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Are More Able Managers Good Future Tellers? Learning from Japan

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Are More Able Managers Good Future Tellers? Learning from Japan

ABSTRACT

Baik, Farber, and Lee (2011) find that high-ability managers in the U.S. are more likely to issue accurate management earnings forecasts. Focusing on Japan, where management earnings forecasts are effectively mandated, we extend the literature by exploring (1) whether the relationship between managerial ability and forecast accuracy is unique to the U.S. disclosure system, where management forecasts are voluntary, and (2) how high-ability managers increase their forecast accuracy. We find that managerial ability is negatively associated with forecast errors based on initial forecasts, suggesting that high-ability managers are more likely to issue accurate forecasts at the beginning of the fiscal year. We then show that high-ability managers are less likely to revise their initial earnings forecasts and less likely to use earnings management to improve the accuracy of their earnings forecasts. Our findings show that, while high-ability managers are more likely to issue accurate initial management forecasts, low-ability managers are more likely to revise their forecasts and conduct earnings management to reduce their forecast errors.

Keywords: managerial ability, management earnings forecast, forecast accuracy, earnings management

JEL Classification: M41

1. Introduction

We examine whether and how managerial ability affects the accuracy of management earnings forecasts. Baik, Farber, and Lee (2011) find that high-ability managers are more likely to issue accurate management earnings forecasts for U.S. firms. In this study, we focus on Japan, where management earnings forecasts are effectively mandated, and extend the literature to explore (1) whether the relationship between managerial ability and forecast accuracy is unique to the U.S. disclosure system, where management forecasts are voluntary, and (2) how high-ability managers increase their forecast accuracy.

The Japanese disclosure system offers a useful research setting for two reasons (Iwasaki et al. 2019). First, as recommended by the Tokyo Stock Exchange (TSE), Japanese listed firms are obliged to issue management earnings forecasts (Kato et al. 2009). In fact, about 94 percent of our sample firms release annual management earnings forecasts at the beginning of the fiscal year. Thus, unlike the U.S. research, studies on management earnings forecasts among Japanese firms are free of sample selection bias (Iwasaki et al. 2019). Second, Japanese stock exchanges also require listed firms to revise their forecasts in case of "significant" changes in management estimates (Kato et al. 2009); inaccurate initial forecasts are mandatorily and systematically updated in Japan. Thus, the frequency of forecast revisions can be used to proxy for the inaccuracy of initial management forecasts.

Baik et al. (2011) examine the relationship between managerial ability and management earnings forecasts in a sample of U.S. listed firms that disclose their forecasts voluntarily. Following Trueman's (1986) signaling theory, they hypothesize and find that the likelihood and frequency of management earnings forecasts increase along with CEO ability. Further, they assume that forecast accuracy reflects CEO ability and show that high-ability managers are more likely to release accurate forecasts.

In this study, we also predict that high-ability managers are more likely to issue accurate forecasts in Japan, where management earnings forecasts are effectively mandated, but for a different reason because the Trueman's theory is based on voluntary disclosure and thus less applicable to a mandatory reporting system. Specifically, we propose that highly capable managers in Japan are likely to have both the ability and incentive to release accurate earnings forecasts. Prior studies argue that high-ability managers are more capable of assessing their earnings prospects and hence issue more accurate earnings forecasts because they are more knowledgeable about their firms and macroeconomic conditions (Demerjian et al. 2013). We argue that, besides being highly able, managers also have an incentive to issue accurate initial earnings forecasts (i.e. annual earnings forecasts at the beginning of the fiscal year) because of the economic consequences of issuing inaccurate ones. Studies have shown that reporting inaccurate management forecasts has led to negative economic consequences for U.S. firms (Williams 1996; Hirst et al. 1999; Lee et al. 2012; Ng et al. 2013; Hui and Matsunaga 2015). The incentive to issue accurate initial earnings forecasts is more pronounced for Japanese firms because management earnings forecasts play an important role in Japanese financial markets under the effectively mandated disclosure system (Suda and Hanaeda 2008). For example, studies examining Japanese firms have found that inaccurate initial forecasts lead to negative market reactions (Gotoh and Sakurai 1993; Han 1998; Kato et al. 2009), increased cost of capital (Muramiya 2005; Kitagawa and Shuto 2019), CEO turnover (Ishida and Hachiya 2020), and decreased management compensation (Otomasa et al. 2020). Thus, Japanese managers bear a cost for inaccurate forecasts and therefore try to issue accurate forecasts from the beginning. In other words, under the effectively mandated disclosure system, managers are encouraged to issue accurate initial forecasts to avoid negative consequences and establish good forecasting reputation (Kato et al. 2009; Iwasaki et al. 2019). Given managers' abilities and incentives, we predict that highly capable managers in Japan are more likely to issue accurate earnings forecasts.

Using data drawn from a large sample of Japanese listed firms covering 2006 to 2014, we examine whether and how managerial ability relates to earnings forecast accuracy through three analyses. First, we analyze the relationship between initial management forecasts and managerial ability, and find that initial forecast accuracy increases with managerial ability. This finding is consistent with our prediction that high-ability managers are better able to predict future earnings than low-ability managers.

Second, we examine the extent to which managers increase their forecast accuracy by revising their initial forecasts. If high-ability managers issue relatively accurate forecasts at the beginning of the fiscal year, they will not have to revise them *ex post*. However, low-ability managers are likely to revise their initial forecasts to decrease their forecast errors and mitigate the negative consequences of missing forecasts. Consistent with this prediction, we find that high-ability managers are less likely to revise their forecasts, and the degree of their revisions tends to be smaller than that of low-ability managers.

Finally, we focus on earnings management, another method managers use to improve their forecast accuracy. Studies have shown that managers use earnings management to meet or beat their management forecasts and mitigate the negative consequences of missing forecasts (Kasznik 1999; Herrmann et al. 2003; Shuto 2010). However, given that high-ability managers are better able to forecast firms' future earnings and expected to release more accurate initial forecasts at the beginning of the fiscal year, they are less likely to rely on earnings management to increase their forecast accuracy. On the contrary, we predict that low-ability managers have stronger incentives to use earnings management to increase their forecast accuracy because of their incompetence to forecast earnings accurately. Consistent with this prediction, we show that high-ability managers are less likely to use discretionary accruals to improve their forecast accuracy, suggesting that high-ability managers adopt less earnings management because of their accurate forecasts.

We then carry out several robustness tests. We test for endogeneity issues and also use alternative measurements of managerial ability, alternative models for earnings management such as real activities manipulation, and alternative measurements of forecast accuracy based on last forecasts. Our results are robust to these additional analyses.

Overall, we find that high-ability managers are more likely to issue accurate management forecasts at the beginning of the fiscal year, while low-ability managers are more likely to revise their forecasts and adopt earnings management to compensate for their poor capabilities.

This study contributes to the literature in several significant ways. This study is closely related to Baik et al. (2011), in that both studies investigate the relationship between managerial ability and management forecast accuracy. However, first, we complement Baik et al. (2011) by focusing on the Japanese setting, where management forecasts are effectively mandated. Under the voluntary management forecast system in the United States, Baik et al. (2011) show that high-ability managers tend to revise their forecasts more frequently during the fiscal year, consistent with Trueman's (1986) signaling theory. By contrast, we show that high-ability managers are *less* likely to revise their forecasts. In a situation where almost all managers issue earnings forecasts regardless of their ability, managers cannot signal ability through voluntary management forecasts. Furthermore, management forecasts play an important role in Japan's financial market, and accuracy/inaccuracy carries serious economic consequences. Thus, Japanese managers have a stronger incentive to issue accurate initial forecasts, as our results indicate. High-ability managers do not have to revise their forecasts owing to their initial accuracy, unlike low-ability managers.

Second, we extend Baik et al. (2011) by examining how managers increase their forecast accuracy. Managers generally have two discretionary options for increasing this accuracy: revisions and earnings management. While Baik et al. (2011) indicate that high-ability (low-ability) managers issue more accurate (less accurate) earnings forecasts, they do not show how managerial ability relates to their two discretionary options. We find that low-ability managers are more likely to revise their forecasts and more likely to use earnings management than high-ability managers. Thus, the methods used to enhance management forecast accuracy differ depending on managerial ability, which highlights the mechanism behind the relationship between managerial ability and management forecast practices.

Finally, this study contributes to the literature on management forecasts in Japanese firms. In particular, Kato et al. (2009) report that initial earnings forecasts are systematically biased upward and that managers revise them downward during the fiscal year to ensure non-negative earnings surprises. We attribute this opportunistic behavior largely to low-ability managers.

2. Institutional background and hypothesis development

2.1. Features of management forecast system in Japan

In Japanese markets, The Financial Instruments and Exchange Act (hereafter, the "Act") governs financial reporting practices and requires public firms to file an annual securities report (*Yuka Shoken Houkokusho*; equivalent to Form 10-K in U.S. SEC filings) within three months of the fiscal year-end. In addition, the Securities Listing Regulations of Japanese stock exchanges require listed firms to file an annual earnings report (*Kessan Tanshin,* or "summary of financial statements") in a timely manner and strongly encourage managers to provide regular sales and earnings forecasts in these reports (Rules 404 and 405 of the Act and *Kessan Tanshin* guidelines). Specifically, listed firms are recommended to release the report within 45 days of the fiscal year-end and report both the actual earnings and one-year ahead point forecasts simultaneously.[2]

[2] In terms of timeliness, our testing sample shows that the mean and median of the number of days between fiscal year-end and report release are 44.3 and 43.0, respectively, with approximately 90 percent of the sample releasing reports within 50 days of the fiscal year-end.

Although the issuance and revision of management forecasts are essentially voluntary, listed firms must disclose their forecast information to the extent that they can reasonably assess their future performance as well as hold estimates and other forecast-equivalent information. This forecast disclosure system is statutorily enforceable under Section 166 of the Act to prevent potential insider transactions. Therefore, except for cases in which managers cannot reasonably estimate future performance, they are expected to issue earnings forecasts at the beginning of the fiscal year.

In examining management earnings forecasts, this Japanese disclosure system provides a fruitful research setting for at least two reasons (Iwasaki et al. 2019). First, unlike in the United States, management earnings forecasts are mandatory for Japanese listed firms under the TSE requirements, as stated above. In fact, 93.5 percent of Japanese listed firms in our initial sample are found to issue management earnings forecasts in their *Kessan Tanshin*.[3] This reporting system provides us with unbiased management earnings forecast observations. Thus, studies on management earnings forecasts carried out in the Japanese setting are free from sample selection bias.[4] This is noteworthy because this setting mitigates the effect of proprietary and/or litigation costs on the issuance and accuracy of management forecasts, which is very difficult to control for theoretically and empirically.[5] Most U.S. studies address sample selection bias by using statistical

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[3] Approximately 6.5 percent of our initial sample do not issue earnings forecasts. According to a survey conducted by Toyo Keizai Inc., one of the biggest newspaper publishers in Japan, firms that have experienced large shocks from natural disasters (e.g. the Great East Japan Earthquake in 2011) and those in the financial sector are more likely to withhold earnings forecasts owing to the difficulty of assessing future performance (article published in June 2012: https://toyokeizai.net/articles/-/9348). The TSE publishes survey reports on *Kessan Tanshin* every year. One report shows that more than 96 percent of its listed firms disclosed management forecasts in 2019. The rest of the firms cite the difficulty of making forecasts as the reason for the absence of management forecasts (https://www.jpx.co.jp/news/1023/nlsgeu0000043h2j-att/nlsgeu0000043h54.pdf).

[4] In this sense, the findings of Baik et al. (2011) might be affected by the self-selection bias of forecast issuers in testing the relationship between managerial ability and forecast accuracy. Specifically, their sample for tests of forecast accuracy might comprise only firms with high-ability managers because such managers are more likely to issue earnings forecasts, as the study found.

[5] Several studies have examined the relationship between proprietary costs and disclosure (Ajinkya et al.

designs such as Heckman's two-stage estimation (e.g. Feng et al. 2009; Hui et al. 2009; Xu 2010; Gong et al. 2011; Shivakumar et al. 2011; Zhang 2012; Feng and Li 2014). However, the literature shows that it is very difficult to mitigate sample selection bias using such statistical procedures (e.g. Lennox et al. 2012).

Second, Japanese stock exchanges require listed firms to revise their forecasts if there are "significant" changes in management estimates, defined as changes in earnings estimates of 30 percent or more (the "Significance Rule"; Kato et al. 2009, p.1577). Therefore, inaccurate initial forecasts are mandatorily and systematically updated in Japan *ex post*, while forecasts in the United States are revised at the discretion of managers. The frequency of forecast revisions in Japan can thus serve as a precise proxy for the accuracy of initial forecasts, reflecting managers' forecast accuracy at the beginning of the fiscal year. This feature is useful for alleviating the effects of managers' reluctance or opportunistic behavior when publicizing bad news under a voluntary disclosure system (Kothari et al. 2009; Malmendier and Tate 2009), which could otherwise make the implications of forecast revisions unclear.[6]

2.2. Managerial ability and management earnings forecast accuracy

Prior studies investigate the determinants of management earnings forecast accuracy, such as the litigation environment, equity incentives, financial distress, external financing, industry concentration, and macroeconomic conditions (Skinner 1994; Frankel et al. 1995; Frost 1997; Aboody and Kasznik 2000; Lang and Lundholm 2000; Baginski et al. 2002; Rogers and Stocken

2005; Wang 2007) and the effect of litigation costs on disclosure (Francis et al. 1994; Skinner 1994; Kasznik and Lev 1995; Baginski et al. 2002; Miller 2002).

[6] To assess the effect of the Significance Rule, we investigate the number of forecast revisions with changes of greater than 30 percent. Our testing sample includes 12,615 instances of earnings forecast revisions. We find that 59.7 percent of revisions are seemingly triggered by the Significance Rule, while the rest of the forecast revisions are likely voluntary. This highlights the importance of the Rule and the forecasting practices enforced by regulations.

