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Chen, Jonas Tao; Xie, Lingmin; Zhang, Yuanyuan

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How does analysts' forecast quality relate to corporate investment efficiency?

Abstract

We examine the impact of financial analysts on the efficiency of firms' investment decisions. We use the accuracy and dispersion of financial analysts' earnings forecasts as proxies of analyst expertise and quality in making forecasts. We find that high quality forecast is associated with higher investment if the firm is more likely to under-invest and lower investment if the firm is more likely to over-invest, suggesting that forecast quality increases firm-level investment efficiency. We further show that such effects are stronger for the firms with higher information asymmetry and lower institutional stock ownership. The results are consistent with the notion that higher quality of analyst forecasts increases the information environment and external monitoring, which in turn increases investment efficiency.

Keyword: investment efficiency; over-investment; under-investment; analysts' forecast quality

JEL classification: G24, G31

1. Introduction

The capital investment decisions are one of the most fundamental and important factors that determine the value of the firm and therefore investors' wealth. Key determinants for a firm to make efficient investment decisions include knowledgeable and dedicated management teams and sufficient availability of capital. Prior literature shows that high quality financial reporting and corporate governance mechanisms can help prevent or mitigate firm's suboptimal investments by disciplining managers' behaviors and reducing the cost of capital. However, there is a lack of investigation into the effects of external financial analysts, which are one of the most important external monitoring agents of company managers. In our study, we attempt to fill this gap in the literature by examining how the quality of the earnings forecasts made by financial analysts impact firms' investment efficiency.

In an ideal world without any frictions, firms invest efficiently by undertaking investment projects with positive net present values (Modigliani and Miller, 1958). However, in reality, managers make over- or under-investments when their private interests deviate from those of shareholders. Financial constraints due to higher returns required by external capital providers who lack information can cause under-investment (Myers, 1984). Alternatively, the "lemons problem" of managers selling overpriced securities gives rise to over-investment (Baker et al., 2003). Prior literature shows that the quality and characteristics of financial reporting disclosed by firms are associated with higher investment efficiency (Biddle et al., 2009; Cheng et al., 2013; Lara et al., 2016). Richardson (2006) finds that the over-investment of free cash flows can be mitigated by certain governance structures such as the presence of activist shareholders and the adoption of anti-takeover provisions. These studies focus on how the firms' disclosures and internal governance mechanisms can help reduce over- and under-investment, but they do not directly examine the effects of one of the most important external monitoring agents and information intermediaries, namely, financial analysts.

Different views regarding the roles played by financial analysts have been widely discussed since the seminal paper of Jensen and Meckling (1976). Recent literature has reached a consensus that financial analysts have influences on firm value as well as the behavior of managers in such matters as earnings management, cash holding decisions, CEO compensations, tax planning activities, and others. We extend this literature by examining whether external

analysts can influence a firm's investment decisions. In particular, we argue that the quality of analysts' earnings forecasts, measured by the dispersion and accuracy of the forecast earnings per share, could affect investment efficiency through three channels.

First, by serving as information intermediaries between firms and outsiders, financial analysts can help capital providers and investors gain more insights about the firms' future prospects and real investment decisions, and this process inhibits managers from undertaking value-destroying activities (e.g., Bowen et al., 2008; Kelly and Ljungqvist, 2012), which is referred to as "information intermediary role" of financial analysts. Second, the process of researching firms and making earnings forecasts involves interfacing with management directly (e.g., communications with the managers and company visits), which allows financial analysts to directly monitor the firms and influence decision making (e.g., Yu, 2008; Chen et al., 2015). When the analysts' earnings forecasts are more accurate and have less dispersion, such monitoring effects on firms tend to be stronger. This is referred to as "monitoring agent role" of financial analysts. Third, financial analysts could create excessive pressure on managers by setting external performance benchmarks (i.e., earnings forecasts) that firm managers usually accept as targets to achieve (e.g., He and Tian, 2013; Allen et al., 2016; Irani and Oesch, 2016). The short-term pressure on managers imposed by financial analysts is expected to exacerbate managerial myopia and impair firms' incentives to invest, which is referred to as "market pressure role" of financial analysts. The first two views predict a positive association between forecast quality and investment efficiency, whereas the third pressure view predicts a negative relationship between forecast quality and investment efficiency.^{1 2}

