Private communications between financial analysts and firm managers: Evidence from China

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Abstract

The thesis comprises three empirical chapters based on a unique dataset from China: corporate site visits. Chapter 2 investigates the impact of the frequency of corporate site visits on the precision of management earnings guidance. In Chapter 3, I study whether sell-side financial analysts' social network improves analysts' forecast accuracy. Chapter 4 identifies analyst-manager collusion in meeting minutes of corporate site visits.

In chapter 2, I find that more frequent corporate site visits before the release of management range guidance leads to more precise management earnings guidance. This effect is stronger for firms with higher information uncertainty and lower information processing capacity, suggesting that firm managers acquire information from financial analysts to reduce earnings uncertainty. I find little empirical support for the organizational impression management explanation that managers proactively release more precise forecasts to impress investors.

In chapter 3, I find that sell-side financial analysts' social network improves analysts' forecast accuracy. Specifically, analysts with a more central position in social networks (higher eigenvector centrality) based on corporate site visits generally have more face-to-face opportunities to learn from their peers, significantly improving their forecast performance. Such a social learning effect exists when more influential peers attend corporate site visits and when forecasted firms with higher information uncertainty.

In chapter 4, I identify a more implicit way for analyst-manager collusion during corporate site visits. Specifically, I observe that analysts engage in collusion when firms announce the proposal of seasoned equity offerings (SEOs) due to competition for potential underwriting mandates. Then, affiliated analysts participate in collusion to defend their client firms' stock prices, especially when client firms are experiencing a challenging time. These collusions have a discernible impact on market reactions and provide analysts with a notable informational advantage. The interpretation behind could be that analysts operate discreetly hidden in teams of visitors made up of multiple institutions, allowing them to assist management implicitly without risking damage to the individual analyst's reputation. Overall, my study uncovers a novel venue of analyst-manager collusion.

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Contents

List of tables

Chapter 2 Tables

Chapter 3 Tables

Chapter 4 Tables

List of figures

Chapter 2 Figures

Chapter 4 Figures

Abbreviations

COVID-19: Coronavirus disease 2019

CSA: China Securities Association

CSRC: China Securities Regulatory Commission

CSV: corporate site visits

DID: differences-in-differences

IPO: initial public offerings

MRG: management range guidance

OIM: organization impression management

OLS: ordinary least squares

PSM: propensity score matching

RDD: regression discontinuity design

ROA: return on assets

SEO: seasoned equity offerings

SOE: state-owned enterprise

SSE: Shanghai Stock Exchange

SZSE: Shenzhen Stock Exchange

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Chapter 1 Introduction

1.1 Introduction

This thesis aims to study the impact of private communications between financial analysts and firm managers on the financial market based on a unique database in China: corporate site visits (CSV). Private communications between financial analysts and firm managers have been a key topic in capital markets. For example, Pike et al. (1993) indicate that analysts' meetings and discussions with firm managers are more significant than reading firm's annual or interim reports. Notably, Holland (1998) underscores analysts' attention toward qualitative aspects, a substantial portion of which is conveyed through confidential communication channels.

China's financial markets are often criticized for strong information asymmetry and deep-seated agency problem (Liu et al., 2016). Compared with mature markets, information disclosure in China lacks comprehensiveness and transparency (Dedman et al., 2017). Especially for Shenzhen Stock Exchange (SZSE), a large number of small and medium-sized companies and family firms exacerbate information asymmetry and corporate governance issues. In this case, the SZSE's mandatory requirement for companies to disclose meeting minutes of corporate site visits is intended to reduce information asymmetry in the Shenzhen market. However, it may also become a means for companies to impress investors through strategic disclosure, thereby exacerbating information asymmetry. Therefore, this study investigates whether the private interaction between analysts and firm managers on SZSE has possible effects on the financial market.

This chapter will be divided into the following parts: Section 1.2 introduces institutional background. Section 1.3 introduces theories related to private interactions between financial analysts and firm managers. Section 1.4 introduces the research purpose and motivation. Section 1.5 demonstrates my main findings from three empirical chapters. Section 1.6 elaborates the contribution of this study. Section 1.7 discusses the practical significance of this study, including implications for firm managers, financial analysts, investors, and regulators. Finally, Section 1.8 illustrates the structure of the remaining chapters of the thesis.

1.2 Institutional back ground

1.2.1 Institutional background of financial analysts

There are two primary types of financial analysts: sell-side analysts and buy-side analysts. Sell-side analysts operate within the equity research divisions of investment banks, where they formulate and disseminate earnings forecasts, buy/hold/sell recommendations, and price targets. They produce research reports intended for use by investors, including fund managers and buy-side analysts (Imam and Spence, 2016). Conversely, buy-side analysts are employed by fund management firms. They utilize information sourced from sell-side analysts and other channels to inform portfolio decisions. Similar to sell-side analysts, they compile confidential research reports for their employers (i.e., fund management firms) but refrain from making them publicly available (Imam and Spence, 2016). Given these distinctions, it is unsurprising that the motivations and objectives of buy-side analysts diverge from those of sell-side analysts (Groysberg et al., 2008; Imam and Spence, 2016).

The research on financial analysts is crucial for understanding capital markets (Imam and Spence, 2016). Acting as information intermediaries, analysts' activities shed light on market mechanisms and the types of information influencing share prices (Imam and Spence, 2016). Considerable evidence indicates that analysts' stock recommendations significantly impact trading behavior and stock market valuations (e.g., Asquith et al., 2005; Frankel et al., 2006; Ho, 1995; Ryan and Taffler, 2006; Womack, 1996; Twedt and Rees, 2012). Consequently, fluctuations in stock market valuations affect a firm's capital-raising capability, overall reputation, investment strategy (e.g., acquisition strategy), compensation policies (e.g., executive pay levels), as well as the reputation and career trajectories of top executives (Kuperman, 2003; Hayward and Boeker, 1998).

However, there are also substantial evidence in the accounting and finance literature supporting that analysts' work is subjective and susceptible to bias (O'Brien et al., 2005). For instance, Fogarty and Rogers (2005) demonstrate that financial analysts are influenced by their institutional environment and overly reliant on management as an information source. Analysts may compromise their independence to maintain client satisfaction and secure future revenue streams. Additionally, Westphal and Clement (2008) illustrate that social influence and reciprocal behavior in the analyst-manager relationship may discourage analysts from downgrading stocks in response to negative company information. Theoretically, by issuing negative recommendations following poor firm performance or strategic actions, analysts can redirect capital and resources away from underperforming firms and self-interested managers toward more effective and productive endeavors (Westphal and Clement, 2008). Thus, analysts can potentially mitigate agency costs and uphold allocative efficiency in financial markets (Jensen, 2004; Zuckerman, 2000). Nevertheless, cross-social factors within the analyst-manager relationship may undermine corporate oversight and financial market efficiency by compromising the objectivity of analysts' stock recommendations. Therefore, this paper attempts to identify scenarios that may enhance analysts' forecast performance as well as comprise analysts' independence.

1.2.2 Institutional background of corporate site visits in China

Normally, analysts can obtain firm information through site visits, road shows, conference calls, and forums with firm management teams and/or employees (Bushee et al., 2018; Green et al., 2014; Solomon and Soltes, 2015). Corporate site visits are an increasingly important form of information acquisition especially for institutional investors and financial analysts (Abramowitz, 2006; Brown et al., 2015; Jackson, 2009). According to Cheng et al. (2016, 2019), analysts can mitigate information asymmetry by taking a closer look at the firm's production activities and operating plants during site visits and conducting face-to-face meetings with the management team and employees. Through site visits, investors can visit firm headquarters or manufacturing facilities, inspect production lines or job sites, talk face-to-face with top managers, assess employee morale, and experience organizational culture firsthand. These interactions allow investors and analysts to gain a deeper understanding of the firm's business and operating conditions, future prospects, and business risk exposures (Brown et al., 2015; Cheng et al. 2016, 2019; Jiang and Yuan, 2018). Therefore, site visits are a more direct and vivid way of obtaining information than conference calls or on-line forums.

All investors can request site visits of listed firms, and listed firms will try their best to meet these requests. Although individual investors play an important role in China's capital markets, they rarely visit listed firms because the time and effort required and the fees incurred are not cost-effective for them (Jiang and Yuan, 2018). Therefore, most site visits delegations are composed of institutional investors and equity research analysts from brokerage firms. Through site visits, analysts can not only obtain firm information but also supervise corporate behavior (Song and Xian, 2024).

Despite the importance of site visits, prior to 2008, information about corporate site visits would not be disclosed to the public. In order to level the playing field, since 2009, the Shenzhen Stock Exchange (SZSE) has implemented new disclosure rules, requiring all listed firms on the SZSE to disclose information on how the firm manages investor relations, including site visits by investors. This disclosure rule makes site visits information that would have been available only to participants now available to the public. In 2006, the Shenzhen Stock Exchange issued Article 41 of the “Guidelines for the Investor Relations Management” to encourage listed firms to meet the requirements of investors and market participants for site visits. In 2009, the SZSE required its listed firms to disclose their investor communication records (e.g., site visits, private internal meetings, conference calls, emails) in their annual reports. Among them, corporate site visits only need to disclose basic information, including the identity of the visitor, the date and location of the visit. In order to ensure comprehensive and timely disclosure of site visits to the public, the SZSE issued new regulations in July 2012. The regulations require firms to disclose details about site visits on stock exchange portals within two trading days of the visit. The Shanghai Stock Exchange (SSE) encourages but does not require such disclosures, and as of December 2019, only 161 SSE-listed firms had released such information (Jiang et al., 2022). Corporate site visits are also popular in European and American markets, but few other markets regulate the disclosure of such information. Therefore, this SZSE regulation provides a valuable opportunity to study how private communications between financial analysts and firm managers affect China’s financial markets.

1.3 Research objectives and motivation

The research objectives of this thesis include: 1) investigating the impact of private interaction between financial analysts and firm managers on information exchange and knowledge sharing; 2) evaluating the role of private interaction in shaping analysts’ perceptions, forecasts, and recommendations regarding firm performance and prospects;

3) exploring the mechanisms through which private interactions influence market perceptions, investor decisions, and stock price movements. 4) examining the potential benefits and drawbacks of private interactions for both financial analysts and firm managers in terms of information advantage, decision-making effectiveness, and market outcomes; 5) identifying factors that moderate the effects of private interactions, such as firm characteristics, industry dynamics, and regulatory environments.

To motivate my research, the question of the effect of private interaction between financial analysts and firm managers is influential but under-explored. Understanding the dynamics of private interaction is critical to clarify the information exchange process of the financial market. Examining the impact of private interaction on market results can enhance the understanding of the effect of market transparency and investor protection for decision makers, regulators and market participants. Factors that affect the effectiveness of private interaction can help firms and analysts optimize their communication strategies and decision-making processes in order to achieve better results in the market.

However, numerous theories provide contradict predictions by indicating both positive and negative effects. For example, from the perspective of social networks, social cognitive theory posits that private interaction has facilitated the expansion of the social network of analysts and managers, thereby fostering the exchange of information, sharing of knowledge, and enhancing the information advantages and skills of both parties. In contrast, social transmission theory suggests that private interactions may also propagate biases, such as overconfidence. Additionally, the abundance of information generated in private interactions may lead to information illusions, fostering illusion of control in both parties and underestimation of other potential risks. Ultimately, private interactions could potentially lead to collusion between analysts and managers to the detriment of third parties, such as investors, in pursuit of their own profits. The impact of collusion can be severe, particularly since investors heavily rely on analysts' recommendations to make investment decisions (DeBondt and Thaler, 1990; Imam and Spence, 2016). Hence, the conflict in theoretical expectations encouraged me to present additional empirical evidence for a comprehensive understanding of private interactions through identifying diverse contexts, and corporate site visits serve as a rare portal to study private interactions between financial analysts and firm managers.

1.4 Theories related to private interactions

As mentioned above, numerous theories document both positive and negative effects of private interaction between financial analysts and firm managers. Therefore, in this section, I introduce social cognitive theory, social transmission theory, information illusion theory, and collusion. In the empirical chapters of this thesis, I provide a separate literature review and discuss the hypothesis development for each specific topic.

1.4.1 Social cognitive theory

The significance of acquiring knowledge through social interactions has been recognized by scholars such as Marshall (1890) and Lucas (1988). Social learning hypothesis, grounded from the widely acknowledged theory that social cognitive theory (Bandura, 1977), highlights the notion that people learn by observing and imitating others, particularly those held in an admired status, as a fundamental aspect of human learning.

Social cognitive theory is an interpersonal-level approach that describes the process of ongoing and active learning through the observation of others. It brings together various components from fields such as psychology, sociology, and political science. It places great emphasis on the importance of observation and cognition in comprehending and anticipating learning and conduct (Glanz et al., 2015). According to this theory, human behavior is the outcome of interactions between personal, cognitive, behavioral, and environmental factors.

Social cognitive theory has a distinctive approach that recognizes the social origins of human thoughts and behaviors (Bandura, 1986; Glanz et al., 2015). Bandura proposes that human behavior is shaped by personal factors, behaviors, and environment. Human interactions are bidirectional, involving one’s thoughts, emotions, biological characteristics, and behaviors (Bandura, 1977; 1986; 1998). From a psychological perspective, Social cognitive theory emphasizes that behavior, environment, and cognition are key factors in development. Bandura (1977) focused on observational learning, which acquiring a wide range of behaviors, thoughts, and emotions through observing others' behaviors. These observations are an important part of lifespan development (Govindaraju, 2021). In Bandura (1986; 1999; 2000)'s contemporary models of learning and development, he explains how individuals develop and maintain specific patterns of behavior, and how their involvement approach is affected in the process. The theory emphasizes the importance of an individual's opinions, attitudes, and knowledge in the processes that occur between external stimuli and real-life reactions.

The environment is a significant factor that can influence an individual's behavior, including both social and physical environments. The former includes family, friends, and colleagues, while the latter encompasses factors such as room size, temperature, and access to certain foods. Environments and situations construct a framework for understanding behavior (Parraga, 1990). Situations are cognitive or psychological representations of the environment that can impact behavior (Glanz, 2002). The three elements of environment, people, and behavior are interconnected and can affect each other. The environment provides a model for behavior, and observational learning occurs when individuals observe others' behavior and the resulting reinforcements (Bandura, 1999).

Researchers often use social cognitive theory to analyze the relationships between personal, behavioral, and environmental factors and to help individuals achieve effective self-adjusting learning. The theory posits a multifaceted causal structure in which beliefs about self-efficacy influence motivation, behavior, and well-being. In addition, values-based recognized goals provide additional self-incentives and guidelines for healthy behavior (Bandura, 1986). Social cognitive theory emphasizes that beliefs about efficacy serve as one of many determinants of motivation, emotion, and behavior.

Human efficiency is grounded in cognition, which involves acquiring, organizing, and developing information. In recent years, cognitive research has focused on information processing, schemata, and action control, while social cognition emphasizes theoretical processes during social interactions. Social cognition refers to the ability to act wisely in social communication (Hogarty and Flesher, 1999), including reading others' thoughts, understanding their perspective, and empathizing (Tuch, 1999). Social cognition is both a set of specific cognitive skills and a field of study that encompasses linguistic and nonverbal communication, empathy, relationships, group processes, social communications, stereotypes, and attribution bias memory (Kar and Kar, 2002). It also relates the problems of psychological control of social cognitive practices and the cognitive origin of "self-awareness" (Govindaraju, 2021).

Social cognition utilizes information processing theory's basic elements, such as responsiveness, awareness, coding, remembrance, and search. Social cognition helps individuals understand the subtleties of group interaction and implicit rules of social interaction games. Individuals who struggle to understand linguistic and nonverbal communication, emotional nuances, or group functions may have difficulty if succeeding socially and feel vulnerable and uncomfortable in social situations (Tuch, 1999). Social cognition research also includes metacognitive monitoring, which involves paying attention to thought categories, content mistakes, contradictions, and false logic. This encompasses various processes such as formulating plans, monitoring activities, evaluating outcomes, and expanding knowledge on effective strategies for addressing specific situations. This knowledge can be applied to make informed decisions regarding educational strategies and problem-solving techniques. Social cognitive research has consistently highlighted certain themes, such as people's aptitude for observing social interactions, drawing inferences from behavioral patterns, stories, stereotypes, and traits (Fiske, 1992). Social cognitive theory emphasizes the interconnectivity between social perception and interaction, as well as the role of activity in enhancing competence and efficiency (Fiske, 1992).

Bandura's theoretical framework of efficacy expectations identifies four primary sources, including "performance accomplishments", which involve using past experiences to achieve success, as well as the act of performing itself. "Vicarious experiences" refer to observing others who have succeeded and understanding their behaviors and strategies for success. "Social persuasion" involves the power of groups or individuals to influence others through verbal persuasion or leading by example. Lastly, "emotional states" refer to the management of emotions to improve performance.

The magnitude of efficacy expectations can vary in strength and generality depending on the complexity of the task. According to Bandura (1977), efficacy beliefs have a significant impact on cognitive, emotional, motivational, and decision-making processes, as they influence how people think, feel, and behave in achieving their goals (Bandura, 1977).

In line with this theory, in chapter 3, I find that financial analysts produce more accurate earnings forecasts if they are more central in the social network based on corporate site visits. Hence, my results support that analysts can learn from peers during corporate site visits.

1.4.2 Social transmission theory

Social transmission is defined as "the process by which attitudes, values, beliefs, and behavioral scripts are passed onto and acquired by individuals and groups (Cavalli-Sforza and Feldman, 1981; Richerson and Boyd, 2005)". Applying this concept to behavioral studies, Cheng et al (2021) propose that overconfidence can spread within the group and can scale up to create group-wide overconfidence. In this case, groups with rampant overconfidence that may be especially vulnerable to risky decision making. They further conduct a series of experiments to confirm that observing overconfident peers causally increases an individual's degree of overconfidence bias. The transmission effect persists over time and across task domains, with overconfidence rising even days after the initial exposure. Moreover, overconfidence can be transmitted via indirect social ties (person to person to person) but only acquired when members in the same group, consistent with the theoretical concept of selective learning bias. Hence, one may argue that firm managers may acquire overconfidence from visitors during corporate site visits because site visits provide a platform for social transmission between mangers and visiting analysts.

1.4.3 Information illusion theory

Organizational information availability refers to how readily available different types of environmental information are to top managers in the organization (Kuvaas, 2002). From the perspective of behavioral decision-making, the availability of information may increase managers' illusion of control simply because they know that information is available or that access to information is being taken care of and institutionalized (Kuvaas, 2002). In particular, research on positive illusions has shown that information may increase the occurrence or magnitude of overconfidence (e.g. Davis et al., 1994; Oskamp, 1965). First, investigations of psychological diagnosis (Oskamp, 1965), consumer decision-making (Jacoby et al., 1974a, 1974b), financial decision-making (Davis et al., 1994) and venture capitalists' investment decisions (Zacharakis and Sheperd, 2001) have shown that people tend to feel more confident about a decision or judgment when they have more information available. Secondly, information can increase people's perceptions and inspire confidence in the organization's ability to deal with problems. Information itself symbolizes rationality and competence and may generate a belief among managers that organizations with more information are better than those with less information (Feldman and March, 1981; Langley, 1989). Similar to the phenomenon that the illusion of control, this general confidence in the organization may lead managers to overestimate the organization's skills in dealing with problems. Furthermore, the effort put into organizational information activities may lead to a feeling that 'no stone was left unturned' (Eisenhardt, 1989) or that the necessary information is always available when it is needed. Thus, even without using or analyzing the information provided by organizational information activities, the availability of information may have a symbolic and ritualistic function, allowing managers to gain a sense of mastery and control and thus perceive problems as more controllable and manageable. If the availability of information has such a comforting effect on managers, then they will be more confident in their estimates of the organization's future performance. Therefore, managers of information-intensive organizations, who are exposed to more information, feel a higher degree of control (Kuvaas, 2002).

1.4.4 Collusion

The etymology of the term integrates two elements: "play" (lūdere) and "together" (col), e.g. to "have a secret agreement" (Hoad, 1993). The etymology of the words may suggest a generally positive connotation of cooperation, while the common understanding of "collusion" suggest that acts have more negative value than cooperations. Thus, if "collusion" and "cooperation" are equally social in nature, they need to be distinguished on the basis of different motivations. For example, many informal definitions of “collusion” invoke cheating, illegality, and deception (Crook and Nixon, 2019).

Collusive behaviors rely on two meanings of sociality. First, the plan requires human interaction. Second, the impact of such a plan includes a significant social consequence: some other people will not experience things as they actually should or as they expect (Crook and Nixon, 2019). A plan must involve concealment if it has consequences designed to upset the expectations of others. Collusion, therefore, needs to be kept secret from at least some of those affected by its consequences. As McGowan (2016) points out, this social aspect is at the root of the complexity of the concept, which makes cases of “task collusion” particularly difficult to judge and predict.

In sum, the term “collusion” describes how two or more people can deliberately undermine the transparency of a state of affairs as understood by others. It is a combination of sociality, intent, and concealment. Daily collusion events can be characterized as “local collusions” (e.g. Borg, 2009), meaning that they can only be confidently identified through knowledge of the local context and the expectations of the actors involved. In contrast, “institutional collusion” is much clearer. In these cases, the violated “understanding” or “expectation” exists as a set of external rules or principles that are defined, shared, and required by certain institutional communities (e.g., securities practitioners). The occurrence and judgment of collusion against these rules can be of great concern to these communities because it can undermine valuable goals or values.

Collusion appears to be easier to judge when the violation is of a clear and formalized institutional expectation, rather than an individual’s uncertain expectation. Indeed, institutional contexts are useful because they provide stable regulatory frameworks within which any complexities in the social dynamics of collusion can be more carefully considered.

1.5 Main findings

To advance understanding of private interactions between firm managers and financial analysts, this thesis consists of three studies examining the role of corporate site visits in financial markets at the firm level, at the financial analyst level, at the site visit level, respectively. Chapter 2 investigates the impact of corporate site visits on the precision of management range guidance (MRG). Chapter 3 explores the effect of corporate site visits on the accuracy of financial analysts' earnings forecasts. Chapter 4 identifies analyst-manager collusion during corporate site visits. Each chapter can be read independent of each other, but all three chapters also share the common objective of investigating the effects of private communications between firm managers and financial analysts, on the basis of a unique dataset of corporate site visits in China.

In chapter 2, I examine the role of corporate site visits on the precision of management range guidance (MRG). I find that more frequent site visits before the release of MRG contribute to more precise guidance. The results are robust to alternative measures of site visits and the precision in MRG, propensity score matching (PSM) method, Heckman two-step selection method, instrumental variables and subsample analysis that aim at addressing reverse causality. I then conduct a battery of tests to uncover the underlying mechanisms for the relationship between corporate site visits and MRG. I find supporting evidence for the information advantage mechanism where more information contributes to more precise MRG. More specifically, corporate site visits have a stronger amplifying effect on MRG precision when firms have higher information uncertainty or firms with lower information processing capacity. I find opposite evidence for the organizational impression management hypothesis that managers strategically publish precise MRG to impress current and potential investors. Therefore, the findings of chapter 2 support social cognitive theory but reject information illusion theory and social transmission bias theory.

In chapter 3, I find that sell-side financial analysts with higher eigenvector centrality of the social network based on corporate site visits provide more accurate earnings forecasts. These findings withstand various sensitivity analyses, encompassing alternative measures of forecast precision, Heckman two-step selection method, instrumental variable, and subsample analyses designed to mitigate concerns regarding reverse causality. Subsequently, corroborative evidence is uncovered for the social learning mechanism. Specifically, it is established that the influence of the social network on forecast accuracy persists under conditions where: 1) there is a greater presence of influential peers during corporate site visits, and 2) forecasted firms exhibit heightened levels of information uncertainty. Therefore, again, the findings of chapter 3 support social cognitive theory.

In chapter 4, I identify a more implicit way for analyst-manager collusion that analysts ask positive questions during corporate site visits. To be more specific, analysts engage in collusion with the purpose of marketing their affiliated investment bank if the firm announces the proposal of seasoned equity offerings (SEO), and affiliated analysts engage in collusion with the purpose of defending client firms' stock prices, especially when their client firms encounter challenging times. The results of collusion with the purpose of marketing are robust to the differences-in-differences (DID) method. Furthermore, I explore the benefits for firm managers and analysts through collusion. My research reveals a notable positive market reaction to corporate site visits accompanied by optimistic questions, especially when firm managers respond with a similar positive tone. Affiliated analysts may possess an informational advantage compared to unaffiliated analysts. For instance, they may have early access to forthcoming SEO information from client firms. Moreover, I find that the motivation behind analyst-manager collusion during corporate site visits may stem from a hiding effect. my findings reflect analyst' inclination to participate in collusion by posing positive questions during corporate site visits because this collusion enables them to discreetly operate within the diverse institutions forming the visitor team, covertly aiding firm managers without compromising their personal reputation. Hence, the findings of this chapter support the collusion theory.

1.6 Research contributions

My contribution is multifaceted. First, I add to the theoretical research on managerial learning by examining the private interactions between managers and analysts. Despite the previous literature's interest in information transfer between managers and analysts (e.g., Ajinkya et al. 2005; Karamanou and Vafeas 2005; Han et al. 2018), there is little empirical evidence on the effects of reciprocal flows of knowledge from analysts to managers due to the rarity of private interaction data. This study, by focusing on the effect on the precision, rather than accuracy, of MRG, contributes to the literature on the information content of MRG. In this "age of the information revolution," where the internet and information systems provide managers with an unimaginable variety of information, the impact of the information environment is of great importance to both management theory and practice (Kuvaas, 2002).

Second, this study contributes to the growing body of research on the social learning hypothesis in finance (Kumar et al., 2022). Unlike previous studies, this study provides a more direct proxy for the peer effect on analysts. Distinct from most previous studies that define peer analysts issuing earnings forecasts for the same firm (e.g. Trueman, 1994; Welch, 2000), this study quantifies the peer effect based on face-to-face interactions using a unique dataset of corporate site visits in China. The valuable dataset allows me to construct a robust social network of analysts, as I believe that if analysts participate in a corporate site visit to the same firm, they should have face-to-face interactions and build strong relationships with each other. To the best of my knowledge, this study is the first to construct an analyst social network based on corporate site visits to measure analyst peer effects.

Third, I find a more insidious way of collusion between analysts and managers. To the best of my knowledge, this study is the first to find collusion between analysts and firm managers in the context of corporate site visits, rather than focusing on analysts' forecasts (e.g. Westphal and Clement 2008). This form of collusion is hidden in private interactions and is inherently more difficult to capture.

Furthermore, I also reveal the dark side of corporate site visits. Previous studies have extensively documented the bright side of corporate site visits, e.g., improving the accuracy of analysts' forecasts (Cheng et al., 2016), improving the accuracy of management's earnings forecasts (Chen et al., 2022), fostering corporate innovation (Jiang and Yuan, 2018), and reducing earnings management (Qi et al., 2021). In contrast, my findings suggest that corporate site visits may also serve as a communication platform for analysts to collude with managers.

Finally, I attempt to explore the motivations of corporate site visits in different contexts, thereby deepening the understanding of the motivations. Corporate site visits may originate from analyst-initiated or firm manager-initiated. Previous studies have focused on the consequences of corporate site visits (e.g., Chen et al. 2022; Cheng et al. 2016; Jiang and Yuan 2018; Qi et al. 2021), but little is known about the motivations behind it. The findings of my study suggest that analysts are highly motivated to visit firms to market their affiliated investment banks if a firm announces the proposal of SEO. Instead, firm managers may invite affiliated analysts to visit if the firm is experiencing a challenging time.

1.7 Research implications

This study has essential implications for firm managers, financial analysts, investors, and regulators. For firm managers, the paper suggests prioritizing the development and maintenance of robust relationships with financial analysts, emphasizing the value of interaction in mitigating uncertainty surrounding forecast returns. Proactive and enhanced communication, such as organizing site visits, meetings or conference calls, is encouraged to facilitate information exchange. It is crucial, however, to remain vigilant about ethical considerations, avoiding collusion with analysts to provide insider information. Collusion carries the potential for reputational damage, heightened earnings uncertainty, increased capital costs, and the risk of firm collapse.

Financial analysts, on the other hand, can build strong social networks through corporate site visits. Establishing strong ties with firm managers can provide an informational advantage, and a robust social network can contribute to knowledge and forecasting skill enhancement through interactions with peers. However, analysts must navigate ethical dilemmas during site visits, particularly concerning potential involvement in analyst-manager collusion. Striking a delicate balance between professional ethics and potential benefits is paramount.

Investors, who heavily rely on equity recommendations from professional financial analysts (DeBondt and Thaler, 1990; Imam and Spence, 2016), are advised to consider an analyst’s social network when evaluating forecast quality, favoring those actively expanding face-to-face contacts. Nevertheless, caution is warranted regarding overly optimistic sentiments expressed during a firm’s SEO or by affiliated analysts influenced by strategic considerations of interests related.

For regulators, the thesis recommends a review and adjustment of existing regulations related to communication between firm managers and analysts. Striking a balance between encouraging productive interactions and ensuring fair access to information for all market participants is critical. Regulators can support social networking opportunities for financial analysts to foster collaboration and information sharing. Simultaneously, they are urged to monitor and enforce fair disclosure practices, investigate collusive behavior during site visits, and revise regulations to address challenges, particularly in SZSE where information asymmetry and corporate governance issues prevail.

1.8 Structure of the thesis

The remainder of the thesis consists of three empirical chapters and a conclusion chapter. Each of the empirical chapter is independent and normally contains five sections: introduction, literature review and hypotheses development, data and sample, empirical results and conclusion. The last chapter concludes the thesis by summarizing the main findings, identifying limitations and future research avenues.

Chapter 2 Beyond accuracy: How analyst site visits boost precision of management range guidance

2.1 Introduction

While existing evidence shows that analysts obtain information from managers during their face-to-face interactions with managers (Han et al., 2018, Cheng et al., 2016, Cao et al., 2023), the reciprocal flow of knowledge - how managers learn from analysts through these interactions - remains largely a blind spot. Such a knowledge gap is surprising in light of analysts' financial and industry expertise, which could be invaluable for managers to make more informed decisions.

This paper fills this gap by investigating whether direct analyst-manager interactions during corporate site visits influence management range guidance. I focus on the interactions during corporate site visits because they are unique information acquisition activities in which analysts regularly visit firms' headquarters (Cheng et al., 2016), which provide rare opportunities for managers and analysts to interact face-to-face and learn valuable information. On the one hand, face-to-face interactions help analysts gain more detailed and contextual information about firms. For example, Cao et al. (2023) find that analysts acquire information from managers during the site visits and disseminate more accurate analyst forecasts to investors of connected firms. On the other hand, analysts site visit enables managers obtain opinions and comments from professional analysts with financial and industry expertise, especially when analysts have obtained more information from other fundamentally connected firms. Hence, this paper examines the effect of direct analyst-manager interactions during corporate site visits on the precision of management range guidance.