2005; Ota 2006). Baik et al. (2011) extend the literature by showing that managerial ability affects management forecasts. Trueman (1986) theorizes that managers voluntarily issue earnings forecasts as a signal to investors that they have the ability to anticipate changes in firms' economic environments. Baik et al. (2011) test the implications of this theory using management earnings forecasts of U.S. firms. Consistent with the theory, they find that the likelihood and frequency of management earnings forecasts increase along with CEO ability. They also assume that forecast accuracy reflects this ability and provide evidence that high-ability managers are more likely to release accurate forecasts.

Moreover, several recent studies provide evidence on the relationship between managerial ability and future forecasts. Demerjian et al. (2013) argue that high-ability managers are more knowledgeable about their firm and macroeconomic conditions and are therefore in a better position to synthesize information into reliable forward-looking estimates. They further hypothesize and show that highly capable managers are more likely to provide accurate estimates in accruals and thus report a higher quality of earnings. Similarly, Demerjian et al. (2020) show that high-ability managers are more likely to intentionally smooth earnings, implying that these managers can correctly assess future performance in order to smooth current earnings. Consequently, these studies suggest that as high-ability managers are very knowledgeable about their firms' inside and outside information, they can incorporate that knowledge into future prospects and publish accurate earnings forecasts.

2.3. Hypothesis development

We conduct three analyses to assess whether high-ability managers are more likely to issue accurate forecasts. First, we examine the relationship between *initial* management forecasts and managerial ability. Under a reporting system where management earnings forecasts are effectively mandated, managers generally have incentives to issue accurate initial earnings forecasts because they are likely to consider the negative consequences of inaccurate initial earnings forecasts when providing them. Studies have shown that the accuracy of management forecasts affects market reactions (Williams 1996; Hirst et al. 1999; Ng et al. 2013). For example, Ng et al. (2013) show that less-credible forecasts trigger smaller market reactions using prior management forecast accuracy as a proxy for credibility. Furthermore, Hui and Matsunaga (2015) find that changes in CEOs' annual bonuses are positively associated with changes in management forecast accuracy. In the context of CEO turnover, Lee et al. (2012) find that the probability of CEO turnover is positively related to the magnitude of absolute initial forecast errors, implying that the board of directors uses management forecast accuracy as an indicator of CEOs' abilities, and that managers bear a cost for inaccurate forecasts. These conditions likely motivate managers to issue accurate earnings forecasts.

This incentive to produce accurate initial forecasts could be more pronounced for Japanese firms than for U.S. firms because management earnings forecasts play an important role in Japanese financial markets, where almost all managers regularly issue earnings forecasts under the effectively mandated disclosure system. Suda and Hanaeda (2008) replicate the survey of Graham et al. (2005) using a sample of Japanese listed firms and show that management earnings forecasts represent the most important earnings benchmark among several performance benchmarks (97.1 percent of those surveyed agree or strongly agree that this benchmark is important).[7,8] Unlike in

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[7] By contrast, Graham et al. (2005) survey U.S. firms and report the following ranking of earnings benchmarks: (i) same quarterly earnings (85.1 percent), (ii) analyst consensus estimates (73.5 percent), (iii) reporting profit (65.2 percent), and (iv) the previous quarter's EPS (54.2 percent). This suggests that management earnings forecasts are particularly important in the Japanese financial market.

[8] Consistent with these survey results, Ota (2010) investigates the value-relevance of management earnings forecasts using Ohlson's (2001) framework and finds that they have a higher correlation and incremental explanatory power for stock prices. He also reveals that more than 90 percent of the changes in analysts' forecasts are explained by management forecasts. The overall results suggest that Japanese management

the United States, where managers can withdraw their forecasts based on their guidance strategies (Feng and Koch 2010), Japanese managers are continuously encouraged to issue accurate initial forecasts to avoid negative economic consequences and establish a good forecast reputation. Consistent with this argument, prior studies using Japanese samples have found that inaccurate initial forecasts lead to negative consequences, such as negative market reactions (Gotoh and Sakurai 1993; Han 1998; Kato et al. 2009), increased cost of capital (Muramiya 2005; Kitagawa and Shuto 2019), CEO turnover (Ishida and Hachiya 2020), and decreased management compensation (Otomasa et al. 2020). This evidence highlights the importance of accurate initial forecasts in the Japanese environment.

However, high-ability managers may use their abilities opportunistically to issue biased forecasts strategically. For example, managers may have an incentive to issue optimistic forecasts based on short-term stock effects. Several studies have found that stock price reactions around announcement dates are more pronounced for forecasted earnings than for actual reported earnings in Japanese markets (Darrough and Harris 1991; Conroy et al. 1998); this could encourage managers to produce biased forecasts. While an optimistic forecast may affect the short-term decisions of investors, this opportunistic behavior is irrational because overly optimistic initial forecasts are more likely to lead to subsequent forecast revisions and errors, which could damage managers' forecast reputations (Kato et al. 2009; Iwasaki et al. 2019). In fact, Kato et al. (2009) find that managers' optimistic forecasts persist from one year to the next but that market participants tend to discount such overly optimistic forecasts. This indicates that managers will have to bear the cost of the damage done to their reputations by issuing inaccurate initial forecasts. Thus, we posit that managers are unlikely to opportunistically issue biased initial forecasts when

forecasts provide useful information to capital markets and have more information content than other earnings benchmarks.

they are able to forecast earnings accurately.[9]

As discussed in the previous section, the common underlying logic concerning why managerial ability is associated with forecast accuracy is that high-ability managers know their firms and macroeconomic conditions well, and are thus more capable of forecasting their firms' future earnings (Demerjian et al. 2013). Therefore, considering both the incentives and abilities of managers to produce accurate forecasts, we predict that competent managers will issue more accurate earnings forecasts from the beginning. We thus propose the following:

HYPOTHESIS 1. *High-ability managers are more likely to issue accurate initial earnings forecasts.*

Second, we examine the relationship between managerial ability and forecast revisions. Kato et al. (2009) find for Japanese firms that managers' initial earnings forecasts are systematically biased upward. They also find that managers revise their forecasts downward during the fiscal year, so that most earnings surprises become non-negative. The evidence suggests that managers generally have an incentive to revise their forecasts to increase their accuracy.

However, if high-ability managers issue relatively accurate earnings forecasts at the beginning of the fiscal year, they will revise their forecasts less frequently during the year. Moreover, such revisions will be relatively small because of their relatively accurate initial forecasts. In contrast, low-ability managers are more likely to revise their forecasts in order to address their forecast errors and compensate for their poor capabilities.

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9 Another possibility is that high-ability managers may provide *conservative* forecasts strategically because of the costs of aiding competitors by revealing proprietary information. Managers may have a particular incentive to reduce proprietary costs by manipulating their forecasts downward at the beginning of the fiscal year. However, we can also predict that managers who have concerns about proprietary costs are *unlikely* to issue conservative forecasts because such forecasts are more likely to lead to subsequent upward revisions and positive forecast errors, which could negatively affect their performance. Therefore, whether high-ability managers tend to issue conservative forecasts remains an open question.

Specifically, we expect that this trend is more pronounced for Japanese than U.S. firms. As explained in Section 2.1, inaccurate initial forecasts are mandatorily and systematically revised because Japanese firms follow the Significance Rule. Since Japanese firms cannot refrain from disclosing bad news (i.e. downward revisions) the way U.S. firms can (Kothari et al. 2009; Malmendier and Tate 2009), we expect that low-ability Japanese managers disclose their earnings forecasts more frequently.[10] Accordingly, this argument leads to our next hypotheses:

HYPOTHESIS 2. *High-ability managers are less likely to revise their earnings forecasts.*

HYPOTHESIS 3. *The degree of revision is smaller for high-ability managers.*

Finally, we investigate the effect of earnings management on the relationship between managerial ability and forecast accuracy. We predict that, to mitigate the negative economic consequences of issuing inaccurate management forecasts, low-ability managers are more likely to conduct earnings management to increase their forecast accuracy. Studies indicate that managers issuing annual earnings forecasts tend to manage their reported earnings toward their forecasts (Kasznik 1999; Herrmann et al. 2003; Shuto 2010). Given that high-ability managers are more capable of forecasting their firm's future earnings, they are less likely to adopt earnings management to increase their forecast accuracy. Consistent with this inference, Demerjian et al. (2013) show that high-ability managers are more likely to report higher-quality earnings. Thus, we propose the following:

[10] By contrast, Baik et al. (2011) hypothesize and reveal that high-ability managers are more likely to revise management forecasts more frequently than low-ability managers during the fiscal year. Consistent with Trueman's (1986) signaling theory, Baik et al. (2011) argue that high-ability managers have incentives to keep the market abreast of changes in their firms' economic environment and thus tend to issue forecasts more often. Hence, the relationship between managerial ability and forecast revisions might be an empirical question. However, we predict that Japanese managers under the effectively mandated disclosure system are less likely to revise their forecasts, as Hypotheses 2 and 3 suggest. We elaborate the reasons for this in detail in the next section.

HYPOTHESIS 4. *High-ability managers are less likely to conduct earnings management to improve the accuracy of their forecasts.*

2.4. Differences between this study and Baik et al. (2011)

This study and Baik et al. (2011) are similar in that both investigate the effect of managerial ability on management forecast accuracy. Baik et al. (2011) provide useful evidence on the relationship between managerial ability and management forecast accuracy but leave several important issues unaddressed, such as (1) whether the relationship is unique to the voluntary disclosure system in the United States and (2) how high-ability managers increase their earnings forecast accuracy. Our study extends their research by providing additional evidence regarding these two issues.

Concerning the former issue, Baik et al. (2011) provide evidence that high-ability managers are more likely to voluntarily issue management forecasts and revise them more frequently during the fiscal year; this is consistent with Trueman's (1986) signaling theory. The difference between our predictions in Hypotheses 2 and 3 and the findings in Baik et al. (2011) is that we predict that high-ability managers are *less* likely to revise their forecasts during the period. One possible interpretation of Baik et al.'s (2011) results is that high-ability managers in highly uncertain environments are more likely to revise their forecasts because they have an incentive to signal useful new information about the firm in a timely manner. Under the U.S. voluntary disclosure system, their predictions based on the signaling theory and results are very convincing. The results suggest that managers have incentives to signal their abilities through rapid and frequent forecasts.

However, it might be difficult to make similar predictions in a situation where almost all managers issue earnings forecasts, as in Japan. Under the effectively mandated disclosure system, Japanese managers regularly issue earnings forecasts regardless of their competence, and so cannot have incentives to signal their abilities through forecast issuance. Moreover, Japanese managers tend to revise their forecasts according to the Significance Rule and also use forecast revisions to avoid negative earnings surprises (Kato et al. 2009), rather than to signal new useful information about the firm. Meanwhile, as stated in the hypothesis development above, managers have an incentive to issue accurate initial earnings forecasts to avoid the negative economic consequences of issuing inaccurate ones (Gotoh and Sakurai 1993; Han 1998; Muramiya 2005; Kato et al. 2009; Kitagawa and Shuto 2019; Ishida and Hachiya 2020; Otomasa et al. 2020). Thus, in contrast to Baik et al. (2011), we predict that high-ability managers are more likely to issue accurate forecasts at the beginning and do not have to revise their forecasts later, resulting in less frequent revisions during the fiscal year.

Concerning the second issue, Baik et al. (2011) show that high-ability (low-ability) managers publish more (less) accurate earnings forecasts but do not reveal *how* managers increase the accuracy of their forecasts. Managers generally have three options for increasing their forecast accuracy. The first one is to issue an accurate initial earnings forecast at the beginning of the fiscal year, which is the main concern of this study. Further, it should be noted that managers have two more discretionary options to increase their forecast accuracy: revising their forecasts *ex post* and conducting earnings management. Opportunistic managers can use these discretionary methods to decrease their forecast errors (Kasznik 1999; Herrmann et al. 2003; Kato et al. 2009; Shuto 2010). Because Baik et al. (2011) use the *last* earnings forecasts (i.e. those issued immediately prior to the earnings announcement date) to measure the accuracy of management earnings forecasts, it is unclear whether forecast accuracy can be substantially attributed to managerial ability. Specifically, Baik et al. (2011) provide evidence that high-ability managers are more likely to revise their forecasts during the fiscal year and report accurate final forecasts based on the last earnings forecasts at fiscal year-ends. Therefore, managers may be able to enhance their forecast accuracy through forecast revisions during the fiscal year.[11] Further, they do not examine the relationship between forecast accuracy and earnings management. We complement Baik et al. (2011) by investigating how managerial ability relates to these two discretionary options for enhancing forecast accuracy. Specifically, we examine whether high-ability (low-ability) managers are less (more) likely to conduct forecast revisions and earnings management to increase the accuracy of their management earnings forecasts. These analyses are important for understanding the mechanism of the relationship between managerial ability and management forecast accuracy.

3. Research design

3.1. Proxy for managerial ability

To measure managerial ability, we employ the Managerial Ability Score (MA Score) method developed by Demerjian et al. (2012). This method uses data envelopment analysis (DEA) and regressions to construct a measure for manager-specific ability. Specifically, Demerjian et al. (2012) first calculate a measure of firm efficiency related to industry peers using DEA, and then estimate the MA Score as the management-specific portion of firm efficiency using Tobit regressions. The underpinning idea is that highly capable managers generate higher revenue for a given resource level or, conversely, minimize the resources used for a given revenue level. Therefore, managers who are talented in this sense should be good at assessing industry trends and predicting future prospects in given situations (Demerjian et al. 2013). Although other measures have been used in prior research (Hayes and Schaefer 1999; Fee and Hadlock 2003; Milbourn 2003; Rajgopal et al. 2006; Francis et al. 2008; Carter et al. 2010), Demerjian et al. (2012) conclude that the MA Score is a cleaner depiction of managerial ability than prior measures. Hence, it is our

[11] Baik et al. (2011) report that they obtain similar (untabulated) results when they analyze the initial forecasts (p. 1659). However, they do not elaborate on why they use the last forecasts to measure forecast accuracy or why managers need to revise their initial "accurate" forecasts frequently.

primary measure of managerial ability although we consider other measures in robustness analyses.

