

Does Managerial Ability Affect properties of analyst forecasts?

Mason Hoseini

Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the degree of Master of Science in
Management

Telfer School of Management
University of Ottawa
Supervisor: Professor Shantanu Dutta

Table of Contents

Summary	v
1 Introduction	1
2 Literature review and hypothesis development	4
2.1 Background on Managerial Ability	4
2.2 Background on disclosure readability	6
2.2.1 Association between disclosure readability and managerial ability	7
2.3 Background on financial analyst forecasts and recommendations.....	8
2.3.1 Analysts' role and effect	8
2.3.2 Factors affecting analysts	11
2.4 Two competing views.....	13
2.5 Hypotheses	16
3 Data and methodology	24
3.1 Data and definitions	24
3.2 Methodology	28
3.2.1 Direct and indirect association of managerial ability, analyst forecast properties, and firms value(Mediation Effect).....	31
4 Results and Findings.....	36
4.1 Managerial ability's relation with forecast error and Dispersion (H 1a, H 1b)...	38
4.2 Managerial ability's relation with analyst following (H 2).....	43

4.3	Managerial ability’s relation with report informativeness (AI), response time, uncertainty (H3a, H3b, H3c).....	45
4.4	Channel effects	51
4.5	Robustness Test with Analyst Following as a Control Variable.....	60
5	Conclusion	63
	Appendix	64
	Managerial ability calculation.....	64
	Variable definition	66
	References	69

List of Tables

Table 1: Panel dataset for analysis.....	27
Table 2: Descriptive Statistics	37
Table 3: Correlation Matrix	38
Table 4: Relationship between managerial ability and analyst forecast error	40
Table 5: Relationship between managerial ability and analyst forecast dispersion.....	42
Table 6: Relationship between managerial ability and analyst following	44
Table 7: Relationship between managerial ability and analyst report informativeness.....	46
Table 8: Relationship between managerial ability and analyst response time.....	48
Table 9: Relationship between managerial ability and analyst report uncertainty	50
Table 10: Direct and Indirect Association of Managerial Ability with Analyst Forecast Error.....	53
Table 11: Direct and Indirect Association of	55
Table 12: Direct and Indirect Association of Managerial Ability with Firm Value	58
Table 13: Robustness Test	61

Summary

This research will contribute to the literature of managerial ability and analyst following as well as narrative disclosure in the following ways. This study is the first to investigate the association between managerial ability and external information intermediaries such as financial analysts to the best of our knowledge. Most of the earlier studies on managerial ability focus on firms' internal information environment such as operating and financial decisions, and limited studies examine the relation between managerial ability with external perception of the information environment and narrative disclosures. We extend this literature by examining how managerial ability impacts the firm's external information environment, affecting informational intermediaries' work processes, such as financial analysts. We find that managers' higher ability leads to better performance by financial analysts regarding their forecast error, dispersion, and willingness to provide coverage on the firm. We also step further by employing more advanced and novel measures to assess managerial ability's impact on market intermediaries' external work and perception. Able managers impact reporting informativeness, response time, and the uncertainty of the forecasts from financial analysts.

Further, we examine informational channels or mediators (i.e., analyst following and readability of narrative disclosure), highlighting how managerial ability can be linked the better performance by financial analysts. We intend to show how variables like disclosure readability and analyst following mediate between managerial ability and analyst forecast properties (i.e., error and Dispersion). In the last part of the research, we answer how analysts' better performance can be a channel to help able managers increase their firms' value (i.e., analyst's forecast error acts as the channel from the managerial ability to firm's performance).

Acknowledgments

I want to express my deepest gratitude to my supervisor Dr. Shantanu Dutta, the superb supervisor. Without his expertise, patience, and unconditional support, this thesis would not have been possible.

I would also like to express a special thank you to my parents, family, and friends for their support during this academic journey. Without them, I would not have had the drive to reach this accomplishment.

Finally, I am grateful to my Telfer School of Management teachers, advisors, and classmates for being there for me, sharing this learning experience with me, and making it enjoyable.

1 Introduction

Financial analysts provide earnings forecasts and recommendations on their covered listed companies employed by market participants in their portfolio and investment decisions or to evaluate the companies' creditworthiness ([Kothari, So, & Verdi, 2016](#)). Analysts use companies' financial disclosures and statements as their principal source of information to produce their reports. Some studies have delved into the association between financial disclosure readability and informativeness, accuracy, and analysts' following ([Lehavy, Li, & Merkley, 2011](#)). However, non-complex and readable financial disclosures may not always be accessible. High-ability managers of listed companies have different incentives to produce more complex or more readable financial disclosures, which takes more time and resources from analysts to process and may lead to less accuracy. This study intends to examine the effect of managerial ability on analyst forecasts' properties, including accuracy, informativeness, and willingness to follow the firms.

The literature indicates two contrasting hypotheses that public companies' high-ability managers may be motivated to be more forthcoming or less. Able managers are competent to choose and execute valuable projects that yield high net present value and profitability. Therefore, able managers have the incentive to be forthcoming in their disclosures since they prefer financial analysts to understand readily, affirm, and broadcast their success in financial markets ([Hasan, 2020](#)).

On the other hand, literature also suggests that managers may opt to obfuscate their actual financial performance by releasing complicated and less transparent disclosures ([Bloomfield, 2002](#); [F. Li, 2010](#)). Financial analysts rely heavily on the management team's guidance in producing their earnings forecasts, suggesting management can misguide analysts with their actions ([Barth & Hutton, 2004](#)). Managers may decide to adopt a weak or misleading

communication channel with information intermediaries such as financial analysts and produce complex disclosures to protect their overcompensations or conceal their investments in highly risky projects.

On the analyst side, studies have extensively shown that analysts create value by enhancing fundamental performance through their monitoring, lowering information asymmetry, and elevating investors' recognition. Optimistic forecasts and recommendations by analysts impact companies' share prices, cost of capital, and financing opportunities, all of which directly benefit firms' management and their recognition and compensations ([K. K. Li & You, 2015](#)). Analysts are, however, less likely to provide accurate forecasts and less willing to follow firms with uncertain and untransparent information environment. Such a situation could be caused by the firm's malfunctioning narrative disclosure system caused by manipulative, withholding, and uncooperative management. On top of that, financial analysts are professionals who possess the skill and expertise to read and fully comprehend complex financial documents and disclosures ([Lehavy et al., 2011](#)). Hence, we argue that able managers should strive to attract more analysts with higher accuracy through the channel of better disclosure practices. This study is an important topic. The study helps entities and their management teams pay attention to information intermediaries' external perceptions about their internal information environment. Managers' best interest is to provide an informationally efficient environment in which analysts can execute their tasks readily. This process helps the sustainable development of the listed firms. No prior study has examined this association and the possible mediation effects to the best of our knowledge.

In this study, we further investigate how able managers can affect analysts' (i) forecast accuracy, (ii) dispersion, (iii) following (willingness to provide coverage for a firm), (iv) report informativeness, (v) response time, and (vi) report uncertainty, as well as the mediation channels

(analyst following, disclosure readability) through which managers have their impact.

Finally, few studies have shown how managers can create value for their firms. This study shows how analyst performance (proxied by the error of their earnings forecast) can mediate the role of able managers to increase their value (proxied by Tobin's Q).

2 Literature review and hypothesis development

2.1 Background on Managerial Ability

Managerial impact on firm performance, productivity, governance, and investment decisions is a significant research question in many studies. Prior finance, accounting, and economic studies have attached importance to managers' specific properties (e.g., ability, education, reputation, or talent) because of their impact on their economic direction and outcome. Studies show that a firm's financial, investment, and organizational practices are affected by the management style ([Bertrand & Schoar, 2003](#)); ([Kor, 2003](#)); ([Silva, 2010](#)); ([Pérez-González, 2006](#)).

Managerial ability is translated as managers' ability to possess a solid understanding of their companies' business environment, industry, and economy. They can effectively take action to allocate available resources to profitable projects efficiently to increase sustainable revenue. Earlier studies consider firm size, past performance, compensation, media mentions, education as proxies for managerial ability. Researchers like [Leverty and Grace \(2012\)](#) use data envelopment analysis¹ (DEA) within specific industries. However, [P. Demerjian, Lev, and McVay \(2012\)](#) argue that the bulk of measures employed demonstrate the firm's properties that are not in control of the management. For example, large companies have more considerable media mention inevitably, and stock abnormal returns are affected by several other factors than the management.

Another example is that an average manager in a prominent company can negotiate better terms with their suppliers than a talented manager in a small company. They offer a measure based on management efficiency in transforming corporate resources to revenue compared to their industry peers as the new managerial ability. They calculate managerial ability ranking and score.

¹ DEA is an optimization method used to evaluate the proportionate efficiency of the units involved in decision making. The calculation of managerial ability using this procedure is explained in appendix.

Compared with less-able managers, [P. Demerjian et al. \(2012\)](#) argue that able peers understand technological advancements and industry trends better, effectively predict demand for the products, invest in worthwhile projects with higher net present value, and they are reliable when it comes to employee management. Other studies support this view, explaining the difference in performance, financing, and investing practices ([Andreou, Karasamani, Louca, & Ehrlich, 2017](#)); ([P. R. Demerjian, Lev, Lewis, & McVay, 2013](#)).

[Chemmanur, Paeglis, and Simonyan \(2009\)](#) find that high-quality managers can make a more prudent investment decision with a higher likelihood of success by having access to more accurate information. They use hand-collected data to examine the quality of a firm's management concerning their investment and financial decisions. They define management team resources (number of management members with their education and certifications), structure (average number of years each member has been with the team), and reputation (number of corporate boards team members sit on) as the measures for management quality. They also look into how managerial quality reduces information asymmetry for their firm in the equity markets.

Some studies ([Cornaggia, Krishnan, and Wang \(2017\)](#) [Bonsall and Miller \(2017\)](#)) show that firms with highly competent managers enjoy higher credit ratings. Credit rating analysts observe managers' ability as a credit risk factor, and managerial ability is beneficial, especially for firms facing competitive environments and financial constraints. [Cho, Halford, Hsu, and Ng \(2016\)](#) suggest that manager ability has explanatory power for higher innovative productivity. [Koester, Shevlin, and Wangerin \(2017\)](#) look at managerial ability and find that executives with superior ability are less prone to employ tax avoidance practices. They mention that earlier studies mainly consider tax avoidance due to firm-level characteristics ([B. B. Francis, Sun, & Wu, 2013](#)). [Leverty and Grace \(2012\)](#) suggest that firms with able CEOs are less likely to incur the cost of insolvency.

They note managerial ability has an inverse relationship with a firm's distress time, failure likelihood, and cost. [B. Francis, Hasan, and Zhu \(2013\)](#) note that firms with high-ability managers benefit from more favorable financing terms and loan contract terms that lower their capital costs. [Krishnan and Wang \(2015\)](#) find that auditors' judgment, efficiency, and audit fees are also influenced by the managers' ability and should not be solely related to the firm-specific characters.

2.2 Background on disclosure readability

Capital market participants, regulators, and supervisory bodies heavily rely on the annual reports filed by publicly traded companies known as 10-Ks in the US as the principal source of information. The literature suggests that firms should be careful with selecting language and text when filling their 10-K reports because of the communicational implications these narrative disclosures have and the reliance of stakeholders on them to understand the companies' fundamentals ([Loughran & McDonald, 2016](#)).

Textual analysis is being increasingly employed to evaluate the readability of 10-K reports. Some studies suggest that US firms, on average, provide less readable information in their annual reports ([F. Li, 2008](#)) ([Bonsall IV, Leone, Miller, & Rennekamp, 2017](#)). Other studies show that less readable disclosure is a strategy to conceal unfavorable information and poor performance ([Bloomfield, 2002](#)). Or it could be a reflection of an ineffective information environment, and more analysts forecast disagreement and dispersion ([Loughran & McDonald, 2011](#)). [Lo, Ramos, and Rogo \(2017\)](#), for example, show that narrative disclosure is less readable for firms that have incentives to engage in earnings manipulation. [Lundholm, Rogo, and Zhang \(2014\)](#) find that foreign firms listed on US stock exchanges provide more readable disclosures to attract US investors. [M. Lang and Stice-Lawrence \(2015\)](#) Show that regulatory incentives could also lead to more transparent disclosures.

[Lehavy et al. \(2011\)](#) have covered the association of annual reports' readability with sell-side analysts' willingness to provide coverage and forecast accuracy. They note that less readable annual reports lead to higher dispersion/ disagreement among analysts, lower accuracy, higher uncertainty, requiring more effort on the analyst side to provide coverage on the firms. [Bonsall and Miller \(2017\)](#) underline the importance of textual analysis of annual reports in credit rating agencies' outcomes for the companies' bonds. They find that less favorable credit rating, more significant disagreement on bond rating, and higher cost of debt result from low readability of annual reports. [M. Lang and Stice-Lawrence \(2015\)](#) show that more transparent disclosure leads to more trading volume, more sell-side analysts' attention, and higher institutional investors ownership. [F. Li \(2008\)](#) looks directly at the firm performance and earnings sustainability. He finds that annual reports of the firms with lower earnings are more challenging to read and decipher, while firms that provide more readable reports have more persistent earnings. These studies clearly demonstrate the implication for market participants stemming from the readability of annual financial reports.

2.2.1 Association between disclosure readability and managerial ability

A part of the literature examines the effects of management characteristics on firms disclosures' readability ([Bamber, Jiang, & Wang, 2010](#)) ([Yang, 2012](#)). Some argue that the management effect is not significant as disclosures are the product of collaboration between all parties, including management, reporting branch, auditors, and executives ([Amernic, Craig, & Tourish, 2010](#)) ([Davis, Ge, Matsumoto, & Zhang, 2015](#)). Others suggest that there should be a specific effect rooting in management view, direction, and even ethnicity ([Amernic et al., 2010](#); [Brochet, Miller, Naranjo, & Yu, 2019](#)).

[Baik, Farber, and Lee \(2011\)](#) mention that more able CEOs provide more accurate and more

frequent management forecasts about their firms' economics, and analysts pay more attention to the contents of projections made by CEOs. [Chemmanur et al. \(2009\)](#) argue that more able and reputable managers reflect a clear image of their firms' value to the markets, thus reducing their firms' information asymmetry in the equity markets. [P. R. Demerjian et al. \(2013\)](#) show that able managers issue fewer forecast restatements, have lower errors in the bad debt provision, provide higher quality and persistent earnings and accruals. All these studies underline the critical role of able managers in providing better condition for their firms and their information/disclosure environment. The ability of CEOs is shown to affect the external perception of market participants regarding the listed firms. Financial analysts are among players whose performance can be affected by the ability of managers.