We test the relationship between forecast quality and investment efficiency using a panel dataset of U.S. publicly listed firms spanning a long sample period from 1983 to 2011. To measure the quality of analyst forecasts, we use the standard deviation of earnings forecasts

¹ In addition, one may argue that financial analysts play the role of enhancing investor recognition for firms' stocks (e.g., Mola et al., 2013; Li and You, 2015). According to this view, analyst forecasts increase a stock's visibility and public awareness of a firm's underlying practices such as investment strategies, therefore increasing the possibility of value-destroying investments being detected. Therefore, high-quality forecasts are likely to dampen firms' incentives to engage in poor investment projects through increasing investor recognition. If analyst forecasts increase investment efficiency through the investor recognition channel, the effect is expected to vary with the level of firm visibility. However, we do not find significant differences in the documented relation between firms with low and high visibility. The results are reported in Table 8.

² We thank an anonymous reviewer for pointing out the potential multiple views with regard to the effect of analyst forecast on investment behaviors.

multiplied by minus one, denoted by *Dispersion*, and the absolute difference between the forecast consensus and actual earnings multiplied by minus one, denoted by *Accuracy*. We follow Biddle et al. (2009) and Cheng et al. (2013) in estimating a firm's likelihood of over-investing or under-investing based on the firm's cash and leverage levels. Our study focuses on the relation between the quality of analyst earnings forecasts and investment levels conditional on a given firm's likelihood of over-investing or under-investing.

Our analyses show that, on average, a one-decile higher *Dispersion* (or *Accuracy*) increases the investment of financially constrained firms by 3.77% (or 2.65%) and decreases the investment of financially abundant firms by 3.01% (or 2.12%). The results suggest that the quality of analyst earnings forecasts, measured by *Dispersion* and *Accuracy*, is associated with lower over-investment and lower under-investment, which supports the predictions of information intermediary role and monitoring agent role but does not support the market pressure role of analyst forecasts. Our regression models explicitly control for the effects of other corporate governance mechanisms that have been documented or hypothesized to be associated with investment efficiency, including the quality of financial reporting, institutional stock ownership, analyst coverage, and the E-index of Bebchuk et al. (2009), an anti-takeover defense measure. Our study confirms the findings reported by Biddle et al. (2009) and Cheng et al. (2013) that the quality of financial reporting, considered as a proxy of information asymmetry, is associated with higher investment efficiency. However, as *Dispersion* and *Accuracy* remain highly significant in reducing over- and under-investments, our findings on analyst forecast quality go beyond the information channel provided by financial reporting.

In sub-sample analyses, we find that the effects of analyst forecast quality on over-investing and under-investing firms are stronger for those that have a higher deviation from the expected investment level, higher information asymmetry, and lower institutional stock ownerships. These results that the effect of analyst forecast quality on investment efficiency are more pronounced for firms with poor information environment and/or weaker governance from other external monitoring mechanisms are consistent with the information role and monitoring role of financial analysts, respectively.

The *Dispersion* and *Accuracy* of analyst earnings forecasts and firms' investment efficiency could be simultaneously determined by some omitted firm-specific variables. To

handle this potential endogeneity problem, we use *Dispersion* and *Accuracy* lagged by two years as instrumental variables and estimate standard two-stage-least-square regressions. We also identify settings where firms are more likely to either over- or under-invest using the ranked variables aggregated at the industry level. Finally, we employ a small sample of firms experiencing an exogenous decrease in analyst coverage. None of these tests nor a battery of other robustness tests alters our conclusions.

Our study contributes to the growing body of literature on the determinants of firm-level investment efficiency (e.g., McNichols and Stubben, 2008; Biddle et al., 2009; Jian and Lee, 2011; Goodman et al., 2013; Cheng et al., 2013; Lara et al., 2016; Chen et al., forthcoming). While the prior literature focuses on how the quality or properties of financial reporting and internal management decisions influence firm-level investment efficiency, our study examines the effects of one of the most important external monitoring mechanisms and information intermediaries, namely, external financial analysts. Our results show that the analyst activity matters for investment efficiency even after controlling for a firm's disclosure quality as well as other governance mechanisms. Therefore, we add to the literature by showing the incremental impact of the information produced and governance performed by financial analysts on investment efficiency.