We describe our MA Score measurement methodology in Appendix A using Japanese data. Although we basically follow Demerjian et al.'s (2012) methodology, our calculation differs slightly from theirs because of the difference in disclosure requirements between the United States and Japan in terms of firms' operating lease assets. Specifically, Demerjian et al. (2012) calculate operating lease assets as the discounted present value of the required operating lease payments for the next five years, which are available in the footnotes to the firms' financial statements and on *Compustat*. However, Japanese firms are required to disclose only their total future minimum lease payments and payments due within one year. Hence, we use the present value of the net operating lease assets, following Kusano et al. (2015; see Appendix A for details).[12]

3.2. Empirical specifications for hypothesis tests

Following Baik et al. (2011) and other relevant studies, we apply the following ordinary least squares (OLS) model to examine the association between managerial ability and management earnings forecasts (Hypotheses 1 to 4). In Equation (1), we use a set of lagged independent variables to mitigate the endogeneity issues stemming from simultaneity and infer the relationship between management forecast behaviors and abilities:

$$\begin{aligned} MF_{i,t} = {} & \alpha + \beta_1 Managerial\ Ability_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Loss\_D_{i,t-1} + \beta_4 Increase\_D_{i,t-1} \\ & + \beta_5 StdDevEarn_{i,t-1} + \beta_6 Beta_{i,t-1} + \beta_7 StdDevResidual_{i,t-1} + \beta_8 Sales\_Conc_{i,t-1} \\ & + \beta_9 ManagerOwn\%_{i,t-1} + \beta_{10} OutsideDir\%_{i,t-1} + \beta_{11} InstOwn\%_{i,t-1} \\ & + \beta_i Firm + \beta_t Year + \varepsilon_{i,t} \end{aligned} \quad (1)$$

[12] Chang et al. (2018) examine the validity of the MA Score using Japanese firms, and report that the measure is also useful in non-U.S. settings. Following Demerjian et al. (2012) and Chang et al. (2018), we conduct validation tests on our estimated MA Score, and find that the measure is correlated with manager fixed effects and is associated with stock price reactions to CEO turnover and changes in future ROA following CEO turnover, consistent with prior studies.

$$MF_{i,t} = \{\textit{Initial Forecast Error}_{i,t}, \textit{Num. Forecast Revisions}_{i,t}, \textit{Magnitude Forecast Rev.}_{i,t}, \textit{Improve}_{i,t}\}.$$

We use *Initial Forecast Error* to test Hypothesis 1 on the relationship between managerial ability and initial earnings forecast accuracy. *Initial Forecast Error* is the absolute value of the price-deflated initial management earnings forecast error multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast|/lagged market value of equity).[13] To test Hypotheses 2 and 3, we use *Num. Forecast Revisions* and *Magnitude Forecast Rev.*, respectively. *Num. Forecast Revisions* is the number of management forecast revisions issued after the initial management forecast. *Magnitude Forecast Rev.* is the absolute value of the price-deflated management earnings forecast revisions multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity). Finally, we use *Improve* to test Hypothesis 4. *Improve* is the value of forecast improvement through earnings management, defined as the difference between the forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity).[14] A high *Improve* value indicates that managers improve their forecast accuracy by reporting discretionary accruals. The last forecasts used in this study are those issued immediately prior to the fiscal year-end (Skinner 1997; Rogers and Stocken 2005). We estimate discretionary accruals

[13] The Japanese disclosure system provides a useful research setting for assessing the accuracy of initial management forecasts because almost all managers issue *point* forecasts at the beginning of the fiscal year with the *same forecast horizon.* The use of midpoints based on *range* forecasts and *different forecast horizons* in U.S. studies introduce biases in the measurement of management forecast accuracy (Baginski and Hassell 1997; Baik et al. 2011; Ciconte et al. 2014; Jensen and Plumlee 2019).

[14] *Improve* captures the extent to which the firm improves its forecast accuracy by reporting discretionary accruals. For example, suppose that a firm has a net income of 130, discretionary accruals of 60, and a last management earnings forecast of 120. Here, pre-managed earnings are calculated as 70 (130 – 60), and the forecast error based on *pre*-managed earnings is 50 (|70 – 120|). However, the forecast error based on *post*-managed earnings is 10 (|130 – 120|). Thus, the firm, by reporting discretionary accruals, improves its forecast accuracy by 40 (50 – 10). *Improve* captures this value of 40.

based on Kothari et al. (2005; see Appendix B for estimation model). All the above earnings are defined in terms of net income, and forecast errors are deflated by the lagged market value of equity (Rogers and Stocken 2005; Baik et al. 2011).

Our variable of interest is *Managerial Ability*, derived through DEA and Tobit regression by industry (see Appendix A). Because the raw MA Score value indicates the *within-industry* relative management ability, it would be difficult to compare it between industries. For example, since the mean and variance can differ across industries, we cannot conclude that managers in a particular industry are superior to those in other industries based on the raw value. Therefore, we use the MA Score decile rank by industry and year, following Demerjian et al. (2013). We also use the continuous MA Score measures/raw values in the robustness analyses. According to our hypotheses, the coefficient should be negative for all estimations.

We consider the following control variables, which Baik et al. (2011) and prior studies have linked to management earnings forecast errors: *Size*, *Loss_D*, *Increase_D*, *StdDevEarn*, *Beta*, *StdDevResidual*, *Sales_Conc*, *ManagerOwn%*, *OutsideDir%*, and *InstOwn%.* First, we control for firm size (*Size*), proxied as the natural log of total sales. We predict that the sign of the coefficient will be both positive and negative because firm size can be a proxy for both business stability and complexity.

Loss_D and *Increase_D* are indicator variables used to control for firms' earnings stream. *Loss_D* takes a value of one if the firm reports losses and zero otherwise, and *Increase_D* takes a value of one if the firm's net income has increased from the previous year and zero otherwise. Firms that have suffered losses are less sensitive to forecasts (Baik et al. 2011), while those with poor earnings histories are more likely to be optimistic and thus issue relatively inaccurate forecasts (Kato et al. 2009).

StdDevEarn, *Beta*, and *StdDevResidual* are all controls for earnings and business uncertainty.

StdDevEarn is the standard deviation of the annual changes in net income scaled by lagged total assets over the past five years; *Beta* is the market model beta over the past 240 days starting from the end of the previous fiscal year; and *StdDevResidual* is the standard deviation of the residual obtained from the market model over the past 240 days starting from the end of the previous fiscal year. Prior studies show that forecast errors increase along with the uncertainty managers face when providing forecasts (Ajinkya et al. 2005; Cheng et al. 2013).

Sales_Conc is the sales concentration, which controls for the firms' proprietary costs and market competition (Bamber and Cheon 1998; Rogers and Stocken 2005; Baik et al. 2011). We measure this variable using the Herfindahl index, which equals the sum of the squares of the firms' sales of shares within the industry. Firms in more concentrated and hence less competitive industries are expected to be reluctant to release forecasts based on accurate inside information and more likely to produce biased forecasts to discourage new entries into the field (Rogers and Stocken 2005).

ManagerOwn% is the percentage of shares held by managers. As insider ownership increases, the need to meet forecasts becomes less important due to the lack of pressing outside demand for precise information (Nagar et al. 2003). Furthermore, *OutsideDir%* and *InstOwn%* are the percentages of outside directors on the board and shares held by institutional investors, respectively. Both control for the strength of outside monitoring and pressure to produce accurate earnings forecasts. Table 1 presents the definitions of all test variables.

Equation (1) includes firm and year fixed effects. Prior studies show that earnings forecast error is persistent and subject to serial correlation (Ota 2006; Kato et al. 2009; Gong et al. 2011; Hilary et al. 2014), suggesting that an unobservable firm-specific factor can systematically affect forecast accuracy. For example, in a sample of Japanese firms, Ota (2006) finds that management forecast errors are positively related to lagged forecast errors, and Kato et al. (2009) report highly persistent manager forecast optimism from year to year. Therefore, we control for firm as well as year fixed effects by including both firm and year indicators.[15]

Insert Table 1 about here

4. Sample selection and descriptive statistics

We summarize our sample selection procedure in Table 2. We collect our initial sample from the *Nikkei NEEDS-FinancialQUEST*, the most comprehensive commercial database for Japanese firms. This database provides financial, stock price, and management forecast data of all listed firms in Japan, including delisted ones. We collect our data on shareholders and board structure from *Nikkei NEEDS-Cges*, a commercial database for corporate governance of Japanese listed firms.

Our initial sample consists of 30,751 firm-year observations covering 2006 to 2014. The sample period begins in 2006 because we require research and development (R&D) data for the preceding five years to estimate the MA Score, and R&D expenses data are available only from 2000 (see Appendix A). Following Demerjian et al. (2012), we exclude all financial sector firms (i.e. firms from the banking, securities, and insurance sector). We also exclude firms that prepare financial statements according to the U.S. Generally Accepted Accounting Principles (GAAP) or

[15] *Managerial Ability* may be persistent over time, as it is a manager-specific measure and is unlikely to change during the manager's tenure (Demerjian et al. 2012). To verify this possibility, we regress $Managerial\ Ability_{i,t}$ on $Managerial\ Ability_{i,t-1}$, a lagged variable, and find that the slope coefficient is 0.82 (p-value < 0.01), supporting the notion of persistence in managerial ability. Although we posit that the firm fixed effects model allows us to assess the effects of different managers of the same firm over time (Demerjian et al. 2020), this result may imply that it is preferable to focus on CEO turnover to extract economically meaningful changes in managerial ability. We address this issue in Section 5.2.1 using CEO turnover observations. Further, we apply the hybrid model suggested by Allison (2009), which combines the virtues of the fixed and random effects models. We include firm-specific means and their deviations for all independent variables, except for *Managerial Ability*. Then, we run a random effects model to ensure that the standard errors reflect the dependence between multiple observations for each firm. We confirm that the empirical results are qualitatively and quantitatively similar when we apply this hybrid model.

International Financial Reporting Standards (IFRS) to alleviate the differences in accounting procedures among firms. For firms that do not prepare consolidated financial statements, we use their unconsolidated accounting data. Thus, our final sample consists of 17,795 firm-year observations.

Insert Table 2 about here

Table 3 reports the descriptive statistics of our testing variables. To reduce the influence of outliers, we use data winsorized at the bottom 1 and top 99 percentile values for each variable by year, except for the indicator variables. The table shows that the mean and standard deviation of *Initial Forecast Error* (7.129 and 14.487, respectively) are much larger than those (1.703 and 3.964, respectively) reported in Baik et al. (2011), whose forecast errors are based on data issued immediately prior to the earnings announcement date. This is apparent but suggests that it is difficult for managers to issue accurate forecasts at the beginning of the fiscal year. For the number of forecast revisions (*Num. Forecast Revisions*), the mean and median are 1.040 and 1.000, respectively, indicating that, on average, firms revise their earnings forecasts at least once after their initial forecast.[16] Moreover, the value of *Improve*, forecast accuracy improvements through discretionary accruals, tends to be positive for the sample (untabulated statistics show that approximately 90 percent of firm-years exhibit positive values). This suggests that most firms report discretionary accruals in a manner that reduces forecast errors, which is in line with the literature (Kasznik 1999; Shuto 2010).

[16] Kato et al. (2009) find more frequent forecast revisions among Japanese firms. However, in counting the frequency, they include forecasts that confirm the initial forecast (Kato et al. 2009, p.1596). In this study, we count the number of forecast revisions based on the difference from prior forecasts; that is, we define revisions as observations that change their forecasts during the fiscal year.

Insert Table 3 about here

Table 4 presents the correlation matrix of the variables used in our regression models. The upper right-hand side of the table reports the Spearman rank-order correlations, while the lower left-hand side presents the Pearson correlations. A correlation analysis shows that *Managerial Ability* is significantly and negatively associated with *Initial Forecast Error*, *Num. Forecast Revisions*, *Magnitude Forecast Rev.*, and *Improve*, as predicted.

Insert Table 4 about here

For more intuitive implications, Table 5 presents the results of a univariate comparison tests between high- and low-ability managers. We classify the sample into two subsamples, *Low-Ability Managers* and *High-Ability Managers*, based on the median of *Managerial Ability* for the entire sample, and test the difference in variables between the two subsamples.[17] Consistent with our hypotheses, the high-ability group exhibits statistically lower values for all dependent variables (*Initial Forecast Error*, *Num. Forecast Revisions*, *Magnitude Forecast Rev.*, and *Improve*), suggesting that competent managers are more likely to issue accurate initial forecasts and are less likely to conduct forecast revisions and improvements through earnings management.

Moreover, the control variable results suggest non-random matching between the manager and firm. In particular, we find significant differences in both the mean and median of *Loss_D*, *Increase_D*, *StdDevEarn*, *Beta*, and *InstOwn%*, indicating that high-ability managers are more likely to be hired by profitable firms with lower earnings volatility, higher stock beta, and larger institutional investor ownership. Although the effects of these factors are controlled for in Equation (1), the findings imply the possibility of endogeneity in managerial ability (Demerjian et al. 2013;

[17] Since *Managerial Ability* is the decile rank by industry and year of the MA Score, the categorization based on the median for the entire sample is essentially by industry and year.

Wang et al. 2017). We discuss these issues in the Robustness Tests section.

Insert Table 5 about here

5. Empirical results

5.1. Main results

Table 6 reports the regression analysis results. We estimate our models using firm and year fixed OLS regression, with the *t*-values based on standard errors clustered at both the firm and year levels (Petersen 2009).

We first examine the relationship between managerial ability and earnings forecast errors based on *initial* forecasts (Hypothesis 1). The regression results summarized in column (1) of Table 6 show that the coefficient on *Managerial Ability*, −0.495, is significantly negative (p-value < 0.01). Consistent with Hypothesis 1, this finding suggests that high-ability managers are more accurate in their earnings predictions at the beginning of the fiscal year. For economic significance, moving from the first to third quartile of the *Managerial Ability* distribution reduces the forecast error by 2.476 percentage points. Given that the mean value is 7.129 percent (see Table 3), this result appears to be economically significant.