2.3 Background on financial analyst forecasts and recommendations

2.3.1 Analysts' role and effect

Many properties of financial analysts' professions have attracted extensive attention in the literature. Earnings forecasts and their accuracy/error/dispersion, buy/sell/hold recommendation reports, initiating/terminating coverage by analysts draw attention from market participants, e.g., individual and institutional investors as well as creditors in capital markets ([Kothari et al., 2016](#)).

Financial analysts collect information from several sources, including financial disclosures, conference calls, news outlets, discussions with the firms' management, etc. These sources could be publicly available or obtained through private channels ([Clement, 1999](#); [Gleason & Lee, 2003](#)). Using their knowledge and skills, they work as intermediaries who receive data on companies and extract information. The outcome of their work includes issuing earnings forecasts, growth prospects, target price, and buy/hold/sell recommendations ([Schipper, 1991](#)).

Information distribution: The information distribution role hypothesis asserts that the

collective effort of analysts affects capital markets by helping the price discovery, which lowers information asymmetry and elevates the market efficiency, meaning market prices reflect all the available information in the markets ([Bhushan, 1989](#)). Their reports, forecasts, and coverage affect share price discovery and stock returns ([Gleason & Lee, 2003](#)). They also show that analysts' ranking, especially when they are All-Star analysts, affects market reaction speed and price adjustment, i.e., investors heed the renowned analysts' words.

Analysts' coverage initiation or termination signals future expected return or crash. [Lee and So \(2017\)](#) find that firms with the highest analyst coverage outperform the firms with the lowest number of analysts following by 80 basis points each month. They attribute, in part, the outperformance to the fact that analysts prefer to cover firms with expected better performance that are underpriced. [Kim, Lu, and Yu \(2019\)](#) also show that investors attach a higher probability of a crash in the stock prices of a firm that loses analyst coverage. [Andrade, Bian, and Burch \(2013\)](#) examine the Chinese stock markets during the 2007 market crash and find that the companies with a higher number of analyst coverage had a smaller price bubble. In their view, analyst coverage coordinates investors' belief in the prices of shares.

[Derrien and Kecskés \(2013\)](#) argue that when a firm faces a decrease in analysts' number, information asymmetry increases, consequently increasing its capital cost. They show that firms that lose one analyst face two percent less investment and financing of total assets. The higher cost of capital for a firm means lower profitability from investment projects and lower investment in different development projects. When there is more uncertainty surrounding the company, the cost of external financing increases, and the optimal amount of funds decreases.

Analyst coverage also influences institutional investors' willingness to invest ([Kothari et al., 2016](#)) and elevates the chance of accessing external financing ([To, Navone, & Wu, 2018](#)).

Monitoring effect: On the corporate level, analysts have another role, namely monitoring impact. The forecasts by analysts improve the information environment surrounding the public companies, which leads to reduced information asymmetry between firms' insiders (managers) and outsiders (investors and creditors) ([K. K. Li & You, 2015](#)). This process takes away the opportunism by firm insiders. As such, analysts are believed to be essential gatekeepers and whistleblowers when detecting corporate fraud ([Dyck, Morse, & Zingales, 2010](#)). For example, analysts following and forecasting curb tax aggressiveness ([Allen, Francis, Wu, & Zhao, 2016](#)).

Analyst following lowers active earnings management through accruals. [Irani and Oesch \(2016\)](#) look closer at earnings management and find that when firms lose analyst coverage, they tend to employ fewer real activities manipulation and instead increase earnings management using accruals. [F. F. Yu \(2008\)](#) discusses that a higher number of analysts following a listed company leads to lower levels of earnings management by the company. Analyst forecast and coverage also push firms to make better investment decisions ([Chen, Xie, & Zhang, 2017](#)) and be more socially responsible ([Adhikari, 2016](#)).

Pressure Effect: The third effect by analysts is called the pressure effect. Analysts might negatively affect the firms by forcing the managers to meet the interim or annual earnings expectations and forego valuable long-term investments and developments that could have long-lasting results ([To et al., 2018](#)), ([Ramnath, Rock, & Shane, 2008](#)). [Irani and Oesch \(2016\)](#) note that manipulating earnings through real activities is a costly deviation from firms' everyday activities. Nevertheless, feeling the pressure to meet analysts' quarterly forecasts, managers tend to undergo such a process. However, when fewer analysts are following a firm, management prefers to employ simpler accrual-based earnings management. Further, under the watch of analysts, a firm might produce fewer patents ([He & Tian, 2013](#)) and cut its R&D expenditures ([Guo, Pérez-Castrillo, &](#)

[Toldrà-Simats, 2019](#))

2.3.2 Factors affecting analysts

In conducting their duties, analysts' work outcomes and interests in firms are affected by various factors. For instance, the regulatory regime, especially post-2000, has lowered the quality of reports ([Espahbodi, Espahbodi, & Espahbodi, 2015](#)), accounting standards like IFRS have increased analysts following ([Tan, Wang, & Welker, 2011](#)). Literature also shows that analysts are more attracted to firms with higher institutional investors, bigger size, more promising return potential, better disclosure policies, and robust corporate governance ([Ackert & Athanassakos, 2003](#)); ([Bhat, Hope, & Kang, 2006](#)); ([M. Yu, 2010](#)); ([Gibbons, Iliev, & Kalodimos, 2019](#)). Accuracy of analysts and agreement among their forecasts (less Dispersion) is improved when the covered firms have better disclosure policies and more readable financial statements ([Lehavy et al., 2011](#)).

One area that the literature has explored has to do with analyst experience and herding. The theory explains that, in many cases, analysts, especially those with younger careers and shorter successful track-record, prefer to follow other analysts' forecasts and not deviate from the existing consensus among analysts. In many cases, the first few buy or sell recommendations draw the next analysts to provide similar recommendations on a company ([Welch, 2000](#)). Afraid of being terminated, inexperienced analysts prefer not to produce bold analyst forecasts. Hence, they stay in line with the consensus ([Hong, Kubik, & Solomon, 2000](#)). However, as analysts increase their success rate, become more experienced, and start working for a prominent broker, they tend to become more independent and provide bolder forecasts on covered firms ([Clement & Tse, 2005](#)). [Gleason and Lee \(2003\)](#) also show that the market cannot distinguish between just herding recommendations or the ones that have new information offering to the investors. Hence, the

market is more interested in knowing whether an All-Star analyst provides a forecast than paying attention to how they came up with the analysis.

Literature also examines the gender of analysts. Using sell-side analysts' investment recommendations sample, [X. Li, Sullivan, Xu, and Gao \(2013\)](#) investigate the difference in female and male financial analysts' performance and career outcome. They find that both genders' recommendations produce similar abnormal returns with less idiosyncratic risk on the women's side due to taking less risk in their recommendations. They also find that women are more likely to be chosen as Star Analysts and be promoted. Before them, with a sample up to 2005, [Green, Jegadeesh, and Tang \(2009\)](#) mentioned that women produce less accurate forecasts but with a higher chance of getting promoted.

Geographical location, industry, and educational background were also associated with the analysts' performance. [O'Brien and Tan \(2015\)](#) study the geographical proximity of analysts to the covered firms. They realize an 80% more likelihood of covering a local firm by an analyst than non-local firms. Moreover, analysts start their coverage on local firms three weeks earlier than those out of their region.

[Bradley, Gokkaya, and Liu \(2017\)](#) hand-collected biographical information for each analyst and found that analysts with prior experience in the industry of the firms they are covering have more accurate forecasts and receive more attention from market participants. In many cases, they are tagged as institutional investor all-stars analysts. Their result emphasizes that industry knowledge is of the highest priority as the quality of an analyst. [Cohen, Frazzini, and Malloy \(2010\)](#) collected data on the financial analysts' educational backgrounds and senior corporate officers to examine the cases where there is an educational link between the parties. They find that when analysts have the same school background as a company's top manager, their stock picks

and recommendations outperform by 6.6%.

In the context of education, [Kang, Li, and Su \(2018\)](#) explore the effect of rigorous designations like the Chartered Financial Analyst (CFA) program on financial analysts' performance. With a sample between 1993-2015, they find that the quality of recommendation reports of CFA charter holders and their chance of becoming Institutional Investor's All-America Research Team has increased.

2.4 Two competing views

The literature clearly shows that able managers can choose to be forthcoming with their motives, disclosure policies, and practices that can ultimately help market participants, including financial analysts, better analyze the listed companies' conditions and prospects. However, the question remains whether able managers use their abilities to move their firms toward a more informationally transparent environment or have their specific motives to manipulate, conceal, or delay some realities ([Hasan, 2020](#)). We discuss two views, namely, superior performance view and opportunistic behavior view, in the context of managerial ability and analysts forecast behavior.

Superior performance view: The notion of managers' higher ability leads to a positive outcome for the firms is well documented. [P. Demerjian et al. \(2012\)](#) provided a well-known measure for assessing managerial ability. They found that high-ability managers use resources efficiently and bring superior firm performance. They also noted that CEO turnover's market reaction is positive when the new CEO is known to be more able. [Baik et al. \(2011\)](#) note that the more skilled CEOs provide more earnings forecasts with higher accuracy. Able managers have the incentive in terms of their equity compensation to send the right to the market. Similarly, [Hoitash, Hoitash, and Johnstone \(2012\)](#) show that able CEOs and CFOs strive to establish an effective internal control system and report them. Their compensation is tied to their performance regarding

this reporting as set out in regulations such as the Sarbanes-Oxley Act of 2002. Able managers also issue fewer restatements ([Plumlee & Yohn, 2010](#)). [Rahaman and Al Zaman \(2013\)](#) show that able managers with efficient practices tend to find better external financing capacity at lower costs of debt for their company, lowering the cost of capital and increasing their firms' valuation. [Leverty and Grace \(2012\)](#) find that firms of the able managers face lower distress risk, lower likelihood, and failure costs. [P. R. Demerjian et al. \(2013\)](#), in specific, argue that more able managers provide higher quality financial reporting because they are, for example, better at estimating higher-quality accrual and need fewer restatements. These suggest that able managers are more likely to have superior performance and prefer to communicate their achievements to the outside world including financial analysts. Studies note that the outcome of the work from financial analysts depends on the managerial direction and proper channels of dialogue.

Opportunistic behavior view (obfuscation hypothesis): On the other hand, some studies suggest that managers do not necessarily have the incentives to be forthcoming and communicative. They do so to keep certain information hidden from market participants. They can misuse their position to accumulate wealth to the detriment of other stakeholders or just hide their poor performance with vague reports ([Hendry, 2005](#)); ([Tian, 2014](#)); ([Cheung, Naidu, Navissi, & Ranjeeni, 2017](#)). Analysts can be misguided by firms' management ([Barth & Hutton, 2004](#)). Since the management team has a better understanding of their firms' internal control and reporting practices, they can commit fraudulent activities and cover their track consequently ([Wolfe & Hermanson, 2004](#)) ([Dellaportas, 2013](#)).

For instance, able management may delay the release of negative news about their firm or even employ accounting practices to conceal the information in their reports. They do so to keep the share price inflated for their stock options, holdings, and cash compensations and retain their

current positions, and even landing in a better job ([Bloomfield, 2002](#); [F. Li, 2010](#)). [Habib and Hasan \(2017\)](#) also show that the firms' able managers tend to over-invest in highly risky projects and may not be willing to disclose the details of risk-taking actions. Then, analysts have no choice but to rely on private and idiosyncratic sources of information, which lowers accuracy and increases the Dispersion among the provided forecasts ([Ali, Liu, Xu, & Yao, 2019](#)). [Gul, Khedmati, Lim, and Navissi \(2018\)](#) also argue that firms in financial distress with able managers show lower accrual quality and a higher likelihood of restatement. These managers tend to employ more opportunistic financial reporting to maximize their equity compensation and deal with debt refinancing pressures, which brings both risk of audit and higher audit fees. Overall, this part of the research suggests that while able managers are competent enough to produce outstanding performance for their firms, they might prefer to exploit the opportunity for their personal gain in their firm. Thus, they have the incentive to make reports less readable to hide their actions and benefits.

2.5 Hypotheses

In light of the above discussion, we present a set of hypotheses and examine them in this study.

Managerial ability and forecast error:

Hypothesis 1a: the higher ability of managers leads to lower earnings forecast errors by financial analysts.

A generous portion of the past studies on managerial ability support ‘superior performance view’ - accordingly, we present the hypotheses predicting that more able managers would create a better informational environment in terms of the readability of financial disclosures that would lead to lower forecast error.

Suppose financial analysts have access to symmetric and transparent information. In that case, the primary source of which is the company's direct disclosure, they have a higher chance of providing more accurate forecasts for the company individually and in their collective efforts. Before releasing the company's actual earnings for each quarter, the mean of the analyst earnings forecasts could be evaluated against the actual earnings figures once released. Variables are defined to measure this error which will be introduced in the methodology section. The managerial ability could then be examined to be connected to analyst forecasts' properties with the forecast error as the primary variable.

The reason the management team should be concerned about the accuracy of the work output by the analysts is that the high accuracy forecasts benefit the covered firms in many aspects, including lower cost of capital and higher future price performance ([K. K. Li & You, 2015](#)). These benefits will directly impact the compensation of the management team, their career success, as well as their chance to land in a better company. So able managers have the incentive to provide

an environment for the analysts to perform their tasks with ease. An informationally efficient environment will lead to lower forecast error by individual analysts.

Hypothesis 1b: Managers' higher ability leads to less dispersion among the forecasts by different analysts.

While forecast error represents the analysts' mean of opinion, forecast dispersion denotes the extent that these forecasts are dispersed. Not all analysts have the same idea about the firms' earnings forecasts and their future performance. As mentioned in the literature review section, the market will listen more carefully to some renowned analysts, and some analysts follow the others' footprints.

Different forms of deviation measures are employed to assess dispersion's level in the forecasts provided by analysts following a firm for each period, with varying scaling options as the denominator. In uncertain times or for companies with massive uncertainty and an untransparent information environment, the task of providing accurate forecasts could be more challenging for some analysts compared to others. Suppose managers tend to make the informational environment unclear. In that case, the cost to process and interpret the information by the analysts will increase, which leads to a higher diversion in analysts' opinions and their interpretation of the company's condition and prospects. The result is higher dispersion among the forecasts of the analysts.

The literature shows that lower forecast error is accompanied by lower forecast dispersion. As argued, able managers should strive to facilitate analysts' tasks, so we predict managers' higher ability will lower the forecast dispersion among analysts.

Managerial ability and analyst following:

Hypothesis 2: the higher ability of managers leads to more analysts following.