Second, our study contributes to the literature that investigates the information and monitoring roles played by financial analysts in corporate activities. Financial analysts monitor firms through releasing private and public information to investors and directly interfacing with firms' managements (e.g., Jensen and Meckling, 1976; Chen et al., 2015). A key issue for financial analysts when making earnings forecasts is to evaluate whether the investment decisions made by the firms are efficient, given the availability of capital and investment opportunities. While prior research has controlled for coverage or presence of financial analysts as a possible governance mechanism to explain investment efficiency³, our study focuses on the quality of earnings forecasts made by financial analysts and finds consistent and significantly positive effects across different model specifications and estimation methodologies.

³ Biddle et al. (2009), Cheng et al. (2013) and Lara et al. (2016) control for the effects of the number of analysts following a firm on investment efficiency in their regression analyses and find insignificant results.

The paper proceeds as follows. Section 2 reviews the relevant literature and develops our hypotheses. Section 3 describes the data sample, measurements of variables, and research methodologies. Section 4 presents our main regression results on the quality of analyst earnings forecasts and how they impact firms' investment efficiency, including the results of sub-sample analyses. Section 5 discusses robustness tests and section 6 concludes.

2. Related literature and hypothesis development

2.1 Management incentives, availability of capital, and investment efficiency

In a frictionless market, firms are expected to invest efficiently by undertaking projects with positive net present values (Modigliani and Miller, 1958), while it has been long recognized that firms make suboptimal investment decisions in reality and either over- or under-invest. Reasons for inefficient investments can be attributed to the conflict of interests between managers and shareholders (Jensen and Meckling, 1976) and the financial constraints faced by firms (Myers and Majluf, 1984). The negative effects of moral hazard and adverse selection problems on firm-level investment efficiency can be mitigated by enhancing the information environment of firms and the effective monitoring conducted by shareholders, financial institutions, and other stakeholders.

The adverse selection problem suggests that firms' insiders possess superior information as to the firm's true value and have the incentives to issue overpriced capital or issue capital when the firm is overpriced. If they are successful in raising funds, excess capital enables over-investment. However, outside capital providers, with informational disadvantages, may detect or suspect such behaviors by firm insiders and respond by increasing the firm's cost of external financing. This can be a pervasive effect that affects all firms including those that do not overprice new issues of shares. As a result, managers who are inclined to protect the existing shareholders might forego profitable investment opportunities, rather than selling under-valued securities, or rely more on internally generated capital for investments. The adverse selection problem affects not only equity financing (e.g., Easley and O'Hara, 2004), but also debt financing, for which lenders, who possess less information than borrowers, will require a higher cost of debt that squeezes out "good borrowers" (Fazzari et al., 1988). Lambert et al. (2012) and Bhattacharya et al. (2011) suggest that providing more information to more investors can reduce a firm's cost of capital.

The principal-agent conflict or moral hazard problem attributes distortions in investment decisions to the misalignment between managerial incentives and shareholder interests. Instead of maximizing shareholders' wealth, managers have other private objectives that might lead them to inefficiently invest the firm's capital. For example, managers make over- or under-investment decisions for empire building, perquisite consumptions, and management entrenchment, as suggested by Jensen (1986) and Aggarwal and Samwick (2006). Blanchard et al. (1994) argue that managers tend to use the firm's cash windfalls to invest in unattractive projects for the purposes of self-gratification or to maintain the independence of their firms with themselves at the helm. Some behavioral traits of managers can also induce over- or under-investments, including managers' career concerns, the incongruity in risk preferences between managers and shareholders (Holmstrom, 1999), managers' preference for a "quite life" (Bertrand and Mullainathan, 2003), and managers' hubris in overestimating their own abilities to identify good investment opportunities. Another consequence of severe agency problems is a higher cost of capital for firms that will cause under-investment.

2.2 Analyst forecast quality and investment level: information intermediary and monitoring agent review

A timely and transparent information environment and an effective monitoring mechanism can help prevent managers from making investment decisions that deviate from the optimal level. We hypothesize that the information and monitoring roles played by expert analysis from external security analysts could reduce the likelihood of over- and under-investment by firms.

There is a large body of literature documenting the roles played by financial analysts as information intermediaries between firms and investors. Financial analysts have information advantages by providing both public and private information to individual and institutional investors (Chen et al., 2015). Several studies have shown that the information contained in analyst earnings forecasts relates to subsequent stock returns, the probability of informed trading in stock markets, and measures of transaction costs (e.g., Diether et al., 2002; Kelly and Ljungqvist, 2012). The analysis conducted by financial analysts also helps to reveal information about other aspects of a firm. For example, Dyck et al. (2010) find that financial analysts are directly involved in the detection of corporate frauds. Therefore, we expect that through the

information discovery channel, the quality of analysts' forecasts relates to a firm's investment decisions, because these forecasts help mitigate the information asymmetry between a firm's insiders and outside capital providers and that between managers and shareholders.