Our second analysis examines the relationship between managerial ability and forecast revision behaviors. Columns (2) and (3) of Table 6 present the findings. Consistent with Hypotheses 2 and 3, the coefficients on *Managerial Ability* are significant and negative (p-value < 0.01), indicating that high-ability managers are less likely to revise their initial forecasts (Hypothesis 2), with relatively small revisions (Hypothesis 3). Moving from the first to third quartile of *Managerial Ability* decreases the number of forecast revisions by 0.062 and the degree of forecast revisions by 1.575. These results appear to be economically significant, given that the mean values are 1.040 and 4.784, respectively (per Table 3).

Finally, we examine whether managerial ability is related to earnings management, which improves management earnings forecast accuracy (Hypothesis 4). Column (4) of Table 6 indicates that the coefficient on *Managerial Ability* is negative and significant (p-value < 0.01), suggesting that high-ability managers are less likely to address their forecast errors through earnings management; this result is consistent with Hypothesis 4. For economic significance, moving from the first to third quartile of *Managerial Ability* decreases the degree of forecast improvement through earnings management by 1.841, accounting for 15.9 percent of the mean value of *Improve*.

Overall, the results shown in Table 6 support our hypotheses and confirm the view that highly capable managers are good at predicting their earnings at the beginning of the fiscal year.

Insert Table 6 about here

5.2. Robustness tests

5.2.1. Endogeneity issues

In this section, we conduct additional tests to assess the robustness of our empirical results. First, we address the endogeneity of managerial ability. Unobservable firm-specific factors (i.e. omitted variables) may affect our empirical results because managerial ability could contain firm-specific elements. Moreover, the univariate tests in Table 5 show that manager and firm matching is not random, and therefore that high- and low-ability managers may tend to be employed by different types of firms, which may also lead to biased results. To address these potential endogeneity issues, we conduct the following analyses: (1) two-stage least-squares (2SLS) analysis, (2) regressions using CEO turnover, and (3) matched-pair sample analysis based on the propensity score.

5.2.1.1. Two-stage least-squares analysis

We follow Demerjian et al. (2020) in our 2SLS analysis. To better assess the causality between managerial ability and intentional earnings smoothness, Demerjian et al. (2020) use the average ability of all managers in the same metropolitan statistical area (MSA) as the instrumental variable. The average ability of those in a particular geographic region may relate to an individual's ability due to the labor market networks of high-ability managers, but is unlikely to be associated with individual firm behaviors (Demerjian et al. 2020, p.426). Following the methodology of Demerjian et al. (2020), we apply the geographical divisions defined in the *Labor Force Survey* conducted by the Statistics Bureau of Japan (equivalent of the MSA in the United States) and use the average ability of all managers in the same industry, year, and region as the instrument.[18]

Table 7 presents the 2SLS analysis results. The column for the first stage shows a significantly positive coefficient for the instrument (*Ave.MA*). A test of under-identification rejects the null that our instrument is irrelevant (based on critical values from Stock and Yogo [2005]), while a weak instrument test rejects the null that the instrument is weak (based on the Cragg–Donald Wald F Statistic). These results indicate that average managerial ability is a valid instrument for the estimation. The columns for the second stage in Table 7 show that the coefficients on the predicted managerial ability (*Pred.MA*) are negative and statistically significant for all the dependent variables. These results are consistent with the main analyses results, suggesting that differences in managerial ability, rather than omitted firm characteristics, lead to the differences in forecast behaviors.

Insert Table 7 about here

[18] Specifically, we form groups based on industry (TSE industry classification), year, and geographical area (11 regions based on the *Labor Force Survey*). We match each firm to a region based on the prefecture/state of the firm's headquarter. Then, we compute the average of the MA Score for each industry-year-region group.

5.2.1.2. Regression using CEO turnover

To further control for firm-specific effects, we focus on CEO turnover observations. Specifically, we use the difference in ability between incoming and outgoing CEOs to test for the causality between managerial ability and forecast behaviors. Demerjian et al. (2013) conduct a similar analysis, focusing on CFOs who switch employers, to examine the association between managerial ability and earnings quality. However, it would be difficult to follow the same sampling method in a Japanese setting because of the unavailability of observations on CEOs employed by multiple firms (Chang et al. 2018). Therefore, we focus on the CEO turnover within firms and calculate change in ability as the simple difference between the incoming and outgoing managers' abilities. This allows us to highlight the variation in the manager-specific factor of the ability measurement, leaving the firm-specific factors constant.

Using the *Nikkei NEEDS-Cges* database mentioned above, we identify 2,448 instances of CEO turnover in the sample. We consider the president of a firm equivalent to its CEO in the U.S. context because the president is the top executive in Japanese firms and typically exercises substantial control over corporate operations (Kaplan 1994; Kang and Shivdasani 1995; Chang et al. 2018). Specifically, in a subsample of CEO turnover instances, we estimate the following modified Equation (1):

$$\begin{aligned} \Delta MF_{i,t} = {} & \alpha + \beta_1 \Delta Managerial\ Ability_{i,t} + \beta_2 \Delta Size_{i,t} + \beta_3 Loss\_D_{i,t-1} + \beta_4 Increase\_D_{i,t-1} \\ & + \beta_5 \Delta StdDevEarn_{i,t} + \beta_6 \Delta Beta_{i,t} + \beta_7 \Delta StdDevResidual_{i,t} + \beta_8 \Delta Sales\_Conc_{i,t} \\ & + \beta_9 \Delta ManagerOwn\%_{i,t} + \beta_{10} \Delta OutsideDir\%_{i,t} + \beta_{11} \Delta InstOwn\%_{i,t} \\ & + \beta_i Industry + \beta_t Year + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where Δ denotes the annual change from year $t-1$ to t, and t is the year the CEO changed. Since we focus on the change in managerial abilities (*ΔManagerial Ability*), all the other variables except for the indicator variables are incorporated as annual change. We include industry fixed effects rather than firm fixed effects because 37.8 percent of the sample firms experience CEO turnover only once during the sample period. A positive value for *ΔManagerial Ability* indicates that the incoming manager is deemed more competent than the outgoing manager, leading to the prediction of a negative coefficient for all estimations. The results are shown in Table 8. The coefficients on change in managerial ability are all negative and statistically significant. This result is consistent with our main results and suggests that the associations we find are more likely attributable to the manager than to the firm.

Insert Table 8 about here

5.2.1.3. Matched-pair sample analysis

As a final test for endogeneity issues, we conduct a matched-pair sample analysis to address concerns about heterogeneity in managers' employment. Francis et al. (2008) argue that "boards of directors hire specific managers due to the reputation and expertise these individuals bring to managing the more complex and volatile environments of these firms," implying that managers are not randomly distributed across firms. In our context, for example, complex and volatile firms may have incentives to hire competent managers to improve their forecast accuracy or address any other management issues, or, conversely, high-ability managers have a motive to be hired by firms whose future performance is easier to predict. Thus, such heterogeneity in operating environments and managers' employment preferences can influence our results.

To address these issues, we carry out propensity-score matching (PSM) as proposed by Rosenbaum and Rubin (1983), which is an ideal method to test the effect of differences in managerial ability with minimized variation in control variables (Wang et al. 2017). Specifically, we construct a matched-pair subsample of high- and low-ability managers with similar firm characteristics by estimating the following logit regression model:

$$\begin{aligned} \textit{High-Ability Manager}_{i,t-1} = {} & \alpha + \beta_1 \textit{Tenure}_{i,t-1} + \beta_2 \textit{Age}_{i,t-1} + \beta_3 \textit{Prior Position}_{i,t-1} \\ & + \beta_4 \ln(\textit{Assets})_{i,t-1} + \beta_5 \textit{Current Return}_{i,t-1} + \beta_6 \textit{Past Return}_{i,t-1} + \beta_7 \textit{ROA}_{i,t-1} \\ & + \beta_8 \textit{MtB}_{i,t-1} + \beta_9 \textit{R\&D\_D}_{i,t-1} + \beta_{10} \textit{R\&D\_D*R\&D}_{i,t-1} + \beta_{11} \textit{Adv\_D}_{i,t-1} \\ & + \beta_{12} \textit{Adv\_D*Adv}_{i,t-1} + \beta_{13} \textit{Loss\_D}_{i,t-1} + \beta_{14} \textit{Increase\_D}_{i,t-1} \\ & + \beta_{15} \textit{StdDevEarn}_{i,t-1} + \beta_{16} \textit{Beta}_{i,t-1} + \beta_{17} \textit{InstOwn\%}_{i,t-1} \\ & + \beta_i \textit{Industry} + \beta_t \textit{Year} + \varepsilon_{i,t-1}, \end{aligned} \tag{3}$$

where *High-Ability Manager* is an indicator variable that takes a value of one when the MA Score is in the top quartile and zero otherwise (Demerjian et al. 2020); *Tenure* is the length of time the CEO has been in his/her position as of year $t-1$; *Age* is the CEO's age as of year $t-1$; *Prior Position* is an indicator variable that takes a value of one when the CEO was appointed from outside the firm within the past three years and zero otherwise; *Assets* is the firm's total assets; *Current Return* and *Past Return* are the current and past year's stock returns, respectively; *ROA* is the net income scaled by average total assets; *MtB* is the market value of equity scaled by the book value of equity; *R&D_D* (*Adv_D*) is an indicator variable that takes a value of one if when the firm reports R&D expenses (advertising expenses) and zero otherwise; and *R&D* and *Adv* are the ratios of R&D and advertising expenses to sales, respectively. The first 12 independent variables are based on Francis et al. (2008), who consider them related to manager reputation. The rest of the independent variables are taken from Table 5, which shows the qualities in which the high- and low-ability manager groups significantly differ. Because we use manager-specific information and the binominal outcomes in Equation (3), the test observations we consider decrease to 16,893 firm-years. In the sample, 4,101 firm-years are deemed to have high-ability managers (i.e. *High-Ability Manager* = 1) and matched to the relatively low-ability managers based on the closest propensity scores, without replacement. Thus, our matched-pair subsample consists of 8,202 firm-years.

The results are presented in Table 9. Panel A shows the logit estimation results of Equation (3). In line with Francis et al. (2008) and Demerjian et al. (2012), the variables for firm performance (*Past Return*, *ROA*, *Increase_D*) are positively related to managerial ability. However, total assets (*Assets*) and expenses (*R&D* and *Adv*) exhibit negative and significant coefficients. This result is consistent with the underlying idea of the MA Score, whereby expenses and assets are treated as inputs that the managers should minimize to a specific output level. Moreover, the coefficient on *Tenure* is significantly negative, implying that long-tenured CEOs are entrenched and thus inefficient in terms of operations (Chang et al. 2018). Panel B of Table 9 compares the mean values of covariates across the matched 4,101 pairs. We find that most of our variables show no significant differences between the treatment (i.e. high-ability managers) and control firm groups, suggesting that the PSM yields control firms with characteristics similar to those of the treatment firms. Panel C of Table 9 shows the matched-pair subsample regression results. All the coefficients on *Managerial Ability* are negative and significant. These findings support our hypotheses and alleviate our concerns about the effect of heterogeneity on managerial employment and operating environments.[19]

Insert Table 9 about here

5.2.2. Alternative measures for Managerial Ability

We use the MA Score estimated in line with Demerjian et al. (2012) for our main analyses. However, as noted in our research design section (Section 3), our DEA calculation differs slightly for operating lease assets, thus leading to measurement bias. To address this issue, we remove operating lease assets from the DEA and calculate the MA Score based on six inputs

[19] In Panel B, we still observe significant differences in *Prior Position*, *Assets*, and *ROA* between the treatment and control groups. Untabulated results show that, before propensity score matching, significant differences are observed in the mean values for 14 out of the 17 independent variables in Equation (3), suggesting that our propensity score matching procedure substantially mitigates concerns about heterogeneity in firms with high-ability managers.

(*MA_6inputs*).[20] Similarly, while our main analyses use the MA Score decile rank, we apply the raw MA Score values (*MA_RawValue*) to assess the sensitivity of our empirical results.

Moreover, we supplement our analysis by considering alternative managerial ability measures. Studies have applied several metrics to estimate managerial ability (such as stock returns, industry-adjusted ROA, CEO tenure, and media mentions), and we cannot deny that those measures may capture a part of managerial ability that the MA Score cannot measure. To address this issue, we follow Baik et al. (2011) and construct a single index, *Principal Component*, based on the principal component analysis using the following three measures: MA Score (*MA_RawValue*), industry-adjusted stock return (*Historical Return*), and industry-adjusted ROA (*Historical ROA*).[21] We define $Historical\ Return_{i,t-1}$ and $Historical\ ROA_{i,t-1}$ using data from the preceding three years (year $t-3$ to year $t-1$).

The results are reported in Table 10. Panels A, B, and C of the table use *MA_6inputs*, *MA_RawValue*, and *Principal Component*, respectively. To avoid redundancy, we report only the coefficients on the variables for managerial ability. Each panel gives results similar to those in the main analyses. Specifically, the coefficients on alternative measures are all negative and significant for all the dependent variables, supporting our hypotheses.[22] These findings suggest that our empirical results are robust to measurement alternatives to the MA Score.

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[20] Demerjian et al. (2012, note 7) also acknowledge the difficulty in estimating operating lease assets and conduct a sensitivity test that excludes them.

[21] Baik et al. (2011) use media mentions/press citations as a CEO ability measure; however, we do not apply this metric because of the absence of an equivalent database to use for article searches in Japan. Most importantly, press citations are more likely for larger firms and therefore could result in sample bias (Demerjian et al. 2012). Instead of the media mention/press citation variable, we add industry-adjusted stock return, which many studies have used as a proxy for managerial ability (Hayes and Schaefer 1999; Fee and Hadlock 2003; Demerjian et al. 2012; Demerjian et al. 2013).