Literature is rich in the factors affecting analysts following ([M. H. Lang & Lundholm, 1996](#)); ([M. Yu, 2010](#)). Analyst following is the total number of analysts following a firm during an accounting period and their willingness to initiate or terminate their forecasts and recommendations on a specific firm.

Analysts are individuals with limited resources who must answer their firms, clients, and investors' interests while considering their interests and passion. Analysts' economic incentives encourage them to follow specific companies' types to bring them recognition, higher salaries, more business, and revenue for their firms. [Kothari et al. \(2016\)](#)

Further, the institutional investors' interest and their ownership increase in a company, for example, has shown to be an underlying catalyst for analysts to initiate coverage on a firm. One reason for such interest is that Institutional investors are potential clients for the analysts' firms.

Instituting international reporting standards like IFRS in a jurisdiction has also shown to provide a better ground for the analyst to give coverage on firms ([Tan et al., 2011](#)). Literature also indicates that analysts are interested in companies that adhere to higher financial disclosure standards, including better corporate governance disclosure and more socially responsible reports. With their competence and ability, the management team could also be a source of attraction for analysts to follow a firm. Literature shows that analysts with the same school ties with the top management are more willing to follow the firm and provide more accurate forecasts and recommendations ([Cohen et al., 2010](#)).

The literature shows analysts are interested in hugely undervalued firms and have a higher

potential for a future price increase. In many cases, the company's undervaluation stems from the firm's uncertainties or its weak financial environment. When the company is too hard to read, understand, and predict, there is more demand from the market participants for analyst services and more interest from the analysts themselves to cover the firm ([Lehavy et al., 2011](#)).

A part of the literature argues that in a complex information environment, analysts seize the opportunity to act as information intermediaries. They can use their analytical skill to process information and sell their opinion at high costs. The higher the uncertainty, the higher the profit analysts can gain from their services ([Schipper, 1991](#)).

However, analysts also bear the cost of processing that information provided by management. Further, if the able management decides to make the disclosure more confusing, it might require the analysts to spend more resources on that company, hoping the reward may not be realized. In the end, the analyst might end up not achieving accurate forecasts and recommendations despite their costly efforts ([Plumlee & Yohn, 2010](#)); ([Hong et al., 2000](#)).

So far, we know that analyst coverage initiation and termination impact public firms ([Lee & So, 2017](#)). [Kim et al. \(2019\)](#) show that a drop in analyst coverage increases the company's stock price's expected crash risk. [Derrien and Kecskés \(2013\)](#) note that a decrease in analyst coverage increases information asymmetry and the cost of capital. As a result, firms have no choice but to decrease their investment and financing.

Considering the points mentioned above, we argue that able managers will do their best to provide an environment that attracts more analysts to follow the firm as it is in their own best interest, as discussed in Hypothesis 1.

Managerial ability and informativeness:

Hypothesis 3a: the higher ability of managers leads to more informativeness of analysts' reports.

Literature has been interested in assessing the release of analysts' reports on the companies' share price movement. [Frankel, Kothari, and Weber \(2006\)](#) provide a measure for the informativeness of the analysts' reports. They measure the information content of analysts' reports as the portion of a stock return associated with the analyst report to the company's total share return from the issuance of the 10-k report till the end of the fiscal year.

We argue that the management ability will help analysts conduct their duty more effectively, which means more accurate reports with less dispersion. In such an environment, the market users will pay more attention to analysts' opinions and act on their reports and recommendations faster, leading to quicker price adjustments following analysts' earnings forecast revisions. Then, the absolute sum of share returns on the days the analysts provided a forecast is expected to be higher. Therefore, we expect to find that the managers' ability results in higher informativeness of analysts' reports.

Hypothesis 3b: the higher ability of managers leads to lower response time by analysts.

Response time is defined as the average length of time in days from the release of the annual 10-k reports by the company to the first quarterly or annual report or revision that analysts prepare in which they provide updated earnings forecasts and recommendations ([Lehavy et al., 2011](#)).

Suppose the company management team declines to provide transparent and easy-to-read reports. In that case, the analysts must spend more resources to understand the company's dynamics, taking more time to issue their opinion. The analysts' updated reports help the market

understand the company's updated prospect sooner, which helps reduce information asymmetry and strengthen the market informational efficiency. This process will help the share price performance of the company, as discussed in the literature. Hence, we predict that ability of the managers is negatively associated with the average analyst response time.

Hypothesis 3c: the higher ability of managers leads to lower uncertainty associated with analyst forecasts.

[Barron, Kim, Lim, and Stevens \(1998\)](#) note that analyst forecasting properties, including forecast error and Dispersion, do not provide all the necessary information about the analyst information environment. These measures assess both the personal and common components of analyst forecast errors, meaning that there must be a common uncertainty and overall uncertainty in analysts' work. These measures take error, Dispersion, analyst following into consideration concurrently. We expect to find a negative association between the management ability and the overall uncertainty of analyst reports. Able managers will impact all the aspects of analyst work, including forecast error, following, and Dispersion.

Mediation Effects (Channels):

The following two hypotheses explore the channels that can help understand the impact of managerial ability on financial analyst performance. The last hypothesis focuses on the explanatory power of financial analyst forecast error as a mediator between managerial ability and firm value.

Hypothesis 4a: Readability of annual reports mediates the relation between managerial ability and forecast errors.

As discussed in the literature, managerial ability is associated with the readability of firm

disclosure. Further, the companies' narrative disclosure's readability impacts financial analysts' performance regarding forecast error and dispersion. We also expect to find that managerial ability is associated with analyst forecast error. Then we will show that the readability of annual reports is a possible channel that the management team can impact analysts' performance.

Managers can affect the internal information environment, i.e., the firms' financial disclosures. By providing more readable and transparent disclosure, the management communicates their performance and accurate picture to financial analysts. Financial analysts will then be enabled to report earnings forecasts closer to the actual EPS of the company.

Hypothesis 4b: The number of analysts following mediates the relation between managerial ability and forecast errors.

In hypothesis 2, we expect to find that high-ability managers attract more financial analysts covering their firm, which is in their interest. We also have argued that high-ability managers will do their best to provide an informationally transparent and efficient environment to make sure analysts can perform their tasks more manageable. This process will lead to lower forecast error. We argue that the higher number of analysts who respond to a more able manager in a firm could be the channel for lower forecast error. [Bhushan \(1989\)](#) interprets the analyst following as the collective effort from analysts to analyze a specific firm. We expect this higher number of analysts to have a synergic effect that provides a more accurate forecasting environment.

Hypothesis 4c: Forecast error mediates the relationship between managerial ability and firm's value

The last hypothesis focuses on the “so what” question. Does the result of the work can

explain how managers can create value for their firms. This part investigates the mediating effect of forecast error on the relationship between managerial ability and firm value (proxied by lead Tobin's Q). Tobin's Q equals the market value of a firm divided by its assets' replacement cost. It measures the ratio of market valuation to intrinsic value. It is used to assess the undervaluation or overvaluation of a given company. If managers have higher ability, it leads to lower forecast error for the firm. Lower forecast error is shown to have a positive effect on the overall value of a firm. We intend to measure the extent to which forecast error is contributing to this relationship.

3 Data and methodology

3.1 Data and definitions

This study will include detailed analyst forecasts of all the Standard & Poor's 1500 (S&P 1500) companies between 1995 to 2016 from the I/B/E/S² database. The database consists of quarterly and annual forecasts for various financial items from the balance sheet, income statements, and cash flow statements (we use quarterly and yearly earnings forecasts), up to 10 years forecasted. Every time an analyst provides or updates their forecast on a company, a new entry is added to the database.

We need to refer to other databases and merge them with I/B/E/S data for other actual and historical financial items. The security-level data will include two datasets of the CRSP³ database. Security prices and daily returns will be extracted from Daily Stock and companies' decile ranking from the Capitalization Decile file. For the firm-level accounting data, we use the CRSP/Compustat Merged database. The WRDS website provides all the databases. The security-level and firm-level databases will be merged with the analyst detailed forecast file. For the final regression, we need the managerial ranking file derived from Peter Demerjian's website at the University of Washington, which has the data from 1994 up to 2016. The other important piece of data comes from the Management Compensation file derived from WRDS, which has information on companies' management teams in the S&P 1500 index.

As discussed in the literature, analysts' lower forecast error means the analysts have a clear image of the company's prospects and performance, enabling them to forecast its future cash flows more accurately. Considering different scenarios, analysts can discount these cashflows with an

² Institutional Brokers Estimate System

³ The Center for Research in Security Prices

appropriate discount rate to develop the predicted future cash flows' net present value. This work process will result in different valuations for the stock price of the company with the breakdown of the next five to ten years of many of the items of the financial statements, including income statement items (e.g., revenue, gross margin, net operating asset, earnings per share, etc.), balance sheet (assets, liabilities, shareholders' equity) and cash flow (financing, operating, investing, net cash balance).

The pivotal piece of information in the analysts' work is the earnings per share (EPS) forecast quarterly and annual for the next five to ten years. Every time a company releases the actual quarterly or fiscal year-end earnings or any other type of disclosure, the analysts covering the firm update and polish their forecasts accordingly to project the newly available information. Before releasing the company's actual figures, the forecasts of all the participating analysts are recorded in databases like I/B/E/S. The forecasts are aggregated to provide consensus figures such as the earnings forecast error, Dispersion, surprise, etc.

I used STATA software to write all the required code for this research and perform all the analysis. After the data collection phase and before defining and calculating all the variables in our STATA code, I prepared and cleaned the data. Our coding starts with the detailed history with annual and quarterly forecasts from the I/B/E/S database, which had 8.75 million observations encompassing all the entries every time an analyst has provided EPS forecast for a company from 1980 to 2018. Dropping observations that had missing actual EPS and company identifier values and those with EPS values announced in currencies other than US dollars (some companies are dual-listed, so EPS is reported in other currencies as well) left us with 8.42 million observations.

Analysts tend to update their forecasts numerous times once new information is available and the inputs to their models change before the actual quarterly or end-of-fiscal-year EPS is

announced by the company. For each company per year, we only keep on forecast per analyst prior and closest to the actual date that the company announced the annual EPS in their annual reports. This process leaves us with 1.22 million observations. There are variables such as Response Time and AI which need to be coded and calculated before this stage but then averaged at the year-company level.

Next, we merge the remaining I/B/E/S dataset with Compustat-Crsp merged file, which encompasses end-of-fiscal-year security prices and actual financial statement items for each company. Since not every company has an analyst following in I/B/E/S and the Compustat-Crsp file data starts from 1990, we are left with 752 thousand observations. At this point, we calculate all the required variables and measures at the year-company or year-analyst level. We ultimately calculate the mean and standard deviation at the year-company level for the year-analyst measures (e.g., the number of companies each analyst is following each year).

Since we intend to do panel regressions, we keep one observation for each company per year before merging the resulted file with the Managerial Raking/Score file. The result is around 79 thousand observations between 1990 to 2018.

The managerial ranking is derived from Peter Demerjian's website, which has data up to 2016. It is also merged with the Management Compensation file derived from WRDS. The dataset includes information on companies' management teams in the S&P1500 index, such as their compensation, salary, gender, etc. Table 1 presents the final dataset after merging the MA score file with the combined result of I/B/E/S, CRSP, and Compustat. The panel data for our final analysis ranges from 1995 to 2016. It depicts the number of companies each year with the average forecast error, MA score, analyst following, and analyst informativeness.

Table 1: Panel dataset for analysis

Table 1 presents the final panel data for our analysis. The table shows the number of companies each year from 1995 to 2016 with the average primary variables in our research. On average, our study covers 1836 companies each year. The average number of analysts covering a listed company in S&P 1500 and their report's informativeness (AI) have increased steadily over the years. Forecast Error also implies that during 2008-9, analysts were more erroneous in their earnings forecasts.

Year	Number of Companies	mean			
		Forecast Error	MA Score	Analyst Following	AI
1995	1,840	0.010	0.032	7.84	0.091
1996	2,001	0.010	0.017	7.63	0.087
1997	2,092	0.009	0.012	7.64	0.087
1998	2,046	0.014	0.012	7.87	0.086
1999	1,937	0.012	0.010	8.39	0.084
2000	1,756	0.016	0.017	8.66	0.085
2001	1,617	0.011	0.011	9.17	0.095
2002	1,674	0.011	0.014	9.28	0.103
2003	1,638	0.006	0.015	9.61	0.116
2004	1,745	0.005	0.014	9.46	0.118
2005	1,804	0.006	0.015	9.58	0.128
2006	1,864	0.006	0.009	9.50	0.130
2007	1,861	0.010	0.014	9.53	0.134
2008	1,798	0.028	0.016	9.47	0.141
2009	1,816	0.015	0.010	9.82	0.142
2010	1,799	0.010	0.009	10.76	0.147
2011	1,805	0.011	0.011	11.44	0.150
2012	1,827	0.011	0.007	11.29	0.156
2013	1,839	0.007	0.004	11.67	0.158
2014	1,900	0.008	0.013	11.37	0.156
2015	1,885	0.011	0.010	11.25	0.158
2016	1,855	0.009	-0.001	11.21	0.157

3.2 Methodology

For the properties of financial analyst forecasting, we use analyst detailed forecast files from the I/B/E/S database. Forecast error for each company is based on [Hirshleifer, Lim, and Teoh \(2009\)](#), which is the difference between analysts' consensus forecasts and the company's actual earnings announcement, scaled by the fiscal year-end share price. We use the managerial ability score⁴ (MA Score) from [P. Demerjian et al. \(2012\)](#). To answer [hypothesis \(1a\)](#), the association between managerial ability and forecast error, we propose the ordinary least square (OLS) regression model on a firm-year level in Equation (1):

$$\begin{aligned} \text{forecast error} &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} \\ &* \text{Sales growth} + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} \\ &* \text{Firm Age} + \text{Beta7} * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} \\ &* \text{Inst_ownership} + \text{Beta10} * \text{hfi_48} + \text{Beta11} \\ &* \text{other analyst characteristics} + \text{Industry \& year fixed effects} \end{aligned} \quad (1)$$

Several control variables relating to the firm are included in the model. Size is the market capitalization of the company at the end of each fiscal year. Sales growth is the year-over-year sales growth of the company. Leverage is the debt to the total asset of the company. Firm age is the number of years since the firm first appeared in the CRSP database. PPE is the property, plant, and equipment of the company. R&D expenditure of the company is also included as a control variable. The institutional investor is the portion of the firm's equity that institutional investors own. Hfi_48 is the Herfindahl index measure market concentration of top 48 largest firms in an industry. It shows whether the industry is competitive or there is a monopoly going on. It adds up the squared market share of the n biggest companies to measure if they have considerable control over the market ([Rhoades, 1993](#)).