I direct my attention to the earnings range guidance, as it is one of the most common forms of management earnings guidance that can significantly affect investors. Management earnings guidance is a voluntary disclosure on the majority of securities exchanges to provide insiders' views on the firm's future performance. It can take three forms: point guidance (i.e., earnings will be at a specific point), range guidance (i.e., earnings will fall into a range) and qualitative guidance (i.e., the future trend of earnings). In China, the second largest economy in the world by nominal GDP, the majority of firms chose to disclose range guidance (71.3% in my sample period) rather than point guidance. Investors in China heavily rely on management range guidance (MRG) to make investment decisions.[1]

Previous studies mainly focus on the accuracy of management earnings guidance (e.g., Ajinkya et al., 2005; Karamanou and Vafeas, 2005; Chen et al., 2022). In general, accuracy captures the reliability of the guidance and is widely defined as the absolute difference between the earnings guidance and the actual earnings. Since most management earnings guidance in China is in the form of range guidance rather than point guidance, researchers often substitute the midpoint of the range for the point guidance when calculating the accuracy of range guidance, i.e., calculating the absolute difference between the midpoint of the range and the actual earnings (e.g., Chen et al., 2022). This approach assumes that the midpoint of the range represents the firm managers' true expectation. However, many researchers (e.g., De Bondt, 1993; O'Connor et al., 2001; Du and Budescu, 2007; Ciconte et al., 2014; Zhu et al., 2022) show that this assumption is biased because firm managers' true expectations are less likely at the midpoint.

By studying MRG, I specifically focus on the precision of earnings guidance. Precision is another important aspect of management's earnings guidance. Because earnings guidance involves judgments about the likelihood of future business activities, precision can serve as an indicator of firm managers' confidence in their guidance. All else being equal, more precise MRG represents lower uncertainty about future business activities and it is often viewed as more informative and authoritative because it serves as a reliable signal for conveying information about firms' strong controls (Hayward and Fitza, 2017). Therefore, precise and detailed MRG is desirable because it helps investors better understand the link between guidance and future earnings (Leuz and Verrechia, 2000) and price stocks more accurately (Choi et al., 2011).

Prior research (e.g., Baginski et al., 1993; Ajinkya et al., 2005; Karamanou and Vafeas, 2005; Chen et al., 2022) has primarily relied on variations in the forms of guidance that

[1] To demonstrate the significance of MRG to investors in China, I conduct an event study as part of the robustness tests and find a significant market reaction to the release of MRG. Additionally, the market significantly reacts to MRG with increased site visits, suggesting that investors attach great importance to these visits.

managers adopt to measure precision. These studies treat point guidance as the most precise form, range guidance as the second most precise, and qualitative guidance as the least precise form. Such an approach, however, simply considers all range guidance as equal and overlooks the varying levels of information conveyed by the range guidance. Unlike them, my study directly evaluates the informativeness of range guidance by measuring the precision of range guidance. Following Hayward and Fitza (2017), I define the precision of MRG as the negative value of the difference between the upper bound and the lower bound of MRG. A higher value indicates higher precision. An increase in MRG precision indicates higher managers confidence in guidance, less uncertainty in future business activities and therefore a higher level of information content.

My test is based on a unique dataset of corporate site visits from the Shenzhen Stock Exchange (SZSE). While site visits are prevalent in the U.S. and Europe (Brown et al., 2015), firms generally do not release archival records of such visits (Cheng et al., 2016). In contrast, firms listed on the SZSE in China have been required to publicly disclose information related to site visits since 2009, providing a unique opportunity to study the direct interaction between managers and analysts during these visits. In addition, firms listed on the SZSE are primarily small and medium-sized, technology and innovation firms. The salient information asymmetry of SZSE firms underscores the need to understand the firms' information acquisition process.

What is the impact of corporate site visits on MRG? Two hypotheses predict that increased corporate site visits lead to more precise MRG. The first hypothesis is based on the information advantage theory, which posits that some economic agents can gain an advantage over others by having access to information that is not publicly available (Brockman et al., 2017; Bowen et al., 2018; Chapman and Green, 2017). Interactions in corporate site visits help managers acquire distinct and valuable insights from visitors who are often professionals in the investment domain, such as analysts, institutional investors, and mutual fund managers (Chen et al., 2022). These professionals possess a breadth of information beyond what is typically available to managers, encompassing industry-wide and macroeconomic factors. Hence, firm managers acquire informational advantage from private interactions in corporate site visits, which help them produce more precise forecasts.

The second hypothesis is the organizational impression management (OIM) hypothesis. The OIM hypothesis argues that organizations have motivations to manage their public image and affect stakeholders' perceptions of the organization by issuing precise earnings guidance to convey managers' control and authority on firms' future performance (Staw et al., 1983; Bolino et al., 2008; Graffin et al., 2011; Graffin et al., 2015; Hayward and Fitza, 2017). Therefore, managers of firms with more frequent corporate site visits could try to impress potential investors with more precise MRG to signal that they are in control of the firm's future earnings.

I also propose two competing hypotheses: information demand and social transmission bias. More frequent corporate site visits contribute to lower information demand, which decreases firm managers' willingness to disclose precise MRG. Also, social transmission bias may lead frequent site visits to more biased MRG. For example, firm managers may acquire overconfidence bias from visitors during corporate site visits because these visits provide a platform for social transmission between managers and visiting analysts. Therefore, these two competing hypotheses may predict no impact or negative impact of site visits on MRG.

My empirical tests show that more corporate site visits increase the precision of MRG (i.e. a narrower range of MRG). This finding is consistent with above hypotheses. However, I firstly reject the social transmission bias hypothesis because I find that most MRG (83.97%) in my sample are not overconfident, i.e., the actual earnings fall within the range of MRG.[2] To differentiate the information advantage and organizational impression management hypotheses, I examine two moderators implied by the information advantage hypothesis through which site visits reduce earnings uncertainty in MRG: information uncertainty and information processing capacity. Higher information uncertainty may induce managers to learn more information from outsiders (Chen et al., 2022), leading to more precise MRG. Firms with lower information

[2] The results do not alter even I control for the accuracy of MRG in my model. It suggests that frequent corporate site visits motivate firms to provide more precise guidance without affecting the accuracy of the guidance. In this case, precise MRG can be viewed as informative and authoritative but not overconfident.

processing capabilities tend to benefit more from financial analysts because analysts can offer valuable information advantages for firms that might struggle with processing complex data or have limited resources to conduct in-depth analyses on their own. Consistent with these conjectures, I find that corporate site visits have a stronger amplifying effect on the precision of MRG when firms have higher information uncertainty and lower information processing capacity.

One may argue that managers with higher information uncertainty or lower information capacity may also be motivated to strategically release more precise MRG to impress current and potential investors. To shed light on this possibility, I test the effect of corporate site visits on MRG after organizational setbacks. Hayward and Fitza (2017) propose that managers should lose their confidence after material setbacks and have greater motivations to express their control of financial performance by issuing precise MRG. Therefore, precise MRG after organizational setbacks can be regarded as an impression management tactic. Distinct from Hayward and Fitza (2017), I find that MRG is less precise after setbacks. In addition, frequent corporate site visits have no impact on MRG after organizational setbacks. Furthermore, I examine the effect of corporate site visits on earnings management in case managers combine impression management strategies with earnings management strategies to avoid large negative earnings surprises. When managers manipulate both disclosures of MRG and actual earnings, the organizational impression management hypothesis indicates that more frequent site visits increase discretionary accruals. My results, however, suggest the opposite: more frequent corporate site visits significantly reduce discretionary accruals. Taken together, I find evidence against the organizational impression management theory.

My result is robust to controlling for firm and MRG characteristics commonly used in previous studies, as well as to a battery of robustness tests to address potential empirical concerns. To alleviate the concern about the sample selection bias that not all firms have site visits before releasing MRG, I use the Propensity Score Matching (PSM) method and the Heckman two-step selection method. Moreover, I employ the firm fixed effect model, instrumental variables and subsample analysis to alleviate the endogeneity concern from omitted variables and reverse causality that managers who are more confident welcome more site visits. My results are consistent across all of these robustness checks.

My contribution is twofold. First, I add to the studies on managerial learning theory by investigating the private interactions between managers and analysts. Despite a great deal of interest in the prior literature on information transmission from managers to analysts (e.g., Ajinkya et al., 2005; Karamanou and Vafeas, 2005; Han et al., 2018), little empirical evidence shows the effect of reciprocal flow of knowledge from analysts to managers in the private interactions. I provide novel evidence that more frequent corporate site visits lead to more precise MRG, therefore reduce corporate earnings uncertainty.

Second, by focusing on the precision rather than the accuracy of management earnings guidance, my paper also contributes to the literature on the information content of MRG. In this “age of the information revolution”, where the internet and information systems provide managers with an unimaginable amount of various types of information, the impact of the information environment is important for both management theories and practice (Kuvaas, 2002). Prior literature (e.g., Ajinkya et al., 2005; Hayward and Fitza, 2017) attempts to explain the disclosure decision solely from managers’ perspectives. For example, the manipulation hypothesis maintains that firms may strategically manipulate the market by issuing favorable earnings guidance for multiple purposes. my paper focuses on a previously unexplored question: can a corporate’s earnings uncertainty be reduced by direct interaction between managers and other key players such as the analysts? my results show that such interactions reduce earnings uncertainty embedded in MRG.

My paper has important implications for both managers and regulators. For managers, it places greater emphasis on building and maintaining strong relationships between managers and financial analysts. Managers should recognize the importance of interacting with analysts to gather insights and reduce forecasted earnings uncertainty. They should actively seek opportunities to increase communications, such as meetings or conference calls, to share information and receive feedback from financial analysts. For regulators, my paper suggests that they should review and adjust existing regulations related to communication between managers and analysts. Regulators should aim to strike a balance between facilitating productive interactions while ensuring fair and equal access to information for all market participants.

The rest of the paper is organized as follows. Section 2.2 presents a brief literature review and develops my hypotheses. Section 2.3 describes my sample. Section 2.4 reports the baseline empirical results and robustness tests. Section 2.5 involves a battery of identification tests. Section 2.6 investigates the plausible underlying mechanisms. Section 2.7 concludes.

2.2 Literature review and hypothesis development

2.2.1 Information advantage

Previous literature has widely documented that forecast quality increases with more relevant information available, while decreases with higher information asymmetry. For example, Zuo (2016) finds that firm managers benefit from incorporating information derived from stock prices into their earnings forecasts, enabling them to produce better earnings forecasts. Gao et al. (2021) report that analysts' forecasts tend to become more uncertain and subjective if the information acquisition activities are restricted, leading to an increase of variations in analysts' opinions.

During corporate site visits, firm managers derive information advantages from private interactions where they leverage the information they have obtained from investors and financial analysts (Brockman et al., 2017; Bowen et al., 2018; Chapman and Green, 2017). Generally, corporate site visitors mainly include buy-side, who are mostly institutional investors, and sell-side analysts. Prior research indicates that investors could possess non-public information (Zuo, 2016). Bowen et al. (2018) demonstrate that visitors may divulge confidential information concerning a firm's competitors and suppliers during private meetings, providing managers with particularly valuable information for forecasting future sales and potential costs. Additionally, Hutton et al. (2012) reveal that analysts possess an information advantage at the macroeconomic level, while managers possess an information advantage at the firm-specific level. Therefore, firm managers may seize opportunities to solicit opinions from visitors regarding their perspectives on the firm, market conditions, and industry outlook. With valuable information from analysts' site visits, managers can have more confidence in their future earnings forecasts and narrow down the range of earnings guidance.

2.2.2 Organizational impression management

The organizational impression management (OIM) hypothesis is rooted in legitimacy theory. It is particularly important when legitimacy has been badly damaged by negative triggers that threaten the reputation of top managers and their organizations (Staw et al., 1983; Bolino et al., 2008). For example, a firm will lose its attractiveness to investors if its financial performance is lower than the industry average. Under this circumstance, the firm is highly motivated to create a perception of stakeholders that leaders of the firm understand what drives firm and industry performance, and they have the authority and control to make changes (Hayward and Fitza, 2017). MRG with a narrow range is a great instrument to help firms regain favorable impressions after setbacks. Therefore, the OIM hypothesis recognizes a very precise MRG after organizational setbacks as one type of impression management tactic.

Based on the organizational impression management argument, firm managers may use precise MRG to impress current and potential investors after organizational setbacks. For example, firm managers are eager to show their control and authority over future earnings to those visitors from buy-side institutions during and after site visits when firms are experiencing setbacks. On the other hand, sell-side analysts may collude with managers to publish MRG with more favorable ranges in order to access more firms' private information. The reciprocal theory (Washburn and Bromiley, 2014) propose that analysts may help managers manipulate MRG because analysts need more access to firms for releasing more accurate analysts' forecasts and increasing their reputation.

In sum, my main hypothesis is that more frequent corporate site visits contribute to a narrower range of MRG, which means more precise MRG.

H1: More frequent corporate site visits before the release of MRG contribute to more precise MRG.

The mechanism(s) underlying *H1* could be one or both of these two mechanisms (i.e., information advantage and organizational impression management). To understand which mechanism(s) is behind the relationship in the main hypothesis, I conduct a series of tests in my empirical analysis.

2.2.3 Competing hypotheses

Although both the information advantage theory and the OIM theory predict that more frequent corporate site visits contribute to more precise and informative MRG, there might be competing hypotheses that predict the opposite.

2.2.3.1 Information demand

By providing valuable information to analysts during their site visits, managers help analysts deliver valuable forecasts to investors. As such, investors might have a lower demand for more precise forecasts from managers. Therefore, it is plausible that the frequency of corporate site visits has no impact on the precision of management earnings forecasts. However, this competing hypothesis is partially refuted by previous literature. For example, Gao et al. (2023) find that site visits encourage firm managers to voluntarily disclose earnings forecasts, improving forecast quality and reducing information asymmetry. Similarly, Chen et al. (2022) support that more frequent site visits contribute to more accurate management earnings forecasts. Therefore, concerns regarding the null hypothesis could be partially alleviated by previous literature.

2.2.3.2 Social transmission bias

This hypothesis is inspired by social transmission bias developed in Hirshleifer (2020), which is bias arises from "the process by which attitudes, values, beliefs, and behavioral scripts are passed onto and acquired by individuals and groups (Cavalli-Sforza and Feldman, 1981; Richerson and Boyd, 2005)" (Cheng et al., 2021, pp. 158). Applying this concept to behavioral studies, Cheng et al. (2021) propose that overconfidence can spread within the group and can scale up to create group-wide overconfidence. In this case, groups with rampant overconfidence would be especially vulnerable to risky decision-making. As a result, managers are overconfident in their formation of future earnings prospect of their firm and thus provide overly precise earnings forecasts.

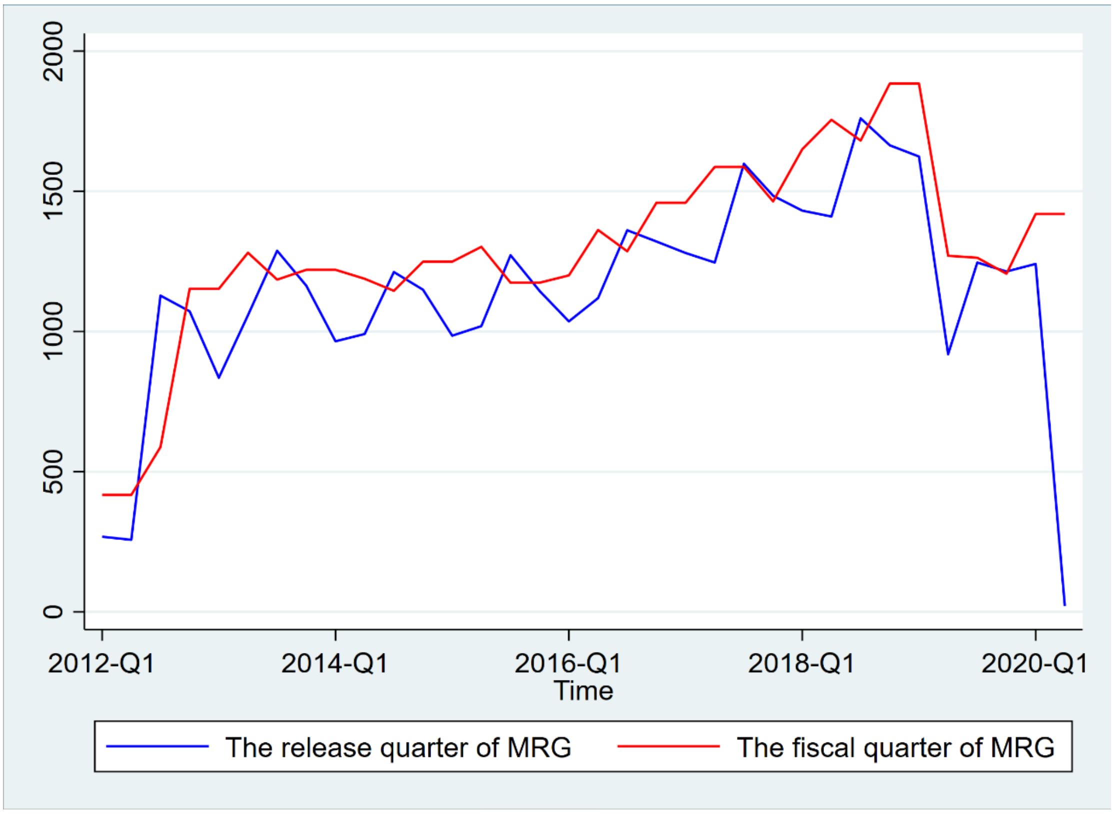
Moreover, overconfidence could emerge within a group of people due to social transmission bias, consistent with the theoretical concept of selective learning bias (Cheng et al., 2021). Selective learning bias comes from confirmatory bias that people may concentrate on the favorable evidence which supports the initial judgment but ignore the contradictory evidence (Fischhoff et al., 1980; Griffin and Tversky, 1992). From this point of view, range forecasts contain the information implied by the initial attempt to estimate the “best guess” point, followed by insufficient adjustments of that point in deciding upper and lower bounds (Tversky and Kahneman, 1974). Range forecasts are more prone to create the confirmatory bias than other forms because there are no clear alternatives for forecasters (Klayman et al., 1999). In this cognitive process, visitors play a significant role to provide new evidence, and managers may selectively believe favorable evidence to make them more overconfident. Therefore, I argue that firm managers could be overconfident to provide overly precise range guidance because of social interactions with financial analysts during corporate site visits.

2.3 Data

I collect data on quarterly MRG, corporate site visits, stock returns, firms’ financial data, and firm headquarters’ locations from the CSMAR database from 2012 to 2020. All MRG in my sample were published on the official website of SZSE and provided earnings guidance for the first quarter in 2012 to the last quarter in 2019. According to the 2006 guidelines on information disclosure of the SZSE, listed firms must report to the China Securities Regulatory Committee (CSRC) two working days before the on-site visits. After site visits, firms must submit the minutes to the CSRC and the SZSE within two working days. The minutes were initially not made public until 2009 when the SZSE required all listed companies to mandatorily disclose the summary minutes of each site visit. Before 2012, MRG is rare and hence my sample starts from 2012. I exclude the earnings guidance published on the same day or after the announcement of the actual earnings guidance. my final sample consists of 2150 listed firms (92.95% of 2313 firms on SZSE) and 42,724 observations.

Figure 2.1 depicts the frequency of MRG over time. It shows that the number of MRG is increasing, which is unsurprising as the number of listed companies in SZSE increased during my sample period. It also shows that there are relatively fewer earnings range guidance reports during the first quarter. Most firms prepare annual financial statements in the first quarter, which distracts their attention from producing MRG for that quarter. In this respect, I control for the quarter fixed effect in my empirical analysis.

Figure 2.1- Quarter distribution of management range guidance (MRG)



Note: Figure 2.1 shows the quarter distribution of MRG from 2012 to 2019. All MRG in my sample were published on the official website of SZSE and provided earnings guidance for the first quarter in 2012 to the last quarter in 2019, the release date is from the first quarter in 2012 until the second quarter in 2020.

I use *Precision*$_{it}$ to measure the degree of precision of MRG. Following Hribar and Yang (2016), Hayward and Fitza (2017) and Jensen and Plumlee (2020), the range of MRG (*Range*$_{it}$) is the upper bound of earnings per share[3] less the lower bound and then scaled

[3] Unlike U.S., most of MRG reports in China only provide forecasts on net profits attributable to the parent company but not EPS (Earnings Per Share). There are only 15.58% (6,656 of 42,724) MRG in my sample providing EPS guidance. Therefore, I calculated the weighted average of the number of outstanding shares 12 months before the release of MRG. I drop observations if the firm age is less than 12 months when calculating the number of outstanding shares. Then, I calculate EPS as net profits attributable to the parent company scaled by the weighted

by the absolute value of the midpoint. The narrower range of the earnings guidance entails higher managerial precision (Hribar and Yang 2016). To facilitate the interpretation of coefficients (i.e., higher coefficients denote higher level of precision), I measure $Precision_{it}$ by taking the negative of $Range_{it}$.

I use the frequency of site visits in 60 days[4] before the release of MRG, $Site\_visit\_60_{it}$, to measure the magnitude of manager-analyst interactions before MRG announcement. Table 1 presents the summary statistics. The average $Precision_{it}$ is -0.27, the sample mean of $Site\_visit\_60_{it}$ is about 0.6 site visits, and most firms do not have corporate site visits in 60 days before the release of MRG.

Table 2.2 reports the sample distribution by industry. Most firms in my sample are manufacturing firms, which indicates the importance of corporate site visits, that is, it provides analysts with rare opportunities to view the firm's tangible assets (such as production lines).

I also report the pairwise correlation between all variables in Table 2.3. Notably, measures of the frequency of site visits in 10 days, 30 days and 60 days before the release of MRG are highly correlated, with correlations ranging from 0.473 to 0.751, and their correlations with other control variables are relatively small. All three site-visit measures have significantly positive correlations with $Precision_{it}$. Furthermore, I categorize all site visitors into different groups according to their work affiliations. Table 2.4 shows that fund managers and security analysts are top two frequent visitors.

average of the number of outstanding shares. To obtain robust results, I use alternative proxies for the range of MRG and find similar results.

[4] In the robustness checks, I also consider other number of days, including 10- and 30-day estimation windows. I also construct a binary site visit variable (0 with no site visit, 1 with any site visit). my conclusions do not alter. my results are strong and consistent.

Table 2.1: Summary statistics

	N	Mean	Std.Dev.	Min	5%	25%	Median	75%	95%	Max
Panel A: Dependent variable										
Precision	38781	-0.270	0.241	-1.429	-0.750	-0.322	-0.204	-0.128	-0.053	-0.020
Panel B: Explanatory variables										
Site_visit_60	38781	0.615	1.378	0.000	0.000	0.000	0.000	1.000	3.000	33.000
Panel C: Control variables										
Bod_size	38781	8.273	1.536	4.000	5.000	7.000	9.000	9.000	11.000	18.000
Bod_dua	38781	0.378	0.056	0.000	0.333	0.333	0.364	0.429	0.500	0.750
Bod_div	38781	0.156	0.125	0.000	0.000	0.077	0.143	0.222	0.400	0.833
Inst_holding	38781	34.689	24.322	0.000	1.735	12.012	32.915	54.918	75.047	99.630
ANA	38781	15.546	22.683	0.000	0.000	1.000	6.000	21.000	63.000	219.000
SOE	38781	0.175	0.380	0.000	0.000	0.000	0.000	0.000	1.000	1.000
ROA	38781	0.025	0.073	-1.879	-0.017	0.006	0.019	0.041	0.094	10.032
MTB	38781	2.389	5.798	0.638	1.062	1.370	1.817	2.605	5.060	636.537
Size	38781	9.361	0.439	6.635	8.758	9.057	9.324	9.606	10.124	12.415
Voluntary	38781	0.049	0.215	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Horizon	38781	-11.954	35.589	-86.000	-68.000	-49.000	9.000	14.000	29.000	171.000
M_holding	38781	19.945	21.252	0.000	0.000	0.120	11.870	37.510	59.400	89.730

This table presents descriptive statistics on all variables in the sample. Summary statistics for Panels A, B and C are based on the sample of 42,724 pieces of range earnings guidance. *Precision* is the upper bound of EPS estimates in MRG in quarter t less the lower bound, scaled by the midpoint, multiply by -1. *Site_visit_60* is the frequency of analysts' site visits in 60 days prior to the earnings guidance which published for quarter t. *Bod_Size* is the number of directors on board in year t-1. *Bod_Dua* is the percentage of independent directors on board in year t-1. *Bod_Div* is the percentage of female directors on board in year t-1. *Inst_holding* is the percentage of institutional holdings in quarter t-1. *ANA* is the number of analysts' annual forecasts at the end of the fiscal year t. *SOE* is an indicator variable coded 1 if the firm is state owned in year t-1, and 0 otherwise. *ROA* is return on assets in quarter t-1. *MTB* is market-to-book in quarter t-1. *Size* is the natural log of the firm's total assets in quarter t-1. *Voluntary* is an indicator variable coded 1 if the earnings guidance is voluntarily encouraged by the regulator, and 0 otherwise. *Horizon* is the number of days between earnings guidance issuance and fiscal quarter end, the larger number indicates the later issuance. *M_holding* is the number of stocks held by the management of firm i in year t-1, scaled by the number of total shares in year t-1.

Table 2.2: Sample distribution by industry of MRG

	Industry categories	*Numbers*	*Percent*	*Cum.*
A	Agriculture, forestry, livestock farming, fishery	645	1.51	1.51
B	Mining	569	1.33	2.84
C	Manufacturing	28,945	67.75	70.59
D	Utilities	785	1.84	72.43
E	Construction	970	2.27	74.7
F	Wholesale and retail	1,140	2.67	77.37
G	Transportation	462	1.08	78.45
H	Hotel and catering industry	92	0.22	78.66
I	Information transmission, software, and IT service	4,833	11.31	89.98
J	Financial Sector	348	0.81	90.79
K	Real estate	859	2.01	92.8
L	Leasing and commerce service	775	1.81	94.61
M	Scientific research and technology service	480	1.12	95.74
N	Water conservancy, environment, and public facilities	803	1.88	97.62
O	Residential services, repair and other services	7	0.02	97.63
P	Education	174	0.41	98.04
Q	Health and social work	247	0.58	98.62
R	Culture, sports, and entertainment	508	1.19	99.81
S	Comprehensive	82	0.19	100
Total		42,724	100	

Note: Table 2.2 presents the sample distribution by industry. It shows that 67.75% firms in my sample are manufacturing firms. It is because the high proportion of manufacturing firms on SZSE (1241 of 2313, 53.65%). Comparing to other industries, more manufacturing firms issue range earnings guidance.

Table 2.3: Pairwise correlations

Variables	Precision	Optmiss	Sitevisit10	Sitevisit30	Sitevisit60	Bod_size	Bod_dua	Bod_div	Inst_holding	ANA	SOE	ROA	MTB	Size	Voluntary	Horizon
Precision	1.000															
Optmiss	0.148***	1.000														
Sitevisit10	0.027***	0.036***	1.000													
Sitevisit30	0.048***	0.047***	0.644***	1.000												
Sitevisit60	0.075***	0.083***	0.473***	0.751***	1.000											
Bod_size	0.011**	-0.008*	0.046***	0.052***	0.061***	1.000										
Bod_dua	-0.007	0.014***	-0.020***	-0.006	-0.012**	-0.584***	1.000									
Bod_div	0.007	0.040***	-0.011**	-0.013**	-0.015***	-0.061***	0.028***	1.000								
Inst_holding	0.021***	0.035***	0.022***	0.022***	0.039***	0.165***	-0.079***	-0.050***	1.000							
ANA	0.179***	0.168***	0.155***	0.192***	0.276***	0.067***	-0.006	0.003	0.107***	1.000						
SOE	-0.017***	-0.053***	0.006	0.002	-0.005	0.235***	-0.061***	-0.124***	0.343***	-0.037***	1.000					
ROA	0.099***	0.108***	0.015***	0.020***	0.047***	0.007	-0.016***	0.023***	0.006	0.179***	-0.066***	1.000				
MTB	-0.001	-0.008	-0.005	-0.005	-0.007	-0.039***	0.016***	0.017***	0.000	0.014***	-0.021***	-0.047***	1.000			
Size	0.060***	0.120***	0.105***	0.120***	0.152***	0.229***	-0.038***	-0.035***	0.270***	0.313***	0.249***	0.001	-0.180***	1.000		
Voluntary	0.096***	0.109***	-0.018***	-0.005	-0.013***	-0.024***	0.018***	0.013***	0.005	0.015***	-0.004	0.028***	-0.013**	0.027***	1.000	
Horizon	0.104***	-0.077***	-0.062***	0.001	-0.061***	-0.066***	0.056***	-0.011**	-0.047***	-0.096***	0.053***	-0.050***	0.017***	-0.094***	0.153***	1.000
M_holding	0.062***	0.059***	0.009*	0.027***	0.038***	-0.140***	0.059***	0.078***	-0.662***	0.065***	-0.403***	0.100***	-0.029***	-0.252***	0.003	-0.008

Table 2.4: The frequency of site visits (categorized by visitor type)

Visitor Type	*Site_visit_60*	
	Freq.	*Percent*
Securities Agency's CSV	20,204	79.14
Funds' CSV	13,512	52.93
Asset Management Company's CSV	8,956	35.08
Other Institutional Visitors' CSV	8,706	34.10
Investment Management Company's CSV	6,724	26.34
Insurance Company's CSV	2,830	11.09
Investment Advisory Agency's CSV	2,709	10.61
Trust Company's CSV	1,223	4.79
Bank's CSV	1,117	4.38
Investment Bank's CSV	425	1.66
Start-up/venture capital Company's CSV	326	1.28
Futures (Brokerage) Company's CSV	186	0.73
Finance Company's CSV	183	0.72
Fund Portfolio's CSV	106	0.42
Self-regulatory organization's CSV	97	0.38
Individual's CSV	96	0.38
Government Agency's CSV	87	0.34
College/University's CSV	30	0.12
Asset Valuation Agency's CSV	19	0.07
Law Firm's CSV	13	0.05
Accounting firm's CSV	6	0.02
Credit Rating Agency's CSV	2	0.01

Note: This table summarizes the frequency of site visits by different types of visitors. I categorize all site visitors according to their work affiliations and aggregate the frequencies of visits of each type. The total number of site visits in 60 days before the release of MRG in my sample is 25,528. I calculate the percent of each type's visitor in the full sample.