[22] We also use *Historical Return* and *Historical ROA* as managerial ability measures. While the significance of the estimated coefficients decreases proportionately, particularly for *Historical ROA*, the results are similar to those shown in Table 6. This may happen because ROA is more likely to be firm-specific (Demerjian et al. 2012) and subject to intentional earnings management (Demerjian et al. 2020), and thus fail to capture manager-specific ability.

Insert Table 10 about here

5.2.3. Sensitivity tests on forecast improvement through earnings management

To test for the sensitivity of our results for Hypothesis 4 (on earnings management for improving forecast accuracy), we conduct additional analyses on the validity of the variable *Improve*. First, we examine whether our findings are robust to alternative discretionary accrual measures. Specifically, aside from following Kothari et al. (2005), we also estimate discretionary accruals following Dechow et al. (1995), Kasznik (1999), and McNichols (2002), and test whether the choice of estimation models affects our results (see Appendix B for each estimation model). We further examine whether managers conduct real activities manipulation. Managers are more likely to engage in real activities to manage their earnings rather than in accrual management (Graham et al. 2005). On this point, we follow Roychowdhury (2006) and estimate abnormal cash flow, abnormal discretionary expenses, and abnormal production costs via industry-year regression (see Appendix C for each estimation model). We reconstruct *Improve* using these discretionary earnings components.

Table 11 shows the sensitivity test results for Hypothesis 4. Panel A uses alternative discretionary accruals to redefine *Improve* and reports the expected negative and significant coefficients on *Managerial Ability*, suggesting that the model selected for discretionary accruals does not change the tenor of the results. In Panel B, we apply three measurements for real earnings management to construct *Improve* based on Roychowdhury (2006). Thus, each column's results are based on different definitions of *Improve*. We find that the coefficients are negative and significant for all estimations. These results are consistent with our assertion that high-ability managers are less likely to adopt activity-based manipulation or accrual management.

Insert Table 11 about here

5.3. Additional analysis

Our findings are so far consistent in suggesting that high-ability managers are more likely to issue accurate initial earnings forecasts and are less likely to revise forecasts and conduct earnings management to improve accuracy. However, in such cases, high-ability managers may bear the cost of missing their forecasts at the fiscal year-end. In other words, high-ability managers may be beaten by low-ability managers who use their discretionary options in terms of the *last* forecast accuracy, suggesting that "honesty does not pay."

To test for this possibility, we conduct further tests using the last forecast accuracy, which is very similar to the approach in Baik et al. (2011). Specifically, we estimate the following OLS regression:

$$\begin{aligned} \mathit{Last\ Forecast\ Error}_{i,t} = \alpha &+ \beta_1 \mathit{Managerial\ Ability}_{i,t-1} + \beta_2 \mathit{Size}_{i,t-1} + \beta_3 \mathit{Loss\_D}_{i,t-1} \\ &+ \beta_4 \mathit{Increase\_D}_{i,t-1} + \beta_5 \mathit{StdDevEarn}_{i,t-1} + \beta_6 \mathit{Beta}_{i,t-1} \\ &+ \beta_7 \mathit{StdDevResidual}_{i,t-1} + \beta_8 \mathit{Sales\_Conc}_{i,t-1} + \beta_9 \mathit{ManagerOwn\%}_{i,t-1} \\ &+ \beta_{10} \mathit{OutsideDir\%}_{i,t-1} + \beta_{11} \mathit{InstOwn\%}_{i,t-1} + \beta_{12} \mathit{Timeliness}_{i,t} \\ &+ \beta_i \mathit{Firm} + \beta_t \mathit{Year} + \varepsilon_{i,t}, \end{aligned} \quad (4)$$

where *Last Forecast Error* is the absolute value of the price-deflated last management earnings forecast error multiplied by 100 (i.e. 100*|actual reported earnings – last management earnings forecast|/lagged market value of equity). Here, the last management forecast is the forecast issued immediately prior to the fiscal year-end.[23] For firms that do not review their forecasts for the current year, the variable takes the initial management earnings forecast error value. Different from

[23] In Japan, a certain number of firms revise their forecasts after the fiscal year-end (i.e. between the fiscal year-end and the earnings announcement date), which is often referred to as "rush revisions" (Tsumuraya 2008). In this case, firms tend to issue final earnings forecasts identical to the actual reported earnings. Accordingly, we define the last earnings forecast relative to the fiscal year-end rather than the earnings announcement date.

the formulation of Equation (1), we add the independent variable *Timeliness* and measure it as the number of days between the last forecast date and the fiscal year-end, controlling for the effect of forecast horizons (Baginski and Hassel 1997; Baik et al. 2011).

Panel A of Table 12 presents the descriptive statics for *Last Forecast Error* and *Timeliness*. The mean value of *Last Forecast Error* (2.945) is much smaller than that of *Initial Forecast Error* (7.129) reported in Table 3. This result is consistent with the notion that firms tend to revise their forecasts in order to reduce their forecast errors (Kato et al. 2009).

Panel B of Table 12 reports the results of Equation (4). Consistent with the results shown in Table 6, we report a negative and statistically significant coefficient on *Managerial Ability* (*p*-value < 0.01), suggesting that forecast accuracy based on the last forecast increases along with managerial ability. We obtain similar untabulated results when we use the alternative MA Score (based on raw values and six inputs) and alternative measures for managerial ability (principal component index).

Insert Table 12 about here

Considered along with the main results, the results in Table 12 provide further implications for managers' forecast behaviors and their consequences. The results suggest that less frequent forecast revisions from high-ability managers do not necessarily lead to increased forecast errors at the fiscal year-end, but rather that competent managers are also more accurate in terms of *last* forecast errors than are incompetent managers who utilize discretionary options. Overall, the results confirm our view that high-ability managers are good at assessing future performance and therefore do not need to rely on revisions and earnings management.

6. Conclusion

We have examined whether and how managerial ability affects the accuracy of management earnings forecasts. Baik et al. (2011) show that high-ability managers are more likely to issue earnings forecasts, with their accuracy increasing along with CEO ability. We extend Baik et al. (2011) by examining (1) whether this relationship is unique to the voluntary disclosure system in the United States, and (2) how high-ability managers increase their earnings forecast accuracy.

Using a large sample of listed firms in Japan, where management earnings forecasts are effectively mandated, we first find that managerial ability is negatively associated with forecast errors based on initial forecasts, suggesting that high-ability managers are more likely to issue accurate initial earnings forecasts. We then show that high-ability managers are less likely to revise their initial earnings forecasts *ex post*. Finally, we show that high-ability managers are less likely to conduct earnings management to increase the accuracy of their management earnings forecasts. Overall, our results suggest that high-ability managers are good at assessing future performance and therefore issue relatively accurate forecasts at the beginning of the fiscal year, whereas low-ability managers are more likely to depend on forecast revisions and earnings management to enhance the accuracy of their management forecasts.

This study has several limitations. First, we use the MA Score employed in Demerjian et al. (2012) to capture managerial ability. Future studies should develop a better proxy for manager ability. Second, we focus on Japanese firms to examine the generalizability of the results of prior studies. However, our sample may have a bias due to the specific features of management earnings forecasts in Japan.

Appendix A: MA Score estimation

To measure managerial ability, we follow Demerjian et al. (2012) and replicate their two-stage estimation process using Japanese data. For the first stage, we use DEA to calculate firm efficiency and solve the following optimization problem:

$$max\theta = \frac{(Sales)}{(v_1 CoGS + v_2 SG\&A + v_3 PPE + v_4 OpsLease + v_5 R\&D + v_6 Goodwill + v_7 OtherIntan)}, \quad \text{(A.1)}$$

where *Sales* is the net revenue earned by the firm; *CoGS* is the cost of goods sold; *SG&A* are selling, general, and administrative expenses; *PPE* is net plant, property, and equipment; *OpsLease* is net operating lease assets; *R&D* is net R&D capital assets (Lev and Sougiannis 1996); *Goodwill* is acquired intangible assets; and *OtherIntan* is other intangible assets. Demerjian et al. (2012) set a single output, *Sales*, and show that seven inputs contribute to revenue generation. For every firm-year observation, each input is assigned a weight, expressed as vector (v), to calculate the efficiency score. The maximization process determines each weight to maximize Equation (A.1) for every firm-year relative to its peer in an industry (i.e. varying weights). We then use these weights to calculate the firm-year efficiency score (*FE Score*) in the industry and scale using the most efficient firm observation; this yields a relative efficiency score between zero and one. Observations with a value of one are the most efficient, with the set of these firms forming the efficient frontier for the industry. Observations enveloped by the frontier (i.e. below the frontier) are inefficient in terms of generating output over the set of possible input combinations. The degree of inefficiency is calculated as the distance from the frontier; this indicates the extent to which the observation should increase revenue or decrease capital and expenses to reach the given input and output levels, respectively. Following Demerjian et al. (2012, footnote 11), we form the efficiency frontier using the variable returns-to-scale (VRS) model (Banker et al. 1984), where the frontier takes the form of a piecewise line connecting the most efficient observations in the industry.

Specifically, we use the input-oriented VRS model to calculate the efficiency score.[24]

Our DEA procedure differs from Demerjian et al.'s (2012) method in two respects. First, Demerjian et al. (2012) use the industry classification based on Fama and French (1997), but we use the TSE industry classification (33 industries) because we lack equivalent classifications for Japanese firms. Unlike other industry classifications, such as the Nikkei Industry Classification, the TSE industry classification yields a relatively well-balanced distribution of firms in each industry.[25] Second, while Demerjian et al. (2012) estimate net operating leases as the discounted present value of the required operating lease payments (appearing as footnotes to financial statements in the United States), Japanese firms do not disclose such information but instead disclose the total future operating lease payments and amounts due within one year. Thus, we follow Kusano et al. (2015) and calculate the present value of the net operating lease assets.

In the second stage, we remove the effect of firm-specific factors through Tobit regressions. Following Demerjian et al. (2012), we estimate the FE Score equation by industry:

$$\begin{aligned} \mathit{FE\ Score}_i = {} & \alpha + \beta_1 \ln(\mathit{Total\ Assets})_i + \beta_2 \mathit{Market\ Share}_i + \beta_3 \mathit{FCF\_D}_i + \beta_4 \ln(\mathit{Age})_i \\ & + \beta_5 \mathit{Business\ Segment\ Concentration}_i + \beta_6 \mathit{Foreign\ Currency\_D}_i + \mathit{Year}_i + \varepsilon_{i,} \end{aligned} \tag{A.2}$$

where the *FE Score* is measured using DEA in the first stage, *Total Assets* is the total assets at the end of year *t, Market Share* is the percentage of revenue earned by the firm in its industry (TSE industry classification) in year *t, FCF_D* is an indicator variable that takes a value of one when the

[24] In the VRS model, one must determine the orientation in calculating the efficiency score. That is, input-oriented models consider the horizontal distance between an inefficient observation and the efficiency frontier indicating the "excess" of inputs given the current level of outputs. Output-oriented models focus on the vertical distance indicating the "shortage" of outputs given the current level of inputs. Unlike the constant returns-to-scale model, the efficiency score can differ depending on this orientation.

[25] The sample size for each industry is important in DEA. When there are too few firms in the industry, a large percentage of firms will be on the frontier (Demerjian et al. 2012), resulting in a higher firm efficiency score. We adopt the TSE industry classification to avoid this sample-size effect.

firm has non-negative free cash flow in year *t* and zero otherwise; *Age* is the number of years since the firm has been established;[26] *Business Segment Concentration* is the sum of the squares of sales from each business segment as a percentage of total sales in year *t* (Bushman et al. 2004); *Foreign Currency_D* is an indicator variable that takes a value of one when the firm reports a non-zero value for foreign currency adjustments in year *t* and zero otherwise; and *Year* denotes a set of year indicators. Demerjian et al. (2012) consider these six factors as firm-specific and thus less relevant to manager-specific ability. *Total Asset* and *Market Share* control for the effect of bargaining power over suppliers and customers. *FCF_D* controls for the firm's investment capacity for pursuing positive net present value projects. *Age* reflects the life cycle of the firm; younger firms are less efficient due to the required start-up investment costs. Both *Business Segment Concentration* and *Foreign Currency_D* indicate the diversification and/or business complexity of the firm; the greater the diversification, the more challenging it is for management teams to allocate capital efficiently. Finally, *Year* controls for year fixed effects, as the *FE_Score* is estimated by industry in DEA. The residual from the estimation of Equation (A.2) generates Demerjian et al.'s (2012) managerial ability measurement.

[26] Our *Age* variable is slightly different from that in Demerjian et al. (2012), who use the number of years the firm has been listed on *Compustat*. Because we use the Japanese database *Nikkei NEEDS FinacialQUEST*, we cannot obtain the data used in Demerjian et al. (2012). Alternatively, we can calculate firm age directly since the database gives the date of establishment for each firm.

Appendix B: Discretionary accruals estimation

To measure discretionary accruals, we apply the following four models: the performance-matched modified Jones model in Kothari et al. (2005; Equation [B.1]), the modified Jones model in Dechow et al. (1995; Equation [B.2]), the CFO modified Jones model in Kasznik (1999; Equation [B.3]), and the modified Dechow-Dichev model in McNichols (2002; Equation [B.4]). We require at least 15 observations for each industry-year group to estimate each of the following equations cross-sectionally:

$$TA_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2(\Delta Sales_{i,t} - \Delta AR_{i,t}) + \beta_3 PPE_{i,t} + \beta_4 ROA_{i,t-1} + \varepsilon_{i,t} \quad \text{(B.1)}$$

$$TA_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2(\Delta Sales_{i,t} - \Delta AR_{i,t}) + \beta_3 PPE_{i,t} + \varepsilon_{i,t} \quad \text{(B.2)}$$

$$TA_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2(\Delta Sales_{i,t} - \Delta AR_{i,t}) + \beta_3 PPE_{i,t} + \beta_4 \Delta CFO_{i,t} + \varepsilon_{i,t} \quad \text{(B.3)}$$

$$\Delta WC_{i,t} = \alpha + \beta_1 CFO_{i,t-1} + \beta_2 CFO_{i,t} + \beta_3 CFO_{i,t+1} + \beta_4 \Delta Sales_{i,t} + \beta_5 PPE_{i,t} + \varepsilon_{i,t}, \quad \text{(B.4)}$$

where *TA* is total accruals scaled by lagged total assets; *Assets* is total assets; *ΔSales* is change in sales scaled by lagged total assets; *ΔAR* is change in account receivables scaled by lagged total assets; *PPE* is net property, plant, and equipment scaled by lagged total assets; *ROA* is net income scaled by total assets; *ΔCFO* is change in cash flow from operations scaled by lagged total assets; *ΔWC* is change in working capital scaled by lagged total assets; and *CFO* is cash flow from operations scaled by lagged total assets. We measure discretionary accruals as the value of the estimated residuals. To construct *Improve*, we multiply each discretionary accrual by lagged total assets.