⁴ The scores are available at Peter Demerjian's website at University of Washington

Hypothesis (1b) takes the forecast dispersion into effect. Forecast dispersion shows the amount of disagreement among the forecasts provided by different analysts for each company. The lower amount shows that analysts collectively have the same opinion about the company's future earnings trend. It is mathematically reasonable to think that higher dispersion among analysts should be in line with higher overall earnings forecast error. It is calculated as the standards deviation of the different forecasts provided by analysts for each firm per year scaled by the actual fiscal year-end earnings. In calculating dispersion, only the latest forecast from each analyst before the actual earnings announcement for a firm each year is considered. The same control variables are used here as well.

$$\begin{aligned}
 \text{Dispersion} = & \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} \\
 & * \text{Sales growth} + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} \\
 & * \text{Firm Age} + \text{Beta7} * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} \\
 & * \text{Inst_ownership} + \text{Beta10} * \text{hfi_48} + \text{Beta11} \\
 & * \text{other analyst characteristics} + \text{Industry \& year fixed effects}
 \end{aligned} \tag{2}$$

Hypothesis (2) concerns the effect of managerial ability on the number of analysts who choose to follow the firm and provide forecasts. Analyst following is the number of analysts providing at least one forecast for each firm each fiscal year. Our initial dataset only kept those observations where at least two financial analysts follow a company. This process will ensure that some measures such as forecast error, dispersion, and standard deviations are meaningful. We would like to understand whether the managers' ability can lead to the attraction of a higher number of analysts following the firm. The model in Equation (3) is proposed accordingly.

$$\begin{aligned}
 \text{Analyst following} = & \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} \\
 & * \text{Sales growth} + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} \\
 & * \text{Firm Age} + \text{Beta7} * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} \\
 & * \text{Inst_ownership} + \text{Beta10} * \text{hfi_48} + \text{Beta11} \\
 & * \text{other analyst characteristics} + \text{Industry \& year fixed effects}
 \end{aligned} \tag{3}$$

Hypothesis (3a) presents the effect of managerial ability on the informativeness of analysts' reports. The measure of analyst report informativeness (AI) is calculated by [Frankel et al. \(2006\)](#). It is the amount of absolute size-adjusted return of the firm stock associated with the days that at least one analyst has provided a forecast divided by the total absolute size-adjusted return for the whole year. To calculate this measure for each company per year, we extracted the dates when at least one analyst has provided updates on the company's quarterly or annual earnings. We then add up the absolute return of the company's share on these dates and divide it by the total absolute return for the whole year. This measure shows how much the market reacts positively or negatively on the days that analysts provide a forecast report. Equation (4) is the proposed model.

$$\begin{aligned}
 AI = & \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} * \text{Sales growth} \\
 & + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} * \text{Firm Age} + \text{Beta7} \\
 & * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} * \text{Inst_ownership} \\
 & + \text{Beta10} * \text{hfi_48} + \text{Beta11} * \text{other analyst characteristics} \\
 & + \text{Industry \& year fixed effects}
 \end{aligned} \tag{4}$$

Hypothesis (3b) examines the association of managerial ability with analysts' response time. We will follow [Lehavy et al. \(2011\)](#) to calculate analyst response time as a dependent variable, a proxy of the effort analysts exert to provide reports following the 10k filing by each listed company. For each company per year, we consider the first report each analyst releases following the company's annual report disclosed. We take the average of these response times for each company per year.

Response time represents how quickly analysts can provide their new forecast about the firm's earnings following its actual announcement. The faster they provide their forecasts, the easier it was to process further information released by the company in their annual disclosures (10k filings). We intend to examine whether the ability of managers can help analysts provide quicker report updates.

Response time

$$\begin{aligned} &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} \\ &* \text{Sales growth} + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} \\ &* \text{Firm Age} + \text{Beta7} * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} \\ &* \text{Inst_ownership} + \text{Beta10} * \text{hfi_48} + \text{Beta11} \\ &* \text{other analyst characteristics} + \text{Industry \& year fixed effects} \end{aligned} \quad (5)$$

Hypothesis (3c) takes error calculation a step forward by accounting for overall uncertainty.

It is interpreted as the sum of idiosyncratic uncertainty (i.e., the uncertainty of analysts' private information) and the common uncertainty (i.e., uncertainty with the information accessible to all the analysts) ([Lehavy et al., 2011](#)). The calculation is provided in the appendix.

Overall Uncertainty (OU)

$$\begin{aligned} &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Firm size} + \text{Beta3} \\ &* \text{Sales growth} + \text{Beta4} * \text{Leverage} + \text{Beta5} * \text{OCF/TA} + \text{Beta6} \\ &* \text{Firm Age} + \text{Beta7} * \text{PPE} + \text{Beta8} * \text{R\&D expenditure} + \text{Beta9} \\ &* \text{Inst_ownership} + \text{Beta10} * \text{hfi_48} + \text{Beta11} \\ &* \text{other analyst characteristics} + \text{Industry \& year fixed effects} \end{aligned} \quad (6)$$

3.2.1 Direct and indirect association of managerial ability, analyst forecast properties, and firms value(Mediation Effect)

So far, we explored the association between managerial ability and analyst forecast properties, including error, dispersion, following, informativeness, response time, and overall uncertainty. Next, we explore the extent to which managerial ability has a direct and indirect association with analyst forecasting properties. Finally, we look at the way that analyst forecast error can bridge managerial ability to firms' value.

The indirect association presents a path from the managerial ability to analyst forecast properties through at least one more variable, such as analyst following or readability of 10k disclosures. The sum of the direct and indirect effects represents the total effect.

The first possible channel is the analyst following, for which we present Equations (7) and

(8). Analyst following was shown to have a significant relationship with forecast error. Literature also provides that a higher number of analysts leads to more agreement among (less dispersion) them and lower forecast error ([Tan et al., 2011](#)).

We will examine whether able managers impact financial analysts' external work by attracting more analysts to follow the firm. In other words, the impact of managers on financial analysts can be explained by their direct impact on forecast error plus the indirect impact that they may have via attracting more analysts. The higher number of analysts mediates the lower forecast error. Figure 1 represents the logic for the mediation effect with analysts following as the mediator.

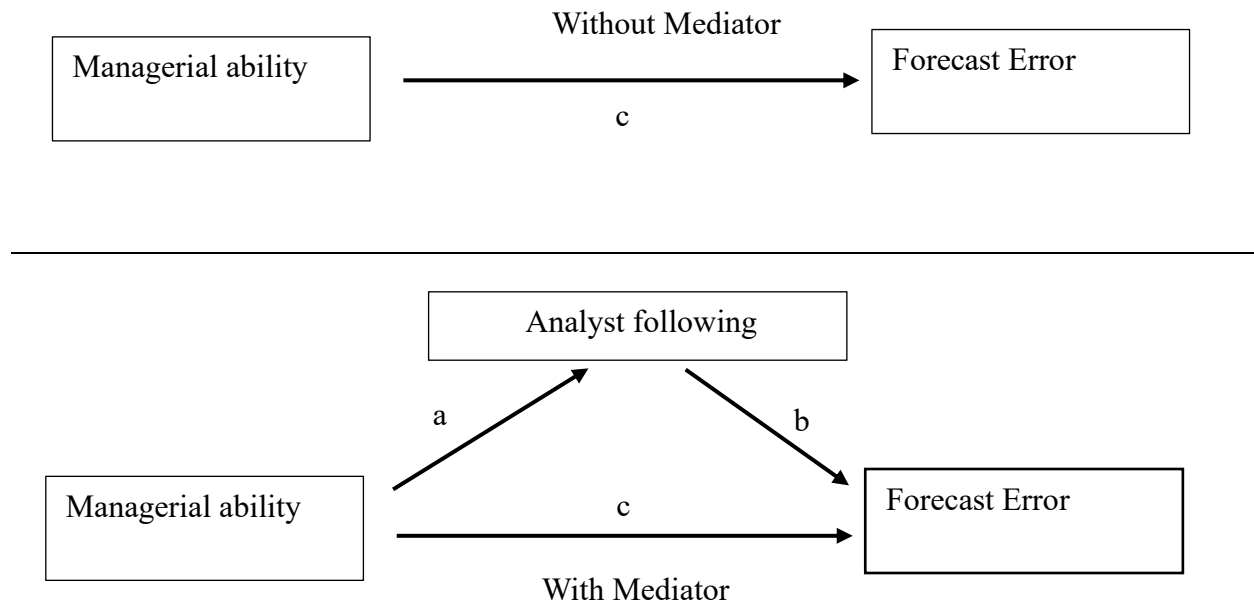


Figure 1: mediation effect of analyst following

Forecast error

$$\begin{aligned}
 &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{analyst following} + \text{Beta3} \\
 &* + \text{Beta4} * \text{size} + \text{Beta5} * \text{sales growth} + \text{Beta6} * \text{leverage} + \text{Beta7} \\
 &* \text{OCT/TA} + \text{Beta8} * \text{firm age} + \text{Beta9} * \text{PPE} + \text{Beta10} * \text{R\&D} \\
 &+ \text{Beta11} * \text{Inst_ownership} + \text{Beta12} \\
 &* \text{other analyst forecasting characteristics} \\
 &+ \text{year and industry fixed effects}
 \end{aligned}
 \tag{7}$$

Analyst following

$$\begin{aligned} &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{size} + \text{Beta3} * \text{sales growth} + \text{Beta4} \\ &* \text{leverage} + \text{Beta5} * \text{OCT/TA} + \text{Beta6} * \text{firm age} + \text{Beta7} * \text{PPE} + \text{Beta8} \\ &* \text{R\&D} + \text{Beta9} * \text{Inst_ownership} + \text{Beta10} \\ &* \text{other analyst forecasting characteristics} + \text{year and industry fixed effects} \end{aligned} \quad (8)$$

Next, we intend to explore how and to what extent the firm's information environment defined by narrative disclosure quality mediates the relationship between managerial ability and analyst forecasting (indirect impact). This analysis would underline the importance of informational transparency (readability of narrative disclosure) on the analyst's forecasting and role as a channel between managerial ability and information intermediaries such as financial analysts. Management of the company can impact the company's internal disclosure environment through financial reporting and disclosure. This environment is externally perceived by information mediators, including financial analysts, who utilize the financial disclosure to assess the company's prospects. They can then release financial forecasts, which provide a close representation of the company's actual earnings. Hence, the disclosure quality of the financial statements could be a potential channel that facilitates financial analysts' work.

To do so, we present the simultaneous equations (9) and (10). Bog index is employed as the measure for the readability of annual 10k filings of the listed companies. The bog index is a multifaceted measure of plain English readability called the Bog index. A higher level of the Bog index represents a lower readable document ([Hasan, 2020](#)). Figure 2 shows the logic behind the mediation effect with disclosure readability as the mediator.

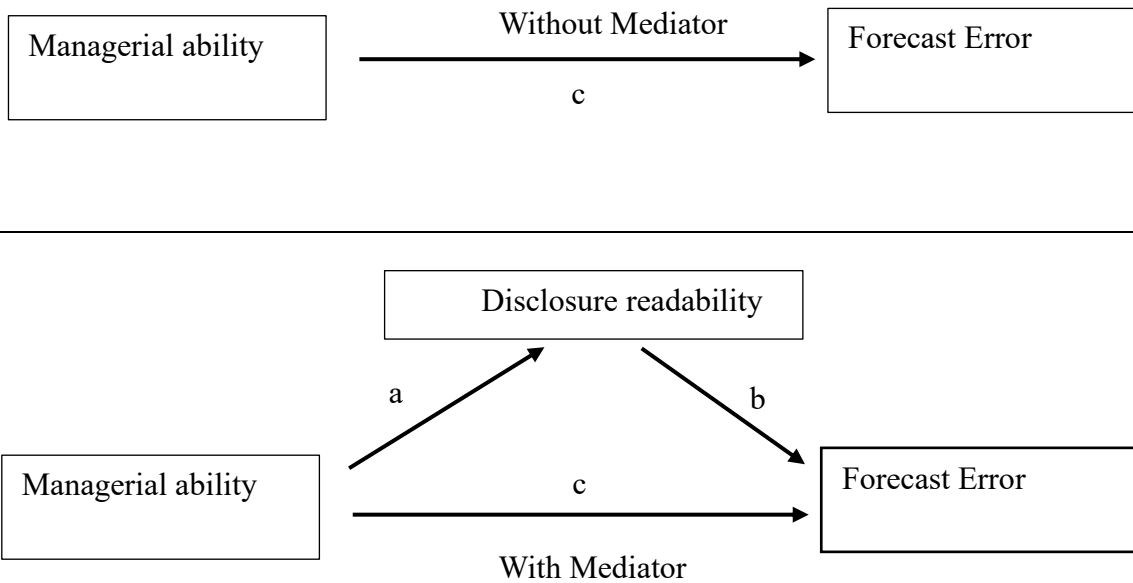


Figure 2: mediation effect of disclosure readability

Forecast error

$$\begin{aligned}
 &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{bog index} + \text{Beta3} * + \\
 &+ \text{Beta5} * \text{size} + \text{Beta4} * \text{sales growth} + \text{Beta5} * \text{leverage} + \text{Beta6} \quad (9) \\
 &* \text{OCT/TA} + \text{Beta7} * \text{firm age} + \text{Beta8} * \text{PPE} + \text{Beta9} * \text{R\&D} \\
 &+ \text{Beta10} * \text{Inst_ownership} + \text{year and industry fixed effects}
 \end{aligned}$$

$$\begin{aligned}
 \text{bog index} &= \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * + \text{Beta3} * \text{size} + \text{Beta4} \\
 &* \text{sales growth} + \text{Beta5} * \text{leverage} + \text{Beta6} * \text{OCT/TA} + \text{Beta7} \quad (10) \\
 &* \text{firm age} + \text{Beta8} * \text{PPE} + \text{Beta9} * \text{R\&D} + \text{Beta10} \\
 &* \text{Inst_ownership} + \text{year and industry fixed effects}
 \end{aligned}$$

Equation (9) exhibits the direct relation between the analyst forecast error and managerial ability. The equation also includes the disclosure readability variable (bog index) shown by [Lehavy et al. \(2011\)](#). Readable disclosures increase informativeness and reduce the error of financial analysts' reports. Equation (10) represents the association between readability and managerial ability. [Hasan \(2020\)](#) notes that able managers create more readable disclosures.

The last question that the research seeks to answer is how these findings can explain the firm value. In line with the literature, we argued that if firm management has high ability, they have the incentive to take proper actions to provide a better information environment surrounding the firm. This process helps the firm's value and will, in the long run, prove to bring value for the managers. To further explore another possible channel effect, we look at the mediating effect of forecast error on the relationship between managerial ability and a firm's value (proxied by lead Tobin's Q). The effect of managerial ability on the firms' value was presented in the literature. Here we measure how much of the possible effect can be attributed to the impact of managerial ability on analyst forecast error, leading to higher firm value. Equations (11) and (12) must be simultaneously considered.