2.4 Empirical Results

2.4.1 Baseline regression results

In my baseline analysis, I examine the relationship between the frequency of corporate site visits and $Precision_{it}$ using the following OLS regression:

$$Precision_{it} = \alpha + \beta_1 Site\_visit\_60_{it} + \gamma Controls$$
$$+ Firm\ and\ Quarter\ Fixed\ Effects + \varepsilon_{it}, \tag{2.1}$$

where $Precision_{it}$ is a measure of the degree of precision in managers' earnings guidance. In my baseline regressions, $Site\_visit\_60_{it}$ is my key independent variable of interest. $Site\_visit\_60_{it}$ measures the frequency of site visits within 60 days prior to the release of MRG. My regression analysis also controls for a set of firm-level characteristics and characteristics of MRG following previous studies. I follow Karamanou and Vafeas (2005) to control for corporate governance indicators, including board size (Bod_size_{it-1}), board duality (Bod_dua_{it-1}), and board diversity (Bod_div_{it-1}). As per Ajinkya et al. (2005), I also include capital structure, an indicator of State-Owned Enterprises (SOE_{it-1}) and the proportion of institutional ownership ($Inst\_holding_{it-1}$). I also control for firms' financial indicators, including return on total assets (ROA_{it-1}), market-to-book (MTB_{it-1}) and the natural log of total assets ($Size_{it-1}$), as in Hribar and Yang (2016). Following Bamber and Cheon (1998) and Graham et al. (2005), I use the number of analysts' annual forecasts (ANA_{it-1}) to proxy for institutional attention. To account for incentives to issue precise MRG, I follow Hayward and Fitza (2017) and Chung and Hribar (2021) to include the number of shares held by managers ($M\_holding_{it}$). Similar to Jaggi (1980) and Hribar and Yang (2016), my regression also controls for the management range guidance characteristics, including the voluntary disclosure dummy ($Voluntary_{it}$) and the horizon of earnings guidance ($Horizon_{it}$). Finally, I control for firm fixed effects and quarter fixed effects to account for unobserved firm and quarter heterogeneity. All control variables are defined in Appendix A.

Table 2.5 shows that the coefficient of $Site\_visit\_60_{it}$ (0.006) is positive and statistically significant at the 1% level, which means more frequent site visits 60 days before the release of MRG are associated with a higher degree of precision in MRG. The regression results are consistent with my main hypothesis that more frequent corporate site visits contribute to more precise MRG.

Table 2.5: Baseline regression results

Dependent Variable: Precision			
	(1)	*(2)*	*(3)*
Site_visit_60	0.009***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)
Bod_size		0.000	0.001
		(0.001)	(0.003)
Bod_dua		-0.030	0.038
		(0.028)	(0.065)
Bod_div		-0.003	0.009
		(0.010)	(0.027)
Inst_holding		0.001***	0.001***
		(0.000)	(0.000)
ANA		0.002***	0.001***
		(0.000)	(0.000)
SOE		-0.001	-0.006
		(0.004)	(0.032)
ROA		0.195	0.095
		(0.146)	(0.090)
MTB		0.000	0.000
		(0.000)	(0.000)
Size		0.009**	0.026**
		(0.004)	(0.012)
Voluntary		0.079***	0.032***
		(0.005)	(0.006)
Horizon		0.001***	0.001***
		(0.000)	(0.000)
M_holding		0.001***	0.001***
		(0.000)	(0.000)
Constant	-0.276***	-0.528***	-0.602***
	(0.015)	(0.048)	(0.113)
Firm FE	Yes	No	Yes
Industry FE	No	Yes	No
Quarter FE	Yes	Yes	Yes
Observations	38781	38781	38781
Adjusted R^2	0.010	0.086	0.026

Note: This table reports the effect of the frequency of corporate site visits on MRG. Column (1) reports the result of univariate regression. Column (2) reports the result that controls for industry and quarter fixed effects. Column (3) reports the result of Equation (1). Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.4.2 Robustness tests

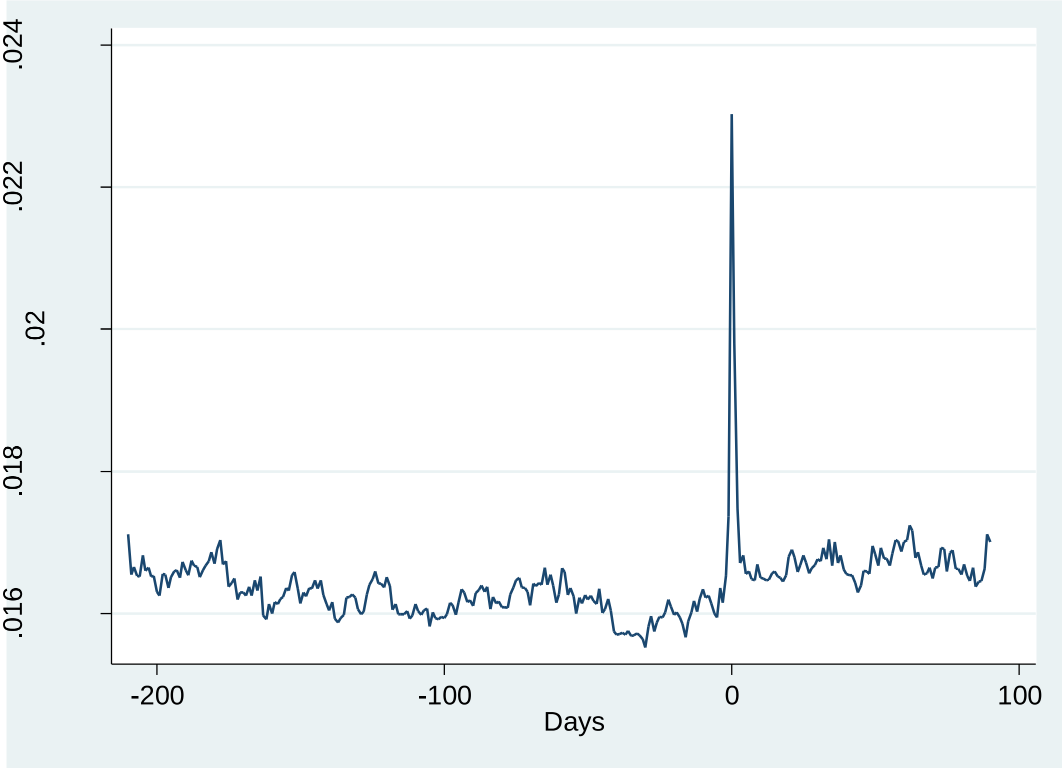
2.4.2.1 Market reaction to MRG

One point worth discussing is whether the market reacts to MRG in my sample. This research will be meaningless if the market does not care about the release of MRG. Therefore, I use an event study to capture the market reaction to MRG.

The event is the release of MRG for each firm in each quarter. The event window is defined as [-3,3], which means 7 days around the event. I estimate the expected normal return based on a market model that assumes a linear relationship between the market return and the return of the focal firm in the estimation window of [-210, -11]. I filter out events occurred on non-trading days.

Figure 2.2 displays the absolute value of cumulative abnormal returns (CARs) across all firms between 210 days before the event and 90 days after the event. It demonstrates that the market significantly reacts to the release of MRG.

Figure 2.2- CARs around MRG



Note: This figure reports absolute value of cumulative abnormal returns (CARs) for each management range guidance. The horizontal line indicates days around the release of MRG and the blue line shows the abnormal returns.

For the next step, I detect the market reactions to MRG with site visits. To test whether the market reacts positively to MRG with frequent site visits, I construct the following model:

$$absCAR_{it} = \alpha + \beta_1 Site\_visit_{it} + \gamma Controls + Firm\ and\ Quarter\ Fixed\ Effects + \varepsilon_{it}, \tag{2.2}$$

where absCAR is the absolute value of cumulative abnormal return in the event window of [-3,3] adjusted by the market return. $Site\_visit_{it}$ measures the frequency of site visits in 10 days, 30 days, 60 days before the release of MRG, respectively. Control variables remain the same as in Equation (2.1). I estimate Equation (2.2) in samples matched on propensity scores. I expect that the market reactions will be more positive if more site visits occur before the release of MRG.

Table 2.6 reports the results. It shows that the market significantly reacts to MRG with more frequent site visits in both 30-day and 60-day windows. In line with my expectation, this result indicates the significance of this research that the market pays more attentions on the release of MRG with more site visits before.

Table 2.6: Regression results of the frequency of site visits and market reaction

Dependent variable=absCAR												
	1:1 Matching			***1:2 Matching***			***1:3 Matching***			***1:4 Matching***		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Site_visit_10	0.004			0.005			0.001			-0.001		
	(0.007)			(0.006)			(0.005)			(0.005)		
Site_visit_30		0.001**			0.002***			0.002***			0.002***	
		(0.001)			(0.000)			(0.000)			(0.000)	
Site_visit_60			0.000			0.000**			0.001**			0.001**
			(0.000)			(0.000)			(0.000)			(0.000)
Bod_size	0.000	0.000	0.000	-0.003	0.000	0.000	-0.003	0.000	0.000	-0.003	0.000	-0.001*
	(0.007)	(0.001)	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
Bod_dua	0.093	0.001	-0.004	0.058	0.000	-0.005	0.024	-0.008	-0.007	0.020	-0.006	-0.008
	(0.148)	(0.013)	(0.009)	(0.104)	(0.011)	(0.008)	(0.089)	(0.010)	(0.008)	(0.090)	(0.009)	(0.008)
Bod_div	0.078	0.011**	0.001	0.001	0.007	0.001	-0.015	0.006	0.000	-0.027	0.003	-0.001
	(0.081)	(0.005)	(0.004)	(0.046)	(0.005)	(0.003)	(0.035)	(0.004)	(0.003)	(0.029)	(0.004)	(0.003)
Inst_holding	0.001	0.000	0.000***	0.000	0.000	0.000***	0.000	0.000**	0.000***	0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ANA	0.000	0.000***	0.000***	0.000	0.000***	0.000***	0.000	0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SOE	0.014	-0.004**	-0.002	0.009	-0.004**	-0.002*	0.001	-0.003**	-0.003**	0.001	-0.003**	-0.002**
	(0.033)	(0.002)	(0.001)	(0.018)	(0.002)	(0.001)	(0.014)	(0.002)	(0.001)	(0.013)	(0.001)	(0.001)
ROA	-0.304	0.004	-0.001	-0.139	0.007	-0.008	0.026	-0.003	-0.006	-0.017	0.000	-0.005
	(0.260)	(0.011)	(0.013)	(0.138)	(0.011)	(0.012)	(0.112)	(0.010)	(0.011)	(0.086)	(0.010)	(0.010)
MTB	0.002	0.001	0.001	0.001	0.001**	0.000	0.000	0.000	0.000	0.004	0.001	0.000
	(0.006)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Size	-0.028	-0.005***	-0.004***	-0.008	-0.003**	-0.004***	-0.013	-0.004***	-0.004***	-0.006	-0.005***	-0.004***
	(0.021)	(0.002)	(0.002)	(0.014)	(0.002)	(0.001)	(0.011)	(0.002)	(0.001)	(0.010)	(0.001)	(0.001)
Voluntary	-0.009	0.000	-0.007**	-0.007	-0.004	-0.006***	0.012	-0.005*	-0.006***	0.033	-0.006**	-0.006***
	(0.030)	(0.004)	(0.003)	(0.013)	(0.003)	(0.002)	(0.022)	(0.003)	(0.002)	(0.023)	(0.003)	(0.002)
Horizon	0.000	0.000***	0.000***	0.000	0.000***	0.000***	0.000	0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M_holding	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.270	0.107***	0.061***	0.111	0.074***	0.067***	0.185	0.087***	0.079***	0.164	0.090***	0.088***
	(0.183)	(0.029)	(0.016)	(0.144)	(0.021)	(0.015)	(0.112)	(0.019)	(0.015)	(0.108)	(0.018)	(0.013)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	141	7681	14906	206	10452	18616	268	12755	20971	324	14659	22620
Observations	0.565	0.068	0.065	0.461	0.068	0.064	0.369	0.065	0.065	0.338	0.066	0.062

Note: This table reports the effect of the frequency of site visits on the market reactions in matched samples. Variable definitions can be found in Appendix A. standard errors in brackets are robust and clustered at firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, t on two-tailed statistical tests.

2.4.2.2 Alternative measures

First, I employ alternative measures of corporate site visits and MRG precision. I report the results respectively in Panels A and B of Table 2.7. To examine whether my baseline results depend on my choice of 60 days for *Site_visit*, I also consider 10 days and 30 days before the release of MRG, respectively. The results are reported in Panel A of Table 2.7. They show that my findings remain unchanged when using the alternative measures of *Site_visit*.

Panel B of Table 2.7 tests whether my results hold when using alternative measures of precise MRG. In my baseline regression, $Precision_{it}$ in Equation (1) based on the range of MRG which is defined as the difference between the upper bound and the lower bound of forecasted EPS, scaled by the absolute value of its midpoint. Following previous literature (Hribar and Yang, 2016; Hayward and Fitza, 2017; Chen et al., 2022), I use four alternative measures. The first measure, HY_range_{it}, is defined as the upper bound of the EPS estimates in MRG in the quarter t less the lower bound, scaled by lagged assets per share in the previous quarter t-1. The second measure, $Price\_range_{it}$, is defined as the upper bound of the EPS estimates in MRG in the quarter t less the lower bound, scaled by price at the beginning of the release month. The third measure, $Prof\_range_{it}$, is defined as the upper bound of the net profit attributable to the parent company in the quarter t less the lower bound, scaled by the midpoint. The fourth measure, TA_range_{it}, is defined as the upper bound of the net profit attributable to the parent company in the quarter t less the lower bound, scaled by total assets in the quarter t-1. Above four variables are all multiplied by -1 to measure precision. Table 2.7 shows that my results are robust to all four alternative measures of the range of MRG. All regression results in Table 2.7 are consistent with my main hypothesis that more frequent corporate site visits contribute to more precise MRG.

Table 2.7: Robustness tests of alternative measures

Panel A: Alternative measures of site visits

	Dependent variable: Precision	
	(1)	*(2)*
Site_visit_10	0.012***	
	(0.004)	
Site_visit_30		0.005***
		(0.002)
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	38781	38781
Adjusted R^2	0.025	0.025

Panel B: Alternative measures of managers' Precision

	HY_Range	*Price_Range*	*Prof_Range*	*TA_Range*
	(1)	*(2)*	*(3)*	*(4)*
Site_visit_60	0.082**	0.014*	0.007***	0.025**
	(0.040)	(0.007)	(0.002)	(0.012)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	38781	38665	38781	38781
Adjusted R^2	0.008	0.001	0.004	0.009

Note: This table reports the robustness test results when using alternative measures of my key variable of interest or the dependent variable. Panel A shows the results when using alternative measures of site visits. Panel B shows the results when using alternative measures of managers' Precision. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.4.2.3 Propensity Score Matching (PSM)

In my sample, not all firms have site visits before the release of MRG. This raises the question whether the differences in the characteristics of these two groups of firms other than corporate site visits drive my results. I use PSM to address this concern.

First, I create a control sample matched on the propensity to conduct analysts' site visits. The benefit of using a control sample is that it allows me to compare the firms that have corporate site visits before the release of MRG to firms that are similar on all observable dimensions but do not have corporate site visits before the MRG release, thus allowing me to more clearly attribute the effect to site visits themselves, rather than to the firm characteristics associated with site visits (Yuan et al., 2016). To identify the propensity-score-matched control sample, I follow Cheng et al. (2016, 2019) and estimate a logistic model (Equation 2.3). I then calculate propensity scores, the conditional probability that a firm has corporate site visits before MRG on all the observable data, for each treated observation (the one with site visits before MRG). For each treated observation, I select four control observations with the nearest propensity scores, and these observations constitute my control sample. Finally, I re-estimate Equation (2.1) using matched samples. The results reported in Table 2.8 show similar patterns to the full sample. This implies that the positive effect of frequent corporate site visits on the precise MRG does not alter after controlling for the sample selection bias.

Table 2.8: PSM method

	Dependent variable: Precision			
	1:1 Matched Sample	*1:2 Matched Sample*	*1:3 Matched Sample*	*1:4 Matched Sample*
	(1)	*(2)*	*(3)*	*(4)*
Site_visit_60	0.004***	0.004***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	19048	23902	27039	29255
Adjusted R^2	0.033	0.032	0.031	0.031

Note: This table reports the results of PSM method. It reports the effect of the frequency of site visits on MRG in matched samples. Column (1) to column (4) report regression results in the 1:1 matched sample, the 1:2 matched sample, the 1:3 matched sample, the 1:4 matched sample, respectively. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.4.2.4 Heckman two-step selection method

To further alleviate the sample self-selection concern, I use the Heckman two-step selection method. First, I follow Cheng et al. (2016, 2019) and use the following regression to estimate the probability of having corporate site visits before the release of MRG and obtain the Inverse Mills Ratio (*IMR*):

$$\begin{aligned} Pr\ (D\_visit\_60_{it}) &= \alpha + \beta_1 Manufacture_{it-1} + \beta_2 Size_{it-1} + \beta_3 ANA_{it-1} \\ &+ \beta_4 Inst\_holding_{it-1} + \beta_5 ROA_{it-1} + \beta_6 MTB_{it-1} + \beta_7 LEV_{it-1} \\ &+ \beta_8 Age_{it-1} + \beta_9 High\_rating_{it-1} + \beta_{10} SOE_{it-1} + \beta_{11} \Delta GDP_{it-1} \\ &+ \beta_{12} Num\_Firms_{it-1} + \beta_{13} Num\_Finst_{it-1} + \varepsilon_{it-1}, \end{aligned} \tag{2.3}$$

where $D\_visit\_60_{it}$ is an indicator variable coded 1 if there is at least one site visit in 60 days before the release of MRG, 0 otherwise. For determinants, I include six sets of explanatory variables following Cheng et al. (2016, 2019). The first set is related to beneficial information, including measurements of an indicator for manufacturing firms ($Manufacture_{it-1}$) and firm size ($Size_{it-1}$), because visiting manufacturing firms can provide great opportunities for analysts to gain more information on the firms' operation assets and production facilities. The second set concerns information demand, including the number of analysts' coverages (ANA_{it-1}) and the proportion of institutional ownership ($Inst\_holding_{it-1}$), which are proxies for institutional attention. It also includes two profit indicators, return on total assets (ROA_{it-1}) and market-to-book (MTB_{it-1}), because previous literature points out that investors pay more attention to firms with better performance (Bushee and Miller, 2012). The third set is about information complexity. Analysts are more likely to visit firms with more complex information. I use firm age (Age_{it-1}) and leverage (LEV_{it-1}) to proxy for information complexity, because firms with a long history and higher leverage may have more complex information. The fourth set is related to information transparency. I measure it using the SZSE's annual evaluation of listed firms' disclosure quality, a rating with four levels from "A" to "D". I construct an indicator ($High\_rating_{it-1}$) of high ratings (A and B) as a proxy for high information transparency. The fifth is the State-Owned Enterprises (SOE_{it-1}) dummy. Analysts are more likely to visit SOE to gain insights into government regulations or policy change, because China's economy is under strong government intervention and SOE enjoy preferential treatment (Cheng et al., 2019). The sixth set is the information related to firm headquarters' location, including GDP growth (ΔGDP_{it-1}), the number of listed firms (Num_Firms_{it-1}) and the number of financial institutions (Num_Finst_{it-1}). Following Jiang and Yuan (2018), Cheng et al. (2019) and Chen et al. (2022), these three variables (ΔGDP_{it-1}, Num_Firms_{it-1}, Num_Finst_{it-1}) are exclusion restrictions. I add these variables in the first stage because they are expected to correlate with corporate site visits, but they are not directly related to management forecast precision. For example, more listed firms in the firm headquarters' location can attract more site visits, because analysts prefer to visit cities where they can visit multiple firms in one trip to save time and expenses, while it is not directly related to the range of MRG. All the variables above are from the previous period of the MRG, which may be the previous quarter or the previous year, depending on whether the information is disclosed on a quarterly or annual basis.

Column (1) of Table 2.9 displays the determinant analysis of site visits. As I expected, the results show that most of the independent variables are significantly associated with the probability of having corporate site visits. In line with Cheng et al. (2019), I find $Manufacture_{it-1}$, $Size_{it-1}$, ANA_{it-1}, $High\_rating_{it-1}$ and Num_Firms_{it-1} are significantly and positively related to the probability of corporate site visits in 60 days before the release of MRG, while $Inst\_holding_{it-1}$ and SOE_{it-1} have no significant effect on the probability of corporate site visits.

In addition, this study may also suffer the sample selection bias from the voluntary issuance of MRG. In specific, managers may have low incentives to provide earnings forecasts to investors, if they manage to help the analysts increase the value of analyst forecasts to outsiders via the private communication during the analysts' site visits. Therefore, I add a two-stage Heckman selection regression analysis to tackle this issue of sample selection that is associated with the incidence of management range guidance. The main determinant variables for the incidence of management earnings forecasts are: (1) the firm's growth prospect ($Growth_{it-1}$); (2) analyst coverage (ANA_{it-1}); (3) the firm's information asymmetry with outsiders, which are measured by corporate governance and disclosure quality ($M\_holding_{it-1}$, Bod_size_{it-1}, Bod_dua_{it-1},

Bod_div_{it-1}, $High\_rating_{it-1}$); (4) the earnings surprise measured by the actual EPS for the current year minus the analysts' consensus forecasts of EPS ($Abssurprise_{it-1}$). It is expected that investors have higher demand for precise MRG when a firm has better growth prospect, lower analyst coverage, greater information asymmetry between corporate insiders and outsiders, or larger earnings surprises, and accordingly, the incidence of MRG would be higher.

$$\begin{aligned} Pr\,(D\_MRG_{it}) = \ & \alpha + \beta_1 M\_holding_{it-1} + \beta_2 Bod\_size_{it-1} + \beta_3 Bod\_dua_{it-1} \\ & + \beta_4 Bod\_div_{it-1} + \beta_5 Growth_{it-1} + \beta_6 Abssurprise_{it-1} \\ & + \beta_7 Size_{it-1} + \beta_8 ANA_{it-1} + \beta_9 ROA_{it-1} + \beta_{10} LEV_{it-1} + \beta_{11} Age_{it-1} \\ & + \beta_{12} High\_rating_{it-1} + \beta_{13} SOE_{it-1} + \varepsilon_{it-1}, \end{aligned} \tag{2.4}$$

Column (2) of Table 2.9 displays the determinant analysis of the issuance of MRG. As I expected, the results show that most of the independent variables are significantly associated with the probability of issuing MRG. In line with my expectation, ANA_{it-1} is significantly and negatively related to the probability of the release of MRG. In terms of information asymmetry, better corporate governance and disclosure quality contribute to lower demand of precise MRG. However, $Growth_{it-1}$ and $Abssurprise_{it-1}$ have no significant effect on the probability of MRG.

Table 2.9: Determinant analysis

	$D\_visit\_60_{it}$	*D_MRG_{it}*
	(1)	*(2)*
$Manufacture_{it-1}$	0.166***	
	(0.026)	
$Inst\_holding_{it-1}$	0.000	
	(0.001)	
MTB_{it-1}	0.002	
	(0.002)	
ΔGDP_{it-1}	-0.775***	
	(0.142)	
Num_Firms_{it-1}	0.000***	
	(0.000)	
Num_Finst_{it-1}	0.002***	
	(0.000)	

	$D\_visit\_60_{it}$	D_MRG_{it}
	(1)	*(2)*
$M\_holding_{it-1}$		-0.056***
		(0.002)
Bod_size_{it-1}		0.021***
		(0.005)
Bod_dua_{it-1}		0.168
		(0.192)
Bod_div_{it-1}		-0.844***
		(0.126)
$Growth_{it-1}$		-0.000
		(0.000)
$Abssurprise_{it-1}$		-0.022
		(0.023)
$Size_{it-1}$	0.416***	-0.074***
	(0.034)	(0.013)
ANA_{it-1}	0.019***	-0.006***
	(0.001)	(0.001)
ROA_{it-1}	0.073	0.929***
	(0.200)	(0.104)
LEV_{it-1}	-0.531***	1.056***
	(0.180)	(0.079)
Age_{it-1}	-0.038***	0.082***
	(0.003)	(0.003)
$High\_rating_{it-1}$	0.744***	-0.335***
	(0.041)	(0.023)
SOE_{it-1}	-0.003	0.758***
	(0.038)	(0.032)
Constant	-5.637***	-3.159***
	(0.313)	(0.291)
Pseudo R^2	0.070	0.192
Observations	38781	64275

Note: This table reports the results of the first stage of Heckman two-step method. Column (1) reports determinant analysis of site visits in 60 days before the release of MRG. Column (2) reports determinant analysis of the issuance of MRG. Variable definitions can be found in Appendix A. The standard errors in brackets are robust. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

In the second stage, I test the effect of the frequency of site visits on the range of MRG by including the IMR estimated from the first step. Table 2.10 shows that, similar to the baseline results reported in Table 2.5, the coefficient of $Site\_visit\_60_{it}$ is significantly positive. These results show that my baseline findings are robust when using the Heckman two-step selection method to adjust for the self-selection bias.

Table 2.10: Heckman two-step selection method

Dependent variable: Precision		
	(1)	*(2)*
Site_visit_60	0.003**	0.006***
	(0.001)	(0.001)
IMR	0.007***	0.002
	(0.002)	(0.005)
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	38781	38781
Adjusted R^2	0.025	0.027

Note: This table reports the results of the second stage of Heckman two-step selection method by including the inverse Mill's ratio (IMR). Variable definitions can be found in Appendix A. The standard errors in brackets are robust. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.5 Identification tests

In the preceding analysis, I control for a large number of firm- and earnings-guidance-level characteristics that may affect the precision of MRG. I also use propensity score to create matched samples and Heckman two-step selection method to address potential sample selection bias. There might still be an endogeneity concern, however, that omitted variables in the baseline models that are related to the frequency of site visits also affect the MRG. Although I include firm and quarter fixed effects to alleviate concerns that MRG is driven by time and firm invariant unobservable variables, there may be other omitted variables that lead to reverse causality. For instance, more confident managers may welcome analysts to visit more and release more optimistic earnings guidance. To alleviate this endogeneity concern, I employ instrumental variables and subsample analysis.

2.5.1 Instrumental variables

I use two different instrumental variables that capture a firm's likelihood of having corporate site visits, but are uncorrelated with MRG, except through the variables I control for. My first instrument is extreme weather conditions (*Extreme_weather*). Following Han et al. (2018), weather can affect the probability of corporate site visits, as it is more difficult to travel to certain places in extreme weather. However, weather is unlikely to affect the precision of MRG. Therefore, I expect significantly negative correlations between the endogenous variable (i.e., the frequency of corporate site visits in 60 days before the release of MRG for target firms) and the first instrument. First, I identify days with extreme weather conditions for each city where firm i's headquarters is located, if the lowest temperature falls below -10℃ or if the highest temperature reaches above 37℃. Second, I calculate the percentage of days with extreme weather conditions for each city in 90 days before the release of MRG. Finally, I use the quintile rank of the percentage of days as the instrumental variable.

The second instrument is the quintile of average site visits for all other firms in the same city in the same time period as target firms. Inspired by Jiang and Yuan (2018) and Lu et al. (2018), firms located in a city with more corporate site visits for peer firms are more likely to have corporate site visits, while the average number of corporate site visits for other firms should be uncorrelated with the target firms' MRG. Therefore, I expect significantly positive correlations between the endogenous variable and the second instrument.

Panel A of Table 2.11 reports the results of the first-stage regressions where the dependent variable is the frequency of corporate site visits in 60 days before the release of MRG, and the explanatory variables include the instruments and the same set of control variables as in Table 2.5. For brevity, I report only the coefficient estimates for the main variables of interest. Consistent with the rationale behind the instruments, the first instrument (*Extreme_weather*) is negatively and significantly (at the 1% level) correlated to the frequency of site visits, the second instrument (*City_peers*) is positively and significantly (at the 1% level) correlated to the frequency of site visits. The F-statistics reported indicate that none of my instruments suffer from weakness. Additionally, the Cragg-Donald's Wald F weak-instrument test statistic produces a p-value of 0.000, further rejecting the null hypothesis that the instruments are weak (Cragg and Donald, 1993; Stock and Yogo, 2005). To further verify the validity of the instruments, I conduct an over-identification test following Hansen (1982), which utilizes both instruments. The p-value from this test indicates that the instruments are valid, i.e., uncorrelated with the error term.

Panel B of Table 2.11 reports the results for the second-stage regressions with the range of MRG as dependent variable. The variable of interest is the variable with the predicted values from regression in the first-stage regressions. The results are consistent with the baseline regressions and support my main hypothesis. Those results imply that my key result is unlikely due to the endogeneity of the frequency of corporate site visits.

Table 2.11: Instrumental variables

Panel A: First-stage regressions	
Dependent variable: Site_visit_60	
Extreme_weather	-0.014***
	(0.005)
City_peers	0.065***
	(0.008)
Controls	Yes
Firm FE	Yes
Quarter FE	Yes
Observations	38781
Adjusted R^2	0.052
F-statistic	58.23***
Cragg-Donald (CD) Wald F-statistic	177.896
Stock and Yogo (2005) weak ID test critical value	19.93
J-statistic for over-identification	0.906
P-value	0.341

Panel B: Second-stage regressions	
Dependent Variable: Precision	
Site_visit_60 (Fitted)	0.020**
	(0.009)
Controls	Yes
Firm FE	Yes
Quarter FE	Yes
Observations	38781
Adjusted R^2	0.066

Note: This table reports the results of instrumental variables method based on two-stage least squares (2SLS) panel regressions. Panel A presents the first-stage regression results in which the dependent variable is *Site_visit_60*. Panel B reports the second-stage regression results. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.5.2 Reverse causality and subsample analysis

Whereas all my identification attempts so far point to a causal effect of the frequency of site visits on the precision of MRG, a plausible alternative interpretation of my main results is that more precise managers welcome more corporate site visits, resulting in the positive relation between the frequency of corporate site visits and the precision of MRG. This alternative interpretation suggests that the causal relationship may operate in the opposite direction. To determine if my results are influenced by reverse causality, I follow Chen et al. (2022) to restrict my sample to a subset of firm-quarter observations for which this problem is less severe. More specifically, I re-examine the effects of corporate site visits after excluding, respectively, the top 10% and 25% precise managers and report the results in Table 2.12. I find that the frequency of corporate site visits continues to be economically and statistically significant in all model specifications. These findings provide further assurance that the effect of corporate site visits does not arise from reverse causation.

Table 2.12: Excluding precise managers

	Dependent variable: Precision	
	Excluding largest 10%	*Excluding largest 25%*
	(1)	*(2)*
Site_visit_60	0.006***	0.006***
	(0.001)	(0.001)
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	34905	29180
Adjusted R^2	0.025	0.023

Note: This table reports the regression results by excluding the most precise managers. The top 10% most precise managers are measured as managers who issue the most 10% precise MRG. The top 25% most precise managers are measured as managers who issue the most 25% precise MRG. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

2.6 The underlying mechanisms

In this section, I examine the underlying mechanisms for the positive relationship between corporate site visits and MRG. I consider the information advantage hypothesis and the OIM hypothesis.