Appendix C: Real activities manipulation estimation

We measure real activities manipulation by following the method of Roychowdhury (2006). Specifically, we expect that high-ability managers are less likely to adopt earnings manipulations and discretionary activities, such as controlling sales, reducing discretionary costs/expenses, and overproduction. We measure these manipulations using the following three models: the abnormal cash flow model (Equation [C.1]), abnormal discretionary expenses model (Equation [C.2]), and abnormal production cost model (Equation [C.3]). We again require at least 15 observations for each industry-year group to estimate the following equations cross-sectionally:

$$CFO_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2 Sales_{i,t} + \beta_3 \Delta Sales_{i,t} + \varepsilon_{i,t} \quad (C.1)$$

$$DISEXP_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2 Sales_{i,t-1} + \varepsilon_{i,t} \quad (C.2)$$

$$PROD_{i,t} = \alpha + \beta_1(1/Assets_{i,t-1}) + \beta_2 Sales_{i,t} + \beta_3 \Delta Sales_{i,t} + \beta_3 \Delta Sales_{i,t-1} + \varepsilon_{i,t} \ , \quad (C.3)$$

where *CFO* is cash flow from operations scaled by lagged total assets; *Assets* is total assets; *Sales* is sales scaled by lagged total assets; *ΔSales* is change in sales scaled by lagged total assets; *DISEXP* is selling, general, and administrative expenses scaled by lagged total assets; and *PROD* is the sum of the cost of goods and change in inventory scaled by lagged total assets. We define real activities manipulation as the value of the estimated residuals and multiply each residual by lagged total assets to construct *Improve*.

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TABLE 1
Definitions of testing variables

Description	*Variable*	*Definition*
Management Earnings Forecasts	*Initial Forecast Error*	The absolute value of forecast error based on the initial forecast, multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income.
	Num. Forecast Revisions	The number of management earnings forecast revised for the earnings in year *t*.
	Magnitude Forecast Rev.	The absolute value of the management forecast revisions, multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income.
	Improve	The value of forecast improvement through earnings management, defined as the differences between forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). Discretionary accruals are based on Kothari et al. (2005).
Managerial Ability	*Managerial Ability*	The decile rank by industry and year of the MA Score based on Demerjian et al. (2012). See Appendix A for the detail.
Control Variables	*Size*	The natural log of total sales.
	Loss_D	An indicator variable that takes a value of one if the firm reports net losses, and zero otherwise.
	Increase_D	An indicator variable that takes a value of one if the firm's net income has increased compared to the previous year, and zero otherwise.
	StdDevEarn	The standard deviation of annual changes in net income scaled by lagged total assets over past five years.
	Beta	The market model beta estimated using daily stock return and market return (TOPIX) over the past 240 days beginning at the end of the previous fiscal year.
	StdDevResidual	The standard deviation of the residual from market model estimated over 240 days beginning at the end of the previous fiscal year.
	Sales_Con	The Herfindahl index measured as the sum of the squares of the sales shares of all firms within the same industry (TSE Industry Classification, 33 industries)
	ManagerOwn%	The percentage of ownership held by managers.
	OutsideDir%	The percentage of outside directors on the board of directors.
	InstOwn%	The percentage of ownership held by institutional investors.
Additional Analysis	*Last Forecast Error*	The absolute value of forecast error based on the last forecast, multiplied by 100 (i.e. 100*|actual earnings – last management earnings forecast|/lagged market value of equity), where earnings are defined as net income. The last forecasts denote forecasts issued immediately prior to the fiscal year-end.
	Timeliness	The difference between the last management forecast date and the date of the fiscal year-end.

TABLE 2
Sample selection reconciliation

Criteria	# firm-year observations
Firm-years that listed on Japanese stock markets for 2006–2014	30,751
Less:	
Fiscal year period does not have just 12 months	(2,956)
The industry classification cannot be identified nor is as financial	(483)
Firm-years with financial statements prepared in U.S. GAAP or IFRS	(372)
Missing data available for the estimation of Eq. (1)	(9,145)
Final Sample	17,795

TABLE 3
Descriptive statistics

	Mean	SD	Min	P25	Median	P75	Max	N
Initial Forecast Error$_{i,t}$	7.129	14.487	0.017	0.842	2.404	6.532	146.992	17,795
Num. Forecast Revisions$_{i,t}$	1.040	0.873	0.000	0.000	1.000	2.000	6.000	17,795
Magnitude Forecast Rev.$_{i,t}$	4.784	10.446	0.000	0.000	1.258	4.445	100.291	17,795
Improve$_{i,t}$	11.598	19.365	−11.338	1.469	5.102	13.692	184.953	17,795
Managerial Ability$_{i,t-1}$	5.454	2.873	1.000	3.000	5.000	8.000	10.000	17,795
Size$_{i,t-1}$	10.534	1.577	6.624	9.394	10.433	11.553	14.544	17,795
Loss_D$_{i,t-1}$	0.185	0.389	0.000	0.000	0.000	0.000	1.000	17,795
Increase_D$_{i,t-1}$	0.547	0.498	0.000	0.000	1.000	1.000	1.000	17,795
StdDevEarn$_{i,t-1}$	0.045	0.063	0.002	0.012	0.025	0.050	0.458	17,795
Beta$_{i,t-1}$	0.673	0.456	−0.218	0.294	0.645	1.003	2.032	17,795
StdDevResidual$_{i,t-1}$	0.024	0.011	0.007	0.016	0.021	0.028	0.086	17,795
Sales_Conc$_{i,t-1}$	0.064	0.040	0.023	0.039	0.051	0.078	0.294	17,795
ManagerOwn%$_{i,t-1}$	0.037	0.085	0.000	0.000	0.002	0.022	0.496	17,795
OutsideDir%$_{i,t-1}$	0.077	0.118	0.000	0.000	0.000	0.143	0.500	17,795
InstOwn%$_{i,t-1}$	0.132	0.146	0.000	0.010	0.077	0.211	0.602	17,795

Notes: *Initial Forecast Error* is the absolute value of forecast error based on the initial forecast, multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Num. Forecast Revisions* is the number of management earnings forecast revised for the earnings in year *t*. *Magnitude Forecast Rev.* is the absolute value of the management forecast revisions, multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Improve* is the value of forecast improvement through earnings management, defined as the differences between forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). *Managerial Ability* is the decile rank by industry and year of the MA Score based on Demerjian et al. (2012). *Size* is the log of total sales. *Loss_D* is an indicator variable that takes a value of one if the firm reports net losses, and zero otherwise. *Increase_D* is an indicator variable that takes a value of one if the firm's net income has increased compared to the previous year, and zero otherwise. *StdDevEarn* is the standard deviation of annual change in earnings scaled by lagged total assets over past five years. *Beta* is the market model beta estimated using daily stock return and market return (TOPIX) over the past 240 days beginning at the end of the previous fiscal year. *StdDevResidual* is the standard deviation of the residual from market model estimated over 240 days beginning at the end of the previous fiscal year. *Sales_Conc* is the Herfindahl index measured as the sum of the squares of the sales shares of all firms within the same industry (TSE Industry Classification). *ManagerOwn%* is the percentage of managerial ownership. *OutsideDir%* is the percentage of outside directors on the board of directors. *InstOwn%* is the percentage of ownership held by institutional investors. All continuous variables are winsorized by year at the bottom 1 percent and top 99 percent levels.

TABLE 4

Correlations matrix among the variables for regression analyses

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Forecast Error$_{i,t}$	(1)		**0.388**	**0.689**	**0.221**	**−0.085**	**−0.198**	**0.284**	**−0.132**
Num. Forecast Revisions$_{i,t}$	(2)	**0.233**		**0.752**	**0.042**	**−0.025**	**0.098**	**0.080**	**−0.057**
Magnitude Forecast Rev.$_{i,t}$	(3)	**0.852**	**0.354**		**0.180**	**−0.052**	**−0.070**	**0.210**	**−0.119**
Improve$_{i,t}$	(4)	**0.403**	**0.035**	**0.346**		**−0.032**	**−0.077**	**0.149**	**−0.089**
Managerial Ability$_{i,t-1}$	(5)	**−0.087**	−0.025	**−0.076**	**−0.028**		**0.034**	**−0.200**	**0.114**
Size$_{i,t-1}$	(6)	**−0.156**	**0.110**	**−0.120**	**−0.083**	0.000		**−0.192**	**0.044**
Loss_D$_{i,t-1}$	(7)	**0.307**	**0.078**	**0.281**	**0.195**	**−0.200**	**−0.197**		**−0.320**
Increase_D$_{i,t-1}$	(8)	**−0.120**	**−0.055**	**−0.118**	**−0.083**	**0.114**	**0.044**	**−0.320**	
StdDevEarn$_{i,t-1}$	(9)	**0.208**	0.017	**0.179**	**0.095**	−0.018	**−0.316**	**0.240**	−0.002
Beta$_{i,t-1}$	(10)	**−0.033**	**0.134**	−0.014	**−0.064**	0.015	**0.344**	−0.017	**0.061**
StdDevResidual$_{i,t-1}$	(11)	**0.297**	0.020	**0.255**	**0.230**	−0.010	**−0.443**	**0.304**	**−0.028**
Sales_Conc$_{i,t-1}$	(12)	0.000	**0.116**	0.015	**−0.069**	−0.013	**−0.039**	0.010	−0.006
ManagerOwn%$_{i,t-1}$	(13)	**0.065**	**−0.079**	**0.041**	**0.037**	0.012	**−0.323**	**0.054**	−0.014
OutsideDir%$_{i,t-1}$	(14)	0.010	0.004	0.009	0.002	0.005	**−0.031**	**0.030**	0.002
InstOwn%$_{i,t-1}$	(15)	**−0.141**	**0.121**	**−0.109**	**−0.172**	**0.044**	**0.631**	**−0.153**	**0.056**

		(9)	(10)	(11)	(12)	(13)	(14)	(15)
Initial Forecast Error$_{i,t}$	(1)	**0.263**	**−0.039**	**0.309**	**0.020**	**0.126**	**−0.029**	**−0.220**
Num. Forecast Revisions$_{i,t}$	(2)	**0.058**	**0.134**	**0.038**	**0.094**	**−0.093**	0.000	**0.122**
Magnitude Forecast Rev.$_{i,t}$	(3)	**0.177**	**0.041**	**0.197**	**0.058**	**0.027**	**−0.020**	**−0.064**
Improve$_{i,t}$	(4)	**0.076**	**−0.068**	**0.176**	**−0.082**	**0.061**	**−0.019**	**−0.194**
Managerial Ability$_{i,t-1}$	(5)	**−0.048**	**0.015**	0.006	−0.009	−0.005	0.000	**0.050**
Size$_{i,t-1}$	(6)	**−0.323**	**0.377**	**−0.431**	**−0.110**	**−0.499**	**0.021**	**0.644**
Loss_D$_{i,t-1}$	(7)	**0.296**	**−0.023**	**0.275**	**0.028**	**0.058**	**0.015**	**−0.163**
Increase_D$_{i,t-1}$	(8)	**−0.028**	**0.059**	**−0.053**	−0.012	**−0.032**	−0.002	**0.048**
StdDevEarn$_{i,t-1}$	(9)		**0.168**	**0.445**	**0.096**	**0.087**	**0.067**	**−0.139**
Beta$_{i,t-1}$	(10)	**0.128**		**0.136**	**0.058**	**−0.337**	**0.037**	**0.504**
StdDev(Residual)$_{i,t-1}$	(11)	**0.484**	**0.127**		**0.062**	**0.200**	0.013	**−0.275**
Sales_Conc$_{i,t-1}$	(12)	0.023	**0.073**	0.024		**−0.029**	**0.066**	**0.017**
ManagerOwn%$_{i,t-1}$	(13)	**0.127**	**−0.149**	**0.194**	**−0.049**		**−0.158**	**−0.388**
OutsideDir%$_{i,t-1}$	(14)	**0.136**	0.017	**0.085**	0.012	**−0.034**		**0.051**
InstOwn%$_{i,t-1}$	(15)	**−0.125**	**0.423**	**−0.253**	0.006	**−0.185**	0.023	

Notes: This table reports Pearson correlation coefficients below the diagonal and Spearman rank correlation coefficients above the diagonal. Correlations are presented in bold when they are statistically significant at the 5 percent level using a two-tailed test. *Initial Forecast Error* is the absolute value of forecast error based on the initial forecast, multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast| /lagged market value of equity), where earnings are defined as net income. *Num. Forecast Revisions* is the number of management earnings forecast revised for the earnings in year *t*. *Magnitude Forecast Rev.* is the absolute value of the management forecast revisions, multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Improve* is the value of forecast improvement through earnings management, defined as the differences between forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). *Managerial Ability* is the decile rank by industry and year of the MA Score based on Demerjian et al. (2012). *Size* is the log of total sales. *Loss_D* is an indicator variable that takes a value of one if the firm reports net losses, and zero otherwise. *Increase_D* is an indicator variable that takes a value of one if the firm's net income has increased compared to the previous year, and zero otherwise. *StdDevEarn* is the standard deviation of annual change in earnings scaled by lagged total assets over past five years. *Beta* is the market model beta estimated using daily stock return and market return (TOPIX) over the past 240 days beginning at the end of the previous fiscal year. *StdDevResidual* is the standard deviation of the residual from market model estimated over 240 days beginning at the end of the previous fiscal year. *Sales_Conc* is the Herfindahl index measured as the sum of the squares of the sales shares of all firms within the same industry (TSE Industry Classification). *ManagerOwn%* is the percentage of managerial ownership. *OutsideDir%* is the percentage of outside directors on the board of directors. *InstOwn%* is the percentage of ownership held by institutional investors. All continuous variables are winsorized by year at the 1 percent and 99 percent levels.