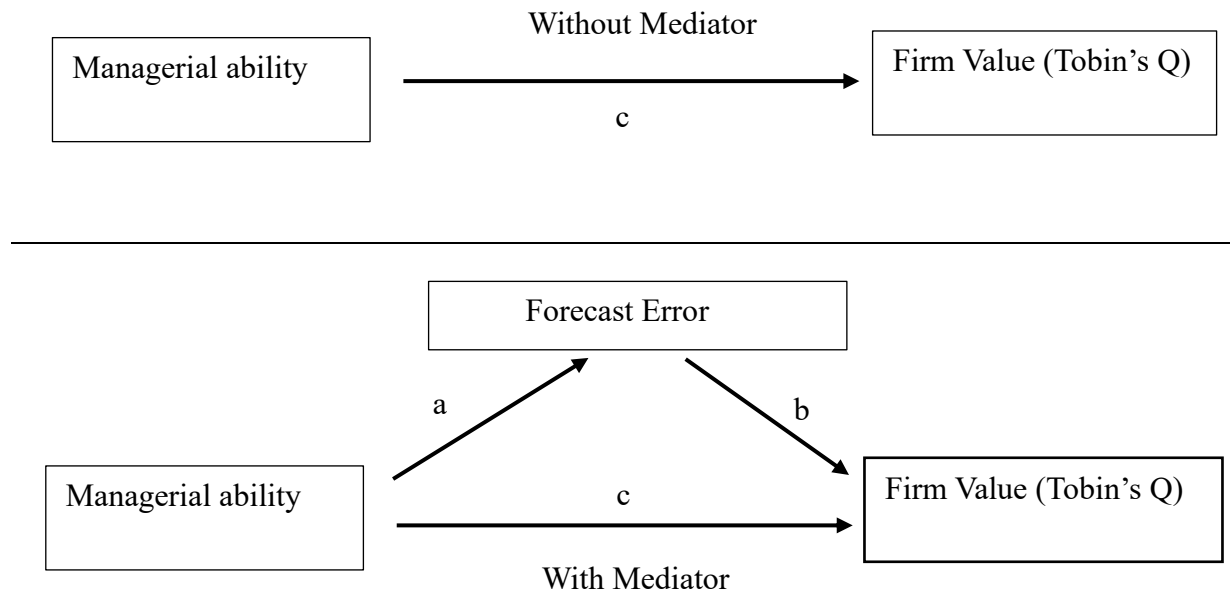


Figure 3: mediation effect of forecast error between managerial ability and firm value

$$\begin{aligned}
\text{Tobin's } Q = & \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{Forecast Error} + \text{Beta3} * \text{firm size} \\
& + \text{Beta4} * \text{sales growth} + \text{Beta5} * \text{sales growth} + \text{Beta6} * \text{leverage} + \text{Beta7} \\
& * \text{OCT/TA} + \text{Beta8} * \text{firm age} + \text{Beta9} * \text{PPE} + \text{Beta10} * \text{R\&D} + \text{Beta11} \\
& * \text{Inst_ownership} + \text{year and industry fixed effects}
\end{aligned} \tag{11}$$

$$\begin{aligned}
\text{Forecast Error} \\
= & \text{Alpha} + \text{Beta1} * \text{MA Score} + \text{Beta2} * \text{size} + \text{Beta3} * \text{sales growth} + \text{Beta4} \\
& * \text{leverage} + \text{Beta5} * \text{OCT/TA} + \text{Beta6} * \text{firm age} + \text{Beta7} * \text{PPE} + \text{Beta8} \\
& * \text{R\&D} + \text{Beta9} * \text{Inst_ownership} + \text{year and industry fixed effects}
\end{aligned} \tag{12}$$

4 Results and Findings

Descriptive Statistics of the main variables in my research are presented in Table 2 with the number of observations, minimum, maximum, mean, and standard deviation measures. Measures calculated from IBES databases encompassing analysts' work include forecast error, dispersion, analyst report informativeness (AI), overall uncertainty, response time, analyst following, etc. pivotal measures for our analysis derived and calculated from other datasets include the Bog Index as the measure of annual report readability, MA score as the measure of managerial ability, and Tobin's Q as the measure of firm value. Other control variables related to the firm characteristics include firm size defined as the end-of-fiscal-year market capitalization of the companies, sales growth, leverage ratio, operating cash flow to total assets, firm age (as they first appeared in the IBES database), property, plant, and equipment, research and development, and institutional investors' ownership in the companies.

The mean managerial ability score (MA Score) is 0.57, similar to prior studies ([Lo et al., 2017](#)). The Mean Bog Index is 84.28, which is in line with prior studies ([Bonsall IV et al., 2017](#)). Based on their explanation, the breakdown of Bog Index intervals is as follows: 0-20 = excellent; 21-40 = good; 41 – 70 = average; 71-100 = poor; 101-130= Bad; 131-1000 dreadful; 1000+ = Gogbledygook. Our data shows the poor readability of narrative disclosures.

The mean of analysts' report informativeness (AI), similar to prior studies' results ([Lehavy et al., 2011](#)), is 0.12. The average analyst response time (28.19) is higher than that of [Lehavy et al. \(2011\)](#), reported at 19. The difference could be mainly because of the different analysis window. Our analysis includes the financial crisis of 2008/09 that could be a significant contributing factor to the higher response time by analysts.

Table 2: Descriptive Statistics

Table 2 presents descriptive statistics of the main variables in my research. The measures related to analysts' work include forecast error, dispersion, analyst report informativeness (AI), overall uncertainty, response time, and analyst following. Variables providing insight regarding the firm's internal environment include the Bog index as the measure of annual report readability, MA score as the measure of managerial ability, and Tobin's Q to measure firm value.

Variable	Obs	Mean	Std. Dev.	Min	Max
Forecast Error	51,171	0.01	0.03	0.00	0.19
Dispersion	51,171	0.01	0.03	0.00	0.18
AI	48,003	0.12	0.09	0.00	0.74
Bog Index	33,634	84.28	7.72	48	139
MA Score	38,118	0.57	0.29	0.1	1
Tobin's Q	40,852	1.93	1.64	0.52	72.43
Overall Uncertainty	51,171	0.02	0.05	0.00	0.43
Response time	48,384	28.19	30.46	0.00	189.00
Analyst Following	51171	9.41	7.56	2.00	31.00
Firm size	51,107	5,145	13,261	0.76	75,013
Sales growth	47,507	0.27	8.24	-25.06	1508.96
Leverage	48,842	0.22	0.20	0.00	3.77
OCF/TA	50,012	0.04	0.17	-6.61	2.23
Firm Age	47,641	17.30	17.22	0.00	91.00
PPE	51,081	0.25	0.22	0.00	0.92
R&D	51,171	0.04	0.25	0.00	1.55
Inst_ownership	46,909	0.56	0.31	0.00	15.57

Table 3 represents the correlation between principal variables in my analysis and the significance of their pairwise t-test at one, five, and ten percent. As an initial analysis and in line with our expectations, all the main variables have a significant pairwise correlation. Forecast error has a positive correlation with dispersion, negative one with analyst report informativeness (AI), positive with Bog index, negative with MA score.

Table 3: Correlation Matrix

Table 3 presents the pairwise correlation matrix of the main variables in my research. Analysts Forecast Error, dispersion among different analysts' forecasts, analyst following, informativeness of analysts' reports (AI), Bog Index as the measure of readability, Ma Score as the measure of CEO ability, Tobin's Q as the firm performance, the number of analysts following a firm each year, market capitalization, and share of institutional investors in the company are correlation against each other.

Variables	MA_Score	Forecast Error	Dispersion	Analyst Following	AI	Response Time	Uncertainty	Bog Index	Tobin's Q
MA_Score	1.000								
Forecast Error	-0.107***	1.000							
Dispersion	-0.122***	0.693***	1.000						
Analyst Following	0.099***	-0.169***	-0.113***	1.000					
AI	0.139***	-0.146***	-0.081***	0.789***	1.000				
Response Time	0.028***	0.034***	0.005	-0.143***	-0.234***	1.000			
Uncertainty	-0.106***	0.869***	0.830***	-0.094***	-0.068***	0.018***	1.000		
Bog Index	-0.061***	0.042***	0.077***	0.130***	0.096***	-0.179***	0.061***	1.000	
Tobin's Q	0.051***	-0.077***	-0.090***	-0.033***	0.025***	-0.024***	-0.083***	0.033***	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.1 Managerial ability's relation with forecast error and Dispersion (H 1a, H 1b)

Table 4 presents the regression analyses on the factors contributing to analysts' forecast error. Model (1) exhibits the fixed effect regression result controlling for firm-fixed and year fixed effects. The model shows a statistically significant relationship between managerial ability and forecast error (coefficient of -3.3821 at 1% significance). Any non-time-variant variable such as industry fixed effect in the fixed effect regression is not applicable. Model (2) presents the result of an ordinary least square (OLS) regression, controlling for year and industry effects. The sign

and significance of the results are the same with (coefficient of -2.2228 at 1% significance). The models present several control variables, including firm size, sales growth, leverage, operating cash flow to total assets (OCF/TA), firm age, property, plant, and equipment (PPE), research and development expenses (R&D), institutional investment, and Herfindahl concentration (hfi_48). The industry-fixed effect is based on the Fama and French 48-industry classification. T-statistics, presented in parenthesis, are based on standard errors robust to heteroscedasticity and are clustered at the firm-year level.

Table 4: Relationship between managerial ability and analyst forecast error

Table 4 presents the relationship between forecast error as the dependent variables and managerial ability (MA Score) as the independent variable. Model (1) is the fixed effect regression where firm fixed effect and year fixed effect are included. Since firm fixed effect regression is employed, any time-invariant effect such as industry fixed effect is not applicable. Model (2) presents the ordinary least square (OLS) regression. Both models show a significant negative relationship (coefficients = -3.3821 and -2.2228 respectively) between MA Score and Forecast Error at 1% level. In both models, year and Fama-French 48 industry fixed effects are included as control variables. The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) Forecast Error	(2) Forecast Error
MA Score	-3.3821*** (0.731)	-2.2228*** (0.593)
Firm size	-0.0949*** (0.022)	-0.1595*** (0.011)
Sales growth	-0.1455*** (0.036)	-0.1596*** (0.058)
Leverage	15.4348*** (1.843)	12.6944*** (1.317)
OCF/TA	-47.1044*** (3.063)	-50.2555*** (2.504)
Firm age	-0.0380 (0.054)	-0.0404*** (0.010)
PPE	22.3926*** (2.803)	5.9210*** (1.273)
R&D	-0.8491** (0.415)	-0.7687* (0.409)
Inst_ownership	-14.0170*** (1.921)	-16.6781*** (1.739)
hfi_48	0.8119 (6.732)	-22.4635*** (6.204)
Constant	16.9790*** (2.618)	25.1694*** (3.317)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	30,250	30,250
R-squared	0.514	0.189
Adj. R-squared	0.429	0.188

*** p<0.01, ** p<0.05, * p<0.10

Table 5 presents analyst forecast dispersion as the dependent variable. Model (1) shows the results from fixed-effect regression, while model (2) offers the ordinary least square (OLS) regression. Both models show a statistically significant relationship between dispersion and managerial ability at 1% significance level (coefficients =-5.0013 and -2.9964, respectively).

The result shows that the high ability of managers leads to lower forecast dispersion by financial analysts. One possible explanation could be that as the number of analysts following a firm increases, more prominent analysts will provide coverage. They are more likely to provide more accurate forecasts. As discussed in the literature, other analysts tend not to deviate from the estimates provided by star analysts.

Table 5: Relationship between managerial ability and analyst forecast dispersion

Table 5 presents the dispersion among analysts' earnings forecasts as the dependent variable and managerial ability (proxied by MA Score) as the independent variables. Model (1) shows the fixed-effect regression, while Model (2) presents the ordinary least square (OLS) regression. Both models show a significant negative relationship between MA Score and Dispersion (coefficients = -5.0013 and -2.9964, respectively). Both models In both models, year and Fama-French 48 industry fixed effects are included as control variables. The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) Dispersion	(2) Dispersion
MA Score	-5.0013*** (0.657)	-2.9964*** (0.538)
Firm size	-0.1453*** (0.023)	-0.1375*** (0.011)
Sales growth	-0.2204*** (0.063)	-0.1632** (0.068)
Leverage	13.3610*** (1.714)	11.1126*** (1.146)
OCF/TA	-47.9485*** (2.829)	-49.8583*** (2.326)
Firm age	0.0069 (0.051)	-0.0314*** (0.011)
PPE	25.1027*** (2.633)	12.1406*** (1.148)
R&D	0.5345 (0.429)	0.7333* (0.426)
Inst_ownership	-13.2960*** (2.322)	-13.2409*** (1.879)
hfi_48	1.0016 (6.951)	-15.3210*** (5.700)
Constant	17.7475*** (2.783)	22.3123*** (3.225)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	30,250	30,250
R-squared	0.520	0.218
Adj. R-squared	0.436	0.217

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

4.2 Managerial ability's relation with analyst following (H 2)

Table 6 looks at the effect of managerial ability on the number of analysts covering the firm. Model (1) and Model (2) both show a significant positive relationship between the managers' ability and financial analysts' interest in providing coverage on the firm. The association is statistically significant at 1%, with a coefficient of 0.7610 in the firm-fixed effect (model (1)) and 2.338 in the OLS (model (2)) regression. The ability of top management of a company, CEO in specific, attracts financial analysts. Analysts can trust these managers' work and may believe the management team would strive to provide an environment where analysts can carry out their tasks accurately. Able managers are shown to have the incentive to provide an informationally transparent environment that contributes to more interest by analysts. Firm controlling variables are also included in the model. The signs of control variables are also in line with the literature. Larger firms with higher institutional investors or higher R&D attract more analysts ([M. H. Lang & Lundholm, 1996](#)).