2.6.1 The information advantage hypothesis

I test the information advantage hypothesis through the channel of information uncertainty and information processing capacity. First, I perform a test to show that firms with high information uncertainty are prone to be affected by visitors and to foster precision in MRG. The effect of site visits can be more significant during periods with high information uncertainty, because it is relatively hard for managers to make accurate predictions in highly uncertain periods while managers intend to learn more information from outsiders (Chen et al., 2022). I use two measures of information uncertainty. The first measure is firm size ($Size_{it-1}$), which is also used by Zhang (2006). Small firms are more prone to be affected by outsiders. Hence, I identify small firms if their firm size is below the median of the full sample. The second one is volatility ($Volatility_{it-1}$). Following Chung and Hribar (2021), I use principal component analysis with stock return volatility and earnings volatility. The KMO test of sampling adequacy is above 0.5, which means the chosen variables have sufficiently high correlation for using principal component analysis. Stock return volatility is measured by the standard deviation of dividend- and split-adjusted daily stock returns from CSMAR over the previous 250 trading days. Earnings volatility is measured by the standard deviation of four previous quarterly earnings over lagged total assets. I exclude observations if firms do not have 250 trading days or do not disclose four previous quarterly earnings. The variable IU_h_{it-1} is an indicator that equals 1 if the value of $Size_{it-1}$ is below than the median of the full sample in the first test, equals 1 when the value of $Volatility_{it-1}$ is above the median in the second test, and equals 1 if the value of $Young_{it-1}$ is below than the median of the full sample in the third test. Then, I test the effect of site visits by adding the interactions of information uncertainty and the frequency of site visits into the baseline model.

Table 2.13 shows that the effect of frequent site visits on precise MRG is amplified in the high uncertainty group, suggesting that the precision increased when firms receive frequent site visits if their information uncertainty is higher. This result also provides evidence to support the information advantage hypothesis that firms with high information uncertainty are more prone to be affected by outsiders to increase precision.

Second, I test whether information processing capacity affects the impact of corporate site visits on management earnings guidance precision. I perform a test to show that firms with low information processing capacity are benefit more from professional visitors because these professionals offer specialized expertise and resources that such firms might lack internally. Therefore, I measure information processing capacity by the proportion of executives with high degrees ($Degree_{it-1}$) or with sophisticated experience ($Experience_{it-1}$) in firms' top management team. Following Chung and Hribar (2021) and Chen et al. (2022), I argue that more experts in the top management team indicate higher information processing capacity. First, I define an expert as a manager with a master's degree or higher ($Degree_{it-1}$). Second, I use managers with sophisticated experience to proxy for experts instead ($Experience_{it-1}$). I predict the component value by using principal component analysis with the proportion of managers with overseas working or studying experience, the proportion of managers with research experience, and the proportion of managers with working experience in financial institutions in the top management team. The KMO test of sampling adequacy is above 0.5, which means the chosen variables have sufficiently high correlations for using principal component analysis. The variable IPC_l_{it-1} is an indicator that equals 1 if the value of $Degree_{it-1}$ or $Experience_{it-1}$ is below the median respectively in the two tests. Then, I test the effect of site visits by including the interactions of information processing capacity and the frequency of site visits into the baseline model.

Panel B of Table 2.13 shows that managers with low information processing capacity produces more precise MRG after corporate site visits. Consistent with my hypothesis, this result implies that the quality of MRG increases when managers with low information processing capacity receive frequent site visits. The results support the information advantage hypothesis that managers with low information processing capacity acquire information advantage from visitors during corporate site visits.

Table 2.13: Information advantage hypothesis

Panel A: Information Uncertainty (IU)

	Dependent variable: Precision	
	Size	*Volatility*
	(1)	*(2)*
Site_visit_60*IU_h	0.004*	0.004**
	(0.002)	(0.002)
Site_visit_60	0.004***	0.003
	(0.001)	(0.002)
IU_h	0.028**	-0.007
	(0.012)	(0.006)
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	38781	17082
Adjusted R^2	0.026	0.029

Panel B: Information Processing Capacity (IPC)

	Dependent variable: Precision	
	Degree	*Experience*
	(1)	*(2)*
Site_visit_60*IPC_l	0.004**	0.004**
	(0.002)	(0.002)
Site_visit_60	0.004**	0.004**
	(0.001)	(0.001)
IPC_l	-0.000	0.008
	(0.006)	(0.005)
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	38781	38781
Adjusted R^2	0.026	0.026

Note: This table reports results when testing the information advantage hypothesis. Panel A reports results of the effect of the frequency of corporate site visits on the MRG for firms with high information uncertainty. In the Panel A, column (1) and (2) use different proxies for firms' information uncertainty. Panel B reports results of the effect of the frequency of corporate site visits on MRG for firms with high information processing capacity. In the Panel B, column (1) and (2) use different proxies for firms' information processing capacity. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical test.

2.6.2 The organizational impression management

Hayward and Fitza (2017) propose that managers should lose their confidence after material setbacks, hence, precise MRG after organizational setbacks will be regarded as an impression management tactic. Following Hayward and Fitza (2017), I also identify three material setbacks in my sample: underperformance, earnings miss and financial constraints. The first setback is whether the firm underperformed industry peers in the quarter before MRG was given. The firm's poor performance will limit its prospects of raising capital on preferential terms and increase the possibility that the firm will be subject to takeovers (Baum and Oliver, 1996; Porac et al., 1999; Hayward and Fitza, 2017). Hence, I argue that managers' confidence should be diminished if the firm's market performance is below the industry average performance. Therefore, I define this setback if the firm's average return in the event window of [-93, -3] is below the industry average return in the same event window whereas Day 0 is the release date of MRG (BIP_{it-1}). The industry classification is based on the CSRC 2012 two-digit industry code.

The second setback is whether the firm optimistically missed its earnings guidance in the prior quarter. The OIM literature has consistently demonstrated that organizational leaders endeavor to cultivate favorable impressions following disappointing performance, encompassing the periods leading up to, during, and after the disclosure of negative earnings surprises (e.g., Westphal and Deephouse, 2011; Westphal et al., 2012). A negative earnings surprise creates a negative impression of CEOs as lacking of control and understanding of the drivers of company performance, or as lacking of authority, control and ability to deliver results (Hayward and Fitza, 2017). As a result, managers choose less precise earnings guidance to increase the likelihood of making correct guidance after their failure to deliver on correct guidance in the prior period, because they would be reluctant to further disappointing stakeholders (including investors). However, the hypothesis contradicts the OIM theory since the motivation of managers to regain the sense of being in control should be stronger after setbacks. Therefore, I define $Coptmiss_{it-1}$ as the second setback that it is coded 1 if the actual earnings fall short of the guidance in the prior quarter, and 0 otherwise.

The third setback is whether the firm is financially constrained. Previous studies have recognized financially constrained firms as the set of firms that do not have sufficient cash to make use of investment opportunities and face significant agency costs in accessing financial markets (Korajczyk and Levy, 2003). I argue that financially constrained firms should have little confidence to deliver precise earnings guidance. Therefore, a precise MRG issued by financially constrained firms should be recognized as OIM tactics for managers to create the sense of being in control. Following Cleary (1999) and Kaplan and Zingales (1997), I construct a financial constraint index by considering firm characteristics as below:

$$Z_{FC} = \beta_1 * Current + \beta_2 * FCCov + \beta_3 * \frac{Slack}{K} + \beta_4 * NI\% + \beta_5 * Sales\ Growth + \beta_6 * Debt, \tag{2.5}$$

Similar to Cleary (1999), I classified the sample firms into two mutually exclusive groups: firms whose dividend per share increased in quarter t and others. Then, I run the equation (2.5) to estimate the probability of increasing dividend per share and assign the value of Z_{FC} for each firm in each quarter. I define a financially constrained firm if the value of its' Z_{FC} is below the sample median (FC_{it-1}). An advantage of this approach is that it takes into account all the characteristics common to a particular firm and translates them into a univariate statistic (Cleary, 1999). Therefore, I treat those financially constrained firms as firms experienced organizational setbacks.

Next, I construct interaction terms of the frequency of site visits and organizational setbacks (*OS*) indicators to detect the effect of site visits on precise MRG in each setback. Panel A of Table 9 reports the results. The OIM hypothesis is rejected in all three setbacks. First, BIP_{it-1}, $Coptmiss_{it-1}$ and FC_{it-1} all significantly reduce the precision in MRG, suggesting that managers issue less precise MRG if they underperformed industry peers, they optimistically miss the actual earnings in the last forecast, or if they are financially constrained. Since managers lost confidence after setbacks, the OIM theory predicts a more precise subsequent MRG to indicate that managers use impression management tactics to manipulate their public image. The results in Panel A of Table 2.14, however, show that managers tend to issue less precise MRG to avoid repeatedly disappointing investors by missing out on the actual earnings again. It supports the information advantage hypothesis but not the OIM hypothesis. In addition, the coefficients of the interaction term between site visits and the three setback proxies are all insignificant, implying that more frequent site visits before the release of MRG have no significant effect on the range of MRG if the firm experienced setbacks.

To shed further lights on the OIM hypothesis, I test the effect of site visits on earnings management. If the OIM hypothesis holds, I should see a positive effect of frequent corporate site visits on earnings management, because firms that issue earnings guidance with impression management strategies are also more likely to utilize earnings management tactics to avoid large earnings surprises (Hayward and Fitza, 2017). In other words, if a firm discloses biased earnings guidance first but releases true earnings later, the market will penalize it for earnings surprise on the date of actual earnings announcement. Therefore, many firms choose a combination of impression management and earnings management to manipulate both disclosures. I follow the three models of estimating discretionary accruals in Choi et al. (2015) and Gao et al. (2017) and test the effect of site visits on earnings management. Larger discretionary accruals indicate more earnings management.

The first model follows Jones (1991), expressed as:

$$\frac{Accruals_{it}}{Assets_{it}} = \alpha * \frac{1}{Assets_{it-1}} + \beta_1 * \left(\frac{\Delta Sales_{it}}{Assets_{it-1}}\right) + \beta_2 * \left(\frac{PPE_{it}}{Assets_{it-1}}\right) + \varepsilon_{it}, \tag{2.6}$$

where Total Accruals *(TA)* of firm *i* and at time *t*, $TA_{it} = Accruals_{it}/Accruals_{it-1}$, is income before extraordinary items minus operating cash flows, scaled by lagged total assets. TA_{it} is regressed on a constant, change in sales ($\Delta Sales_{it}$), and plant and equipment (PPE_{it}), all scaled by lagged assets ($Assets_{it}$) to mitigate the effect of heteroscedasticity. Discretionary total accruals are residuals from the regression model, labeled as $DTACC_{it}$.

The second method follows Bergstresser and Philippon (2006) and employs discretionary current accruals. The third method uses discretionary working capital accruals, following Teoh, Welch, and Wong (1998). Current accruals ($CACC_{it}$) and working capital accruals ($WCACC_{it}$) are defined in Equations (2.7) and (2.8), respectively:

$$CACC_{it} = (\Delta CA_{it} - \Delta CL_{it} - \Delta CASH_{it} + \Delta STD_{it} - DEP_{it})/Assets_{it-1}, \tag{2.7}$$

$$CACC_{it} = (\Delta CA_{it} - \Delta CL_{it} - \Delta CASH_{it} + \Delta STD_{it} - DEP_{it})/Assets_{it-1}, \tag{2.8}$$

where ΔCA_{it} is the change in the current assets of firm i at time t; ΔCL_{it} is the change in current liabilities; $\Delta CASH_{it}$ is the change in cash holdings; and ΔSTD_{it} is the change in short-term debt. DEP_{it} is the depreciation and amortization expense of the firm; and $Assets_{it-1}$ is lagged total assets.

These two alternative measures of accruals, $CACC_{it}$ and $WCACC_{it}$, are then fed into Equation (2.6), and residuals from it are labeled as $DCACC_{it}$ and $DWCACC_{it}$, respectively. Equation (2.6) is estimated cross-sectionally using all firms that have non-missing values in the relevant variables for each two-digit coded industry in each quarter. EM_h_{it} is an indicator that equals 1 if discretionary accruals are above the median of the full sample. Next, I construct interaction terms of the frequency of site visits and discretionary accruals indicators to detect the effect of site visits on precise MRG when considering earnings management.

Panel B of Table 2.14 reports the results. The coefficients of the interaction terms are negative and statistically significant in all models. It shows that more frequent site visits with large discretionary accruals contribute to less precise MRG. This result is also in line with the findings in Qi et al. (2021) and Broadstock et al. (2022) that more frequent corporate site visits reduce earnings management. Since I expect more precise MRG after site visits with higher earnings management under the OIM hypothesis, a significantly negative coefficient indeed rejects it. Therefore, the results of both tests reject the OIM hypothesis.

Table 2.14: Organizational impression management (OIM) hypothesis

Panel A: Organizational setback (OS)

	Dependent variable: Precision		
	BIP	*Coptmiss*	*FC*
	(1)	*(2)*	*(3)*
Site_visit_60*OS	-0.001	0.005	-0.000
	(0.002)	(0.004)	(0.002)
Site_visit_60	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)
OS	-0.020***	-0.052***	-0.029***
	(0.003)	(0.006)	(0.005)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	31647	38781	38781
Adjusted R^2	0.027	0.029	0.028

Panel B: Earnings management (EM)

	Dependent variable: Precision		
	DTACC	*DCACC*	*DWCACC*
	(1)	*(2)*	*(3)*
Site_visit_60*EM_h	-0.002*	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Site_visit_60	0.007***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
EM_h	0.010***	0.009***	0.004
	(0.003)	(0.003)	(0.003)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	38495	38495	38495
Adjusted R^2	0.026	0.026	0.026

Note: This table reports results when testing the OIM hypothesis. Panel A reports results of the effect of the frequency of corporate site visits on MRG after organizational setback. In the Panel A, column (1), (2) and (3) use different proxies for organizational setbacks. Panel B reports results of the effect of the frequency of corporate site visits on MRG when firms with high discretionary accruals. In the Panel B, column (1), (2) and (3) use different proxies for discretionary accruals. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical test.

2.7 Conclusion

This chapter utilizes a distinctive dataset in China to investigate the impact of corporate site visits on the accuracy of MRG. The analysis reveals that a higher frequency of site visits prior to the release of MRG leads to greater precision in MRG. These findings remain robust when considering alternative measures of site visits and MRG precision. Additionally, various methods including propensity score matching, the Heckman two-step selection method, instrumental variables, and subsample analysis are employed to address potential self-selection bias and endogeneity concern.

Furthermore, a series of tests are conducted to elucidate the underlying mechanisms driving the relationship between corporate site visits and MRG. The results provide supporting evidence for the information advantage mechanism, suggesting that increased information leads to more accurate MRG. Specifically, corporate site visits have a more pronounced impact on MRG precision when firms face higher information uncertainty or possess lower information processing capacity. Conversely, evidence contradicting the organization impression management hypothesis is found.

My study highlights the significant information transmission in direct interactions between analysts and firm managers. I show that analysts' frequent site visits contribute to precise MRG, which has important implications for investors, managers and regulators.

Appendix 2.1 Mediation test for ROA

One may argue that a higher MRG precision may not be an outcome of site visits, but a result of stronger business performance. Better firms with more informed managers are more profitable, and profitable firms are more likely to be visited by analysts/investors. The argument could be supported by the correlation matrix Table 2.3: precision is positively correlated with ROA, and ROA is positively correlated with site visits.

To address this concern, I use structure equation modelling to check whether site visits affect management forecast precision directly or indirectly via business performance. Table A2.1 reports the results. However, the results in Panel A column (2) show that stronger business performance do not attract more corporate site visits. In accordance, the result of Sobel test in Panel B is insignificant. Therefore, both panels show that the impact of site visits on management forecast precision do not directly or indirectly through firm performance.

Table A2.1: Mediation test for ROA

Panel A: Structure equation modelling			
	Precision	*Site visit*	*Precision*
	(1)	*(2)*	*(3)*
ROA	0.215***	-0.070	0.216***
	(0.017)	(0.094)	(0.017)
Site visit			0.005***
			(0.001)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	38,781	38,781	38,781
Adjusted R^2	0.063	0.085	0.064

Panel B: Sobel test	
	Sobel test
z	-0.743
P>|z|	0.458

Note: This table reports results of mediation test for ROA. Panel A reports results of structure equation modelling. Column (1) reports the effect of ROA on precision, column (2) reports the effect of ROA on site visits, column (3) reports the effect of site visits and ROA on precision. Panel B reports the result of Sobel test. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical test.

Appendix 2.2 Other instrumental variables

One may argue that weather uncertainty or extreme weather conditions in the 90 days before the release of MRG might also affect the managers' mood and thereby impair their forecast precision, as recent literature (Dong et al., 2021) has shown that air pollution reduces analyst forecast accuracy. Therefore, following Lu et al. (2018), I use a better instrument instead: geographic distances between the firm's headquarters and the four economic centers (Beijing, Shanghai, Shenzhen, and Guangzhou) in China. I also calculate the average distance of the firm's headquarters and these four cities ($Fin\_Distance$).

Table A2.2 reports the results. Unfortunately, the results show that geographic distance is a weak instrument in my sample, evidenced by insignificant results in both Panel A and B. For all five measures, geographic distance cannot meet the relevance condition that geographic distance is significantly related to the frequency of site visits before the release of MRG.

Table A2.2: Other instrumental variables

Panel A: First-stage regressions					
Dependent variable: Site_visit_60					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
DistanceBJ	-0.000				
	(0.000)				
DistanceSH		0.000			
		(0.000)			
DistanceSZ			0.000		
			(0.000)		
DistanceGZ				0.000	
				(0.000)	
Fin_Distance					0.000
					(0.000)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	38781	38781	38781	38781	38781
adj. R-sq	0.006	0.006	0.006	0.006	0.006
Cragg-Donald (CD) Wald F-statistic	0.051	0.022	0.271	0.277	0.185

Panel B: Second-stage regressions					
Dependent variable: Precision					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
sitevisit60	-0.810	2.428	0.206	0.182	0.770
	(3.717)	(16.556)	(0.534)	(0.497)	(1.832)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	38781	38781	38781	38781	38781
adj. R-sq	0.007	0.007	0.007	0.007	0.007

Note: This table reports the results of instrumental variables method based on two-stage least squares (2SLS) panel regressions. Panel A presents the first-stage regression results in which the dependent variable is *Site_visit_60*. Panel B reports the second-stage regression results. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Chapter 3 Sell-side financial analysts' social network and forecasts accuracy

3.1 Introduction

Sell-side financial analysts play a crucial role in capital markets, and their opinions have a significant impact on the valuation of assets (Bradshaw, 2004; Gleason and Lee, 2003; Jegadeesh et al. 2004; Stickel, 1992). Most of previous studies focus on the determinants of financial analysts' forecast performance by regarding individual analyst characteristics and information environment (Brown 1983; Brown and Rozeff 1979; Byard et al. 2011; Clement 1999; Hope 2003; Jacob et al. 1999; Lang and Lundholm 1996; Mikhail et al. 1997), while some researchers also indicate the significance of analysts' peer effects. That is, analysts are significantly concerned with the opinions of other analysts about the firms they cover (e.g. Graham, 1999; Horton and Serafeim, 2009; Zhao et al., 2014; Hou et al., 2018; Kumar et al., 2022).

There might be two explanations for analysts' peer effects in different scenarios. First, analysts' forecasts could be influenced by strategic herding behavior, where analysts pay more attention to peers' forecasts and recommendations for the same target firm (Graham, 1999; Horton and Serafeim, 2009; Trueman, 1994; Welch, 2000). Strategic herding behavior can arise from information cascades, which can also be called as "informational herding", where analysts infer information of the target firm from other analysts' earnings estimates (Bikhchandani et al., 1992). Alternatively, strategic herding behavior can arise from intentional and strategic behavior, where analysts are afraid to deviate from consensus for professional reasons (Hong et al., 2000). The ability to extract information from the current actions of others may be an important source of analyst expertise (Clement et al., 2011).

Second, Kumar et al. (2022) proposed a quite new explanation for peer effects on different target firms. They argue that sell-side equity analysts engage in social learning to improve their forecast performance. Specifically, Kumar et al. (2022) indicate that an analyst's earnings forecast for a target firm is additionally influenced by the actions and opinions of peer analysts who follow the same firms in that analyst' following portfolio. For example, if the analyst follows a range of firms from firm k_1 to k_{10}, but only issues earnings forecasts for the firm k_1. That earnings forecast may be influenced by the actions and opinions of other peer analysts who also follow firm k_1 to k_{10}, or follow some of these firms, but not only those analysts who follow k_{10}. According to limited attention theory, analysts may pay more attention to other analysts' views on firms in their own following portfolio, but pay relatively less attention to similar information on other firms that are out of their portfolio. Therefore, the heterogeneity of analysts' following portfolios leads to the heterogeneity in analysts' information sets. Analysts can correct their bias by learning from peers. For example, if peer analysts are systematically optimistic (pessimistic) about other firms within the analysts' following portfolio, the analyst may learn from peers and update his views on the target firm, that is, issue a more pessimistic (optimistic) forecast to correct the perceived bias, thereby improving the accuracy of the forecast.

Social learning hypothesis, grounded from the widely acknowledged theory that social cognitive theory (Bandura, 1977), highlights the notion that people learn by observing and imitating others, particularly those held in an admired status, as a fundamental aspect of human learning. The finance and economics literature defines "social learning" as a process where individuals learn from others in a way that extends beyond pure informational herding (Ellison and Fudenberg, 1993; Kaustia and Rantala, 2015; Moretti, 2011). Instead of intentional strategies, the social learning hypothesis suggests that analysts' forecast performance could also be improved by their social network. For example, Malmendier and Shanthikumar (2014) find that analysts may not learn from their own past mistakes, but they could learn from their peers. Do and Zhang (2020) demonstrate how the forecasting performance of existing analysts is influenced by the arrival or departure of star analysts. They argue that star analysts offer incumbent analysts role models and give them the opportunity to observe and learn (e.g., the star analyst's work ethic and way of interacting with clients and other members of the team). These tacit lessons are helpful in improving incumbents' overall performance.

Distinct from previous studies, my research provides more direct empirical evidence on the social learning hypothesis of analysts' peer effects. I attempt to recognize social learning beyond pure informational herding by examining the impact of private interactions among analysts on their overall forecast performance. I use a dataset of corporate site visits from the Shenzhen Stock Exchange (SZSE) to construct a social network of analysts based on face-to-face interactions among analysts during corporate site visits. Specifically, I first construct a social network of analysts based on their attendance of corporate site visits. I argue that analysts should socially connected with each other if they attend the same corporate site visits. Then, I calculate the eigenvector centrality of each analyst. The eigenvector centrality can fully account for indirect and direct social interactions. Finally, I examine the effect of analysts' eigenvector centrality on their overall forecast performance.

My research is distinct from Horton and Serafeim (2009) and Cheng et al. (2016) in that I investigate the effect of analysts' social network rather than information acquisition from corporate site visits. Although I find similar results that corporate site visits contribute to improving analysts' earnings forecasts, the mechanism behind it might be different. Following Kumar et al. (2022), my research design supports social learning hypothesis but not informational herding hypothesis through the improvement of analysts' overall forecast performance. That is, informational herding hypothesis could be the underlying mechanism only if analysts improve their forecast performance for the visited firm after corporate site visits, which is examined by Cheng et al. (2016). However, I do not impose any requirement that these analysts forecast visited firms after corporate site visits. In fact, most of analysts in my sample do not publish earnings estimates for visited firms. Therefore, the improvement of analysts' overall forecast performance for analysts with a more central position in the social network based on analysts' attendance of corporate site visits indeed signals the social learning explanation rather than informational herding hypothesis.

In addition, my research is also distinct from Kumar et al. (2022) in that my proxy for peer analysts is more direct to test the social learning hypothesis. Kumar et al. (2022) define peer analysts as analysts who publish earnings estimates for same firms within analysts' following portfolios, while these analysts may not know each other personally, which means that analysts can only extract information from peers' public earnings estimates. On the contrary, I define peer analysts if they attend the same corporate site visits. I argue that the face-to-face communications among analysts during corporate site visits can bring numerous new information, new knowledge, new opinions, and new sentiment, which should have more direct and stronger effects than peers' public earnings estimates.

In sum, I find that analysts' social network improves analysts' forecast accuracy. Specifically, analysts with higher eigenvector centrality in the social network based on corporate site visits generally provide more accurate earnings forecasts relative to other analysts. I conduct a battery of robustness tests to address potential empirical concerns. My result is robust to the control of the firm' and analysts' characteristics that are commonly used in the previous studies and to the use of alternative measures of forecast accuracy.

To alleviate the concern of sample selection bias that not all analysts have site visits before publishing earnings forecasts, I use the Heckman's two-step selection method. Moreover, my model may suffer the endogeneity concern that analysts publish more accurate earnings forecasts will attend more corporate site visits. The unobservable omitted variables, for example, analysts' personality, may be also related to analysts' forecast performance and their position in the social network. Therefore, I employ the fixed effect model, instrumental variables, and subsamples to alleviate the concern of omitted variables and reverse causality. Following Han et al. (2018), I use the extreme weather as the instrumental variable to take out the endogenous effect because the extreme weather significantly affects the possibility of corporate site visits while seems not correlates with analysts' forecast performance. Following Chen et al. (2022), I restrict my sample to a subset of firm-quarter observations for which the reverse causation problem is less severe. My conclusions do not alter after these robustness checks.

To further substantiate my main results relating to the social learning hypothesis, I examine two situations implied by the hypothesis through which social network improves analysts' forecast accuracy: influential peers and information uncertainty. According to Centola (2010) and Aral and Walker (2012), influential peers have a significant effect on the diffusion of knowledge, ideas, and behaviors within social networks. They suggest that influential individuals not only possess more information but also have a greater ability to persuade others to adopt certain beliefs or practices.

Moreover, Bonaccio and Dalal (2006) and Chen et al. (2022) demonstrate that individuals are more likely to seek advice from others and are more receptive to learning from the experiences and knowledge of influential peers in uncertain situations. Their studies highlight the role of uncertainty in driving individuals to actively seek and learn from others. Therefore, I follow these studies to argue that analysts should learn more from peers when more influential peers attended corporate site visits or when forecasted firms with higher information uncertainty.

This study contributes to the growing body of research on the social learning hypothesis in Finance. Distinct from the prior studies, this study provides a more direct proxy for analysts' peer effects. Unlike most of previous research define peer analysts if they issue earnings estimates for the same firms, this study quantifies the peer effects based on face-to-face interactions with a unique dataset of corporate site visits in China. Although corporate site visits are common in the United States and Europe, firms usually do not report historical records of these visits. However, firms listed on the SZSE in China have been obligated to disclose information regarding site visits since 2009, creating a distinct prospect to scrutinize the direct interactions between analysts during these visits. The valuable dataset allows me to construct a powerful analysts' social network because I believe that analysts should have face-to-face communications and build strong relationships with each other if they attend the same corporate site visits.

From psychological literature (Carr, 2011; Turkle, 2011), virtual and textual information, for example, public earnings estimates, often lacks the nuances and subtleties necessary for genuine peer effects to take place. Instead, face-to-face interactions have a stronger peer effect than virtual and textual information. Psychological literature emphasizes the unique qualities and depth of in-person communication, highlighting the limitations of digital media in fully capturing the richness of human interaction. To the best of my knowledge, this study is the first to construct the analysts' social network based on corporate site visits to measure analysts' peer effects.

My results that analysts' face-to-face social network contributes to improving analysts' forecast performance has several implications for regulators, investors, firm managers, and financial analysts themselves. First, regulators can encourage or facilitate networking opportunities for financial analysts, such as organizing industry conferences or events where analysts can meet and interact face-to-face. By recognizing the value of social networks in improving forecast accuracy, regulators can promote a more collaborative and information-sharing environment within the financial industry.

Second, investors can consider the social network of financial analysts as an additional factor when evaluating the quality of their forecasts. Investors may prioritize analysts who actively expand their face-to-face social networks, as these analysts are more likely to have access to diverse information sources and benefit from the exchange of insights and perspectives with influential peers.

Third, firm managers can support and encourage financial analysts to engage in networking activities and build relationships with influential peers. Firms can facilitate opportunities for analysts to attend industry events, participate in professional organizations, or engage in cross-departmental collaboration within the organization. By fostering a culture of networking and knowledge sharing, firms can enhance the accuracy of their financial forecasts.

Finally, financial analysts themselves can proactively expand their face-to-face social networks to improve their forecast accuracy. They can attend industry conferences, join professional organizations, and actively engage with influential peers in their field. By building strong relationships with knowledgeable and well-connected individuals, analysts can gain access to diverse information, receive feedback on their analyses, and benefit from the expertise and insights of others. Financial institutions, for example, brokers, can support and incentivize networking efforts by incorporating social network expansion as a performance metric or providing resources for analysts to attend relevant conferences and events. By recognizing the value of social networks, institutions can encourage analysts to invest time and effort into cultivating relationships that can enhance their forecast accuracy.

Overall, the implication of knowing that expanding face-to-face social networks can improve analysts' forecast accuracy suggests the importance of collaboration, knowledge sharing, and relationship-building within the financial industry. By recognizing and leveraging the power of social networks, regulators, investors, firms' managers, and financial analysts can enhance the quality and reliability of financial forecasts.

The rest of the paper proceeds as follows. Section 3.2 covers data and variable definitions, section 3.3 discusses empirical results, section 3.4 presents some cross-sectional analyses, and section 3.5 concludes.

3.2 Data and variables

I obtain information on analysts' earnings forecasts and corporate site visits for all listed firms on Chinese SZSE market from fiscal years 2012-2021. I start my sample in 2012 because corporate site visits in earlier years are sparse in the CSMAR database. I include the analysts' latest published EPS forecasts for each fiscal year and no later than the fiscal year-end. Because I compare analysts' relative forecast performance for a particular firm within a year, I eliminate firm-years for which only one analyst provides a forecast. I remove analysts who did not attend any corporate site visits during the fiscal year because no network connection is constructed based on those analysts. my final sample consists of 142,601 analyst-firm-year observation.

3.2.1 Social network and centrality measures

I construct analysts' social network based on their attendance at corporate site visits. To measure how well connected an analyst is in the social network based on corporate site visits, I follow Hirshleifer et al. (2021) and construct a network centrality degree, eigenvector centrality (EC), which is commonly used in graph theory to characterize the extent to which the prominence or importance of a node in the network. In the analysts' social network, the security analyst is selected as the node and with N = 1, . . , n. The edge between analyst i and analyst j, denoted as a_{ij}, represents the connection between the two analysts based on corporate site visits.