TABLE 5
Univariate tests

	Low-Ability Managers (*Managerial Ability$_{i,t-1}$* < Median)		*High-Ability Managers* (*Managerial Ability$_{i,t-1}$* > Median)		Two group comparison	
	Mean	Median	Mean	Median	[*t*-value]	[*z*-value]
Initial Forecast Error$_{i,t}$	8.180	2.654	6.063	2.169	[9.788]***	[9.855]***
Num. Forecast Revisions$_{i,t}$	1.049	1.000	1.024	1.000	[1.941]*	[1.959]*
Magnitude Forecast Rev.$_{i,t}$	5.408	1.376	4.152	1.154	[8.051]***	[5.446]***
Improve$_{i,t}$	12.151	5.486	11.038	4.818	[3.837]***	[4.361]***
Size$_{i,t-1}$	10.518	10.332	10.550	10.539	[−1.345]	[−5.042]***
Loss_D$_{i,t-1}$	0.248	0.000	0.122	0.000	[22.045]***	[21.712]***
Increase_D$_{i,t-1}$	0.499	0.000	0.596	1.000	[−13.077]***	[−13.013]***
StdDevEarn$_{i,t-1}$	0.046	0.026	0.044	0.024	[1.983]**	[5.129]***
Beta$_{i,t-1}$	0.666	0.637	0.680	0.653	[−2.030]**	[−2.152]**
StdDev(Residual)$_{i,t-1}$	0.024	0.021	0.023	0.021	[2.030]**	[−0.049]
Sales_Conc$_{i,t-1}$	0.064	0.051	0.063	0.051	[0.765]	[0.581]
ManagerOwn%$_{i,t-1}$	0.036	0.002	0.037	0.001	[−0.457]	[2.187]**
OutsideDir%$_{i,t-1}$	0.076	0.000	0.077	0.000	[−0.670]	[−0.395]
InstOwn%$_{i,t-1}$	0.125	0.068	0.139	0.090	[−6.605]***	[−7.483]***
N	8,596		8,839			

Notes: This table shows results of univariate comparison tests. We construct two subsamples of high- and low-ability managers based on the median of *Managerial Ability$_{i,t-1}$*. We test the differences of variables using Welch's *t*-Test and Wilcoxon rank sum test for means and medians, respectively. *Initial Forecast Error* is the absolute value of forecast error based on the initial forecast, multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast| /lagged market value of equity), where earnings are defined as net income. *Num. Forecast Revisions* is the number of management earnings forecast revised for the earnings in year *t*. *Magnitude Forecast Rev.* is the absolute value of the management forecast revisions, multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Improve* is the value of forecast improvement through earnings management, defined as the differences between forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). *Managerial Ability* is the decile rank by industry and year of the MA Score based on Demerjian et al. (2012). *Size* is the log of total sales. *Loss_D* is an indicator variable that takes a value of one if the firm reports net losses, and zero otherwise. *Increase_D* is an indicator variable that takes a value of one if the firm's net income has increased compared to the previous year, and zero otherwise. *StdDevEarn* is the standard deviation of annual change in earnings scaled by lagged total assets over past five years. *Beta* is the market model beta estimated using daily stock return and market return (TOPIX) over the past 240 days beginning at the end of the previous fiscal year. *StdDevResidual* is the standard deviation of the residual from market model estimated over 240 days beginning at the end of the previous fiscal year. *Sales_Conc* is the Herfindahl index measured as the sum of the squares of the sales shares of all firms within the same industry (TSE Industry Classification). *ManagerOwn%* is the percentage of managerial ownership. *OutsideDir%* is the percentage of outside directors on the board of directors. *InstOwn%* is the percentage of ownership held by institutional investors. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 6
Regression results

	Predict sign	(1)		(2)		(3)		(4)	
		Initial Forecast Error$_{i,t}$		*Num. Forecast Revisions$_{i,t}$*		*Magnitude Forecast Rev.$_{i,t}$*		*Improve$_{i,t}$*	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Managerial Ability$_{i,t-1}$	−	−0.495	[−6.057]***	−0.012	[−3.301]***	−0.315	[−9.096]***	−0.368	[−5.590]***
Size$_{i,t-1}$	+/−	2.964	[1.607]	0.113	[1.768]*	2.568	[1.992]**	1.007	[0.718]
Loss_D$_{i,t-1}$	+	3.172	[4.064]***	0.017	[0.461]	2.428	[4.849]***	3.692	[5.564]***
Increase_D$_{i,t-1}$	−	−0.246	[−0.448]	−0.034	[−1.641]	−0.226	[−0.658]	−0.309	[−0.767]
StdDevEarn$_{i,t-1}$	+	−28.183	[−1.952]*	−0.788	[−2.286]**	−17.131	[−1.650]*	−26.617	[−3.792]***
Beta$_{i,t-1}$	+	−2.073	[−1.582]	−0.005	[−0.103]	−1.502	[−1.643]	−1.858	[−1.132]
StdDevResidual$_{i,t-1}$	+	14.672	[0.230]	−1.919	[−1.215]	−8.197	[−0.177]	46.731	[0.852]
Sales_Conc$_{i,t-1}$	−	−41.855	[−1.736]*	−1.751	[−1.732]*	−28.054	[−1.727]*	2.171	[0.063]
ManagerOwn%$_{i,t-1}$	+	1.296	[0.313]	−0.003	[-0.009]	2.791	[0.941]	−0.793	[−0.201]
OutsideDir%$_{i,t-1}$	−	−2.283	[−1.001]	0.010	[0.115]	−0.028	[−0.023]	−2.541	[−1.109]
InstOwn%$_{i,t-1}$	−	−14.095	[−2.975]***	−0.284	[−1.645]*	−8.109	[−2.124]**	−25.141	[−3.237]***
Firm Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adjusted R^2		0.337		0.267		0.276		0.342	
N		17,795		17,795		17,795		17,795	

Notes: This table reports the regression results for Equation (1). *Initial Forecast Error* is the absolute value of forecast error based on the initial forecast, multiplied by 100 (i.e. 100*|actual earnings – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Num. Forecast Revisions* is the number of management earnings forecast revised for the earnings in year *t*. *Magnitude Forecast Rev.* is the absolute value of the management forecast revisions, multiplied by 100 (i.e. 100*|last management earnings forecast – initial management earnings forecast|/lagged market value of equity), where earnings are defined as net income. *Improve* is the value of forecast improvement through earnings management, defined as the differences between forecast errors based on pre-managed earnings and actual reported earnings (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). *Managerial Ability* is the decile rank by industry and year of the MA Score based on Demerjian et al. (2012). *Size* is the log of total sales. *Loss_D* is an indicator variable that takes a value of one if the firm reports net losses and zero otherwise. *Increase_D* is an indicator variable that takes a value of one if the firm's net income has increased compared to the previous year and zero otherwise. *StdDevEarn* is the standard deviation of annual change in earnings scaled by lagged total assets over past five years. *Beta* is the market model beta estimated using daily stock return and market return (TOPIX) over the past 240 days beginning at the end of the previous fiscal year. *StdDevResidual* is the standard deviation of the residual from market model estimated over 240 days beginning at the end of the previous fiscal year. *Sales_Conc* is the Herfindahl index measured as the sum of the squares of the sales shares of all firms within the same industry (TSE Industry Classification). *ManagerOwn%* is the percentage of managerial ownership. *OutsideDir%* is the percentage of outside directors on the board of directors. *InstOwn%* is the percentage of ownership held by institutional investors. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 7

Two-stage least-squares analysis using instrument variable

	First stage		Second stage							
	Dependent Variable = *Managerial Ability*$_{i,t-1}$		(1) *Initial Forecast Error*$_{i,t}$		(2) *Num. Forecast Revisions*$_{i,t}$		(3) *Magnitude Forecast Rev.*$_{i,t}$		(4) *Improve*$_{i,t}$	
	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Ave.MA$_{i,t-1}$	22.344	[22.405]***								
Pred.MA$_{i,t-1}$			−1.870	[−5.546]***	−0.033	[−2.186]**	−1.164	[−4.606]***	−1.090	[−2.462]**
Size$_{i,t-1}$	1.254	[17.843]***	4.781	[6.902]***	0.102	[2.400]**	3.689	[7.106]***	1.960	[2.155]**
Loss_D$_{i,t-1}$	−0.953	[−23.263]***	1.818	[4.006]***	0.025	[0.915]	1.591	[4.679]***	2.981	[5.002]***
Increase_D$_{i,t-1}$	0.277	[9.974]***	0.147	[0.635]	−0.037	[−2.604]***	0.016	[0.093]	−0.103	[−0.339]
StdDevEarn$_{i,t-1}$	2.067	[4.973]***	−25.174	[−7.806]***	−0.807	[−4.077]***	−15.274	[−6.320]***	−25.037	[−5.913]***
Beta$_{i,t-1}$	0.257	[4.791]***	−1.676	[−4.027]***	−0.007	[−0.278]	−1.257	[−4.030]***	−1.649	[−3.018]***
StdDevResidual$_{i,t-1}$	5.808	[2.829]***	22.347	[1.431]	−1.967	[−2.051]**	−3.459	[-0.295]	50.759	[2.475]**
Sales_Conc$_{i,t-1}$	0.497	[0.266]	−38.856	[−2.755]***	−1.770	[−2.044]**	−26.202	[−2.479]**	3.745	[0.202]
ManagerOwn%$_{i,t-1}$	0.000	[0.000]	1.227	[0.412]	−0.002	[−0.011]	2.749	[1.232]	−0.829	[−0.212]
OutsideDir%$_{i,t-1}$	0.144	[0.689]	−2.220	[−1.403]	0.010	[0.103]	0.011	[0.009]	−2.508	[−1.207]
InstOwn%$_{i,t-1}$	3.712	[11.738]***	−8.534	[−3.105]***	−0.319	[−1.889]*	−4.675	[−2.270]**	−22.222	[−6.158]***
Firm Fixed Effects	Included		Included		Included		Included		Included	
Year Fixed Effects	Included		Included		Included		Included		Included	
Adj. R^2			0.077		0.071		0.153		0.032	
N			17,619		17,619		17,619		17,619	
Under-identification Test:										
χ2 statistic	486.464									
p-value	(<0.001)									
Weak Instrument Test:										
F statistic	501.973									
p-value	(<0.001)									

Notes: This table reports the results of two-stage least-squares analysis using instrument variable. We use *Ave.MA* as an instrument, defined as the average ability of all managers in the same industry, year, and geographical region based on the *Labor Force Survey* by the Statistics Bureau of Japan. In the first stage, the dependent variable is *Managerial Ability*. In the second stage, the predicted *Managerial Ability* from the first stage (*Pred.MA*) is used as an independent variable. All other variables are defined in Table 1. Critical values for the under-identification test are based on Stock and Yago (2005). The weak instrument test is based on the Cragg-Donald Wald F statistic. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 8
Regression analysis using CEO turnover observations

	Predict Sign	(1)		(2)		(3)		(4)	
		ΔInitial Forecast Error$_{i,t}$		*ΔNum. Forecast Revisions*$_{i,t}$		*ΔMagnitude Forecast Rev.*$_{i,t}$		*ΔImprove*$_{i,t}$	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Constant		3.332	[1.350]	0.185	[2.020]**	2.199	[1.137]	1.096	[0.403]
ΔManagerial Ability$_{i,t}$	−	−0.476	[−2.658]***	−0.019	[−3.395]***	−0.355	[−2.905]***	−0.356	[−1.679]*
ΔSize$_{i,t}$	+/−	6.594	[2.295]**	0.125	[0.934]	0.173	[0.068]	4.716	[0.896]
Loss_D$_{i,t-1}$	+	8.292	[3.712]***	0.254	[3.432]***	6.103	[2.746]***	2.358	[1.430]
Increase_D$_{i,t-1}$	−	−7.838	[−3.584]***	−0.231	[−3.507]***	−5.078	[−4.104]***	−1.374	[−1.223]
ΔStdDevEarn$_{i,t}$	+	−175.346	[−3.773]***	−0.170	[−0.194]	−107.793	[−3.205]***	−50.217	[−2.003]**
ΔBeta$_{i,t}$	+	−2.020	[−0.963]	−0.101	[−1.435]	−1.883	[−2.003]**	−0.098	[−0.043]
ΔStdDevResidual$_{i,t}$	+	169.016	[2.885]***	7.536	[2.620]***	160.464	[3.314]***	345.871	[4.227]***
ΔSales_Conc$_{i,t}$	−	−12.212	[−1.422]	−1.073	[−3.392]***	−12.003	[−1.839]*	−37.725	[−2.523]**
ΔManagerOwn%$_{i,t}$	+	6.201	[0.680]	0.978	[1.037]	−1.030	[−0.100]	16.492	[1.756]*
ΔOutsideDir%$_{i,t}$	−	−20.355	[−2.460]**	−0.186	[−0.795]	−10.299	[−1.374]	0.053	[0.005]
ΔInstOwn%$_{i,t}$	−	−10.964	[−0.772]	0.380	[0.487]	−3.675	[−0.370]	−4.172	[−0.274]
Industry Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adj. R^2		0.171		0.075		0.153		0.032	
N		2,448		2,448		2,448		2,448	

Notes: This table reports the regression results for Equation (2) using a subsample of firm-years that show CEO turnover. All variables except for indicator variables are annual changes from year *t−1* to year *t*, where *t* is the year in which the CEO changed. All variables are defined in Table 1. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 9
Regression analysis using matched-pair subsample