Table 6: Relationship between managerial ability and analyst following

Table 6 presents the number of analysts following a firm as the dependent variable and Managerial ability (MA Score) as the independent variable. Model (1) depicts the fixed effect regression, controlling for firm fixed effect and year. Model (2) shows the result of ordinary least square regression that controls for year and industry fixed effects. Both models present a significant positive relationship (coefficients = 0.7610 and 2.3338 respectively at 1%). The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) An_follow	(2) An_follow
MA Score	0.7610*** (0.117)	2.3338*** (0.135)
Firm size	0.1216*** (0.007)	0.2175*** (0.006)
Sales growth	-0.0286*** (0.009)	0.0211*** (0.005)
Leverage	0.3862 (0.237)	1.5694*** (0.175)
OCF/TA	0.6387** (0.254)	0.3878 (0.348)
Firm age	0.0136 (0.016)	0.0319*** (0.004)
PPE	2.8937*** (0.435)	3.3999*** (0.284)
R&D	0.4889*** (0.103)	2.2159*** (0.167)
Inst_ownership	4.1449*** (0.842)	8.9313*** (0.916)
hfi_48	-6.3971*** (1.108)	-4.4022*** (1.148)
Constant	6.8323*** (0.875)	-0.9689 (0.731)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	30,250	30,250
R-squared	0.836	0.402
Adj. R-squared	0.807	0.401

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

4.3 Managerial ability's relation with report informativeness (AI), response time, uncertainty (H3a, H3b, H3c)

Table 7 reports the regression finding for the relationship between analysts' report informativeness and managerial ability. We hypothesized that the higher ability of the managers would lead to higher informativeness of analysts' reports. Model (1) presents the firm-fixed regression. The MA score has a statistically significant and positive relationship with analysts' reports informativeness (AI) at %1 (coefficient of 0.8774). Model (2) is the result of ordinary least square (OLS) regression. The sign and significance are the same as the model (1), with a coefficient of 2.7818. This relationship means that companies' stock prices with able managers on average react more when analysts provide earnings update reports.

Table 7: Relationship between managerial ability and analyst report informativeness

Table 7 considers Analyst Report Informativeness (AI) as the dependent variable and managerial ability (MA Score) as the independent variable. Model (1) shows the fixed effect regression, while model two is the result of ordinary least square regression. Both models show a significant positive relationship between MA Score and AI (Coefficients = 0.8774 and 2.7881 respectively). In both models, year and Fama-French 48 industry fixed effects are included as control variables. The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) AI	(2) AI
MA Score	0.8774*** (0.177)	2.7818*** (0.165)
Firm size	0.1064*** (0.012)	0.2684*** (0.006)
Sales growth	-0.0165* (0.009)	0.0198* (0.011)
Leverage	0.5648* (0.343)	0.5937*** (0.208)
OCF/TA	0.8610** (0.346)	0.5165 (0.441)
Firm age	0.0163 (0.022)	0.0145*** (0.004)
PPE	4.3444*** (0.641)	6.7268*** (0.346)
R&D	0.7068*** (0.139)	1.1442*** (0.173)
Inst_ownership	4.8036*** (1.109)	9.4465*** (1.150)
hfi_48	-8.1556*** (1.687)	-3.9625*** (1.482)
Constant	10.8807*** (1.236)	-0.0755 (0.917)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	28,583	28,583
R-squared	0.757	0.456
Adj. R-squared	0.715	0.455

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

One potential measure that shows how able managements are successful in providing an informationally effective environment is the length it takes for analysts to provide updated reports on companies. Table 8 provides the regression results to examine the relationship between analysts' report response time and managerial ability. Model (1) is the result of the firm-fixed effect, while model (2) shows the result of ordinary least square regression. Model (1) shows a negative and statistically significant relationship between Managerial ability and analyst response time at %5 with a coefficient of -1.6147. Model (2) shows a negative and statistically significant relationship between Managerial ability and analyst response time at %10 with a coefficient of -0.9966. This result means the managers' higher ability will lead to faster response time (i.e., speedier revision or update reports). After the companies release their new earnings reports, it takes some time for analysts to process the latest information and update their opinion regarding that company. Able managers could put efforts to help information processing easier for analysts.

Table 8: Relationship between managerial ability and analyst response time

Table 8 presents the analysts' response time as the dependent variables and MA Score as the independent variable. Model (1) shows the fixed effect regression, while Model (2) presents the ordinary least square (OLS) regression. Both models show a significant negative association between Response Time and MA Score (Coefficients = -1.6147 and -0.9966, respectively). In both models, year and Fama-French 48 industry fixed effects are included as control variables. The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) Response Time	(2) Response Time
MA Score	-1.6147** (0.713)	-0.9966* (0.553)
Firm size	0.0095 (0.030)	0.0508*** (0.013)
Sales growth	-0.0386 (0.027)	-0.0502** (0.023)
Leverage	-0.1973 (1.475)	0.2825 (0.784)
OCF/TA	-3.4738** (1.381)	1.4205 (1.132)
Firm age	0.2413* (0.141)	0.0031 (0.010)
PPE	-0.6284 (2.664)	2.9488*** (1.134)
R&D	-0.9310* (0.513)	-1.7166*** (0.450)
Inst_ownership	-4.1273*** (1.047)	-11.1050*** (1.281)
hfi_48	19.7331** (8.783)	21.9509*** (7.041)
Constant	8.7616** (4.314)	30.0006*** (3.488)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	28,826	28,826
R-squared	0.430	0.188
Adj. R-squared	0.331	0.186

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

To further analyze the relationship between managerial ability and analysts' forecast properties, we use analysts' overall uncertainty derived from [Barron et al. \(1998\)](#). We expected to see a similar result to the relationship between managerial ability and analyst forecast error. models (1) and (2) show that the MA score has a statistically significant and negative association with the overall uncertainty of analysts forecast at %1 with coefficients of -0.0073 and -0.0040, respectively. This result indicates that the managers' higher ability lowers the overall uncertainty attached to financial analysts' earnings reports. Other control variables are all statistically significant at 1% and show the same results as Table 4.

Table 9: Relationship between managerial ability and analyst report uncertainty

Table 9 illustrates the association between overall uncertainty and MA Score. Model (1) present the fixed effect regression with a significant negative relationship between Overall Uncertainty and MA Score (Coefficient = -0.0073). Model (2) is the result of ordinary least square (OLS) regression with a 1% significant coefficient equal to -0.0040. In both models, year and Fama-French 48 industry fixed effects are included as control variables. The models also control for various firm-related variables. Robust standard errors clustered by firms are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definition of variables and their calculation methods are provided in Appendix A.

VARIABLES	(1) overall uncertainty	(2) overall uncertainty
MA Score	-0.0073*** (0.001)	-0.0040*** (0.001)
Firm size	-0.0002*** (0.000)	-0.0002*** (0.000)
Sales growth	-0.0002*** (0.000)	-0.0002** (0.000)
Leverage	0.0274*** (0.003)	0.0238*** (0.002)
OCF/TA	-0.0807*** (0.005)	-0.0794*** (0.004)
Firm age	-0.0000 (0.000)	-0.0001*** (0.000)
PPE	0.0400*** (0.005)	0.0173*** (0.002)
R&D	0.0001 (0.001)	0.0008 (0.001)
Inst_ownership	-0.0194*** (0.003)	-0.0179*** (0.002)
hfi_48	0.0017 (0.012)	-0.0323*** (0.010)
Constant	0.0236*** (0.004)	0.0295*** (0.006)
Year FE	YES	YES
Industry FE	NA	YES
Firm FE	YES	NO
Observations	30,250	30,250
R-squared	0.500	0.173
Adj. R-squared	0.412	0.171

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

4.4 Channel effects

To further explore our models' relationships, we examine the direct and indirect relationship between managerial ability and analyst forecast error. So far, we showed that managerial ability has a negative association with forecast error. A higher MA score leads to lower forecast error. In this section, we explore the extent to which managerial ability has a direct and indirect association with firm value. More specifically, we would like to examine possible mediators between MA score and forecast error. These two channels are the number of analysts following the company (analyst following) and the company's disclosure readability. As explained in the hypothesis development, managers can affect the internal information environment of the company. The way analysts perceive this information environment affects the level of their forecast error.

The first measure that is proposed as a channel is the analyst following. In our analysis, the direct association is between MA score and forecast error. The indirect association is a path from the managerial ability (proxied by MA Score) to forecast error that is channelized through analyst following. The sum of indirect and direct effects represents the total effect.

Table 10 (Panel A) presents the mediating role of analyst following in the association between MA Score and forecast error. Model (1) shows a significant relationship between forecast error and both MA score (Coefficient = -3.199) and analyst following (Coefficient = -0.501), similar to results in Table 4. Model (2) represents the significance of the relationship between Analyst following and MA Score (Coefficient = 0.932), while model (3) shows the significance between forecast error and MA Score (Coefficient = -3.760). These models suggest that forecast error has a negative association with both MA Score and analyst following, where analyst following has a positive association MA Score.

Table 10 (Panel B) reports the indirect, direct, and total association between forecast error

and managerial ability score. The results show that forecast error and managerial ability have a negative relationship for both direct effect (coefficient = -3.20) and indirect effect (coefficient = -0.46). Overall, the results illustrate that analyst following plays a significant mediator role between managerial ability and analyst forecast error.

Table 10: Direct and Indirect Association of Managerial Ability with Analyst Forecast Error

Table 10 reports the result from the simultaneous equation (i.e., Equation (7) and (8)), which reports both direct and indirect association (through analyst following) of managerial ability and forecast error.

Panel A: Simultaneous equation results

Panel A reports the different associations between dependent (forecast error), independent (managerial ability), and the mediator variable (analyst following). Model (1) presents the relationship between forecast error and both MA Score and Analyst following. Model (2) considers the analyst following (channel) as the dependent variable while model (3) is demonstrating the result of *Table 4*. All the models control for year and Fama-French 48 industry fixed effects. Robust standard errors are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definitions of variables and their estimation methods are provided in Appendix A.

VARIABLES	(1) Forecast Error	(2) Analyst Following	(3) Forecast Error
MA Score	-3.1995*** (0.595)	0.9323*** (0.095)	-3.7604*** (0.597)
Analyst Following	-0.5011*** (0.031)		
Firm size	-0.0775*** (0.023)	-0.1127*** (0.003)	-0.0957*** (0.022)
Sales growth	-0.1750*** (0.044)	-0.0203*** (0.007)	-0.1693*** (0.044)
Leverage	-55.9032*** (1.003)	0.1818 (0.172)	16.6715*** (1.012)
OCF/TA	-47.0131*** (0.982)	1.4789*** (0.162)	-56.7123*** (0.986)
Firm age	-0.0269*** (0.021)	0.0793*** (0.005)	-0.0666 (0.021)
PPE	14.0158*** (1.586)	4.0109*** (0.285)	12.5156*** (1.605)
R&D	-1.2720* (0.515)	0.7934*** (0.080)	-1.7526*** (0.514)
Constant	16.2003*** (5.190)	2.5566*** (1.198)	14.9256*** (5.345)
Year & Industry FE	Yes	Yes	Yes
Observations	35,696	35,696	35,695

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Panel B: Mediation effect

Panel B shows the joint test results of the channel. Bootstrap methods are employed to estimate standards errors. The Direct effect is captured using Equation (7), while the indirect effect is calculated using Equation (8). Indirect and direct effects both have a negative relation with forecast error. One unit increase in MA score decreases Forecasts error by 3.199. For the indirect effect, the MA score has a positive relation with analyst following, but analyst following negatively relates to forecast error. The product of one positive and one negative relation is the negative relationship with the coefficient of -0.467.

Forecast Error	Coefficient	Bootstrap Std. Err.	z	p-value
Indirect (Analyst Following)	-0.467	0.074	-6.330	0.000
Direct (MA Score)	-3.200	0.771	-4.150	0.000
Total (Direct + Indirect)	-3.667	0.766	-4.780	0.000

The next proposed channel that mediates the relationship between managerial ability and forecast error is the disclosure readability of annual 10k filings (proxied by Bog Index). Table 11, Model (1) represents a significant negative relationship between forecast error and MA Score (Coefficient = -2.550) and a positive one with Bog Index (Coefficient = 0.101). Model (2) suggests that high-ability managers improve the readability of financial disclosures.

Table 11 (Panel B) reports the direct association between forecast error and managerial ability as well as the indirect association through Bog Index. The results show that forecast error and managerial ability have a negative relationship for both direct effect (coefficient = -1.890) and indirect effect (coefficient = -0.065). Overall, the results indicate that the Bog index is a significant mediator between forecast error and MA Score.

Table 11: Direct and Indirect Association of

Table 11 reports the result from the simultaneous equation (i.e., Equation (9) and(10)), which reports both direct and indirect association (through disclosure readability, i.e., Bog Index) of managerial ability and forecast error.

Panel A: Simultaneous equation results

Panel A reports the different associations between the dependent (forecast error), independent (MA Score), and the mediator variable (bog index). Model (1) presents the regression result where both MA Score and Bog Index are independent variables. Model (2) has the Bog Index (mediator) as the dependent variable, while Model (3) shows the association of forecast error with the readability of 10K reports (proxied by Bog Index). All the models control for year and Fama-French 48 industry fixed effects. Robust standard errors are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definitions of variables and their estimation methods are provided in Appendix A.

VARIABLES	(1) Forecast Error	(2) Bog Index	(3) Forecast Error
MA Score	-2.5506*** (0.684)	-0.6452*** (0.089)	-3.7604*** (0.597)
Bog Index	0.1019*** (0.038)		
Firm size	-0.1105*** (0.028)	0.0237*** (0.004)	-0.0957*** (0.022)
Sales growth	-0.1395*** (0.042)	0.0017 (0.001)	-0.1693*** (0.044)
Leverage	12.9378*** (1.118)	1.6761*** (0.120)	16.6715*** (1.012)
OCF/TA	-49.4804*** (1.087)	-0.3527*** (0.076)	-56.7123*** (0.986)
Firm age	-0.0722*** (0.023)	-0.0270*** (0.004)	-0.0666 (0.021)
PPE	13.8214*** (1.896)	-2.538*** (0.252)	12.5156*** (1.605)
R&D	-1.3228** (0.538)	0.7381*** (0.078)	-1.7526*** (0.514)
Constant	6.0181 (6.290)	71.9403*** (0.984)	14.9256*** (5.345)
Year & Industry FE	Yes	Yes	Yes
Observations	34,662	41,130	35,695

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Panel B: Mediation effect

Panel B shows the joint test results of the channel. The bootstrap method is employed to estimate standard errors. The Direct effect is captured using Equation (9), while the indirect effect is calculated using Equation (10). Indirect and direct effects both have a negative relation with the forecast error. One unit increase in MA_Score decreases the forecast error by 1.89. For the indirect impact, MA_Score has a negative association with bog index but bog index a positive relationship with forecast error. The product of one positive and one negative relation is the negative relationship with the coefficient of -0.065.