Self-links or loops (a node transferring information to itself) are not allowed in the graph ($a_{ii} = 0$). The undirected ($a_{ij} = a_{ji}$) and weighted ties among analysts are reflected in the symmetric adjacency matrix $A = \{a_{ij}\}_{N\times N}$, that is:

$$A = \begin{Bmatrix} 0 & \cdots & a_{1i} & \cdots & a_{1n} \\ \vdots & \ddots & \square & \square & \vdots \\ a_{i1} & \square & 0 & \square & a_{in} \\ \vdots & \square & \square & \ddots & \vdots \\ a_{n1} & \cdots & a_{ni} & \cdots & 0 \end{Bmatrix}$$

(3.1)

where N is the number of analysts and a_{ij} is the number of corporate site visits links between two analysts.

EC accounts for the transmission of signals along longer paths and walks (Bonacich, 1972; Borgatti, 2005). The EC of a node i is the i_{th} element of the principal right eigenvector of the adjacency matrix. The centrality of a node is also proportional to the average centrality scores of its direct neighbors. Therefore, a node will be more central if it is adjacent to nodes that are themselves highly central. The advantage of EC is that it fully allows for indirect and direct social interactions.

3.2.2 Analysts' forecast accuracy

Following Clement and Tse (2005), my baseline measure of an analyst i's forecast accuracy for firm k in year t is based on the absolute forecast error (AFE) of her forecast relative to those of others who follow firm k in year t. I first calculated AFE of analyst i for firm k in year t as:

$$AFE_{ikt} = |Forecasted\ EPS - Actual\ EPS|,$$

(3.2)

Then, I scale the difference between the maximum AFE of firm k and analyst i's AFE of firm k by the range of AFE for analysts following firm k in year t:

$$Accuracy_{ikt} = \frac{AFEmax_{kt} - AFE_{ikt}}{AFEmax_{kt} - AFEmin_{kt}},$$

(3.3)

In this way, $Accuracy_{ikt}$ increases with analyst i's own forecast performance. It measures the least accurate forecast (highest AFE) as 0 and the most accurate forecast (lowest AFE) as 1.

3.3 Empirical results

3.3.1 Baseline regression results

To assess whether analysts' forecast accuracy increases as a function of her eigenvector centrality in the social network, I estimate the following regression model:

$$Accuracy_{ikt} = \alpha + \beta_1 EC_{it} + \gamma Controls + Fixed\ Effects + \varepsilon_{ikt}. \tag{3.4}$$

My controls for other determinants of analysts' relative accuracy include analysts' characteristics and firm characteristics. Following Clement and Tse (2005) and Hirshleifer et al. (2019), I control for analysts' characteristics including: analysts' forecast frequency (*ForFrequency*), forecast horizon (*ForHorizon*), firm-specific forecast experience (*FirmExperience*), general forecast experience (*GenExperience*), the number of firms (*FollowF*) and industries (*FollowI*) each analyst follows, the number of analysts covers a firm (*FollowA*), analysts' brokerage size (*BrokerSize*) and forecast accuracy in the prior year (*LagAccuracy*). Following Han et al. (2018), I control for firm characteristics including: firm size (*size*), leverage (*LEV*), age (*Age*) and return on assets (*Roa*). Following Han et al. (2018) and Hirshleifer et al. (2019), I control for analyst-firm fixed effects and year fixed effects to account for unobserved analyst-firm and year heterogeneity.

I report descriptive statistics in Table 3.1. The average forecast accuracy in my sample is over 0.5, which suggests that analysts who attended corporate site visit have higher forecast accuracy above the average of peer analysts. However, other relative characteristics of analysts in my sample are all below 0.5, indicating that analysts who attend corporate site visits are generally less experienced (in both general and firm-specific experience), issue less frequent forecasts and more recent forecasts, follow fewer firms and industries, and in smaller brokerages.

Table 3.1: Summary statistics

	N	Mean	SD	Min	p5	p25	Median	p75	p95	Max
Accuracy	142601	0.638	0.330	0.000	0.000	0.390	0.741	0.929	1.000	1.000
EC	142601	0.005	0.015	0.000	0.000	0.000	0.000	0.002	0.033	0.167
ForFrequency	142601	0.307	0.322	0.000	0.000	0.032	0.200	0.500	1.000	1.000
ForHorizon	142601	0.374	0.338	0.000	0.000	0.092	0.255	0.668	1.000	1.000
FirmExperience	142601	0.229	0.333	0.000	0.000	0.000	0.000	0.333	1.000	1.000
GenExperience	142601	0.263	0.277	0.000	0.000	0.077	0.167	0.375	1.000	1.000
FollowF	142601	0.326	0.274	0.000	0.000	0.118	0.250	0.460	1.000	1.000
FollowI	142601	0.322	0.273	0.000	0.000	0.115	0.250	0.462	1.000	1.000
FollowA	142601	49.335	36.464	2.000	8.000	22.000	41.000	68.000	119.000	290.000
BrokerSize	142601	0.479	0.311	0.000	0.000	0.239	0.450	0.698	1.000	1.000
LagAccuracy	142601	0.721	0.275	0.000	0.071	0.579	0.813	0.937	1.000	1.000
Size	142601	23.034	1.602	19.321	21.012	21.923	22.740	23.783	26.105	31.191
LEV	142601	0.430	0.199	0.009	0.127	0.272	0.420	0.576	0.771	2.579
Age	142601	17.359	5.784	3.000	8.000	13.000	17.000	21.000	27.000	63.000
Roa	142601	0.067	0.062	-3.911	0.006	0.033	0.060	0.095	0.165	0.590

Note: This table presents descriptive statistics on variables. *Accuracy* is analyst i's forecasts' accuracy for firm k in year t relative to other analysts following firm k in year t. *Centrality* is the eigenvector centrality based on the network of corporate site visits for each analyst i in year t. *ForFrequency* is analyst i's forecast frequency for firm k in year t relative to other analysts following firm k in year t. *ForHorizon* is the time from the forecast date to the end of the fiscal period for analyst i following firm k in year t relative to other analysts following firm k in year t. *FirmExperience* is the number of years of firm specific experience for analyst i following firm k in year t relative to other analysts following firm k in year t. *GenExperience* is the number of years of experience for analyst i following firm k in year t relative to other analysts following firm k in year t. *FollowF* is the number of companies followed by analyst i following firm k in year t relative to other analysts following firm k in year t. *FollowI* is the number of industries followed by analyst i following firm k in year t relative to other analysts following firm k in year t. *FollowA* is the number of analysts who cover firm k in year t. BrokerSize is the number of analysts employed by the brokerage employing analyst i following firm k in year t relative to other analysts following firm k in year t. *LagAccuracy* is analyst i's forecasts' accuracy for firm k in year t-1 relative to other analysts following firm k in year t-1. *Size* is the natural log of firm k's total assets at the end of the fiscal year t. *LEV* is the debt-to-assets ratio of firm k at the end of the fiscal year t. *Age* is the number of years from firm k's listed year to the year t. *Roa* is the income before extraordinary items deflated by total assets of firm k at the end of the fiscal year t.

I report regression results in Table 3.2. Results in column (1) and (2) in Table 3.2 indicate that, on average, the accuracy of forecast increases as a function of analysts' eigenvector centrality in the social network. In column (2), the coefficient on my key independent variable, *EC*, is 0.394 and is significant at the 1% level. This suggests that, on average, a one-unit increase in *EC* leads to a forecast that is 0.394 units more accurate relative to others. This is an economically meaningful effect. This result supports my hypothesis that analysts who are more central in the social network provide more accurate earnings forecasts relative to others.

Table 3.2: Baseline regression results

Dependent Variable: Accuracy		
	(1)	*(2)*
EC	0.934***	0.342**
	(0.220)	(0.151)
ForFrequency		-0.318***
		(0.006)
ForHorizon		-0.003
		(0.005)
FirmExperience		-0.410***
		(0.005)
GenExperience		-0.005
		(0.009)
FollowF		-0.038**
		(0.018)
FollowI		-0.019
		(0.012)
FollowA		-0.006
		(0.010)
BrokerSize		0.001***
		(0.000)
LagAccuracy		-0.007
		(0.009)
Size		-0.006
		(0.008)
LEV		-0.032
		(0.022)
Age		-0.011***
		(0.002)
Roa		0.252***
		(0.041)
_cons	0.900***	1.345***
	(0.012)	(0.181)
Analyst-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	142601	142601
Adjusted R^2	0.039	0.304

Note: This table reports the effect of analyst i's centrality on her forecast accuracy. Column (1) reports the result of univariate regression. Column (2) reports the result of Equation (3.3): $Accuracy_{ikt} = \alpha + \beta_1 EC_{it} + \gamma Controls + Fixed\ Effects + \varepsilon_{ikt}$. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the analyst level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.2 Robustness tests

3.3.2.1 Alternative measures of forecasts accuracy

In my baseline regression, I follow Clement and Tse (2005) to define forecast accuracy as expressed in Equation (1) and (2). In this section, I employ two alternative measures of forecast accuracy. First, following Han et al. (2018), I replace the AFE in $Accuracy_{ikt}$ by the AFE scaled by share price of firm k in two days before the forecast, other calculations are the same as $Accuracy_{ikt}$. Second, following Kumar et al. (2022), I measure forecast accuracy as the average AFE for analysts who follow firm *k* in year t minus the AFE of analyst *i* following firm *k* in year *t*, with this difference scaled by the average of AFE for analysts following firm *k* in year *t*, expressed as:

$$Accuracy_{ikt} = \frac{AFEmean_{kt} - AFE_{ikt}}{AFEmean_{kt}}, \tag{3.5}$$

Results in Table 3.3 show that my results are robust to all three alternative measures of forecast accuracy. For brevity, I report only the coefficient estimates for the main variables of interest. All regression results in Table 3.3 are consistent with my main hypothesis that more analysts with higher eigenvector centrality provide more accurate earnings forecasts relative to their peers.

Table 3.3: Alternative measures of forecast accuracy

	Accuracy2	*Accuracy3*
	(1)	*(2)*
EC	0.284*	1.034**
	(0.156)	(0.433)
Controls	Yes	Yes
Analyst-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	118018	142601
Adjusted R^2	0.295	0.276

Note: This table reports the robustness test results when using alternative measures of analysts' forecast accuracy. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the analyst level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.2.2 Heckman two-step selection method

Not all analysts have site visits when making earnings forecasts. I cannot estimate analysts' eigenvector centrality score of the social network based on corporate site visits if they have no corporate site visits. This raises the question whether the differences in the characteristics of these two groups of analysts drive my results. To alleviate the sample self-selection concern, I use the Heckman two-step selection method. I follow Cheng et al. (2016, 2019) and use the following regression to estimate the probability of analysts attending corporate site visits and obtain the Inverse Mills Ratio (IMR):

$$P\,r(EC\_treat_{it}) = \alpha + \beta_1 Num\_Firms_{kt} + \beta_2 \Delta GDP_{kt} + \gamma Controls + \varepsilon_{ikt}, \tag{3.6}$$

where EC_treat_{it} is an indicator variable coded 1 if the analyst i has at least one corporate site visit to measure her eigenvector centrality in year t, and 0 otherwise. For determinants, I add two instruments that the information related to firm headquarters' city, including the number of listed firms (Num_Firms_{kt}) and GDP growth (ΔGDP_{kt}). Following Jiang and Yuan (2018), Cheng et al. (2019) and Chen et al. (2022), these two variables are exclusion restrictions. I add these two variables in the first stage because they are expected to correlate with analysts' eigenvector centrality score of the social network based on corporate site visits, but they are not directly related to analysts' forecast accuracy. For example, more listed firms in the firm headquarters' location can attract more site visits, because analysts prefer to visit cities where they can visit multiple firms in one trip to save time and expenses, while it is not directly related to analysts' forecast accuracy. Similarly, the changes in cities' GDP where firm headquarters is located attract more site visits to explore reasons behind, while it is not directly related to analysts' forecast accuracy.

Table 3.4 reports the results. Colum (1) presents the determinant analysis. As I expected, Num_Firms_{kt} and ΔGDP_{kt} are both significantly related to the probability of analysts attending corporate site visits. In the second stage, I test the effect of analysts' eigenvector centrality score on forecast accuracy by including the IMR estimated from the first step. Column (2) of Table 3.4 shows that, similar to the baseline results reported in Table 3.4, the coefficient of EC_{it} is positive and statistically significant at the 1% level. These results show that my baseline findings are robust when using the Heckman two-step selection method to adjust for the self-selection bias.

Table 3.4: Heckman two-step selection method

	EC_treat	*Accuracy*
	(1)	*(2)*
Num_Firms	0.046***	
	(0.003)	
ΔGDP	-0.959***	
	(0.109)	
EC		0.330**
		(0.149)
IMR		0.173***
		(0.039)
Controls	Yes	Yes
Analyst-Firm FE	No	Yes
Year FE	No	Yes
Observations	179453	131946
Pseudo /Adjusted R^2	0.061	0.310

Note: This table reports the results of the Heckman two-step selection method. Column (1) reports the determinant analysis of the probability of analysts attending corporate site visits. It presents the logistic regression results for Equation (3.5): $Pr\ (EC\_treat_{it}) = \alpha + \beta_1 Num\_Firms_{kt} + \beta_2 \Delta GDP_{kt} + \gamma Controls + \varepsilon_{ikt}$. Column (2) reports the effect of analysts' eigenvector centrality on forecast accurcy by including the inverse Mill's ratio (IMR). Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.2.3 Instrumental variable

One may concern that the omitted variables in the baseline models that are related to analysts' eigenvector centrality of the social network also affect forecast accuracy. Although I include analyst-firm and year fixed effects to alleviate concerns that forecast accuracy is driven by time and analyst-firm invariant unobservable variables, there may be other omitted variables that lead to reverse causality. For instance, analysts with higher level of professional skills attend more corporate site visits and provide more accurate forecasts. To alleviate this endogeneity concern, I employ the instrumental variable and two-stage least square method.

I use the instrumental variable approach to identify the causal relationship between analysts' eigenvector centrality and forecast accuracy. Following Han et al. (2018), I use an exogenous variable, extreme weather conditions (*ExtrmWeather*) in the city of the firm headquarter, as an instrument for corporate site visits. Weather affects the probability of corporate site visits, which affects analysts' eigenvector centrality score of the social network based on corporate site visits, as it is more difficult to travel to places during extreme weather. However, weather is unlikely to affect analysts' forecast accuracy. Thus, I expect extreme weather to represent a valid IV estimation of analysts' eigenvector centrality. I define a day as an extreme weather day (*ExtrmDay* = 1) if the lowest temperature falls below -10℃ or if the highest temperature reaches above 37℃. *ExtrmWeather* is defined as the percentage of days in year t with extreme weather conditions in the city where the firm's headquarters is located:

$$ExtrmWeather_{kt} = \frac{\sum ExtrmDay_{kt}}{TotalDays_t}. \tag{3.7}$$

I use the quintile rank of *ExtrmWeather* as the instrumental variable. Table 3.5 presents the results. Column (1) of Table 3.5 reports the results of the first-stage regressions where the dependent variable is analysts' eigenvector centrality score, and the explanatory variables include the instrument and the same set of control variables as in Table 3.2. For brevity, I report only the coefficient estimates for the main variables of interest. Consistent with the rationale behind the instrument, *ExtrmWeather* is positively and significantly (at the 1% level) correlated to analysts' eigenvector centrality, suggesting that my instrument is valid. The reported F-statistics are large, the p-value of the Cragg-Donald's Wald F weak-instrument test statistic is 0.000, both rejecting the null hypothesis that the instrument is weak (Cragg and Donald, 1993; Stock and Yogo, 2005). Column (2) of Table 3.5 reports the results for the second-stage regressions with analysts' forecast accuracy as dependent variable. The variable of interest is the variable with the predicted values from the regression in the first-stage regressions. The results are consistent with the baseline regressions and support my main hypothesis. Those results imply that my key result is unlikely due to the endogeneity of the analysts' social network.

Table 3.5: Instrumental variable

	First stage	*Second stage*
	EC	*Accuracy*
	(1)	*(2)*
ExtrmWeather	0.022***	
	(0.005)	
EC (Fitted)		19.174***
		(5.673)
Controls	Yes	Yes
Analyst-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	130267	130267
Adjusted R^2	0.027	0.302
F-statistic	586.66***	
Cragg-Donald (CD) Wald F-statistic	26.596	
Stock and Yogo (2005) weak ID test critical value	16.38	

Note: This table reports the results of instrumental variables method based on two-stage least squares (2SLS) panel regressions. Column (1) presents the first-stage regression results in which the dependent variable is *EC*. Column (2) reports the second-stage regression results. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.2.4 Reverse causality

Whereas all my identification attempts so far point to a causal effect of the eigenvector centrality of analysts on their forecast accuracy, a plausible alternative interpretation of my main results is that analysts who are more accurate in their earnings forecast attend more corporate site visits, resulting in the positive relation between the centrality of analysts and forecast accuracy. This alternative interpretation indicates the direction of causality could be the other way around. To gain insights about whether my findings are driven by reverse causality, I follow Chen et al. (2022) to restrict my sample to a subset of firm-quarter observations for which the reverse causation problem is less severe. More specifically, I re-examine the effects of analysts' eigenvector centrality after excluding, respectively, the top 10% and 25% accurate analysts. I report the results in Table 3.6. I find that the eigenvector centrality of analysts based on the social network of corporate site visits continues to be economically and statistically significant in all model specifications. These findings provide further assurance that the effect of corporate site visits does not appear to arise from reverse causation.

Table 3.6: Excluding top analysts

	Dependent variable: Accuracy	
	Excluding largest 10%	*Excluding largest 25%*
	(1)	*(2)*
EC	0.401**	0.449***
	(0.158)	(0.168)
Controls	Yes	Yes
Analyst-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	125856	106761
Adjusted R^2	0.313	0.283

Note: This table reports the regression results by excluding the most accurate analysts. The top 10% analysts are measured as analysts who issue the top 10% accurate earnings forecasts. The top 25% analysts are measured as analysts who issue the top 25% accurate earnings forecasts. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.3 Cross-sectional analysis of social learning hypothesis

My previous results are consistent with the social learning hypothesis that sell-side analysts learn from their peers to improve forecast accuracy. In this section, I conduct a series of cross-sectional analyses to further validate the social learning channel.

3.3.3.1 Influential peers

Psychological literature indicates the significant peers effect of influential peers. For example, Centola (2010) conducted a large-scale online social network experiment to examine how different types of influence shape behavior adoption. The results showed that participants were more likely to adopt a behavior when they were exposed to influential peers who had already adopted that behavior. Aral and Walker (2012) conducted a study to identify influential and susceptible individuals within social networks and examine their impact on behavior adoption. The research combined large-scale data from an online social network with a randomized experiment. The findings revealed that influential peers had a greater effect on behavior adoption compared to non-influential peers, supporting the argument that people learn more from influential peers. Therefore, I identify influential peers in corporate site visits and expect to see influential peers significantly affect analysts to improve forecast accuracy under the social learning hypothesis.

Following Chen et al. (2022), I recognize influential analysts as analysts with more expertise. Therefore, I identify influential peers if their affiliations are top 10 brokers, if they are star analysts, if they have a PhD degree, or if they are experienced analysts. Based on the sample median of these proxies I run split sample regressions, and the results in Table 3.7 are in line with my expectations. The coefficients of *EC* on *Accuracy* are all significantly positive in subsamples with more influential analysts, and all insignificant in subsamples with less influential analysts. Hence, analysts with a higher eigenvector centrality in the social network based on corporate site visits forecast more accurate than others if the percentage of analysts from top 10 brokers is higher, the percentage of star analysts is higher, the percentage of analysts with a PhD degree is higher, or the percentage of experienced analysts is higher in corporate site visits. It shows that analysts learn more from influential peers, that is, peers with more expertise.

Table 3.7: Influential peers

	Dependent variable: Accuracy							
	Top_10		*Star*		*PhD*		*Experienced*	
	High	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
EC	0.530**	-0.008	0.682**	0.263	0.473*	0.447	0.583**	0.143
	(0.223)	(0.284)	(0.292)	(0.245)	(0.254)	(0.281)	(0.294)	(0.234)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69418	73183	53666	88935	68600	74001	62571	80030
AdjustedR^2	0.371	0.273	0.372	0.285	0.328	0.287	0.375	0.296

Note: This table presents the results of cross-sectional analyses for the social learning hypothesis by considering influential peers. Column (1) and (2) use the percentage of analysts from top 10 brokers to measure influential peers and run the split sample regressions based on its sample median. Column (3) and (4) use the percentage of star analysts to measure influential peers and run the split sample regressions based on its sample median. Column (5) and (6) use the percentage of analysts with a PhD degree to measure influential peers and run the split sample regressions based on its sample median. Column (7) and (8) use the percentage of analysts with more than 5 years of forecast experience to measure influential peers and run the split sample regressions based on its sample median. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.3.2 Information uncertainty

Previous literature indicates that individuals tend to look to others for cues on how to behave in uncertain situations. Moreover, Bandura (1977) suggests that efficacy expectation can vary because of the level of difficulty of the task. Previous literature also confirmed that learning from others provides diverse perspectives that enhances individual learning outcomes when individuals face challenging tasks (Bonaccio and Dalal, 2006). Therefore, I argue that analysts have more motivations to learn from peers when forecasting earnings is more difficult. I expect that analysts should learn more from peers when forecasted firms with higher information uncertainty.

I measure the difficulty level of forecasting a firm by the its information uncertainty, which is higher if the firm has larger volatility of daily stock returns, larger volatility of adjusted ROA, or it is a larger firm or younger firm. Based on the sample median of these proxies I run split sample regressions, and the results are shown in Table 3.8.

The results in Table 3.8 align with my expectations. The coefficients of *EC* on *Accuracy* are all significantly positive in subsamples with higher information uncertainty, and all insignificant in subsamples with lower information uncertainty. It suggests that analysts with a higher eigenvector centrality in the social network based on corporate site visits forecast more accurate than others if the firm has larger volatility of daily stock returns, larger volatility of adjusted ROA, or is a larger firm or a younger firm. It shows that analysts learn more from peers if the firm is more difficult to forecast.

Table 3.8: Information uncertainty

	Dependent variable: Accuracy							
	Firm risk1: Daily_stock_return		*Firm risk2: Adjusted_ROA*		*Large_firms*		*Young_firms*	
	High	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
EC	0.462**	-0.223	0.499**	0.155	0.566**	0.214	0.397**	0.249
	(0.183)	(0.441)	(0.239)	(0.248)	(0.271)	(0.188)	(0.190)	(0.261)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75044	67557	78157	64444	71293	71308	74203	68398
AdjustedR^2	0.325	0.268	0.329	0.268	0.264	0.356	0.350	0.270

Note: This table presents the results of cross-sectional analyses for the social learning hypothesis by considering information uncertainty. Column (1) and (2) use the natural log of standard deviation of firm k's daily stock returns to measure firm risk and run the split sample regressions based on its sample median. Column (3) and (4) use the standard deviation of firm k's adjusted ROA to measure firm risk and run the split sample regressions based on its sample median. Column (5) and (6) use the size of firm k to measure firm k's information uncertainty and run the split sample regressions based on its sample median. Column (7) and (8) use the age of firm k to measure firm k's information uncertainty and run the split sample regressions based on its sample median. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.3.4 Additional analysis

In this section, I test whether the positive association between analysts' social network and forecast accuracy would be weaker for the analysts who do not experience corporate site visits. Therefore, I collect all analysts' forecasts, including those who participate in site visits, as well as those who do not participate. I count the number of times each analyst participated in site visits during the year ($Count_{it}$) and re-run the regressions. If the analyst does not participate in site visits that year, her eigenvector centrality is recorded as 0.

The results in Table 3.9 are in line with my expectations. Column (1) and (2) show that the coefficients of EC and $Count$ on $Accuracy$ are all significantly positive in the full sample. It suggests that analysts with a higher eigenvector centrality in the social network based on corporate site visits forecast more accurate than others do not attend site visits. Also, analysts attend more site visits significantly contribute to more accurate forecast. Results in column (3) show that the social network effect on forecast accuracy is still strong even I control for the number of times each analyst participated in site visits. Therefore, my results are robust after considering the number of times of site visits.

Table 3.9: Additional analysis

	Dependent Variable: Accuracy		
	(1)	*(2)*	*(3)*
EC	0.388**		0.354**
	(0.153)		(0.165)
Count		0.001**	0.001
		(0.000)	(0.000)
Controls	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	200308	200308	200308
Adjusted R^2	0.303	0.303	0.303

Note: This table reports the effect of analyst i's centrality and the number of site visits on her forecast accuracy in the full sample. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the analyst level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

3.4 Conclusion

This paper employs a unique dataset of corporate site visits disclosed in China to examine the role of sell-side analysts' social network on analysts' forecast accuracy. I find that analysts with higher eigenvector centrality of the social network based on corporate site visits provide more accurate earnings forecasts. The results are robust to alternative measures of forecast accuracy.

To mitigate the concern of sample selection bias that not all firms have site visits, I use Heckman two-step selection method to control for factors that affect the possibility of site visits. To mitigate the endogeneity concern of omitted variables and reverse causality, I use extreme weather as an instrumental variable and subsample analysis of removing analysts with high forecast accuracy. My results do not alter after these tests.

I then conduct a battery of tests to uncover the underlying mechanism for the relationship between centrality and forecast accuracy. I find supporting evidence for the social learning mechanism. I find that the effect of social network on forecast accuracy exists when: 1) there are more influential peers in corporate site visits; 2) forecasted firms have higher information uncertainty.

My study highlights the positive effect of direct interactions between analysts. I show that analysts with higher centrality of social network provide more accurate earnings forecasts, which has important implications for analysts, investors and regulators.

Chapter 4: Analyst-manager collusion during corporate site visits

4.1 Introduction

Conflict of interests within financial institutions have garnered significant attention from both regulators and academics, as extensively discussed by Mehran and Stulz (2007). A particularly concerning area of focus revolves around the inherent conflict arising when financial institutions provide both analyst research and investment banking services. This conflict is rooted in analysts delivering optimistic research coverage in an effort to gain favor with their affiliated institutions' existing clients or secure future investment banking business. Previous literature has extensively documented conflict of interests between analysts and securities underwriters of these firms, as highlighted by Lin and McNichols (1998) and Cowen et al. (2006).

The financial services industry encompasses intricate business networks capable of influencing participants' behavior. These networks often yield benefits, such as improving analysts' forecast performance (Do and Zhang, 2020; Kumar et al., 2022) and enhancing firm managers' forecast accuracy (Ke et al., 2019; Chen et al., 2022). However, these networks can also induce institutions to engage in reciprocal actions, occasionally leading to implicit complicity (Fehr and Schmidt, 1999). The prospect of reciprocal behavior in investment banking has attracted regulatory attention. For instance, Enrich and Raice (2015) report that certain European banks allocate business to competitors based, in part, on the volume of business received. Regulatory scrutiny of analyst research peaked in the early 2000s, culminating in the Global Analyst Research Settlement (the Settlement) in 2003. The primary objective of the Settlement, alongside concurrent changes to self-regulatory organization (SRO) rules, was to mitigate conflict of interests by segregating investment banking and research roles within banks. Prior research indicates shifts in analyst behavior following the settlement (Kadan et al., 2009). However, evidence from Brown et al. (2015), Corwin et al. (2017) and Mao and Song (2021) suggest that these conflicts may not have been entirely eradicated.

My test is based on a unique dataset of corporate site visits from the Shenzhen Stock Exchange (SZSE). While site visit is prevalent in the U.S. and Europe (Brown et al., 2015), these firms generally do not keep archival records of site visits (Cheng et al., 2016). In contrast, the SZSE mandates firms to release a condensed summary report of their meetings on the SZSE website within two business days after each meeting. These reports include a section summarizing the questions and answers discussed during the meetings. The compulsory disclosure requirement provides me a unique opportunity to study the direct interaction between firm managers and analysts.

Distinct from previous studies (e.g. Lin and McNichols, 1998; O'Brien et al., 2005; Mao and Song, 2021) that commonly underscore analysts cultivating favor with firm managers through issuing optimistic research reports, I posit a novel venue that analysts may seek to garner favor by asking positive questions in corporate site visits. I further distinguish this collusion into two scenarios: prior to a firm's seasoned equity offering (SEO) and affiliated analysts. Previous literature has documented two situations where firm managers are satisfied with analysts' optimistic earnings forecasts: 1) when firms plan to issue or sell stocks before the release of earnings reports; 2) when firms face the risk of losing their positions, e.g. the firm is at risk of debt rating downgrade or bankruptcy. In many other scenarios, firm managers may tend towards pessimistic forecasts, for instance, if their bonuses depend on meeting analysts' forecasts (Rogers and Stocken, 2005). Given my focus on the optimism in meeting minutes of corporate site visits, following previous literature (Feng and McVay, 2010; O'Brien et al., 2005), I identify two scenarios: during SEO and challenging periods. The superiority of experimental settings in the SEO phase lies in the direct and significant impact of investment banking underwriting revenues on individual analysts (Bradshaw et al., 2003; Westphal and Clement, 2008). During challenging periods, I believe that affiliated analysts bonding with underwriting relationships will face greater pressure to support the client firm (O'Brien et al., 2005).

To be more specific, I argue that analysts engage in collusion when firms are likely to become clients of their affiliated investment banking, given that a portion of analysts' compensation is contingent on contribution of deals. Particularly, underwriting mandates stand out as the most lucrative profit contribution (Bradshaw et al., 2003; Westphal and Clement, 2008), with media reports highlighting intense competition among analysts for such opportunities. Therefore, I utilize a firm's initial announcement of a proposed SEO as a signal indicating the initiation of potential underwriting business. My focus is on corporate site visits conducted between a firm's initial announcement of SEO and the formal listing and circulation of issued shares. I conjecture that during this period, analysts may adopt a positive questioning stance with firm managers during corporate site visits to cultivate favor and establish potential opportunities for underwriting business, driven by profit motives.

Additionally, when a firm has already established an underwriting relationship with the analyst's affiliated investment bank, the analyst may support the firm during challenging periods due to the existing interest bond. Analysts often exhibit reluctance in favoring firms with established business ties, driven by concerns about potential damage to their personal reputations. However, as indicated in an internal memo from Morgan Stanley (Wall Street Journal, July 14, 1992), the investment bank expressed a preference for a firm-wide policy refraining from negative or controversial comments about its clients: "Our objective…is to adopt a policy, fully understood by the entire firm, including the research department, that we do not make negative or controversial comments about my clients as a method of sound business practice."