Panel A: Estimation of propensity score

	Predict Sign	*High-Ability Manager*$_{i,t-1}$ Coef.	[z-value]
Constant		1.179	[4.412]***
$Tenure_{i,t-1}$	+	−0.007	[−2.792]***
$Age_{i,t-1}$	+	0.003	[1.030]
$Prior\ Position_{i,t-1}$	+	0.128	[2.998]***
$\ln(Assets)_{i,t-1}$	+	−0.244	[−11.559]***
$Current\ Return_{i,t-1}$	+	0.021	[0.392]
$Past\ Return_{i,t-1}$	+	0.147	[3.253]***
$ROA_{i,t-1}$	+	9.158	[14.392]***
$MtB_{i,t-1}$	+	0.121	[6.413]***
$R\&D\_D_{i,t-1}$	+	−0.611	[−9.628]***
$R\&D\_D*R\&D_{i,t-1}$	+	−19.028	[−13.432]***
$Adv\_D_{i,t-1}$	+	−0.167	[−3.443]***
$Adv\_D*Adv_{i,t-1}$	+	−4.908	[−3.286]***
$Loss\_D_{i,t-1}$	−	0.046	[0.618]
$Increase\_D_{i,t-1}$	+	0.119	[2.807]***
$StdDevEarn_{i,t-1}$	?	0.361	[0.996]
$Beta_{i,t-1}$	?	−0.002	[−0.035]
$InstOwn\%_{i,t-1}$	?	1.783	[9.115]***
Industry Fixed Effects		Included	
Year Fixed Effects		Included	
Pseudo R^2		0.071	
N		16,893	

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Panel B: Mean comparison across matched pairs

	Treatment Group (Firms with high-ability managers)	Control Group (Firms with relatively low-ability managers)	Differences
	Mean	Mean	[*t*-value]
$Tenure_{i,t-1}$	7.328	7.297	[0.182]
$Age_{i,t-1}$	60.786	60.707	[0.449]
$Prior\ Position_{i,t-1}$	0.327	0.353	[−2.541]**
$\ln(Assets)_{i,t-1}$	10.349	10.293	[1.749]*
$Current\ Return_{i,t-1}$	0.076	0.074	[0.190]
$Past\ Return_{i,t-1}$	0.147	0.150	[−0.194]
$ROA_{i,t-1}$	0.030	0.026	[3.089]***
$MtB_{i,t-1}$	0.115	0.117	[−0.310]
$R\&D\_D_{i,t-1}$	0.622	0.617	[0.432]
$R\&D\_D{*}R\&D_{i,t-1}$	1.374	1.362	[0.391]
$Adv\_D_{i,t-1}$	0.604	0.596	[0.766]
$Adv\_D{*}Adv_{i,t-1}$	0.011	0.011	[−0.57]
$Loss\_D_{i,t-1}$	0.373	0.371	[0.183]
$Increase\_D_{i,t-1}$	0.006	0.006	[−0.438]
$StdDevEarn_{i,t-1}$	0.047	0.048	[−0.877]
$Beta_{i,t-1}$	0.665	0.661	[0.371]
$InstOwn\%_{i,t-1}$	0.135	0.132	[0.829]
N	4,101	4,101	

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Panel C: Regression analysis using matched-pair subsample

	Predict Sign	(1) *Initial Forecast Error$_{i,t}$* Coef.	[*t*-value]	(2) *Num. Forecast Revisions$_{i,t}$* Coef.	[*t*-value]	(3) *Magnitude Forecast Rev.$_{i,t}$* Coef.	[*t*-value]	(4) *Improve$_{i,t}$* Coef.	[*t*-value]
Managerial Ability$_{i,t-1}$	−	−0.326	[−3.166]***	−0.018	[−2.346]**	−0.166	[−2.788]***	−0.232	[−1.796]*
Size$_{i,t-1}$	+/−	2.337	[0.889]	0.128	[1.314]	1.498	[1.007]	−1.396	[−0.627]
Loss_D$_{i,t-1}$	+	3.997	[3.363]***	0.029	[0.608]	3.558	[4.753]***	2.575	[1.616]
Increase_D$_{i,t-1}$	−	−0.505	[−0.815]	−0.035	[−1.419]	−0.481	[−1.183]	−0.821	[−1.676]*
StdDevEarn$_{i,t-1}$	+	−21.091	[−1.677]*	−0.444	[−1.048]	−10.714	[−1.350]	−17.201	[−1.862]*
Beta$_{i,t-1}$	+	−1.667	[−1.423]	0.005	[0.111]	−1.276	[−1.401]	0.475	[0.445]
StdDevResidual$_{i,t-1}$	+	−25.340	[−0.438]	−2.831	[−1.365]	−42.521	[−1.032]	−39.796	[−1.039]
Sales_Conc$_{i,t-1}$	−	−44.181	[−1.867]*	−0.984	[−0.527]	−50.893	[−2.705]***	−17.091	[−0.330]
ManagerOwn%$_{i,t-1}$	+	6.767	[0.850]	0.026	[0.054]	5.242	[1.403]	1.216	[0.144]
OutsideDir%$_{i,t-1}$	−	−2.322	[−0.394]	−0.173	[−0.915]	−2.075	[−0.611]	−0.200	[−0.055]
InstOwn%$_{i,t-1}$	−	−7.067	[−1.294]	−0.290	[−1.105]	−3.356	[−0.729]	−18.052	[−2.834]***
Firm Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adj. R^2		0.332		0.289		0.277		0.343	
N		8,202		8,202		8,202		8,202	

Notes: This table reports the results of matched-pair subsample based on propensity score. Panel A shows logit estimation results of Equation (3), where dependent variable is *High-Ability Manager*, an indicator variable that takes a value of one if the MA Score is in the top quartile and zero otherwise (Demerjian et al. 2020). Panel B compares the means between treatment and control groups using *t*-Test. Panel C presents regression results using the matched-pair subsample based on estimated propensity score, derived from the logit estimation. In the sample, 4,101 firm-years are deemed high-ability (*High-Ability Manager* = 1) and matched to the relatively low-ability managers based on the closest propensity score, without replacement. As a result, the matched-pair subsample consists of 8,202 firm-years. *Tenure* is the length of time the CEO has been in his/her position as of year *t−1*; *Age* is the CEO's age as of year *t−1*; *Prior Position* is an indicator variable that takes a value of one if the CEO was appointed from outside of the firm within past three years and zero otherwise; *Assets* is the firm's total assets; *Current Return* and *Past Return* are the current and past year's stock returns, respectively; *ROA* is net income scaled by average total assets, *MtB* is the market value of equity scaled by the book value of equity; *R&D_D* (*Adv_D*) is an indicator variable that take a value of one if the firm reports R&D expenses (advertising expenses) and zero otherwise; and *R&D* and *Adv* are the ratios of R&D and advertising expenses to sales, respectively. All other variables are defined in Table 1. *z*-values and *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 10
Robustness tests using alternative measurement of Managerial Ability

Panel A: Managerial Ability using 6 inputs

	Predict Sign	(1)		(2)		(3)		(4)	
		Initial Forecast Error$_{i,t}$		*Num. Forecast Revisions$_{i,t}$*		*Magnitude Forecast Rev.$_{i,t}$*		*Improve$_{i,t}$*	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
MA_6inputs$_{i,t-1}$	−	−0.580	[−6.112]***	−0.013	[−2.879]***	−0.363	[−6.737]***	−0.395	[−7.270]***
Contorls		Included		Included		Included		Included	
Firm Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adj. R^2		0.338		0.267		0.277		0.342	
N		17,795		17,795		17,795		17,795	

Panel B: Raw value of Managerial Ability

	Predict Sign	(1)		(2)		(3)		(4)	
		Initial Forecast Error$_{i,t}$		*Num. Forecast Revisions$_{i,t}$*		*Magnitude Forecast Rev.$_{i,t}$*		*Improve$_{i,t}$*	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
MA_RawValue$_{i,t-1}$	−	−20.444	[−5.787]***	−0.430	[−2.550]**	−14.009	[−6.099]***	−15.721	[−5.900]***
Contorls		Included		Included		Included		Included	
Firm Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adj. R^2		0.338		0.267		0.277		0.342	
N		17,795		17,795		17,795		17,795	

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Panel C: Principal component index

	Predict Sign	(1)		(2)		(3)		(4)	
		Initial Forecast Error$_{i,t}$		*Num. Forecast Revisions$_{i,t}$*		*Magnitude Forecast Rev.$_{i,t}$*		*Improve$_{i,t}$*	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Principal Component$_{i,t-1}$	−	−0.494	[−6.798]***	−0.010	[−2.482]**	−0.281	[−6.733]***	−0.514	[−7.428]***
Contorls		Included		Included		Included		Included	
Firm Fixed Effects		Included		Included		Included		Included	
Year Fixed Effects		Included		Included		Included		Included	
Adj. R^2		0.339		0.269		0.273		0.344	
N		17,537		17,537		17,537		17,537	

Notes: This table reports the regression results using alternative measures for *Managerial Ability*. *MA_6inputs* is the decile rank by industry and year of the MA Score based on DEA using 6 inputs (i.e. without operating lease assets). *MA_RawValue* is the raw value of the MA Score which is continuous. *Principal Component* is the decile rank by industry and year of the factor yielded from principal component analysis using *MA_RawValue*, *Historical Return*, and *Historical ROA*. *Historical Return* is the value-weighted industry-adjusted historical stock return in year *t−1*, where the historical stock return in year *t−1* is defined as the buy-and-hold return from year *t−3* to *t−1*. *Historical ROA* is the value-weighted industry-adjusted ROA in year *t−1*, where ROA is defined as the percentage of the cumulative net income from year *t−3* to *t−1* on the average total assets for the three years. *Controls* indicates a set of control variables defined in Equation (1). All other variables are defined in Table 1. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. *** and ** indicate statistical significance at the 1 percent and 5 percent levels, respectively.

TABLE 11

Sensitivity tests on forecast improvement through earnings management (Hypothesis 4)

Panel A: Alternative discretionary accruals

	Predict Sign	(1) Dechow et al. (1995)		(2) Kasznik (1999)		(3) McNichols (2002)	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Managerial Ability$_{i,t-1}$	−	−0.569	[−5.416]***	−0.620	[−5.032]***	−0.295	[−2.421]**
Controls		Included		Included		Included	
Firm Fixed Effects		Included		Included		Included	
Year Fixed Effects		Included		Included		Included	
Adj. R^2		0.341		0.323		0.286	
N		17,795		17,795		17,340	

Panel B: Real activities management based on Roychowdhury (2006)

	Predict Sign	(1) *Abnormal cash flow*		(2) *Abnormal Discretionary expense*		(3) *Abnormal production cost*	
		Coef.	[*t*-value]	Coef.	[*t*-value]	Coef.	[*t*-value]
Managerial Ability$_{i,t-1}$	−	−0.373	[−4.701]***	−0.304	[−2.996]***	−0.501	[−1.951]*
Controls		Included		Included		Included	
Firm Fixed Effects		Included		Included		Included	
Year Fixed Effects		Included		Included		Included	
Adj. R^2		0.334		0.675		0.654	
N		17,795		17,795		17,458	

Notes: This table reports the regression results using alternative definitions for *Improve*. Each column in Panel A uses *Improve* as dependent variables, measured with discretionary accruals based on Dechow et al. (1995), Kasznik (1999), and McNichols (2002), respectively (i.e. 100*(|actual earnings – discretionary accruals – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity). In Panel B, we apply metrics on real activities manipulation introduced by Roychowdhury (2006). In each column, *Improve* is defined with abnormal cash flow (i.e. 100*(|actual earnings + abnormal cash flow – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity), abnormal discretionary expense (i.e. 100*(|actual earnings + abnormal discretionary expense – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity), and abnormal production cost (i.e. 100*(|actual earnings – abnormal production cost – last management earnings forecast| – |actual earnings – last management earnings forecast|)/lagged market value of equity), respectively. *Controls* indicates a set of control variables defined in Equation (1). All other variables are defined in Table 1. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 12
Additional tests using last forecast errors

Panel A: Descriptive statistics for Last Forecast Error and Timeliness

	Mean	SD	Min	P25	Median	P75	Max	N
Last Forecast Error$_{i,t}$	2.945	6.249	0.005	0.382	1.012	2.660	65.766	17,741
Timliness$_{i,t}$	204.710	111.158	40.000	97.000	185.000	362.000	371.000	17,741

Panel B: Regression results using Equation (4): Last Forecast Error

	Predict Sign	*Last Forecast Error*$_{i,t}$	
		Coef.	[*t*-value]
Managerial Ability$_{i,t-1}$	−	−0.131	[−4.417]***
Size$_{i,t-1}$	+/−	0.477	[0.902]
Loss_D$_{i,t-1}$	+	1.011	[3.614]***
Increase_D$_{i,t-1}$	−	−0.006	[−0.033]
StdDevEarn$_{i,t-1}$	+	−7.761	[−1.911]*
Beta$_{i,t-1}$	+	−0.376	[−0.724]
StdDev(Residual)$_{i,t-1}$	+	12.583	[0.481]
Sales_Conc$_{i,t-1}$	−	−12.201	[−1.932]*
ManagerOwn%$_{i,t-1}$	+	−1.083	[−0.475]
OutsideDir%$_{i,t-1}$	−	−1.049	[−1.310]
InstOwn%$_{i,t-1}$	−	−5.413	[−3.035]***
Timeliness$_{i,t}$	+	0.001	[1.512]
Firm Fixed Effects		Included	
Year Fixed Effects		Included	
Adj. R^2		0.300	
N		17,741	

Notes: This table reports the regression results for Equation (4). *Last Forecast Error* is the absolute value of forecast error based on the last forecast, multiplied by 100 (i.e. 100*|actual earnings – last management earnings forecast|/lagged market value of equity). The last earnings forecasts denote management earnings forecasts issued immediately prior to the fiscal year-end. *Timeliness* is the difference between the last management forecast date and the date of firm's fiscal year-end. All other variables are defined in Table 1. *t*-values are two-tailed and based on standard errors clustered at both firm and year levels. *** and * indicate statistical significance at the 1 percent and 10 percent levels, respectively.