Forecast Error	Coefficient	Bootstrap Std. Err.	z	p-value
Indirect (Bog Index)	-0.065	0.026	-2.540	0.011
Direct (MA_Score)	-1.890	0.761	-2.480	0.013
Total (Direct + Indirect)	-1.955	0.753	-2.600	0.009

The ability of managers is supposed to be used to increase firm value. We would like to examine the direct and indirect association between managerial ability (proxied by MA Score) and firm value (proxied by Tobin's Q) where forecast error mediates the connection. Table 12, Panel A presents the relationship between firms' value and managerial ability and forecast error. Model (1) indicates a significant positive relationship between Tobin's Q and MA Score (Coefficient = 0.4120) and a negative relationship with forecast error (Coefficient = -0.0019).

Table 11 (Panel B) reports the direct association between firm value (Tobin's Q) and managerial ability (MA Score) as well as the indirect association through forecast error. The results show that firm value and managerial ability positively affect both direct effect (coefficient = 0.007) and indirect effect (coefficient = 0.412). Overall, the results indicate that analyst forecasting accuracy mediates the association between managerial ability and firm value.

Table 12: Direct and Indirect Association of Managerial Ability with Firm Value

Table 12 reports the result from the simultaneous equation (i.e., Equation (11) and (12)), which reports both direct and indirect association (through disclosure readability) of managerial ability and forecast error.

Panel A: Simultaneous equation results

Panel A reports the different associations between the dependent (firm value proxied as Tobin's Q), independent (MA Score), and the mediator variable (Forecast Error). Model (1) presents the regression result where both MA Score and Forecast Error are presented as independent variables. Model (2) shows the forecast error (mediator) as the dependent variable, while Model (3) shows the association of Tobin's Q with the managerial ability (proxied by MA Score). All the models control for year and Fama-French 48 industry fixed effects. Robust standard errors are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definitions of variables and their estimation methods are provided in Appendix A.

VARIABLES	(1) Tobin's Q	(2) Forecast Error	(3) Tobin's Q
MA Score	0.4120*** (0.000)	-3.7604*** (0.597)	0.4035*** (0.019)
Forecast Error	-0.0019*** (0.025)		
Firm size	0.1055*** (0.000)	-0.0957*** (0.022)	0.0097*** (0.000)
Sales growth	0.0037** (0.001)	-0.1693*** (0.044)	0.000 (0.000)
Leverage	-0.3778*** (0.046)	16.6715*** (1.012)	-0.0988*** (0.027)
OCF/TA	-0.4103*** (0.046)	-56.7123*** (0.986)	-0.4825*** (0.016)
Firm age	-0.0085*** (0.001)	-0.0666*** (0.021)	-0.0089 (0.000)
PPE	-0.3834*** (0.071)	12.5156*** (1.605)	-0.3238*** (0.000)
R&D	-0.1299*** (0.022)	-1.7526*** (0.078)	-0.1604*** (0.049)
Constant	2.3292 (0.250)	14.9256*** (0.514)	1.9657*** (0.181)
Year & Industry FE	Yes	Yes	Yes
Observations	31,630	35,695	66,681

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Panel B: Mediation effect

Panel B shows the joint test results of the channel. The bootstrap method is employed to estimate standards errors. The Direct effect is captured using Equation (11), while the indirect impact is calculated using Equation (12). Indirect and direct effects both have a positive relationship with the firm value (Tobin's Q). One unit increase in MA_Score increases the firm value by 0.412. To justify the sign of indirect effect, the MA score has a negative association with forecast error while forecast error shows a negative association with firm value. The product of one positive and one negative relation is the negative relationship with the coefficient of 0.007.

Tobin's Q	Coefficient	Bootstrap Std. Err.	z	p-value
Indirect (Forecast Error)	0.007	0.001	5.370	0.000
Direct (MA_Score)	0.412	0.037	11.110	0.000
Total (Direct + Indirect)	0.419	0.037	11.290	0.000

4.5 Robustness Test with Analyst Following as a Control Variable

Studying the measures related to financial analysts' work, forecast error, and analyst following are pivotal. The number of analysts following a firm could affect the overall accuracy of their collective efforts. In this section, we consider the analyst following as an independent variable to test the robustness of all the regression models proposed. Forecast error, dispersion, analyst report informativeness (AI), response time, and overall uncertainty are the dependent variables.

Panel A shows the fixed effect regressions results where the models control for firm and year fixed effects. Panel B is the ordinary least square (OLS) model where industry fixed effect is also present. All the signs and insignificance levels are in line with our previous sections.

Table 13: Robustness Test

Table 13 presents regressions where analyst following is introduced as a control variable and all the other analyst-related variables are presented as dependent variables.

Panel A: Fixed Effect Regression with analyst following control variables

Panel A presents the result of the fixed effect regression. When controlling for the analyst following, all the signs and significant levels stay consistent with our base regression results. All the models control for firm and year fixed effects. Any time-invariant variable such as industry is fixed effect is not applicable for these regressions. Robust standard errors are in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively.

Definitions of variables and their estimation methods are provided in Appendix A.

VARIABLES	(1) Forecast Error	(2) Dispersion	(3) AI	(4) Response Time	(5) Uncertainty
Analyst Following	-0.1430*** (0.038)	0.1605*** (0.039)	0.7044*** (0.012)	-0.1528*** (0.041)	0.0003*** (0.000)
MA Score	-3.2733*** (0.731)	-5.1234*** (0.657)	0.3268** (0.154)	-1.4950** (0.712)	-0.0075*** (0.001)
Firm Size	-0.0775*** (0.023)	-0.1649*** (0.024)	0.0017 (0.011)	0.0282 (0.030)	-0.0002*** (0.000)
Sales Growth	-0.1496*** (0.037)	-0.2158*** (0.062)	0.0034 (0.010)	-0.0431 (0.027)	-0.0002*** (0.000)
Leverage	15.4901*** (1.842)	13.2990*** (1.718)	0.2739 (0.284)	-0.1260 (1.474)	0.0273*** (0.003)
OCF/TA	-47.0131*** (3.058)	-48.0510*** (2.835)	0.4941** (0.245)	-3.3695** (1.378)	-0.0809*** (0.005)
Firm Age	-0.0361 (0.055)	0.0047 (0.051)	0.0063 (0.019)	0.2434* (0.141)	-0.0000 (0.000)
PPE	22.8063*** (2.809)	24.6383*** (2.631)	2.2593*** (0.533)	-0.1583 (2.666)	0.0390*** (0.005)
R&D	-0.7792* (0.415)	0.4560 (0.428)	0.3716*** (0.126)	-0.8543* (0.513)	-0.0001 (0.001)
Inst_ownership	-13.4244*** (1.880)	-13.9611*** (2.523)	1.6549*** (0.451)	-3.4999*** (0.995)	-0.0207*** (0.003)
hfi_48	-0.1026 (6.724)	2.0281 (6.932)	-3.4543** (1.357)	18.7439** (8.780)	0.0037 (0.012)
Constant	17.9557***	16.6511***	6.2533***	9.8259**	0.0214***
Year FE	YES	YES	YES	YES	YES
Industry FE	NA	NA	NA	NA	NA
Firm FE	YES	YES	YES	YES	YES
	(2.519)	(2.778)	(0.732)	(4.312)	(0.004)
Observations	30,250	30,250	28,583	28,826	30,250
R-squared	0.514	0.520	0.810	0.430	0.500
Adj. R-squared	0.429	0.437	0.777	0.331	0.413

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Panel B: OLS regression with analyst following as the control variable.

Panel B shows the result of the ordinary least square (OLS) regressions controlling for analyst following. Here as well, all the sign and the significance levels remain consistent with our base regressions models.

VARIABLES	(1) Forecast Error	(2) Dispersion	(3) AI	(4) Response Time	(5) Uncertainty
Analyst Following	-0.3711*** (0.033)	-0.1145*** (0.038)	0.8054*** (0.009)	-0.3410*** (0.027)	-0.0002*** (0.000)
MA Score	-1.3568** (0.600)	-2.7291*** (0.551)	0.7412*** (0.125)	-0.1839 (0.560)	-0.0035*** (0.001)
Firm Size	-0.0788*** (0.014)	-0.1125*** (0.016)	0.0199*** (0.006)	0.1250*** (0.015)	-0.0001*** (0.000)
Sales Growth	-0.1518*** (0.058)	-0.1608** (0.068)	0.0063 (0.009)	-0.0436* (0.023)	-0.0002** (0.000)
Leverage	13.2768*** (1.319)	11.2923*** (1.147)	-0.3713** (0.157)	0.8493 (0.784)	0.0241*** (0.002)
OCF/TA	-50.1115*** (2.467)	-49.8139*** (2.313)	0.1879 (0.194)	1.5534 (1.101)	-0.0793*** (0.004)
Firm Age	-0.0286*** (0.009)	-0.0277*** (0.010)	0.0074*** (0.003)	0.0142 (0.009)	-0.0001*** (0.000)
PPE	7.1826*** (1.281)	12.5299*** (1.174)	3.6134*** (0.253)	4.1586*** (1.135)	0.0180*** (0.002)
R&D	0.0536 (0.389)	0.9870** (0.405)	-0.2337* (0.121)	-0.9689** (0.441)	0.0012* (0.001)
Inst_ownership	-13.3639*** (1.644)	-12.2182*** (2.067)	2.7865*** (0.378)	-8.1137*** (1.130)	-0.0161*** (0.002)
hfi_48	-24.0971*** (6.194)	-15.8251*** (5.699)	-0.5515 (1.048)	20.3319*** (7.026)	-0.0332*** (0.010)
Constant	24.8098*** (3.264)	22.2013*** (3.215)	0.8483 (0.522)	29.7405*** (3.468)	0.0293*** (0.006)
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO
Observations	30,250	30,250	28,583	28,826	30,250
R-squared	0.195	0.219	0.687	0.193	0.174
Adj. R-squared	0.193	0.217	0.686	0.191	0.172

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

5 Conclusion

This study examines the relationship between managerial ability and properties of financial analysts' work in terms of forecast error, dispersion, uncertainty, report response time, report informativeness, and financial analysts' willingness to follow a firm. We also explored possible channels that managers can affect analysts' work, including their impact on the company's information environment. Managers are considered responsible for the companies' narrative disclosure that financial analysts use in their analysis and forecasts.

Using a large sample of listed companies in the S&P1500 index, we find that managerial ability is negatively associated with financial analysts' earnings forecasts. The negative relationship is also present between managerial ability and forecast dispersion, i.e., able managers help analysts achieve lower disagreement in their forecasts. We also show that managerial ability has a statistically significant direct and indirect effect on forecast error. Able managers also reduce the overall uncertainty of analyst reports, increase their reports' informativeness, and reduce the time they need to release their update of revision reports. We also find that financial analysts show more interest. We find that our results align with the literature and robust in analysis through different regression models.

Our study contributes to the managerial ability literature as well as financial analysts' work and performance.

Appendix

Managerial ability calculation

Managerial ability measure, first developed by [P. Demerjian et al. \(2012\)](#), follows a two-step process to calculate Managerial Ability Score (MA-Score).

They use a non-parametric model called Data Envelopment Analysis (DEA) to estimate firm Efficiency. Firm efficiency is a measure of how properly a firm generates revenue using its available resources compared to other firms in its industry category. The industry category is employed based on [Fama and French \(1997\)](#). The following model is optimized.

$$\max \frac{\text{sales}}{y_1 \text{COGS} + y_2 \text{SG\&A} + y_3 \text{PP\&E} + y_4 \text{OPL} + y_5 \text{R\&D} + y_6 \text{GD} + y_7 \text{OTI}} \quad (13)$$

The optimization problem in Equation (13) aims to find the optimal weights for each firm's seven variables as a vector. The maximization problem ranges from 0 (lowest efficiency) to 1 (highest efficiency). COGS denotes the cost of goods sold, SG&A denotes sales, general, and administrative, PP&E denotes property, plant, and equipment, OPL denotes net operating lease, R&D denotes research and development, GD denotes purchased goodwill OTI denotes other intangible assets.

The efficiency measure calculated in the first step encompasses the efforts of the manager and firm simultaneously. To extract the managerial ability, a Tobit regression analysis is employed.

The following regression model is estimated by industry:

$$\text{Efficiency} = \beta_0 + \beta_1 \text{LN(TA)} + \beta_2 \text{MS} + \beta_3 \text{PFCF} + \beta_6 \text{FCD} + \beta_4 \text{LN(AGE)} + \beta_5 \text{BSC} + \text{Years} + \varepsilon \quad (14)$$

The residual value from Equation (14) is considered the managerial score (MA-Score). TA denotes total assets, MS denotes the market share of a company within its industry, PFCF is a

dummy variable that equals 1 when the firm has positive free cash flow, FCD is also another dummy variable that equals 1 when a firm has foreign operations, Age is a firm's age, BSC denotes the concentration of business segments, and Year denotes year dummy.

Variable definition

MA Score	Managerial ability score developed by P. Demerjian et al. (2012)
Bog Index	A multifaceted measure of plain English readability called Bog index. A higher level of Bog index represents a lower readable document.
Tobin's Q	Tobin's Q is calculated as the sum of total assets and market value of equity less common book equity, divided by total assets. Tobin's Q not only indicates the firm performance but also states the relationship between uncertainty and investment opportunity (Leahy and Whited. 1996; Gulen and Ion 2016) Tobin's Q, as measured by: $(AT + CSHO \times PRCC_F - CEQ - TXDB) / AT$
Forecast Error	difference between the actual earning announced by the firm in each year and Consensus scaled by the end of fiscal year share price [source: I/B/E/S] $Error^5 = (Actual - Consensus) / (end\ of\ fiscal\ year\ price) \quad (15)$ Actual = The actual earning announced by a company at the end of each fiscal year Consensus = Is the mean ⁶ of the EPS forecasts provided by different analysts for a firm each year
Accuracy	$Accuracy = (Actual - Consensus)^2 / (end\ of\ fiscal\ year\ price) \quad (16)$
Analyst Following	Analyst following which is the number of analysts following a firm each year [source: I/B/E/S]
Analyst_Exp	Mean experience of the analysts who are following a firm each year. Experience is measured based on the first time analyst name appeared in the I/B/E/S database
AI	Analyst informativeness is Calculated as the amount of absolute size-adjusted return of the firm stock associated with the days that at least one analyst has provided a forecast divided by the total absolute size-adjusted return for the whole year [source: I/B/E/S, CRSP] $AI = \frac{\sum_1^{N_{revs}} R_{t,s} - Rdocile_{t,s} }{\sum_1^{250} R_{t,s} - Rdocile_{t,s} } \quad (17)$
Response time	The mean of the time it takes for analysts to provide their earnings revision report after the company's actual announcement. [Source: I/B/E/S]

⁵ Some studies scaled this measure by the standards deviation of forecasts.

⁶ Some studies like have used the median of analysts' forecasts for each company per year.