My findings suggest analyst-manager collusion embedded in corporate site visits. That is, analysts will ask more positive questions if the firm announces the proposal of SEO. Also, affiliated analysts will ask more positive questions than unaffiliated analysts. The results of collusion during SEO are robust to the differences-in-differences (DID) method. Furthermore, I corroborate that affiliated analysts tend to engage in collusion when their client firms encounter challenging times, aiming to safeguard stock prices.

In addition, I examine the benefits of analyst-manager collusion for firm managers and analysts, respectively. I find that the market reacts significantly positively to corporate site visits with more positive questions, particularly if firm managers respond with a similar positive tone. For affiliated analysts, they may have an informational advantage over unaffiliated analysts. For example, affiliated analysts have early access to client firms' future SEO information.

Finally, this study suggests that the “hiding effect” may contribute to analyst-manager collusion during corporate site visits. The famous Hawthorne experiment (Franke and Kaul, 1978) demonstrate that individuals tend to behave ethically when they are under observation by others. Similarly, my findings indicate that analysts exhibit a willingness to engage in collusion by posing positive questions during corporate site visits, because this participation allows them to operate with a degree of anonymity within the visitors from various institutions, covertly assisting firm managers without damaging their personal reputation.

My contributions are fourfold. First, I identify a more implicit way of analyst-manager collusion. To the best of my knowledge, my paper is the first to detect collusion between analysts and firm managers within the context of corporate site visits, as opposed to focusing on analysts’ forecasts (e.g. Feng and McVay, 2010; O’Brien et al., 2005). This form of collusion, concealed within private communications, is inherently more challenging to capture.

Second, I uncover a dark side of corporate site visits. Previous studies have widely document bright sides of corporate site visits, for example, improving analysts’ forecast accuracy (Cheng et al., 2016), enhancing the accuracy of management earnings forecasts (Chen et al., 2022), fostering corporate innovation (Jiang and Yuan, 2018), reducing earnings management (Qi et al. 2021). By contrast, my findings suggest that corporate site visits may also serve as a communication platform for analyst-manager collusion.

Third, I shed light on understanding the motivations driving the occurrence of corporate site visits. These visits can be initiated by analysts or by firm managers. While prior research predominantly explores the consequences of corporate site visits (e.g., Chen et al., 2022; Cheng et al., 2016; Jiang and Yuan, 2018; Qi et al., 2021), there is a scarcity of knowledge regarding the motivations behind them. My study suggests that analysts may be highly motivated to visit firms if the announcement of a proposal of SEO is made. On the other hand, firm managers may invite affiliated analysts to visit the firm if they are experiencing challenging times.

Fourth, my research contributes to the literature on the network effects of analysts' behavior. For instance, Cohen et al. (2010) demonstrate that analysts acquire superior information about covered firms through their school relationships with senior corporate officials. Cheng et al. (2016) and Han et al. (2018) both find that analysts acquire information advantage through corporate site visits. By contrast, my research reveals that the social ties between analysts and managers is a double-edged sword. On the one hand, analysts' strong social ties with firm managers can assist them in acquiring greater informational advantages, thereby facilitating more accurate forecasts and fortifying analysts' reputations (Brown et al., 2015; Cheng et al., 2016; Han et al., 2018). However, this practice may also subject analysts to increased reciprocal pressures, indirectly resulting in reputational damage.

My findings have significant implications for firm mangers, analysts, investors, and regulators. For firm managers, engaging in collusion raises ethical concerns, as it may involve providing preferential treatment to certain analysts, potentially compromising the principle of fair and equal access to information for all participants on the financial market. The ethical concern may damage firms' reputation, increase firms' earnings uncertainty, hence increasing firms' cost of capital and crash risk. For analysts, I remind that potential reputation damage from the analyst-manager collusion. Analysts may face ethical dilemmas if they become aware of collusion during site visits. They may need to navigate the balance between benefits for their affiliated investment banks and their personal reputation, maintain professional integrity and not participate in or encourage improper practices. For investors, my findings suggest that investors should be cautious to meeting minutes of corporate site visits conducted in the during SEO period or conducted by affiliated analysts, as the tone of these meeting minutes tend to be excessively optimistic, recognizing that it may be influenced by strategic considerations rather than objective assessments of the firm's performance. For regulators, they play a crucial role in monitoring and enforcing fair disclosure practices. If they become aware of analyst-manger collusion during site visits, they may investigate potential violations of securities regulations and take appropriate enforcement actions to maintain market integrity. Regulators could revise existing regulations or introduce new guidelines to address the challenges posed by collusion. They may emphasize the importance of fair and timely information dissemination to ensure a level playing field for all market participants. I suggest that regulators should review and adjust existing regulations related to communication between managers and analysts, especially for disclosures of corporate site visits on SZSE. Due to the severe information asymmetry and corporate governance issue of listed firms on SZSE, regulators should aim to strike a balance between facilitating productive interactions while ensuring fair and equal access to information for all market participants.

The rest of the paper is organized as follows. Section 4.2 presents a brief literature review. Section 4.3 develops my hypotheses. Section 4.4 describes my data and sample. Section 4.5 interprets my variables and methods. Section 4.6 reports the baseline empirical results and identification tests. Section 4.7 provides additional analyses. Section 4.8 concludes.

4.2 Literature review

4.2.1 Institutional background

Listed firms in China have long grappled with challenges related to asymmetric information, unclearly defined property rights, and a lack of legal protection for the rights of minority shareholders (Liu et al., 2016). Information disclosure in China is notably less comprehensive compared to mature markets, and these issues extend to various facets of financing. For instance, Dedman et al. (2017) criticized the contentious matters stemming from limited transparency in the Chinese market in their examination of dividend policy.

To curb abuses in the issuance process, the government has introduced a series of accounting-based security regulations and policies since 1994, undergoing revisions more than a dozen times (Chen and Wang, 2007). However, these regulations do not consistently carry the full force of law (Liu et al., 2016). Their moral authority is continually contested, leading to common infringements, and wrongdoers may face repercussions in the form of future market skepticism (Liu et al., 2013). Despite the establishment of sanctions for malfeasance in the Securities Law and the Company Law, the enforcement of laws and regulations is impeded by weak and inefficient regulators and market environments (Liu et al., 2016). Accounting results are manipulated and underreported to serve the personal interests of promoters and intermediaries who exert effective pressure. A specific dysfunctional impact of these imperfections is the erosion of trust in the market, deterring long-term, sophisticated institutional, and international investors, upon whom the market's future success relies (Liu et al., 2016).

4.2.2 Conflict of interests

According to Michaely and Womack (1999), investment banks traditionally derive income from three principal sources: (1) corporate financing, encompassing securities issuance and merger advisory services; (2) securities brokerage services; and (3) proprietary trading. These revenue streams may give rise to conflict of interests within the bank and between the bank and its clients. Conflicts between the financing departments and brokerage departments are more commonplace and readily observable. The financing division is primarily tasked with executing transactions such as initial public offerings (IPOs), seasoned equity offerings (SEOs), and mergers and acquisitions for both potential and existing clients. Conversely, the equity research department of the securities brokerage aim to maximize value for clients by delivering timely, high-quality (and potentially unbiased) information.

A notable source of conflict in the investment banking industry is the compensation structure of equity research analysts (Michaely and Womack, 1999). A significant portion of research analysts' compensation often hinges on their contributions to the financing department. This contribution is measured by the analyst's ability to generate revenue and profits, which is most likely from underwriting mandates. At major investment banks, the distinction between analysts from vice president to managing director (or partner) is highly correlated with their contribution to underwriting fees (Raghavan, 1997). Simultaneously, the external reputation of research analysts is another crucial factor influencing compensation. This external reputation is, to some extent, dependent on the quality of their research reports. However, conflicts may arise when analysts issue recommendations on firms with which their affiliated investment banks' financing departments engage in business, potentially resulting in positively biased recommendations.

The conflict between the imperative of financing departments to complete deals and the need of equity research analysts to safeguard and enhance their reputations may be particularly pronounced during the equity offering process. First, this equity offering market represents a lucrative avenue for the investment banking industry (Michaely and Womack, 1999). Second, with limited information available to potential investors, issuers are incentivized to engage reputable lead managers to bolster their own reputations. Nevertheless, the reputation-intensive nature of investment banking imposes substantial barriers to entry into the industry, given that building or transferring a positive reputation is a formidable task (Ljungqvist et al., 2009).

4.2.3 Analyst-manager collusion

Previous literature has widely documented that analysts curry favor with firm managers through optimistic research reports. Further, previous research identifies two scenarios: one where firms offer underwriting opportunities benefiting investment banks affiliated with analysts (Rogers and Stocken, 2005). In this scenario, analysts compete for underwriting business by issuing optimistic research reports (Dechow et al., 2000). For example, Feng and McVay (2010) and Ljungqvist et al. (2009) both find that overly optimistic reports have been shown to enhance investment banks' likelihood of securing future underwriting mandates. Although Ljungqvist et al. (2006) find that banks competing for dominance in managing U.S. bond or equity issues did not systematically gain an immediate competitive advantage when their research analysts provided favorable assessments of issuing firms from 1993 to 2002, optimistic coverage increases the likelihood of winning co-management appointments, subsequently leading to future lead mandates. This surge in business may also directly benefit individual analysts, as their remuneration or status within the firm is tied to investment banking revenues.

The other scenario arises when firms face crises, such as the risk of credit downgrades. In these circumstances, firms rely on optimistic reports from analysts to boost investor confidence and defend stock prices (Rogers and Stocken, 2005; Westphal and Clement, 2008). Further, affiliated analysts who have already established underwriting relationships are often subject to greater pressure to support their client firms in these bad times. For example, O'Brien et al. (2005) demonstrate that affiliated analysts tend to disclose firms' negative news at a slower rate. Dugar and Nathan (1995) and Lin and McNichols (1998) both indicate that analysts tend to exhibit excessive optimism when their affiliated investment banks enter underwriting relationships with firms. Additionally, the presence of this affiliation bias suggests that analysts' optimism contributes to the enhanced future business prospects of affiliated investment banks.

The potential explanation of such analyst-manager collusion could be derived from reciprocal hypothesis. The concept of reciprocity was initially introduced in the field of economics by Rabin (1993), who observed that individuals tend to exhibit reciprocal behavior, such as returning kindness with kindness and retaliating when harmed, even if it involves a cost. While Rabin's work is emotion-centric, subsequent theoretical models on reciprocity tend to adopt an incentive-based and utility-driven approach. For instance, Fehr and Schmidt (1999) formulate models of reciprocity by incorporating an economic agent's utility, which is influenced by both the agent's payoff and the degree to which the agent's payoff differs from that of others, with a focus on fairness. My study provides some evidence whether reciprocity exists in the financial market and to what extent reciprocity affects the dissemination of information in the market.

4.3 Hypotheses

4.3.1 Hypothesis development

Building upon the discussions in prior studies, I further categorize analyst-manager collusion before and after SEO. I argue that the firm's announcement of the proposal of SEO suggests the emergence of a new underwriting opportunity in the investment banking market. Therefore, all analysts will vigorously compete to assist the affiliated investment bank in securing this underwriting business. During this phase, analysts actively engage in collusion to facilitate the underwriting process.

Furthermore, when an investment bank has already established an underwriting relationship with a firm, analysts continue to advocate for the client firm when necessary, adhering to standard business practices. However, in the absence of the direct incentive of underwriting revenue, analysts may give more consideration to their individual reputations. Consequently, affiliated analysts often assume a more passive role in collusion for purposes of supporting client firms.

In contrast to earlier research, which predominantly focused on analysts producing positive research reports for firms (e.g. Feng and McVay, 2010; O'Brien et al., 2005), I focus on questions in meeting minutes of corporate site visits. I argue that corporate site visits offer analysts the opportunity to blend in with multiple visitors and implicitly support firm managers by positively asking questions. Established studies, such as the Hawthorne studies, have extensively observed that individuals tend to act more ethically when they are being watched. I contend that analysts are inclined to issue research reports with caution, given the substantial scrutiny they receive from investors and the direct connection to the analyst's personal reputation and career advancement. However, meeting minutes of corporate site visits are issued by firms and not under the direct discretion of the analyst. As a result, investors' focus is directed more toward the firm's disclosure of meeting minutes than the specific analyst. Additionally, visitors often consist of multiple institutions, and the meeting minutes do not explicitly assign questions to a particular institution. This provides analysts opportunities to position themselves as part of a larger group of site visitors and avoid being singled out for asking positive questions. Therefore, I propose my hypothesis as below:

H1: Analysts collude with firm managers by asking positive questions during corporate site visits.

4.3.2 Alternative hypotheses

There are at least two alternative explanations for the optimism bias observed in underwriters. The first explanation is rooted in cognitive biases documented in the psychological literature. It posits that affiliated analysts might genuinely believe that the firms they underwrite are superior to those underwritten by other investment banks. This line of reasoning aligns with what Kahneman and Lovallo (1993) term the "inside view". According to this theory, affiliated analysts perceive equity offerings underwritten by their investment banks through a uniquely narrow lens, akin to parents who believe their children are exceptional. They may struggle to acknowledge the statistical reality that many of the IPOs underwritten by their investment banks yield average or below-average performance. In contrast, unaffiliated analysts adopt an "outside view", assessing the quality of firms with equity offerings by considering all comparable situations and relevant statistical information. Consequently, they can pose questions more broadly and, notably, more appropriately. An associated cognitive bias is the "anchoring bias". Due to their prolonged exposure to companies, affiliated analysts tend to anchor their views and opinions early on firms with equity offerings. As a result, they encounter challenges in promptly adjusting their estimates when negative news surfaces.

The second potential explanation is that underwriters may be selected partly due to their favorable research reports of the firm (Michaely and Womack, 1999; O'Brien et al., 2005). In this context, their recommendations and opinions reflect what is commonly known as the "winner's curse" or selection bias (e.g. McNichols and O'Brien, 1997). Hence, the affiliated analyst's prior is inherently optimistic. Owing to this positive prior, the affiliated analyst interprets the new information signal differently from other unaffiliated analysts.

While most empirical findings align with the (unintentional) cognitive bias and selection bias explanations, as well as the (strategic and intentional) conflict of interest explanations, there is some evidence (e.g. Lang and Lundholm, 2000; Michaely and Womack, 1999; Teoh et al., 1998) suggesting that the cognitive bias explanation may be less predominant.

A plausible alternative theory posits that the recommendations of affiliated analysts are not only unbiased but also more accurate than those of independent analysts. Several authors (e.g. Allen and Faulhaber, 1989), have argued that affiliated analysts acquire an informational advantage during the marketing and due diligence process. Therefore, they may possess superior information and make more accurate forecasts than those independent analysts.

4.4 Data and Sample

I collected meeting minutes of each corporate site visits, each firm's stock returns, SEOs data and financial data from the CSMAR database from 2012 to 2019. Following July 2012, the disclosure requirements of the SZSE underwent a change, mandating firms to release meeting minutes within two business days after each meeting. Until December 2019, the outbreak of Coronavirus (COVID-19) in Wuhan (China) significantly impacted travel, leading to a transition in most corporate site visits from physical field trips to virtual conference calls. Therefore, my sample starts from 2012 and ends in 2019, including all disclosed site visits conducted by SZSE-listed firms. By excluding missing values of variables, my final sample consists of 44,351 corporate site visits.

4.5 Variables and Methods

4.5.1 Tone in meeting minutes

I employ a method outlined by Bowen et al. (2018) and Piotroski et al. (2017) to analyze the tone in meeting minutes. Specifically, I extract questions and answers in the meeting minutes, measured the tone by calculating the difference between the number of positive and negative words, and scaled by one plus the sum of the number of positive and negative phrases (Bowen et al. 2018; Piotroski et al. 2017). I use Yao et al.'s (2021) Chinese annual reports dictionary to identify positive words and negative words. The ratio is calculated as:

$$Tone\ Ratio = \frac{\#Positive\ Phrases\ -\ \#Negative\ Phrases}{\#Positive\ Phrases +\ \#Negative\ Phrases +\ 1}, \tag{4.1}$$

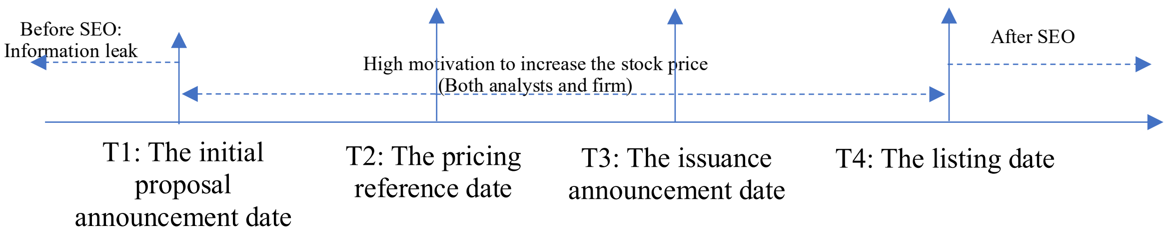
I define $Question\ tone_{it}$ as the tone ratio of questions in meeting minutes for each site visit, and $Answer\ tone_{it}$ as the tone ratio of answers in meeting minutes for each site visit. A larger value signifies a more positive tone, while a smaller value indicates a more negative tone.

4.5.2 SEO period

In China, when a firm satisfies the criteria set by the China Securities Regulatory Commission (CSRC) and intends to initiate equity offerings, it must present a proposal to the board of directors. Following approval from both directors and shareholders, the firm then submits the necessary application materials to the CSRC. According to Humera et al. (2010), the entire process of issuance typically spans six months, from the prospectus signing to the receipt of proceeds, on average.

As shown in Figure 4.1, I identify four key dates during SEOs. The first is the initial proposal announcement date. On this date, the firm typically discloses a plan of the offering, such as the expected number of shares, total funds to be raised, intended projects, and the current financial position. It may indicate the first time that the news of equity offerings is transferred to market. However, the names of the underwriters are not revealed at this stage. In equity offerings, analysts are typically brought into the procedure late. Therefore, they do not gain details about the issuance significantly earlier than the public, at least not at the official level (Kolasinski and Kothari, 2008). The second is the pricing reference date. The average stock price for the 20 trading days prior to the pricing reference date serves as a reference for determining the issue price. The firm agrees that the issue price will not be lower than a certain percentage of the reference price, usually 90%. The third is the issuance announcement date, which is normally two business days before the listing date. On this day, all details about the SEO, including the underwriters and the official issue price, will be confirmed. The final date is the listing date, marking the day when the offering shares are listed and indicating the end of the SEO.

Figure 4.1: The timeline of SEO



I define the during-SEO period ($During\_SEO_{it}$) as days between the initial proposal announcement and the listing date. I construct an indicator variable that equals 1 if corporate site visits occur in this period, and 0 otherwise. In this period, analysts may engage in collusion with firm managers due to their strong incentive to market their affiliated investment banks in securing offering business. Furthermore, firm managers heavily rely on favorable analyst reviews to boost stock prices and alleviate concerns regarding underpricing.

4.5.3 Affiliated analysts

Following previous studies (e.g. Mao and Song, 2021), I define affiliated analysts as those who work for investment banks that have underwritten securities offerings as lead managers or co-managers. To be more specific, there are four types of affiliation: the analyst's affiliated institution is the focal firm's lead or co-lead underwriters for IPO, or lead or co-lead underwriters for SEOs. I use dummy variables to identify corporate site visits with affiliated analysts. $Affiliated\_analysts_{it}$ is an indicator variable at the site visit level, coded 1 if at least one affiliated analyst attended the corporate site visit. It recognizes corporate site visits attended by affiliated analysts after the issuance. For example, the investment bank k is not one of underwriters for the focal firm i's IPO in 2013, but it is one of underwriters for the focal firm i's SEO in 2016. The listing date of firm i's SEO is February 15, 2016. Therefore, $Affiliated\_analysts_{it}$ will be coded as 1 if this is a site visit attended by at least one analyst works for the investment bank k after February 15, 2016, and coded as 0 if this is a site visit in which analysts at the investment bank k attended before February 15, 2016. No site visits occurred on the listing date. As indicated by O'Brien et al. (2005), this research design mitigates to some extent the concern of unclear causation.

I argue that analyst-manager collusion could be passive for affiliated analysts. That is, analysts, whose goal is to provide investors with independent, unbiased, and accurate research reports, may be reluctant to collude with the firm. However, affiliated analysts have developed strong interest ties with the firm after equity offerings. The firm, as clients for analysts' affiliated investment bank, may pressure affiliated analysts to defend the firm's stock price by expressing excessive optimism. Therefore, corporate site visits with affiliated analysts could be a tool for managers to support the firm and defend the stock price.

4.5.4 Collusion

I categorize analyst-manager collusion into marketing purpose and supporting purpose based on the analyst's motivation. As discussed above, I identify collusion with the purpose of marketing when analysts visit the firm in its during-SEO period, because analysts have strong marketing incentives to assist affiliated investment banks in acquiring potential equity offering business. I recognize collusion with the purpose of supporting when affiliated analysts visit the firm after equity offerings, because the client firms may pressure analysts to participate in collusion if the firm needs to enhance the stock price. It is possible that affiliated analysts also visit the firm in the firm's during-SEO period, particularly for firms with more than one SEO. Therefore, I construct interaction terms in Section 7.1 to capture the marketing motives of affiliated analysts during SEOs and the supporting motives during challenging periods.

4.5.5 Control variables

Following Bowen et al. (2018), I control for a set of firm-level characteristics that may also explain variation in market reaction. I control for corporate governance indicators, including board size (Bod_size_{it-1}), board duality (Bod_dua_{it-1}), and board diversity (Bod_div_{it-1}); capital structure characteristics, including an indicator of State-Owned Enterprises (SOE_{it-1}) and the proportion of institutional ownership ($Inst\_holding_{it-1}$); firms' financial indicators, including research and development intensity ($R\&D\_intensity_{it-1}$), return on total assets (ROA_{it-1}) and the natural log of total assets ($Size_{it-1}$); information asymmetry indicators, including firm age (Age_{it-1}), the percentage of the top one compensation over all executive compensation (Top_salary_{it-1}), the number of shares held by managers ($M\_holding_{it-1}$). All control variables are defined in Appendix A.

4.6 Empirical results

4.6.1 Summary statistics

Table 4.1 presents summary statistics for the sample. For tone in meeting minutes, my results are in alignment with prior research (e.g. Hong and Kubik, 2003) that analysts express a systematic optimistic bias in reports, as indicated by the predominantly positive tone of their questions (mean = 0.607 > 0). This inclination may be attributed to the significance of private communication between analysts and management as a pivotal tool for gathering information essential for analyst forecasting (Brown et al., 2015). Consequently, analysts may strategically utilize positive questions in private communications (e.g. corporate site visits) to cultivate a favorable relationship with the firm and gain access to more privileged information about the firm. In contrast, the tone of answers in research tends to be even more positive (mean=0.796). It suggests that firms endeavor to project a positive image by utilizing optimistic tone responses, thereby seeking to make a favorable impression on the public.

In terms of collusion with the purpose of marketing, 14.70% of corporate site visits occurred in the during-SEO period. For corporate site visits with affiliated analysts, lead underwriters on IPOs (mean = 0.055) more frequently attend site visits compared to co-lead underwriters (mean = 0.015), potentially attributable to the heightened supervisory responsibilities shouldered by lead underwriters. In the context of SEOs, lead underwriters (mean = 0.003) exhibit a lower frequency of involvement in site visits relative to lead underwriters on IPOs, potentially stemming from the limited observations of firms issuing SEOs in the sample.

Table 4.1: Summary statistics

Variables	N	Mean	SD	Min	5%	25%	Median	75%	95%	Max
Question tone$_{it}$	44351	0.603	0.287	-0.875	0.000	0.500	0.667	0.800	0.900	0.987
Answer tone$_{it}$	44351	0.796	0.166	-0.667	0.478	0.725	0.837	0.914	0.973	0.997
During_SEO$_{it}$	44351	0.147	0.354	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Non_SEO$_{it}$	44351	0.853	0.354	0.000	0.000	1.000	1.000	1.000	1.000	1.000
Affiliated_analysts$_{it}$	44351	0.070	0.255	0.000	0.000	0.000	0.000	0.000	1.000	1.000
IPO_lead$_{it}$	44351	0.055	0.228	0.000	0.000	0.000	0.000	0.000	1.000	1.000
IPO_co-lead$_{it}$	44351	0.015	0.121	0.000	0.000	0.000	0.000	0.000	0.000	1.000
SEO_lead$_{it}$	44351	0.003	0.058	0.000	0.000	0.000	0.000	0.000	0.000	1.000
SEO_co-lead$_{it}$	44351	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Market-adjusted-CARs$_{it}$	44351	0.001	0.042	-0.395	-0.055	-0.019	-0.003	0.017	0.073	0.388
Market-model-CARs$_{it}$	44351	0.000	0.045	-0.999	-0.059	-0.020	-0.002	0.017	0.072	0.393
FF-3-CARs$_{it}$	44351	0.000	0.047	-2.468	-0.059	-0.020	-0.002	0.017	0.072	0.916
R&D_intensity$_{it-1}$	44351	0.054	0.063	0.000	0.003	0.029	0.041	0.063	0.147	7.083
Bod_size$_{it-1}$	44351	9.990	2.573	4.000	7.000	9.000	9.000	11.000	15.000	26.000
Bod_dua$_{it-1}$	44351	0.388	0.075	0.200	0.300	0.333	0.375	0.429	0.533	0.800
Bod_div$_{it-1}$	44351	0.147	0.119	0.000	0.000	0.067	0.125	0.222	0.357	0.833
SOE$_{it-1}$	44351	0.193	0.395	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Size$_{it-1}$	44351	22.008	1.261	18.435	20.375	21.122	21.788	22.622	24.670	26.761
LEV$_{it-1}$	44351	0.362	0.189	0.008	0.086	0.206	0.344	0.503	0.688	1.696
Age$_{it-1}$	44351	14.720	5.519	2.000	6.000	11.000	14.000	18.000	24.000	51.000
ROA$_{it-1}$	44351	0.059	0.053	-1.220	0.003	0.029	0.054	0.085	0.147	0.482
Top_salary$_{it-1}$	44351	0.177	0.069	0.055	0.094	0.131	0.164	0.205	0.304	1.000
M_ holding$_{it-1}$	44351	21.785	22.453	0.000	0.000	0.310	13.340	40.720	63.540	94.270
Inst_holding$_{it-1}$	44351	40.019	25.767	0.000	2.952	15.380	40.491	62.254	80.437	100.010

This table presents descriptive statistics on main variables in the sample. Summary statistics are based on the sample of 44,351 times of corporate site visits. Variable definitions can be found in Appendix A. *Question tone* is the tone ratio in questions during corporate site visits. *Answer tone* is the tone ratio in answers during corporate site visits. *During_SEO* is an indicator variable coded 1 if this corporate site visit occurred in the during-SEO period. *Non_SEO* is an indicator variable coded 1 if this corporate site visit occurred in other days than the during-SEO period. *Affiliated_analysts* is an indicator variable coded 1 if this corporate site visit was attended by at least one affiliated analyst, and 0 otherwise. *CARs* are cumulative abnormal returns during the window (0, +2) around the event date. *R&D_intensity* is R&D expense divided by revenue in year t-1. *Bod_Size* is the number of directors on board in year t-1. *Bod_Dua* is the percentage of independent directors on board in year t-1. *Bod_Div* is the percentage of female directors on board in year t-1. *SOE* is an indicator variable coded 1 if the firm is state owned in year t-1, and 0 otherwise. *Size* is the natural log of the firm's total assets in quarter t-1. *LEV* is the Debt-to-assets ratio of firm i at the end of the year t-1. *Age* is the number of years from firm i's listed year to the year t-1. *ROA* is return on assets in quarter t-1. *Top_salary* is the percentage of the top 1 compensation over all executive compensation in year t-1. *M_holding* is the number of stocks held by the management of firm i in year t-1, scaled by the number of total shares in year t-1. *Inst_holding* is the percentage of institutional holdings in quarter t-1.

4.6.2 Baseline results of analyst-manager collusion

I examine analyst-manager collusion in the setting of corporate site visits. I argue that analysts may collude with firm managers by asking positive questions during corporate site visits. The regression model can be expressed as:

$$Question\ tone_{it} = \alpha + \beta_1 Collusion_{it} + \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \tag{4.2}$$

where $Collusion_{it}$ is categorized into the marketing purpose ($During\_SEO_{it}$) and the supporting purpose ($Affiliated\_analysts_{it}$). I control for a series of firm characteristics and firm and year fixed effects. Standard errors are clustered at the firm level.

Table 4.2 illustrates the results. In line with my hypothesis, results in column (1) and (2) show that collusion exists in corporate site visits. That is, visitors will ask questions positively when the focal firm is in the during-SEO period, or when their affiliated investment banks are underwriters of the focal firm. The results in column (1) are consistent with previous studies (e.g. Ljungqvist et al., 2006) that analysts provide favorable research reports for competing underwriting mandates. The results in column (2) are also aligned with previous studies (e.g. O'Brien et al., 2005; Mao and Song, 2021) that affiliated analysts are motivated to respond promptly to good news but prefer not to issue bad news about client firms.

