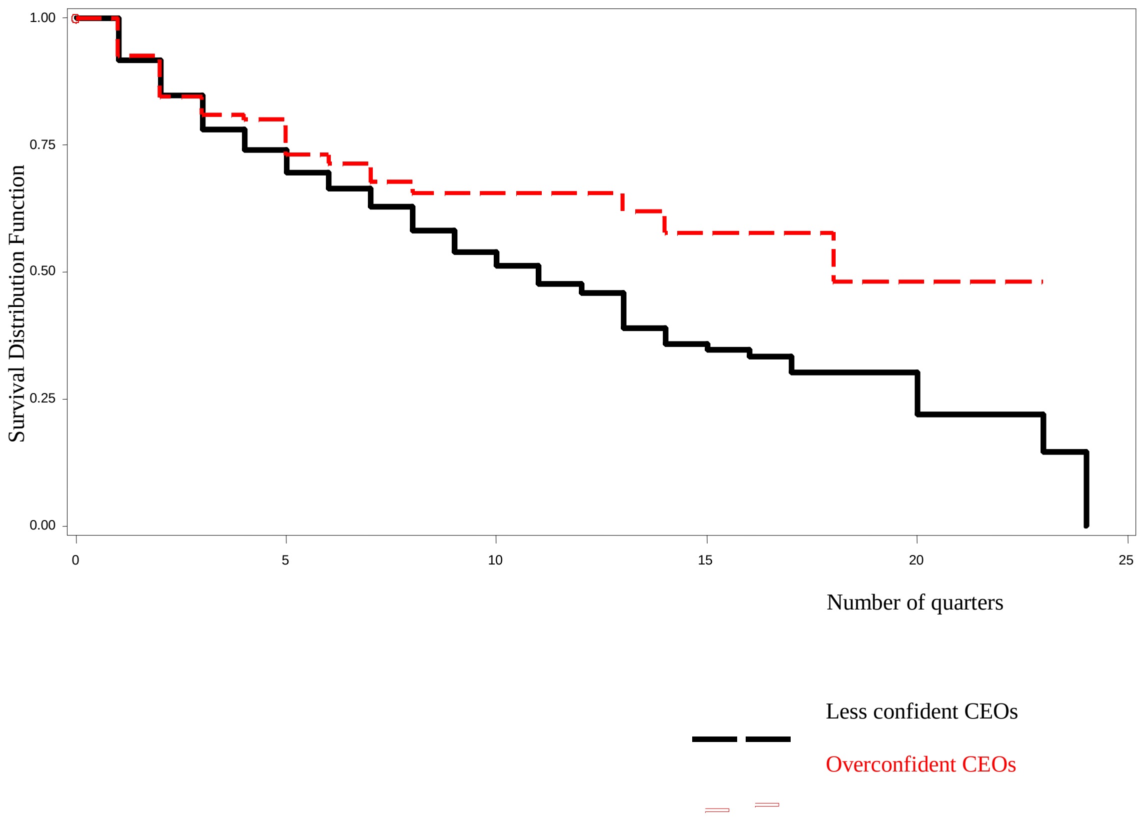
Two tailed p-values are reported in the parentheses.

Panel C: Conditional logit regression on determinants of analysts' choice of the focal firms and the major customer firms

This table examines the determinants of analysts' choice of the focal firms and the major customer firms. The dependent variable, *SUPPLY_CHAIN_FIRMS* equals 1 if a firm is a focal firm or a major customer of a focal firm, and 0 for "other" firms in same analyst's portfolio. The sample comprises 31,616 supply chain analyst-firm-years observations over the sample period with the necessary financial data. Note all firms followed by each supply chain analyst are classified into one of the three groups: focal firms, i.e., for firms for which an analyst also covers at least one major customers, major customers of a focal firm for the analyst, and "other" firms which include all remaining firms in the analyst's portfolio. Definitions of the variables are in Appendix 3.1. The z-test statistics are reported in the parentheses. ***, **, and *, are marked based on one-tailed z-statistics at the 1%, 5%, and 10% significance levels respectively. Marginal effects for each independent variable in the full model are calculated as the change in the probability that a firm is chosen to be a focal firm or a major customer firm for a unit change of the independent variables.

Independent variables	Predicted sign	Dependent variable: SUPPLY_CHAIN_ FIRMS			
		(1)	(2)	(3)	Marginal effects (4)
INVESTMENT_BANKING	+	0.015 (0.04)		-0.185 (-0.48)	-0.00015
LOG_TRADINGVALUE	+		0.153*** (14.00)	0.161*** (14.15)	0.00012
LOG_ NUMBER_FIRM_SIC1	+			0.686*** (13.07)	0.00051
PRIMARY_INDUSTRY	+			-0.078* (-1.93)	-0.00005
SALE_GROWTH	+			-0.123*** (-3.86)	-0.00009
MARKET_TO_BOOK	+			-0.004** (-1.92)	-0.00000
ROA	+			-0.901*** (-6.46)	-0.00067
AD_RATIO	+			-3.294*** (-3.94)	-0.00246
RD_RATIO	+			-0.042** (-1.65)	-0.00003
Pseudo-R squared		0.000	0.01	0.033	
Number of observations		27,360	27,334	27,169	

Figure 2.1: Survival rate for overconfident CEOs versus less confident CEOs



The figure represents the survival function of the initial forecasting behavior for 168 overconfident CEOs and 201 less confident CEOs. The x-axis represents the time dimension of the survival function, measured by the cumulative number of quarters since the managers issue their first forecasts. The y-axis is the probability of survival of managers' initial forecasting behavior.

Figure 2.2: Timeline of events in the model