Dispersion	Analyst dispersion Is the Standard Deviation divided by the Consensus. [source: I/B/E/S] Standard deviation = the standard deviation of forecasts provided by analysts for each firm per year
Overall Uncertainty	$OU = \left(1 - \frac{1}{Analyst\ Following}\right) * Dispersion + Accuracy \quad (18)$
Common Uncertainty	$CU = \frac{Accuracy - \frac{Dispersion}{Analyst\ Following}}{OU} \quad (19)$
Earnings Surprise	Difference between this year's actual earnings with last year's, divided by the end of fiscal year share price [Source: I/B/E/S] $Surprise = \frac{Actual_t - Actual_{t-1}}{end\ of\ fiscal\ year\ price_t} \quad (20)$
Company Following	Number of companies each analyst is following each year [source: I/B/E/S]
Horizon	Number of days between the last forecast provided by an analyst for a firm each year and the date the actual EPS announced by the company [source: I/B/E/S]
Forecast Revision	the number of times an analyst has revised their forecast for a company each year. We take the average for each company per year [Source: I/B/E/S]
Firm size	Total number of shares multiplied by the firm's share price [source: CRSP]
Brokerage size	
Sales growth	Firm's sales growth, as measured by $\Delta SALE / SALE_{t-1}$. The quarterly sales data are taken to compute the year-on-year sales growth.
Book to market value	Book value of equity divided by market value of equity [source: CompuStat]
Inst_ownership	The percentage of outstanding shares owned by institutions. Higher institutional ownership is linked with greater management disclosure and causing lower information asymmetry (Boone & White, 2015). We obtain Institutional data from WRDS SEC Thomas Reuter's F13 File.
PPE	Property, plant, and equipment
Firm Age	The number of years since the firm first appeared on the CRSP database
Leverage	Leverage. Firm's leverage, as measured by: $(DLTT + DLC) / AT$

OCF/TA	Operating Cash Flow to Total Assets of the company
Hfi_48	<p>is Herfindahl index measure market concertation and is used to determine market competitiveness.</p> <p>It shows whether the industry is competitive or there is a monopoly going on.</p> $hfi = s_1^2 + s_2^2 + s_3^2 + \dots s_n^2$ <p><i>s_n = is the market share percentage of firm n</i></p>
R&D	<p>Research and development expenditure scaled by the total asset. Research and development (XRD) over sales (SALE). We replace missing XRD with zero</p>

References

- Ackert, L. F., & Athanassakos, G. (2003). A simultaneous equations analysis of analysts' forecast bias, analyst following, and institutional ownership. *Journal of Business Finance & Accounting*, 30(7-8), 1017-1042.
- Adhikari, B. K. (2016). Causal effect of analyst following on corporate social responsibility. *Journal of Corporate Finance*, 41, 201-216.
- Ali, A., Liu, M., Xu, D., & Yao, T. (2019). Corporate disclosure, analyst forecast dispersion, and stock returns. *Journal of Accounting, Auditing & Finance*, 34(1), 54-73.
- Allen, A., Francis, B. B., Wu, Q., & Zhao, Y. (2016). Analyst coverage and corporate tax aggressiveness. *Journal of Banking & finance*, 73, 84-98.
- Amernic, J., Craig, R., & Tourish, D. (2010). *Measuring and assessing tone at the top using annual report CEO letters*: The Institute of Chartered Accountants of Scotland.
- Andrade, S. C., Bian, J., & Burch, T. R. (2013). Analyst coverage, information, and bubbles. *Journal of Financial and Quantitative Analysis*, 48(5), 1573-1605.
- Andreou, P. C., Karasamani, I., Louca, C., & Ehrlich, D. (2017). The impact of managerial ability on crisis-period corporate investment. *Journal of Business Research*, 79, 107-122.
- Baik, B., Farber, D. B., & Lee, S. (2011). CEO ability and management earnings forecasts. *Contemporary Accounting Research*, 28(5), 1645-1668.
- Bamber, L. S., Jiang, J., & Wang, I. Y. (2010). What's my style? The influence of top managers on voluntary corporate financial disclosure. *The Accounting Review*, 85(4), 1131-1162.
- Barron, O. E., Kim, O., Lim, S. C., & Stevens, D. E. (1998). Using analysts' forecasts to measure properties of analysts' information environment. *Accounting Review*, 421-433.
- Barth, M. E., & Hutton, A. P. (2004). Analyst earnings forecast revisions and the pricing of accruals. *Review of accounting studies*, 9(1), 59-96.
- Bertrand, M., & Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4), 1169-1208.
- Bhat, G., Hope, O. K., & Kang, T. (2006). Does corporate governance transparency affect the accuracy of analyst forecasts? *Accounting & Finance*, 46(5), 715-732.
- Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics*, 11(2-3), 255-274.
- Bloomfield, R. J. (2002). The 'incomplete revelation hypothesis' and financial reporting.
- Bonsall IV, S. B., Leone, A. J., Miller, B. P., & Rennekamp, K. (2017). A plain English measure of financial reporting readability. *Journal of Accounting and Economics*, 63(2-3), 329-357.
- Bonsall, S. B., & Miller, B. P. (2017). The impact of narrative disclosure readability on bond ratings and the cost of debt. *Review of accounting studies*, 22(2), 608-643.
- Boone, A. L., & White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of financial economics*, 117(3), 508-533.
- Bradley, D., Gokkaya, S., & Liu, X. (2017). Before an analyst becomes an analyst: Does industry experience matter? *The journal of finance*, 72(2), 751-792.
- Brochet, F., Miller, G. S., Naranjo, P., & Yu, G. (2019). Managers' cultural background and disclosure attributes. *The Accounting Review*, 94(3), 57-86.
- Chemmanur, T. J., Paeglis, I., & Simonyan, K. (2009). Management quality, financial and investment policies, and asymmetric information. *Journal of Financial and Quantitative Analysis*, 1045-1079.
- Chen, T., Xie, L., & Zhang, Y. (2017). How does analysts' forecast quality relate to corporate

- investment efficiency? *Journal of Corporate Finance*, 43, 217-240.
- Cheung, K. T. S., Naidu, D., Navissi, F., & Ranjeeni, K. (2017). Valuing talent: Do CEOs' ability and discretion unambiguously increase firm performance. *Journal of Corporate Finance*, 42, 15-35.
- Cho, C., Halford, J. T., Hsu, S., & Ng, L. (2016). Do managers matter for corporate innovation? *Journal of Corporate Finance*, 36, 206-229.
- Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3), 285-303.
- Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The journal of finance*, 60(1), 307-341.
- Cohen, L., Frazzini, A., & Malloy, C. (2010). Sell-side school ties. *The journal of finance*, 65(4), 1409-1437.
- Cornaggia, K. J., Krishnan, G. V., & Wang, C. (2017). Managerial ability and credit ratings. *Contemporary Accounting Research*, 34(4), 2094-2122.
- Davis, A. K., Ge, W., Matsumoto, D., & Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of accounting studies*, 20(2), 639-673.
- Dellaportas, S. (2013). Conversations with inmate accountants: Motivation, opportunity and the fraud triangle. *Accounting forum*, 37(1), 29-39.
- Demerjian, P., Lev, B., & McVay, S. (2012). Quantifying managerial ability: A new measure and validity tests. *Management science*, 58(7), 1229-1248.
- Demerjian, P. R., Lev, B., Lewis, M. F., & McVay, S. E. (2013). Managerial ability and earnings quality. *The Accounting Review*, 88(2), 463-498.
- Derrien, F., & Kecskés, A. (2013). The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The journal of finance*, 68(4), 1407-1440.
- Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud? *The journal of finance*, 65(6), 2213-2253.
- Espahbodi, H., Espahbodi, P., & Espahbodi, R. (2015). Did analyst forecast accuracy and dispersion improve after 2002 following the increase in regulation? *Financial Analysts Journal*, 71(5), 20-37.
- Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of financial economics*, 43(2), 153-193.
- Francis, B., Hasan, I., & Zhu, Y. (2013). Managerial style and bank loan contracting. *Bank of Finland Research Discussion Paper*(29).
- Francis, B. B., Sun, X., & Wu, Q. (2013). Managerial ability and tax avoidance. *Available at SSRN*, 2348695.
- Frankel, R., Kothari, S., & Weber, J. (2006). Determinants of the informativeness of analyst research. *Journal of Accounting and Economics*, 41(1-2), 29-54.
- Gibbons, B., Iliev, P., & Kalodimos, J. (2019). Analyst information acquisition via EDGAR. *Available at SSRN* 3112761.
- Gleason, C. A., & Lee, C. M. (2003). Analyst forecast revisions and market price discovery. *The Accounting Review*, 78(1), 193-225.
- Green, C., Jegadeesh, N., & Tang, Y. (2009). Gender and job performance: Evidence from Wall Street. *Financial Analysts Journal*, 65(6), 65-78.
- Gul, F. A., Khedmati, M., Lim, E. K., & Navissi, F. (2018). Managerial ability, financial distress, and audit fees. *Accounting Horizons*, 32(1), 29-51.

- Guo, B., Pérez-Castrillo, D., & Toldrà-Simats, A. (2019). Firms' innovation strategy under the shadow of analyst coverage. *Journal of financial economics*, 131(2), 456-483.
- Habib, A., & Hasan, M. M. (2017). Managerial ability, investment efficiency and stock price crash risk. *Research in International Business and Finance*, 42, 262-274.
- Hasan, M. M. (2020). Readability of narrative disclosures in 10-K reports: Does managerial ability matter? *European Accounting Review*, 29(1), 147-168.
- He, J. J., & Tian, X. (2013). The dark side of analyst coverage: The case of innovation. *Journal of financial economics*, 109(3), 856-878.
- Hendry, J. (2005). Beyond self-interest: Agency theory and the board in a satisficing world. *British Journal of Management*, 16, S55-S63.
- Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The journal of finance*, 64(5), 2289-2325.
- Hoitash, R., Hoitash, U., & Johnstone, K. M. (2012). Internal control material weaknesses and CFO compensation. *Contemporary Accounting Research*, 29(3), 768-803.
- Hong, H., Kubik, J. D., & Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *The Rand journal of economics*, 121-144.
- Irani, R. M., & Oesch, D. (2016). Analyst coverage and real earnings management: Quasi-experimental evidence. *Journal of Financial and Quantitative Analysis*, 51(2), 589-627.
- Kang, Q., Li, X., & Su, T. (2018). Sell-Side Financial Analysts and the CFA® Program. *Financial Analysts Journal*, 74(2), 70-83.
- Kim, J.-B., Lu, L. Y., & Yu, Y. (2019). Analyst coverage and expected crash risk: evidence from exogenous changes in analyst coverage. *The Accounting Review*, 94(4), 345-364.
- Koester, A., Shevlin, T., & Wangerin, D. (2017). The role of managerial ability in corporate tax avoidance. *Management science*, 63(10), 3285-3310.
- Kor, Y. Y. (2003). Experience-based top management team competence and sustained growth. *Organization Science*, 14(6), 707-719.
- Kothari, S. P., So, E., & Verdi, R. (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics*, 8, 197-219.
- Krishnan, G. V., & Wang, C. (2015). The relation between managerial ability and audit fees and going concern opinions. *Auditing: A Journal of Practice & Theory*, 34(3), 139-160.
- Lang, M., & Stice-Lawrence, L. (2015). Textual analysis and international financial reporting: Large sample evidence. *Journal of Accounting and Economics*, 60(2-3), 110-135.
- Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. *Accounting Review*, 467-492.
- Lee, C. M., & So, E. C. (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of financial economics*, 124(2), 331-348.
- Lehavy, R., Li, F., & Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, 86(3), 1087-1115.
- Leverly, J. T., & Grace, M. F. (2012). Dupes or incompetents? An examination of management's impact on firm distress. *Journal of Risk and Insurance*, 79(3), 751-783.
- Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2-3), 221-247.
- Li, F. (2010). Survey of the Literature. *Journal of accounting literature*, 29, 143-165.
- Li, K. K., & You, H. (2015). What is the value of sell-side analysts? Evidence from coverage initiations and terminations. *Journal of Accounting and Economics*, 60(2-3), 141-160.

- Li, X., Sullivan, R. N., Xu, D., & Gao, G. (2013). Sell-side analysts and gender: A comparison of performance, behavior, and career outcomes. *Financial Analysts Journal*, 69(2), 83-94.
- Lo, K., Ramos, F., & Rogo, R. (2017). Earnings management and annual report readability. *Journal of Accounting and Economics*, 63(1), 1-25.
- Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The journal of finance*, 66(1), 35-65.
- Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4), 1187-1230.
- Lundholm, R. J., Rogo, R., & Zhang, J. L. (2014). Restoring the tower of Babel: How foreign firms communicate with US investors. *The Accounting Review*, 89(4), 1453-1485.
- O'Brien, P. C., & Tan, H. (2015). Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics*, 59(1), 41-59.
- Pérez-González, F. (2006). Inherited control and firm performance. *American Economic Review*, 96(5), 1559-1588.
- Plumlee, M., & Yohn, T. L. (2010). An analysis of the underlying causes attributed to restatements. *Accounting Horizons*, 24(1), 41-64.
- Rahaman, M. M., & Al Zaman, A. (2013). Management quality and the cost of debt: Does management matter to lenders? *Journal of Banking & finance*, 37(3), 854-874.
- Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1), 34-75.
- Rhoades, S. A. (1993). The herfindahl-hirschman index. *Fed. Res. Bull.*, 79, 188.
- Schipper, K. (1991). Analysts' forecasts. *Accounting Horizons*, 5(4), 105-121.
- Silva, A. C. (2010). Managerial ability and capital flows. *Journal of Development economics*, 93(1), 126-136.
- Tan, H., Wang, S., & Welker, M. (2011). Analyst following and forecast accuracy after mandated IFRS adoptions. *Journal of Accounting Research*, 49(5), 1307-1357.
- Tian, J. J. (2014). Board monitoring and endogenous information asymmetry. *Contemporary Accounting Research*, 31(1), 136-151.
- To, T. Y., Navone, M., & Wu, E. (2018). Analyst coverage and the quality of corporate investment decisions. *Journal of Corporate Finance*, 51, 164-181.
- Welch, I. (2000). Herding among security analysts. *Journal of financial economics*, 58(3), 369-396.
- Wolfe, D. T., & Hermanson, D. R. (2004). The fraud diamond: Considering the four elements of fraud.
- Yang, H. I. (2012). Capital market consequences of managers' voluntary disclosure styles. *Journal of Accounting and Economics*, 53(1-2), 167-184.
- Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of financial economics*, 88(2), 245-271.
- Yu, M. (2010). Analyst forecast properties, analyst following and governance disclosures: A global perspective. *Journal of International Accounting, Auditing and Taxation*, 19(1), 1-15.