Table 4.2: Analyst-manager collusion

Dependent variable: Question tone in corporate site visits		
	Marketing purpose	*Supporting purpose*
	(1)	*(2)*
During_SEO	0.041***	
	(0.006)	
Affiliated_analysts		0.014**
		(0.005)
R&D_intensity	0.043	0.045
	(0.043)	(0.043)
Bod_size	0.001	0.001
	(0.001)	(0.001)
Bod_dua	-0.051	-0.045
	(0.041)	(0.041)
Bod_div	0.007	0.007
	(0.048)	(0.048)
SOE	-0.043	-0.044
	(0.035)	(0.035)
Size	-0.013	-0.020**
	(0.009)	(0.009)
LEV	-0.020	0.011
	(0.032)	(0.032)
Age	0.014***	0.015***
	(0.002)	(0.002)
ROA	0.083	0.105
	(0.067)	(0.067)
Top_salary	-0.032	-0.029
	(0.058)	(0.059)
M_ holding	-0.000	-0.000
	(0.000)	(0.000)
Inst_holding	0.000	0.000
	(0.000)	(0.000)
_cons	0.649***	0.790***
	(0.172)	(0.170)
Year fixed effect	Yes	Yes
Firm fixed effect	Yes	Yes
N	44351	44351
adj. R-sq	0.014	0.012

This table reports analyst-manager collusion under different motives of analysts. Column (1) reports collusion with analysts' marketing purpose. Column (2) reports collusion with analysts' supporting purpose. Regressions in all columns control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

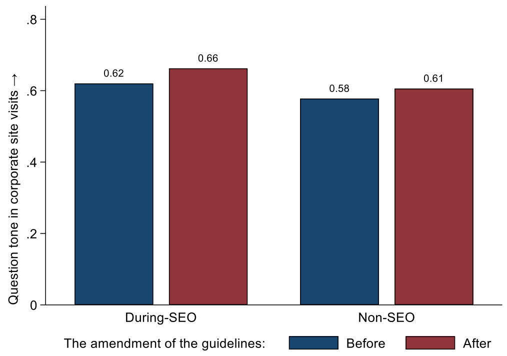
4.6.3 Identification tests

4.6.3.1 Differences-in-differences (DID) method

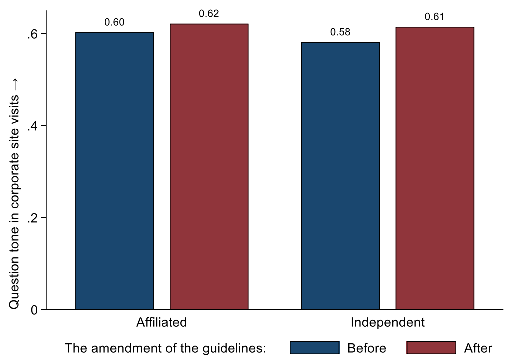
To mitigate the endogeneity concern of omitted variables, I use differences-in differences (DID) method to employ the amendment of regulations as an exogenous shock. The China Securities Association (CSA) organized the industry to draft the “Guidelines on the Information Wall System for Securities Companies” (hereafter, “Guidelines”), which came into effect as of January 1, 2011, in order to guide securities firms to establish a sound information wall system, improve the ability to prevent insider trading and manage conflicts of interest, and establish a good image of honesty and trustworthiness in the securities industry. The “Guidelines” require securities firms to adopt a series of measures to control the improper flow and use of sensitive information between businesses with conflicting interests. On March 11, 2015, the CSA amended the “Guidelines” on the basis of extensive consultation with all parties and officially issued them for implementation after the vote of the association’s executive council. The new “Guidelines” remove all words of “conflict of interests” and place greater emphasis on insider information. I believe that the amendment is an exogenous shock which have intensified the conflict of interests. Therefore, analyst-manger collusion could be more rampant after the amendments.

Figure 4.2 provides preliminary results for my hypothesis. In Panel A, the two blue bars show that before the amendment, question tone is more positive in the during-SEO period (0.62) than other days (0.58). Further, the two red bars show that question tone becomes more positive after the amendment, for both corporate site visits in the during-SEO period (0.66) and in other days (0.61). Panel B shows a similar pattern but with less growth after the amendment. The preliminary results shown in Figure 4.2 support my hypothesis that analyst-manager collusion is more rampant after the amendment of the “Guidelines”.

Figure 4.2: DID method



Panel A: Marketing purpose



Panel B: Supporting purpose

Note: This figure reports analyst-manager collusion in the DID setting. The blue bar describes the mean value of question tone in meeting minutes before the amendment of the "Guidelines", while the red bar represents the question tone after the amendment.

To further verify my conjecture, I define an indicator variable ($Post_{it}$) coded 1 if corporate site visits occurred after the amendment date, and 0 otherwise. Control variables remain the same as Equation (4.2). I use the Equation (4.3) to examine whether the effect of the amendment is statistically significant:

$$\begin{aligned} Question\ tone_{it} \\ &= \alpha + \beta_1 Collusion_{it} * Post_{it} + \beta_2 Collusion_{it} + \beta_3 Post_{it} \\ &+ \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \end{aligned} \tag{4.3}$$

Table 4.3 reports the results. The coefficient of interaction term (β_1= 0.22) in column (1) is statistically significant at the 10% level, indicating that analysts ask more positive questions in the during-SEO period after the amendment. However, the coefficient of interaction term in column (2) is not significant, which means that the amendment of the "Guidelines" has no significant effect on collusion with the purpose of supporting. In sum, the amendment of regulations significantly encouraged collusion with the purpose of marketing, but has no effect on the purpose of supporting.

Table 4.3: Differences-in-differences (DID) method

Dependent variable: Question tone in corporate site visits		
	Marketing purpose	*Supporting purpose*
	(1)	*(2)*
During_SEO*Post	0.022*	
	(0.011)	
During_SEO	0.026***	
	(0.009)	
Affiliated_analysts *Post		-0.013
		(0.011)
Affiliated_analysts		0.022**
		(0.009)
Post	0.029**	0.038***
	(0.013)	(0.013)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Firm fixed effect	Yes	Yes
N	44351	44351
adj. R-sq	0.014	0.012

Note: This table reports results of DID method. Column (1) reports collusion with marketing purpose in the DID setting. Column (2) reports collusion with supporting purpose in the DID setting. Regressions in all columns control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.6.3.2 Parallel assumption

One might concern that the control and the treatment group in my sample may have systematic differences. Hence, I examine the dynamics of the relation between the amendment and question tone following the framework of Pirinsky and Wang (2006). I include a series of interaction terms in the standard regression to trace out the year-by-year effects:

$$\begin{aligned} Question\ tone_{it} &= \alpha + \beta_1 D_{it}^{-3} * During\_SEO_{it} + \beta_2 D_{it}^{-2} * During\_SEO_{it} + \cdots \\ &+ \beta_7 D_{it}^{3} * During\_SEO_{it} + \beta_8 D_{it}^{4} * During\_SEO_{it} + \gamma Controls \\ &+ Fixed\ Effects + \varepsilon_{it,} \end{aligned} \tag{4.4}$$

where the deregulation dummy variables, the “D’s,” equal 0, except as follows: D_{it}^{-j} equals 1 for corporate site visits in the j^{th} year before the amendment of the “Guidelines”, while D_{it}^{+j} equals 1 for corporate site visits in the j^{th} year after the amendment. The year -1 is omitted in the regression.

Table 4.4 reports the results. The results in Table 4.4 show that D_{it}^{-j} show no significant impact on question tone in corporate site visits in my sample. It means that before the amendment, there is no statistically significant difference between my control group and treatment group. In other words, there is no systematic difference in the trend of question tone before the sample period. On the other hand, D_{it}^{+j} has significant impact in the current year and the following years. It means that after the amendment, there is a pronounced difference between my control group and treatment group.

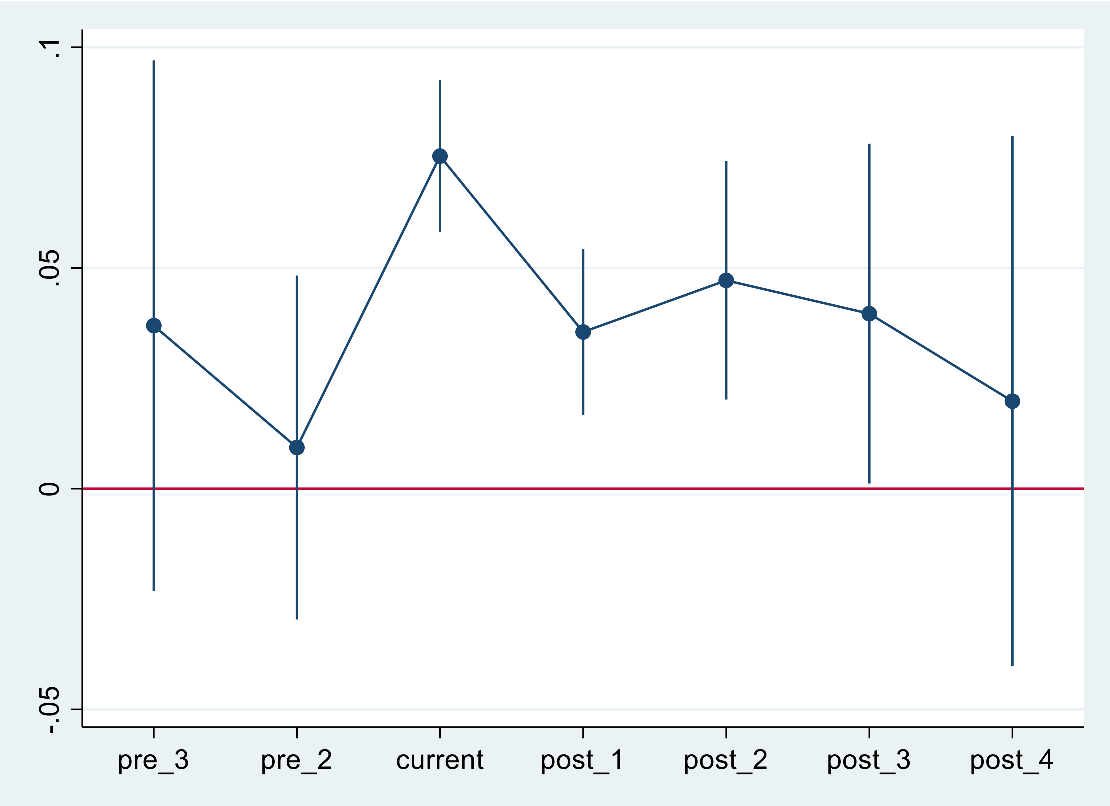
Table 4.4: Parallel assumption test

Dependent variable: Question tone in corporate site visits	
$Before_3$* During_SEO	0.037
	(0.031)
$Before_2$* During_SEO	0.009
	(0.020)
Current* During_SEO	0.075***
	(0.009)
$After_1$* During_SEO	0.035***
	(0.010)
$After_2$* During_SEO	0.047***
	(0.014)
$After_3$* During_SEO	0.040**
	(0.020)
$After_4$* During_SEO	0.020
	(0.031)
Controls	Yes
Year fixed effect	Yes
Firm fixed effect	Yes
N	44351
adj. R-sq	0.012

This table reports results of parallel assumption of DID method. The regression controls for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Figure 4.3 plots the results and the 95% confidence intervals with standard errors clustered at firm-level. Results in Figure 4.3 also support my hypothesis that before the amendment, there is no systematic difference between my control group and treatment group, and there is a pronounced difference after the amendment.

Figure 4.3: Parallel assumption test



Note: This figure plots the causal effect of the amendment on the question tone in meeting minutes. I estimate a 8-year window, spanning from 3 years before the amendment to 4 years after the amendment. I omit observations in one year prior to the amendment. The vertical lines represent 95% confidence intervals, adjusted for firm-level clustering.

4.7. Additional analyses

4.7.1 Affiliated analysts' collusion in different scenarios

One may argue that affiliated analysts may also engage in collusion during the firm's SEO period, particularly for firms with more than one SEO. Therefore, I construct two interaction terms to examine whether affiliated analysts actively collude with firm managers for securing potential underwriting mandates. The first interaction term is between affiliated analysts and the during-SEO period. I also include the variable of during-SEO period to capture the general tone. The coefficient of the interaction term captures the marginal effect of affiliated analysts on question tone in the during-SEO period. If affiliated analysts engage in collusion for marketing themselves to potential clients, they should ask more positive questions than unaffiliated analysts in the during-SEO period. Similarly, I construct the second interaction term between affiliated analysts and the non-SEO period (i.e. other days than the during-SEO period). I believe that affiliated analysts participated in collusion because of reciprocal pressure from client firms to defend their stock prices. As a result, affiliated analysts would express excessive optimism beyond that of unaffiliated analysts in the non-SEO period. The regression can be expressed as Equation (4.5), where SEO_time is divided into the during-SEO period ($During\_SEO$) and the non-SEO period (Non_SEO).

$$\begin{aligned} Question\ tone_{it} \\ &= \alpha + \beta_1 SEO\_time * Affiliated\_analysts_{it} + \beta_2 SEO\_time_{it} \\ &+ \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \end{aligned} \tag{4.5}$$

Panel A of Table 4.5 reports the results. Results in Column (1) illustrate that affiliated analysts do not display excessive optimism in the during-SEO period (β_1=0.004, p-value > 10%), which means that affiliated analysts do not engage in collusion for marketing purposes. By contrast, results in Column (2) demonstrate that affiliated analysts express excessive optimism in the non-SEO period (β_1= 0.015, p-value < 1%), although the general question tone is particularly negative in that period (β_2= -0.042, p-value < 1%). It indicates that affiliated analysts engage in collusion because of client firms' reciprocal pressure.

During the non-SEO period, the firm may require affiliated analysts to defend the firm's stock price in certain circumstances, for example, where the firm is experiencing bad time. To further analyze collusion with the purpose of supporting, I identify three scenarios of the focal firm's bad time which may require analysts to defend stock prices. First, the focal firm is underperforming among their peers. Following previous studies (e.g. Hayward and Fitza, 2017), I believe that a firm is experiencing bad time if it was underperformed industry peers before the site visit. The firm's poor performance will limit its prospects of raising capital on preferential terms and increase the possibility that the firm will be subject to takeovers (Baum and Oliver, 1996; Porac et al., 1999; Hayward and Fitza, 2017). Therefore, I define an indicator ($BIP90_{it}$) coded 1 if the firm's average stock return is below the industry average return in 90 days before the site visit, and 0 otherwise. The industry classification is based on the CSRC 2012 two-digit industry code.

Second, the focal firm is suffering financial constraints. A firm is certainly experiencing bad time if it is financially constrained. Previous studies have widely document that financially constrained firms do not have sufficient cash to make use of investment opportunities and face significant agency costs in accessing financial markets (e.g. Korajczyk and Levy, 2003). Following Kaplan and Zingales (1997) and Hadlock and Pierce (2010), I firstly sort all firms in ascending order according to their size, age and cash dividend payout ratio. I define an indicator of financial constraints as a variable coded 1 if the firm is below 33% of all firms, and 0 if the firm is above 66% of all firms. Then, I run a logit model (Equation 4.6) to calculate the probability of financial constraints (FC_{it}) for each firm in each year. FC_{it} is a continuous variable with a value lies between 0 and 1. The larger value indicates the higher probability of financial constraints.

$$Z_{it} = \alpha + \beta_1 Size_{it} + \beta_2 LEV_{it} + \beta_3 \left(\frac{CashDiv}{TA}\right)_{it} + \beta_4 MTB_{it} + \beta_5 \left(\frac{NWC}{TA}\right)_{it} + \beta_6 \left(\frac{EBIT}{TA}\right)_{it}, \tag{4.6}$$

The third scenario of bad time is high firm risk. Firms with high risk may heavily rely analysts to defend their stock prices. I follow Miller and Leiblein (1996) and John et al. (2008) to use the volatility of ROA (Return On Assets) to represent firm risk, which is calculated as the standard deviation of adjusted ROA in a 5-year window, as shown in Equation (4.7). The adjusted ROA is the firm's actual ROA (ROA_{it}) minus the industry peers' average ROA ($inROA_{it}$). $Firm\_risk_{it}$ is a continuous variable, the larger value indicates the higher firm risk.

$$Firm\_risk_{it} = \sqrt{\frac{1}{5}\sum_{t=1}^{5}(ROA_{it} - inROA_{it})^2}, \tag{4.7}$$

Then, I construct interaction terms of the firm's bad time and affiliated analysts to examine the marginal effect of affiliated analysts on question tone during the firm's bad time. I include the variable of the firm's bad time to capture the general question tone. The regression can be expressed as Equation (2.8), where Bad_time is recognized as: underperformance ($BIP90_{it}$), financial constraints (FC_{it}), high firm risk ($Firm\_risk_{it}$). Control variables remain the same as the equation (1).

$$\begin{aligned} Question\ tone_{it} &= \alpha + \beta_1 Bad\_time * Affiliated\_analysts_{it} + \beta_2 Bad\_time_{it} \\ &+ \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \end{aligned} \tag{4.8}$$

Panel B of Table 4.5 reports the results. The coefficients on interaction terms in all columns are significantly positive, indicating that affiliated analysts ask more positive questions than unaffiliated analysts when the focal firm is experiencing bad time. The coefficients on bad time in all columns are negative, although some of them are not statistically significant, indicating that question tone of corporate site visits is generally negative during the firm's bad time. Again, the results support my hypothesis that affiliated analysts engage in collusion because of reciprocal pressure from client firms to defend stock prices.

Table 4.5: Affiliated analysts' behavior in various scenarios

Dependent variable: Question tone in corporate site visits

Panel A: Marketing purpose

	(1)	*(2)*
During_SEO*Affiliated_analysts	0.004	
	(0.014)	
During_SEO	0.041***	
	(0.006)	
Non_SEO*Affiliated_analysts		0.015***
		(0.006)
Non_SEO		-0.042***
		(0.006)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Firm fixed effect	Yes	Yes
N	44351	44351
adj. R-sq	0.013	0.014

Panel B: Supporting purpose

	(1)	*(2)*	*(3)*
BIP90* Affiliated_analysts	0.017*		
	(0.009)		
BIP90	-0.020***		
	(0.004)		
FC*Affiliated_analysts		0.028***	
		(0.009)	
FC		-0.014	
		(0.021)	
Firm_risk* Affiliated_analysts			0.001***
			(0.000)
Firm_risk			-0.000
			(0.000)
Controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
N	33235	43473	27722
adj. R-sq	0.012	0.012	0.007

Note: This table reports results of affiliated analysts' behavior in various scenarios. Panel A reports the marginal effect of affiliated analysts' corporate site visits on question tone in meeting minutes during the SEO period. Panel B reports the marginal effect of affiliated analysts' corporate site visits on question tone in meeting minutes during the firm's bad time. Regressions in all panels control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.7.2 Consequences of collusion- benefits for firms

In this section, I examine whether firms benefit from analyst-manager collusion. Following previous literature (e.g. Bowen et al., 2018), I use market reaction to measure benefits for firms. To analyze the daily abnormal stock returns for each hosting firm around the event date, I employed three methods: market-adjusted returns, market-model and Fama-French three-factors (FF-3) risk-adjusted returns. Initially, I obtained daily stock returns from the CSMAR database. Then, I follow previous studies (e.g. Bowen et al., 2018; Kothari and Warner, 2007) to calculate cumulative abnormal returns (CARs) by taking the difference between the stock returns of three-day window (0, +2) around the event and the anticipated stock return by running the market model and the FF-3 model during the estimation window (-255, -43) days before the site visit. However, corporate site visit is a regular event and it can occur frequently, which means that there could be an overlap between event windows and estimation windows. Therefore, I also calculate the market-adjusted returns instead. I define CARs as the sum of differences between returns of the stock i and returns of the market portfolio during three-day window (0, +2) around the event. A larger value signifies a more positive market reaction, while a smaller value indicates a more negative market reaction. Equations for calculating abnormal returns by three methods are expressed as below:

(1) Market-adjusted returns:

$$AR_{it} = R_{it} - R_{mt},$$

(2) Market-model adjusted returns:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}),$$

(3) Fama-French three-factors (FF-3) risk-adjusted returns:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt} + \beta_i SMB_t + \beta_i HML_t),$$

I examine whether the tone in meeting minutes affect CARs. The regression model can be expressed as:

$$CAR_{it} = \alpha + \beta_1 Question\ tone_{it} + \beta_2 Answer\ tone_{it} + \gamma Controls + Fixed\ Effects + \varepsilon_{it}, \tag{4.12}$$

where $Question\, tone_{it}$ is the tone ratio of questions in meeting minutes during corporate site visits, $Answer\ tone_{it}$ is the tone ratio of answers in meeting minutes. Control variables remain the same as Equation (4.2).

Panel A of Table 4.6 shows the results. All coefficients on tone in questions are positive and significant, whereas all coefficients on tone in answers are insignificant. It demonstrates that positive tone in visitors' questions contribute to positive CARs during the event window, while positive tone in firms' answers cannot affect CARs. In line with my hypothesis, the results indicate that the market values financial analysts' opinions and react positively to corporate site visits with more optimistic visitors. However, the market does not care about the firm's answers during site visits. The results are in line with previous studies that superior stock price performance is associated with favorable analyst coverage (e.g., Womack, 1996)

To examine the robustness of my results, I follow Binder (1985) to employ multivariate regression model in event studies. This method is especially useful in testing whether a regulatory event has a significant effect on asset prices of a sample of firms (Hein and Westfall, 2004). Therefore, I use a dummy variable to identify dates of corporate site visits ($Visit\_dummy_{it}$) and an interaction term to capture the effect of positive tone in meeting minutes. I additionally control for Fama-French three factors to adjust risk. The regression model can be expressed as:

$$\begin{aligned} R_{it} = \alpha + \beta_1 Visit\_dummy_{it} + \beta_2 Visit\_dummy_{it} * Tone + \beta_3 R_{mt} \\ + \beta_4 SMB_t + \beta_5 HML_t + \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \end{aligned} \tag{4.13}$$

Again, results in Panel B of Table 4.6 illustrate a similar pattern that the market positively reacts to corporate site visits only if visitors ask questions in a positive tone, indicated by the significantly positive coefficient (0.001, p-value < 0.01) on the interaction term of visit dummy and positive tone in questions. However, the market has no significant reactions to corporate site visits if firm managers answer positively.

Table 4.6: Consequences of collusion-benefits for firms (CARs)

Panel A: CARs and Tone

	Dependent variable: CARs		
	(1)	*(2)*	*(3)*
	Market-adjusted	*Market-model*	*FF-3*
Question tone	0.002***	0.001*	0.002*
	(0.001)	(0.001)	(0.001)
Answer tone	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
N	44351	44351	44351
adj. R-sq	0.002	0.003	0.003

Panel B: Multivariate regression model

	Dependent variable: Stock returns	
	Question tone	*Answer tone*
	(1)	*(2)*
Visit_dummy	0.000	0.000
	(0.000)	(0.001)
Visit_dummy*Question tone	0.001***	
	(0.000)	
Visit_dummy*Answer tone		0.001
		(0.001)
R_m	1.006***	1.006***
	(0.001)	(0.001)
SMB	0.839***	0.839***
	(0.003)	(0.003)
HML	-0.237***	-0.237***
	(0.004)	(0.004)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Firm fixed effect	Yes	Yes
N	2684062	2684062
adj. R-sq	0.297	0.297

Note: This table reports the effect of the tone in meeting minutes of corporate site visits on market reactions. Column (1) of Panel A reports the result of market-adjusted CAR. Column (2) of Panel A reports the result of market-model CAR. Column (3) of Panel A reports the result of FF-3 factors CAR. Panel B reports the results of multivariate regression model. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.7.3 Consequences of collusion- benefits for affiliated analysts

Previous literature has widely documents benefits for analysts if they engage in collusion (e.g. Ljungqvist et al., 2009). That is, analysts' excessive optimism can contribute to more underwriting mandates. Therefore, in this section, I examine whether affiliated analysts benefit from collusion in my sample. I argue that affiliated analysts may acquire information advantage as benefits. I posit that analysts with strong ties to the firm may be privy to information about the upcoming SEO in advance, leading them to visit the firm early enough to secure potential underwriting business. Hence, I define the before-SEO period as 180 days[5] prior to the initial proposal announcement. I believe that, comparing to unaffiliated analysts, affiliated analysts are more likely to visit the firm in the before-SEO period. Independent investment banks may approach the firm in the during-SEO period because initial proposal announcements often fail to disclose underwriters. However, the absence of underwriters does not necessarily mean that the firm has not selected underwriters. Negotiations or discussions regarding underwriting business may already be underway. Thus, I argue that analysts who approach the firm in the before-SEO period have information advantage while analysts face a lag in obtaining information if they approach the firm in the during-SEO period. I use the logistic model (Equation 4.15) to examine the possibility that affiliated analysts visit the focal firm in the before-SEO period.

$$\begin{aligned}\Pr(Before\_SEO)_{it} \\ &= \alpha + \beta_1 Affiliated\_analysts_{it} + \gamma Controls + Fixed\ Effects \\ &+ \varepsilon_{it,}\end{aligned} \tag{4.14}$$

Table 4.7 reports the results. As discussed above, the timing of approaching the focal firm indicates the ability to obtain SEO information. In line with my hypothesis, the significantly positive coefficient on affiliated analysts indicates that affiliated analysts have early access to firms with SEO. To be more specific, the lead underwriter of the firm's IPO is most likely to visit the firm in the before-SEO period, while the co-lead underwriters of the firm's SEO do not visit the firm.

[5] I also try 30 days, 90 days and 360 days before the initial announcement. I find similar results for different days.

Table 4.7: Consequences of collusion- benefits for affiliated analysts

Dependent variable: Probability of corporate site visits in the before-SEO period		
	(1)	*(2)*
Affiliated_analysts	0.191**	
	(0.080)	
IPO_lead		0.169*
		(0.090)
IPO_co-lead		0.236
		(0.170)
SEO_lead		0.476
		(0.355)
SEO_co-lead		0.000
		(.)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year fixed effect	Yes	Yes
Observations	44351	44351
Pseudo R^2	0.072	0.072

Note: This table reports the effect of the tone in meeting minutes of corporate site visits on the probability of early access to firms' SEO. Column (1) reports that the probability of affiliated analysts' visits in the before-SEO period. Column (2) reports that the probability of various types of affiliated analysts' visits in the before-SEO period. Regressions in all columns control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.7.4 Tests of collusion

One may argue that collusion refers to a deceitful agreement or secret cooperation between two parties to limit open competition by deceiving, misleading or defrauding others of their legal right, and involves essentially the behaviors and/or actions of both parties of interest (i.e., both analysts and managers). In terms of the engagement of both parties, answer tone could also be affected by the question tone in meeting minutes (e.g. Engwall, 1983; Gendall et al., 1996). Therefore, I further examine the effect of question tone on answer tone and the effect of the consistency of question tone and answer tone on market reactions.

First, I argue that the positive tone in the questions raised by analysts is highly positively associated with the positive tone and/or content of the answers by managers during the analysts' site visits. To examine this hypothesis, I use the OLS regression to test the effect of question tone on answer tone in meeting minutes. Panel A of Table 4.8 reports the results. In line with my hypothesis, results show that more positive question tone leads to more positive answer tone in meeting minutes.

Second, I argue that investors will positively react to meeting minutes if analysts and firm managers hold similar positive beliefs. Hence, I construct four more indicators: 1) An indicator variable ($High\_high_{it}$) coded 1 if the positive tone ratio of questions is higher than the median of the full sample and the positive tone ratio of answers is higher than the median of the full sample, and 0 otherwise; 2) An indicator variable ($High\_low_{it}$) coded 1 if the positive tone ratio of questions is higher than the median of the full sample and the positive tone ratio of answers is lower than the median of the full sample, and 0 otherwise; 3) An indicator variable (Low_high_{it}) coded 1 if the positive tone ratio of questions is lower than the median of the full sample and the positive tone ratio of answers is higher than the median of the full sample, and 0 otherwise; 4) An indicator variable (Low_low_{it}) coded 1 if the positive tone ratio of questions is lower than the median of the full sample and the positive tone ratio of answers is lower than the median of the full sample, and 0 otherwise. I include each group into the OLS regression model, respectively.

Panel B of Table 4.8 reports the results. Again, I find results support my hypothesis that investors react positively to meeting minutes if analysts and managers hold similar positive beliefs. In addition, investors react negatively to meeting minutes if analysts and managers hold similar negative beliefs. Therefore, firm managers will benefit more from positive question tone if they answer positively in consistent with positive questions.

Table 4.8: Tests of collusion

Panel A: The effect of question tone on answer tone	
Dependent variable: Answer tone	
Question tone	0.153***
	(0.005)
Controls	Yes
Year fixed effect	Yes
Firm fixed effect	Yes
N	44351
adj. R-sq	0.115

Panel B: Market-adjusted CARs and tone in different groups

	Dependent variable: Market-adjusted CARs			
	(1)	*(2)*	*(3)*	*(4)*
High_High	0.001**			
	(0.001)			
High_Low		-0.000		
		(0.001)		
Low_High			0.000	
			(0.001)	
Low_Low				-0.001**
				(0.000)
Controls	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
N	44351	44351	44351	44351
adj. R-sq	0.002	0.001	0.001	0.002

Note: This table reports the tests of collusion. Panel A reports the results of the relationship between question tone and answer tone in meeting minutes. Panel B reports the results of the reinforcement effect in market-adjusted CARs. Regressions in all panels control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.7.5 The hiding effect

As discussed in the introduction, I identify a more implicit way for analyst-manager collusion: unlike previous literature that exclusively concentrated on analysts issuing favorable research reports on firms, corporate site visits allow analysts to conceal themselves among visitors and implicitly assist firm managers by optimistically posing questions. Previous studies (e.g. Hawthorne studies) have widely documented that individuals tend to behave more ethically when they are under observation by others. I posit that analysts are likely to exercise caution in issuing research reports due to the significant attention they receive from investors, coupled with the direct linkage to the analyst's personal reputation and career development.

In contrast, summary reports on corporate site visits are issued by firms, not under the analyst's name. Consequently, investor attention is directed more towards the firm's disclosure rather than the individual analyst. Moreover, visitors of each site visit often comprises multiple institutions, and the meeting minutes do not distinctly attribute questions to a specific institution. Consequently, analysts may be more inclined to participate in collusion by optimistically posing questions as they can blend in among the numerous institutions.

However, in cases where only one institution is attended in corporate site visits, investors are likely to realize that all questions originate from this singular institution. In this case, this institution becomes exposed to investor scrutiny, potentially dissuading them from participating in analyst-manager collusion, prompting them to pose questions more discreetly.

Given these considerations, I identify corporate site visits involving only a single institution and explore how question tone might change. I construct an indicator ($Only\_one$) coded 1 for corporate site visits exclusively involving a single institution. Additionally, I construct two interaction terms of the indicators and collusion, respectively. The coefficients on interaction terms capture the marginal effect of single institution on analyst-manager collusion.

$$Question\ tone_{it} = \alpha + \beta_1 Only\_one * Collusion + \beta_2 Collusion + \gamma Controls + Fixed\ Effects + \varepsilon_{it,} \quad (4.15)$$

Table 4.9 reports the results. In line with my hypothesis, results in column (1) show that the question tone can drop significantly if only one institution participates in corporate site visits. Results in column (2) and (3) show that collusion decline significantly if only one institution participates in corporate site visits. These results corroborate my finding of a more insidious form of collusion, thereby distinguishing my study from previous literature that primarily focuses on analysts issuing favorable research reports.

Table 4.9: The hiding effect

Dependent variable: Question tone in corporate site visits			
	(1)	*(2)*	*(3)*
Only_one	-0.013***		
	(0.003)		
Only_one* During_SEO		-0.020**	
		(0.008)	
During_SEO		0.046***	
		(0.006)	
Only_one* Affiliated_analysts			-0.047***
			(0.017)
Affiliated_analysts			0.018***
			(0.006)
Controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
N	44351	44351	44351
adj. R-sq	0.012	0.014	0.012

Note: This table reports the results of hiding effect. Column (1) reports the effect of a singular institution's participation in corporate site visits on question tone in meeting minutes. Column (2) reports the marginal effect of a singular institution's corporate site visits on question tone in meeting minutes in the during-SEO period. Column (3) reports the marginal effect of a singular institution's corporate site visits on question tone in meeting minutes if the institution is affiliated. Regressions in all columns control for firm characteristics and firm and year fixed effects. Variable definitions can be found in Appendix A. The standard errors in brackets are clustered at the firm level. ***, **, * indicate the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

4.8 Conclusion

To conclude, I identify a more implicit way for analyst-manager collusion that analysts ask positive questions during corporate site visits. I further classify collusions with different motives. That is, due to the marketing purpose, analysts engage in collusion if the firm announces the proposal of SEO. Additionally, due to the supporting purpose, affiliated analysts engage in collusion to defend client firms' stock prices, especially when their client firms encounter challenging times. The results of collusion with the purpose of marketing are robust to the DID method.

Additionally, I explore the benefits derived by firm managers and analysts through collusion. My research reveals a notable positive market reaction to corporate site visits accompanied by optimistic questions, especially when firm managers reciprocate with a positive tone. Affiliated analysts may possess an informational advantage compared to unaffiliated analysts. For instance, they may have early access to forthcoming SEO information from client firms.

Ultimately, I posit that the motivation behind analyst-manager collusion during corporate site visits may stem from a hiding effect. Drawing parallels to the well-known Hawthorne experiment (Franke and Kaul, 1978), which suggests that individuals tend to behave ethically when under observation, my findings reflect analyst' inclination to partake in collusion by posing positive questions during corporate site visits because this collusion enables them to discreetly operate within the diverse institutions forming the visitor team, covertly aiding firm managers without compromising their personal reputation.

In sum, my findings contribute to previous research on corporate site visits and reciprocity behavior between analysts and firm managers, and have multiple implications for practitioners.

Chapter 5 Conclusion

This chapter concludes the thesis. In the following, Section 5.1 provides summary of findings of three empirical chapters. Section 5.2 reflects limitations of current empirical work and provides potential avenues for future research.

5.1 Summary of findings

In chapter 2, I explore the impact of corporate site visits on the accuracy of management range guidance (MRG). My findings suggest that a higher frequency of site visits prior to the release of MRG results in more precise guidance. This conclusion remains robust even after controlling for various firm and MRG characteristics commonly examined in prior research, and after conducting a bunch of robustness tests to address potential empirical concerns. To address the issue of sample selection bias, as not all firms conduct site visits before releasing MRG, I employ both the Propensity Score Matching (PSM) method and Heckman's two-step selection method. Additionally, I mitigate concerns about endogeneity by utilizing firm fixed effect models, instrumental variables, and subsample analyses to account for omitted variables and potential reverse causality. My findings remain consistent across all these robustness checks.

Furthermore, I conduct a series of tests to uncover the underlying mechanisms behind the relationship between corporate site visits and MRG. My results provide support for the information advantage mechanism, indicating that increased information leads to more precise MRG. Specifically, I observe that corporate site visits have a more pronounced impact on MRG precision in firms facing higher information uncertainty or with lower information processing capacity. Conversely, I find contrary evidence for the organizational impression management hypothesis, because corporate site visits could not promote the strategic release of more precise MRG after experiencing organizational setbacks. Instead, corporate site visits can reduce earnings management, suggesting that managers do not strategically release precise MRG to impress investors.

In chapter 3, my analysis reveals that financial analysts' social network positively influences the accuracy of their forecasts. Specifically, analysts who have higher eigenvector centrality within the social network established through corporate site visits tend to produce more precise earnings forecasts compared to their counterparts. To ensure the robustness of my findings, I conduct a series of rigorous tests to address potential empirical challenges. My results remain consistent even after controlling for firm and analyst characteristics commonly examined in previous studies, as well as when utilizing alternative measures of forecast accuracy. To mitigate concerns regarding sample selection bias, as not all analysts participate in site visits before issuing earnings forecasts, I employ the Heckman’s two-step selection method.

Moreover, I address potential endogeneity concerns by employing fixed effect models, instrumental variables, and subsample analyses to account for omitted variables and potential reverse causality. I utilize extreme weather conditions as an instrumental variable to mitigate endogeneity by following the approach of Han et al. (2018), as extreme weather significantly impacts the likelihood of corporate site visits but is seemingly unrelated to analysts’ forecast performance. Additionally, following Chen et al. (2022), I refine my sample to a subset of firm-quarter observations to mitigate the severity of the reverse causation issue. Importantly, my conclusions remain robust across these various robustness checks.

To further substantiate my main findings concerning the social learning hypothesis, I investigate two scenarios implied by the hypothesis, namely, the influence of influential peers and information uncertainty on analysts’ forecast accuracy. Building on the work of Centola (2010) and Aral and Walker (2012), who emphasize the significant impact of influential peers on knowledge diffusion within social networks, I posit that influential individuals possess not only more information but also greater persuasive abilities to influence beliefs and practices. Moreover, drawing from the findings of Bonaccio and Dalal (2006) and Chen et al. (2022), which highlight individuals’ propensity to seek advice and learn from influential peers, particularly in uncertain contexts, I argue that analysts are more likely to learn from peers when more influential peers participate in corporate site visits or when forecasting firms exhibit higher levels of information uncertainty.

In chapter 4, I reveal the presence of analyst-manager collusion within corporate site visits. Specifically, I find that analysts tend to pose more positive questions when firms announce plans for SEO proposals, indicating analysts' marketing purpose. Additionally, affiliated analysts tend to ask more positive questions compared to unaffiliated analysts, suggesting affiliated analysts' supporting purpose. These findings remain robust even after employing the differences-in-differences (DID) method to account for various factors.

Furthermore, my analysis suggests that affiliated analysts refrain from engaging in collusion for promotional purposes, opting instead for collusion when their client firms face challenging circumstances, with the aim of defending stock prices. Moreover, I investigate the benefits of analyst-manager collusion for both firm managers and analysts. I observe a significant positive market response to corporate site visits characterized by more positive questions, particularly when firm managers respond in a similarly positive manner. Affiliated analysts may possess an informational advantage over independent analysts, such as early access to future SEO information from client firms.

Finally, I propose that the motivation behind analyst-manager collusion during corporate site visits may be attributed to the "hiding effect." Drawing parallels with the well-known Hawthorne experiment (Franke and Kaul, 1978), where individuals tend to behave ethically when observed by others, my findings suggest that analysts may engage in collusion by posing positive questions during site visits to discreetly assist firm managers while maintaining their personal reputation within the visitor team, thereby operating covertly among various institutions.

5.2 Limitations and future studies

This study still exhibits several limitations. Firstly, while I indicate the distinctiveness of the archival records of corporate site visits, some queries arose regarding the differentiation between this method and other company communication channels, such as conference calls and web forums. Compared to invitation-only conference calls, corporate site visits allow broader participation, with firms striving to facilitate access whenever possible. Moreover, in contrast to web forums, corporate site visits typically involve more professional analysts rather than individual investors. Additionally, corporate site visits place greater emphasis on the efficacy of face-to-face interaction, which is perceived as more credible and influential than telephone or online formats.

However, my empirical findings fail to interpret this power of face-to-face interaction. I believe that a more robust experimental setup would involve considering the impact of COVID-19, given its unpredictable nature as a black swan event that exerted a significant exogenous influence on financial markets. During the pandemic, travel restrictions necessitated a shift from face-to-face corporate site visits to online tele-conferences due to China's lock down policy. Utilizing this as a comparative backdrop would better illustrate the unique advantages of corporate site visits. Unfortunately, the sample periods for both chapter 2 and chapter 4 are truncated up to 2019, predating the outbreak. Although the sample period for chapter 3 includes 2020, I did not conduct a pre- and post-pandemic comparison. As China recently lifted its lock down policy, I anticipate comparing the impact of firms' corporate site visits on financial markets before and after COVID-19 in future studies.

Another avenue to explore the impact of corporate site visits on financial markets involves incorporating text transcripts from online formats, such as conference calls and web-based communication platforms, into the regression model to assess whether the impact of corporate site visits complements or substitutes the impact of other communication platforms. However, manually collecting records of conference calls and web-based communication platforms entails a substantial amount of work, and I plan to incorporate additional data in future studies.

Secondly, despite of my best efforts, questions may remain whether three essays fully address the issue of endogeneity, which is a tricky concern in empirical research. Omitted variables and potential reverse causality may violate OLS assumptions and lead to biased coefficient estimates. Although I employ instrumental variables and subsample analysis in chapter 2 and chapter 3 to mitigate endogeneity concerns, it has been argued that satisfying both the relevance and exclusive conditions simultaneously is challenging for instrumental variables. For instance, in both chapter 2 and chapter 3, extreme weather is utilized as an instrumental variable. While many scholars (e.g. Han et al., 2018) contend that extreme weather is unlikely to be related to the outcome variable, others posit that extreme weather affects mood to some extent (Meier et al., 2019; Khanthavit, 2017; Jacobsen and Marquering, 2008; Duhaime and Moulton, 2018; Bassi et al., 2013; Guven and Hoxha, 2015), and emotions are thought to influence investment decisions, risk aversion, and financial choices, encompassing numerous outcome variables in corporate finance (Guven and Hoxha, 2015).

In chapter 4, I employ a change in policy as an exogenous shock and test the effect using Differences-In-Differences method. However, the policy change I selected is a nationwide alteration that would uniformly affect all listed firms in China. Identifying a regional policy change or a piloted policy before replication would better elucidate the difference between the treatment and control groups. In future research, I intend to identify more suitable instrumental variables, utilize better exogenous shocks, and explore alternative experimental designs, such as staggered DID or stack DID or RDD (Regression Discontinuity Design), wherever possible.

Finally, each of the three empirical chapters presents individual limitations. In chapter 2, although I conduct the Heckman's two-step selection method on both the dependent and independent variables, this practice is uncommon in previous literature.

In chapter 3, I exclusively focus on eigenvector centrality in social networks and do not present results for other alternative centrality metrics. This decision stems from the insignificant effects observed with other centrality metrics, such as degree centrality and percolation centrality, on analyst forecast accuracy. Although much of the literature (e.g., Hirshleifer et al., 2021) contends that eigenvector centrality is superior as it captures both direct and indirect social connections, the insignificant effects of alternative metrics may suggest a lack of robustness in my empirical results.

In chapter 4, I argue that business ties between analysts and management may push analysts to engage in collusion with management. However, I do not account for the pressure exerted by analysts' social ties to management. For instance, shared schools or hometowns between financial analysts and firm managers could potentially influence analysts to engage in collusion, particularly in a relationship focus society like China. However, existing databases lack comprehensive disclosure of data regarding analysts' and managers’ schools and hometowns, making manual collection of this information extremely challenging. In future research, efforts to supplement this test could enhance the value of the study.

Overall, private interactions between financial analysts and firm managers are vague and attractive. Future research could attempt to provide more robust empirical evidence for examining multiple theories in this area.

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Appendix A

Table A1: Definitions of variables

Variables	*Definitions*
Panel A: Variable definitions for Chapter 2	
absCAR	The absolute value of cumulative abnormal return in the event window of [-3,3] adjusted by the market return. The estimation window is [-210,-11].
$Abssurprise_{it-1}$	The earnings surprise measured by the actual EPS for the current year minus the analysts' consensus forecasts of EPS.
Age_{it-1}	Firm age, measured as the number of years since firm i obtained listing status until year t-1.
ANA_{it-1}	Analyst coverage, measured as the total number of analysts issuing earnings forecasts for firm i in year t-1.
ANA_{it-1}	Analyst coverage, measured as the total number of analysts issuing earnings forecasts for firm i in year t-1.
$Assets_{i,t-1}$	Total assets of the firm i in quarter t-1.
BIP_{it-1}	An indicator variable coded 1 if the firm i's average return in the event window [-93, -3] is below the industry average return in the same event window, and 0 otherwise. The industry classification is based on the CSRC 2012 two-digit industry code.
Bod_div_{it-1}	The percentage of female directors on board in year t-1.
Bod_dua_{it-1}	The percentage of independent directors on board in year t-1.
Bod_size_{it-1}	The number of directors on board in year t-1.
$City\_peers_{it}$	The quintile of average site visits for all other firms in the same city in the same time period as target firms.
$Coptmiss_{it-1}$	An indicator variable measures whether a firm optimistically missed its earnings guidance in the prior quarter, t-1. It is coded 1 if the guidance was optimistically missed and 0 otherwise.
$Current_{it-1}$	Current ratio.
$D\_visit\_60_{it}$	An indicator variable coded 1 if the firm has at least one corporate site visit in 60 days prior to the earnings guidance published for quarter t,

Variables	*Definitions*
	and 0 otherwise.
D_MRG_{it}	An indicator variable coded 1 if the firm issued MRG for quarter t, and 0 otherwise.
$DCACC_{it}$	The absolute value of residuals from regression model (5).
$Debt_{it-1}$	Debt ratio.
$Degree_{it-1}$	The proportion of executives with a Master or higher degree in the top management team of firm i in year t-1.
DEP_{it}	The depreciation and amortization expense of the firm i from quarter t-1 to quarter t.
$DistanceBJ_{it}$	The geographic distance between the city of the firm's headquarters and one of economics center of China, Beijing.
$DistanceGZ_{it}$	The geographic distance between the city of the firm's headquarters and one of economics center of China, Guangzhou.
$DistanceSH_{it}$	The geographic distance between the city of the firm's headquarters and one of economic centers of China, Shanghai.
$DistanceSZ_{it}$	The geographic distance between the city of the firm's headquarters and one of economic centers of China, Shenzhen.
$DTACC_{it}$	The absolute value of residuals from regression model (4).
$DWCACC_{it}$	The absolute value of residuals from regression model (6).
EM_h	An indicator variable coded 1 if the discretionary accruals, i.e., $DTACC_{it}$, $DCACC_{it}$, $DWCACC_{it}$, is higher than the median of the full sample, 0 otherwise.
$Experience_{it-1}$	I predict the component value by using principal component analysis with the proportion of executives with oversea working or studying experience, the proportion of executives with research experience, the proportion of executives with working experience in financial institutions, in the top management team of firm i in year t-1.
$Extreme\_weather_{it}$	First, I identify days with extreme weather conditions for each city where firm k's headquarters is located, if the lowest temperature falls below -10°C or if the highest temperature reaches above 37°C. Second, I calculate the percentage of days with extreme weather conditions for

Variables	*Definitions*
	each city in 90 days before the release of MRG. Finally, I use the quintile rank of the percentage of days as the instrumental variable.
FC_{it-1}	An indicator variable coded 1 if a firm is financially constrained in the prior quarter, t-1, and 0 otherwise.
$FCCov_{it-1}$	Fixed charge coverage.
$Fin\_Distance_{it}$	The average geographic distance between the city of the firm's headquarters and four economic centers of China.
$Growth_{it-1}$	The growth of ROA of the focal firm.
$High\_Rating_{it-1}$	An indicator variable that equals 1 for A or B disclosure ratings, and 0 for C or D disclosure ratings in year t-1. The information disclosure quality ratings are yearly assigned by the Shenzhen Stock Exchange to the listed firms, which are classified into A, B, C, and D.
$Horizon_{it}$	The number of days between earnings guidance issuance and fiscal quarter end, the larger number indicates the later issuance.
HY_range_{it}	The upper bound of the EPS estimates in MRG in quarter t less the lower bound, scaled by logged assets per share in quarter t-1, multiply by -1.
$Inst\_holding_{it-1}$	The percentage of institutional holdings in quarter t-1.
$Inst\_holding_{it-1}$	The percentage of institutional holdings in quarter t-1.
IPC_l	*IPC_l* in the column (1) in Panel B in Table 8 is an indicator variable coded 1 if $Degree_{it-1}$ is below than the median of the full sample, 0 otherwise. *IPC_l* in the column (2) in Panel B in Table 8 is an indicator variable coded 1 if $Experience_{it-1}$ is below than the median of the full sample, 0 otherwise.
IU_h	*IU_h* in the column (1) in Panel A in Table 8 is an indicator variable coded 1 if $Size_{it-1}$ is lower than the median of the full sample, 0 otherwise. *IU_h* in the column (2) in Panel A in Table 8 is an indicator variable coded 1 if $Volatility_{it-1}$ is higher than the median of the full sample, 0 otherwise.
LEV_{it-1}	Leverage of firm i in quarter t-1, defined as the ratio of total debt to total assets.

Variables	***Definitions***
$M\_holding_{it-1}$	The number of stocks held by the management of firm i in year t-1 scaled by the number of total shares in year t-1.
$Manufacture_{it-1}$	An indicator variable coded 1 if the firm is a manufacturing firm, and 0 otherwise. Manufacturing firms refer to firms with industry code in the Manufacturing division based on the CSRC 2012 industry classification.
MTB_{it-1}	Market-to-book in quarter t-1.
MTB_{it-1}	Market-to-book in quarter t-1.
$NI\%_{it-1}$	Net income margin.
Num_Finst_{it-1}	The number of securities' headquarters and funds' headquarters in the province where the firm i's headquarter is, in year t-1.
Num_Firms_{it-1}	The number of listed firms in the province where the firm i's headquarters is, in year t-1.
OS	*OS* in the column (1) in Panel A in Table 9 is BIP_{it-1}. *OS* in the column (2) in Panel A in Table 9 is $Coptmiss_{it-1}$. *OS* in the column (2) in Panel A in Table 9 isFC_{it-1}.
$PPE_{i,t}$	Gross plant, property and equipment of the firm i in quarter t.
$Precision_{it}$	The upper bound of EPS estimates in MRG in the quarter t less the lower bound, scaled by the midpoint, multiply by -1.
Price_range	The upper bound of the EPS estimates in MRG in quarter t less the lower bound, scaled by price at the beginning of the release month, multiply by -1.
$Prof\_range_{it}$	The upper bound of the net profit attributable to the parent company in quarter t less the lower bound, scaled by the midpoint, multiply by -1.
ROA_{it-1}	Return on assets in quarter t-1.
ROA_{it-1}	Return on assets in quarter t-1.
$Sales\ grwoth_{it-1}$	The change in sales.
$Site\_visit\_10_{it}$	The frequency of corporate site visits in 10 days prior to the earnings guidance published for quarter t.
$Site\_visit\_30_{it}$	The frequency of corporate site visits in 30 days prior to the earnings guidance published for quarter t.

Variables	*Definitions*
$Site\_visit\_60_{it}$	The frequency of corporate site visits in 60 days prior to the earnings guidance published for quarter t.
$Size_{it-1}$	The natural log of the firm's total assets in quarter t-1.
$Slack/K_{it-1}$	Slack/ net fixed assets. Slack is calculated as: cash + short term investments + (0.50 * inventory) + (0.70 * accounts receivable) - short term loans.
SOE_{it-1}	An indicator variable coded 1 if the firm is state owned in year t-1, and 0 otherwise.
SOE_{it-1}	An indicator variable coded 1 if the firm is state owned in year t-1, and 0 otherwise.
TA_range_{it}	The upper bound of the net profit attributable to the parent company in quarter t less the lower bound, scaled by total assets in quarter t-1, multiply by -1..
$TA_{i,t}$	Income before extraordinary items minus operating cash flows of the firm i in the quarter t, scaled by total assets in quarter t-1.
$Volatility_{it-1}$	I predict the component value by using principal component analysis with stock return volatility and earnings volatility. Stock return volatility is measured by standard deviation of dividend- and split-adjusted daily stock returns from CSMAR over the previous 250 trading days. Earnings volatility is measured by the standard deviation of four previous quarterly earnings over lagged total assets.
$Voluntary_{it}$	An indicator variable coded 1 if the earnings guidance is voluntarily encouraged by the regulator, and 0 otherwise.
Z_{FC}	The discriminant score (Z) is calculated using discriminant analysis according to equation (3).
$\Delta CA_{i,t}$	The change in the current assets of the firm i from quarter t-1 to quarter t.
$\Delta CASH_{i,t}$	The change in cash holdings of the firm i from quarter t-1 to quarter t.
$\Delta CL_{i,t}$	The change in current liabilities of the firm i from quarter t-1 to quarter t.
ΔGDP_{it-1}	The growth of GDP of the city where the firm's headquarters is,

Variables	Definitions
	calculated as the city's GDP in year t− 1 divided by the GDP in year t-2, minus 1.
$\Delta Sales_{i,t}$	The change in sales of the firm i from quarter t-1 to quarter t.
$\Delta STD_{i,t}$	The change in short-term debt of the firm i from quarter t-1 to quarter t.
Panel B: Variable definitions for Chapter 3	
$Accuracy2_{ikt}$	This measure replaces the absolute forecast error in $Accuracy_{ikt}$ by the absolute forecast error scaled by share price of firm k in two days before the forecast, other calculations are the same as $Accuracy_{ikt}$.
$Accuracy3_{ikt}$	Following Kumar et al. (2022), this measure is calculated as the average absolute forecast error for analysts who follow firm k in year t minus the absolute forecast error of analyst i following firm k in year t, with this difference scaled by the average of absolute forecast errors for analysts following firm k in year t.
$Accuracy_{ikt}$	Following Clement and Tse (2005), this measure is calculated as the maximum absolute forecast error for analysts who follow firm k in year t minus the absolute forecast error of analyst i following firm k in year t, with this difference scaled by the range of absolute forecast errors for analysts following firm k in year t.
Adjusted_ROA	I also follow John et al. (2008) to use the standard deviation of adjusted ROA to represent firm risk (FR2). $Adj\_ROA_{kt} = \frac{EBIT_{kt}}{ASSET_{kt}} - \frac{1}{X}\sum_{x=1}^{X}\frac{EBIT_{kt}}{ASSET_{kt}}$, where Adj_ROA_{kt} is the ROA of the firm k in year t minus annual industry average. In addition, the standard deviation of industry-adjusted ROA (Adj_ROA_{kt}) is calculated separately on a rolling basis using every five years (from year t-4 to t) as an observation period. The firm risk is calculated by $FR2_{kt} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(Adj\_ROA_{kt} - \frac{1}{T}\sum_{t=1}^{T} Adj\_ROA_{kt})^2} \mid T = 5$.
Age_{kt}	The number of years from firm k's listed year to the year t.
$BrokerSize_{ikt}$	It is a measure of the analyst's brokerage size, calculated as the number

Variables	*Definitions*
	of analysts employed by the brokerage employing analyst i following firm k in year t minus the minimum number of analysts employed by brokerages for analysts following firm k in year t, with this difference scaled by the range of brokerage size for analysts following firm k in year t.
$Count_{it}$	The number of times each analyst participated in site visits during the year t.
Daily_stock_return	I use the natural logarithm of the standard deviation of daily stock return to measure firm risk (FR1). $FR1_{kt} = \ln(\sqrt{\frac{1}{T}\sum_{d=1}^{T}(r_{kdt} - \frac{1}{T}\sum_{d=1}^{T} r_{kdt})^2})$ where $FR1_{kt}$ is the daily stock return of firm k on day d in year t. T is the number of total days in year t.
EC_treat_{it}	An indicator variable coded 1 if the analyst i has at least one corporate site visit to measure her eigenvector centrality in year t, and 0 otherwise.
EC_{it}	The eigenvector centrality based on the network of corporate site visits for each analyst i in year t.
Experienced	The percentage of analysts with more than 5 years of forecast experience in year t.
ExtrmWeather	First, I identify days with extreme weather conditions for each city where firm k's headquarters is located, if the lowest temperature falls below -10°C or if the highest temperature reaches above 37°C. Second, I calculate the percentage of days in a year t with extreme weather conditions for each city. Finally, I use the quintile rank of the percentage of days scaled by 100 as the instrumental variable.
$FirmExperience_{ikt}$	It is a measure of analyst i's firm specific experience, calculated as the number of years of firm specific experience for analyst i following firm k in year t minus the minimum number of years of firm specific experience for analysts following firm k in year t, with this difference scaled by the range of years of firm specific experience for analysts

Variables	*Definitions*
	following firm k in year t.
$FollowA_{kt}$	The number of analysts who cover firm k in year t.
$FollowF_{ikt}$	It is a measure of the number of companies analyst i follows in year t, calculated as the number of companies followed by analyst i following firm k in year t minus the minimum number of companies followed by analysts who follow firm k in year t, with this difference scaled by the range in the number of companies followed by analysts following firm k in year t.
$FollowI_{ikt}$	It is a measure of the number of industries analyst i follows in year t, calculated as the number of industries followed by analyst i following firm k in year t minus the minimum number of industries followed by analysts who follow firm k in year t, with this difference scaled by the range in the number of industries followed by analysts following firm k in year t. The industry classification is based on the CSRC 2012 two-digit industry code.
$ForFrequency_{ikt}$	It is a measure of analyst i's forecast frequency for firm k, calculated as the number of firm k forecasts made by analyst i following firm k in year t minus the minimum number of firm-j forecasts for analysts following firm k in year t, with this difference scaled by the range in the number of firm-j forecasts issued by analysts following firm k in year t.
$ForHorizon_{ikt}$	It is a measure of the time from the forecast date to the end of the fiscal period, calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm k in year t minus the minimum forecast horizon for analysts who follow firm k in year t, with this difference scaled by the range of forecast horizons for analysts following firm k in year t.
$GenExperience_{ikt}$	It is a measure of analyst i's general experience, calculated as the number of years of experience for analyst i following firm k in year t minus the minimum number of years of experience for analysts following firm k in year t, with this difference scaled by the range of

Variables	*Definitions*
	years of experience for analysts following firm k in year t.
$LagAccuracy_{ikt}$	It is a measure of analyst i's prior year forecast accuracy for firm k, calculated as the maximum Accuracy for analysts who follow firm k in year t-1 minus the Accuracy for analyst i following firm k in year t-1, with this difference scaled by the range of Accuracy for analysts following firm k in year t-1. This measure is replaced by the median of analysts' prior year forecast accuracy for firm k if it has missing value.
Large_firms	An indicator variable coded 1 if the firm k's size is larger than the median of the full sample, and 0 otherwise.
LEV_{kt}	Debt-to-assets ratio of firm k at the end of the fiscal year t.
Num_Firms_{kt}	The number of listed firms in the province where the firm k's headquarters is, scaled by 100, in year t.
PhD	The percentage of analysts with a PhD degree in year t.
Roa_{kt}	Income before extraordinary items deflated by total assets of firm k at the end of the fiscal year t.
$Size_{kt}$	Natural logarithm of firm k's total assets at the end of the fiscal year t.
Star	The percentage of star analysts in year t.
Top_10	The percentage of analysts from top 10 brokers in year t.
Young_firms	An indicator variable coded 1 if the firm k's age is younger than the median of the full sample, and 0 otherwise.
ΔGDP_{kt}	The growth of GDP of the city where the firm k's headquarters is, calculated as the city's GDP in year t divided by the GDP in year t-1, minus 1.
Panel C: Variable definitions for Chapter 4	
$Affiliated\_analysts_{it}$	It is an indicator variable coded 1 if this corporate site visit was attended by at least one affiliated analyst, and 0 otherwise.
Age_{it-1}	The number of years from firm i's listed year to the year t-1.
$Answer\ tone_{it}$	The tone ratio in answers during corporate site visits.
$Before\_SEO_{it}$	An indicator variable coded 1 if the corporate site visit occurs during the before-SEO period, and 0 otherwise.

Variables	*Definitions*
$BIP90_{it}$	An indicator variable coded 1 if the firm's average stock return is below the industry average return in 90 days before the site visit, 0 otherwise.
Bod_div_{it-1}	The percentage of female directors on board in year t-1.
Bod_dua_{it-1}	The percentage of independent directors on board in year t-1.
Bod_size_{it-1}	The number of directors on board in year t-1.
$CARs_{it}$	Cumulative abnormal returns during the window (0, +2) around the event date.
$During\_SEO_{it}$	An indicator variable coded 1 if the corporate site visit occurs during the SEO period (starts from the first announcement date, ends on the listing date), and 0 otherwise.
FC_{it}	It is a continuous variable with a value lies between 0 and 1 to estimate the probability of financial constraints
$Firm\_risk_{it-1}$	The standard deviation of the firm's adjusted ROA in a 5-year window. The adjusted ROA is the firm's actual ROA minus the industry peers' average ROA.
$High\_high_{it}$	An indicator variable coded 1 if the positive tone ratio of questions is higher than the median of the full sample and the positive tone ratio of answers is higher than the median of the full sample, 0 otherwise;
$High\_low_{it}$	An indicator variable coded 1 if the positive tone ratio of questions is higher than the median of the full sample and the positive tone ratio of answers is lower than the median of the full sample, 0 otherwise;
HML_{it}	High book-to-market ratio minus low.
$Inst\_holding_{it-1}$	The percentage of institutional holdings in year t-1.
$IPO\_co\text{-}lead_{it}$	It is an indicator variable coded 1 if this corporate site visit was attended by at least one analyst affiliated with the co-lead underwriter for the focal firm's IPO, and 0 otherwise.
IPO_lead_{it}	It is an indicator variable coded 1 if this corporate site visit was attended by at least one analyst affiliated with the lead underwriter for the focal firm's IPO, and 0 otherwise.
LEV_{it-1}	Debt-to-assets ratio of firm i at the end of the year t-1.

Variables	*Definitions*
Low_high_{it}	An indicator variable coded 1 if the positive tone ratio of questions is lower than the median of the full sample and the positive tone ratio of answers is higher than the median of the full sample, 0 otherwise;
Low_low_{it}	An indicator variable coded 1 if the positive tone ratio of questions is lower than the median of the full sample and the positive tone ratio of answers is lower than the median of the full sample, 0 otherwise.
$M\_ holding_{it-1}$	The number of stocks held by the management of firm i in year t-1 scaled by the number of total shares in year t-1.
Non_SEO_{it}	An indicator variable coded 1 if the corporate site visit occurs during the non-SEO period (the days of the year other than the Before-SEO period and the During-SEO period), and 0 otherwise.
$Only\_one_{it}$	An indicator coded as 1 for corporate site visits exclusively involving a single institution, 0 otherwise
$Post_{it}$	An indicator variable coded 1 if corporate site visits occurred after the amendment date of the “Guidelines”, and 0 otherwise.
$Question\ tone_{it}$	The tone ratio in questions during corporate site visits.
$R\&D\_intensity_{it-1}$	R&D expense divided by revenue in year t-1.
R_{mt}	The return of the market portfolio.
ROA_{it-1}	Return on assets in year t-1.
$SEO\_co\text{-}lead_{it}$	It is an indicator variable coded 1 if this corporate site visit was attended by at least one analyst affiliated with the lead underwriter for the focal firm’s SEO, and 0 otherwise.
SEO_lead_{it}	It is an indicator variable coded 1 if this corporate site visit was attended by at least one analyst affiliated with the lead underwriter for the focal firm’s SEO, and 0 otherwise.
$Size_{it-1}$	The natural log of the firm’s total assets in year t-1.
SMB_{it}	Small market capitalization minus big.
SOE_{it-1}	An indicator variable coded 1 if the firm is state owned in year t-1, and 0 otherwise.
Top_salary_{it-1}	The percentage of the top 1 compensation over all executive compensation in year t-1.

Variables	Definitions
$Visit\_dummy_{it}$	It is an indicator variable coded 1 if there is a corporate site visit on the trading day, and 0 otherwise.

All variables were collected and calculated from the CSMAR database, Wind database and the CNRDS database.