Financial analysts also serve as an important external monitoring mechanism on firms through researching the firms and revealing information via their earnings forecasts to the public. Knyazeva (2007) argues that the information produced by financial analysts provides a substitute mechanism of corporate governance to the monitoring conducted by the board of directors and large institutional investors. Studies have found that analysts influence different aspects of corporate governance including managers' engagement in earnings management, a firm's liquidity policy, valuation of a firm's cash holdings, CEO compensations, and a firm's probability of undertaking value-destroying activities (e.g., Yu, 2008; Chen et al., 2015). From one aspect, market participants and large outside shareholders can infer information about firm performance and managerial incentives from analyst forecasts. For example, Miller (2006) shows that the press cites financial analysts frequently as a source for allegations of accounting malfeasances conducted by managers. From another aspect, financial analysts can directly communicate with managers and influence management decision makings. Graham et al. (2005) interviewed more than 400 executives in their survey study and report that about 36% of managers rank financial analysts as the most important economic agent in influencing their stock price. Expert analysis from external analysts is expected to play a monitoring role that helps to increase the investment efficiency of firms by constraining management from making suboptimal investments and reducing firms' cost of capital.

Investments are important value-creation activities of a company and earnings represent a summary measure of the payoffs from investments. Therefore, forecasting each potential project's future payoff and precisely estimating the project's net present value are important information that financial analysts should incorporate into their forecasting process. A well-known example providing evidence to analysts' interest in and influence on firms' investment behaviors is that Citigroup slashed its dividend and set out to raise more capital following suggestion made by Meredith Whitney, an analyst for Oppenheimer & Co. Inc., after her finding

that Citigroup's dividend exceeded its profits and calling for the company to raise capital, sale assets and/or slash its dividend⁴.

Based on the above discussions, we hypothesize that, *ceteris paribus*, analyst forecasts provide valuable information on and monitor firms' investment activities, leading to higher investment efficiency of firms. Specifically, we expect that the quality of analyst earnings forecasts help to reduce over- and under-investment by firms and we form the following hypothesis:

H1a: analysts' forecast quality is positively associated with investment efficiency.

2.3 Analyst forecast quality and investment level: market pressure view

Managers believe that missing an earnings target can cause drops in stock price (Graham et al., 2006) and firms experience a loss of stock market valuation when failing to meet market expectation (Bartov et al., 2002). Managers of these firms experience a reduction in compensation, a greater likelihood of turnover and a loss of reputation (e.g., Matsunaga and Park, 2001; Graham et al., 2005; Hazarika et al., 2012). Given these expected costs to managers and firms, analysts are expected to impose great pressure on managers in meeting or beating earnings benchmarks, which may give rise to adverse externalities such as short-termism and opportunistic behaviors (e.g., He and Tian, 2013; Irani and Oesch, 2016).

Managers' desire to hit or meet the analyst forecasts of future earnings are expected to sacrifice a firm's long-term value to meet short-term reporting objectives (Graham et al., 2005) and lead to managerial myopia in investments. Investment projects are usually long term that might not generate immediate returns and of high risk that are associated with great uncontrollability and uncertainty. As managers' tolerance for short-term failure and uncertainty is reduced when facing pressure created by analysts, the market pressure view predicts that analyst forecasts impair firms' incentives to invest and lead to investment inefficiency.

H1b: analysts' forecast quality is negatively associated with investment efficiency.

We measure the expertise and quality of analysts by the accuracy and dispersion of their earnings forecasts. Other things being equal, more accurate forecasts are reflective of higher

⁴ Michael Lewis, "The rise and rise of Meredith Whitney", Bloomberg, April 9, 2008.

expertise and greater investigative effort of the analysts (Yu, 2010).⁵ Moreover, earnings forecasts that are more accurate and have less dispersion amongst analysts tend to have a stronger effect on investors' views about the future performance of the covered firm. In addition, the value of a firm equals the present value of expected future cash flows, so analyst earnings forecasts should be based on their prediction of a firm's future cash flows. Firms with accurate forecast and low forecast dispersion are associated with less future cash flow uncertainty. For example, Guntay et al. (2010) argue that dispersion of analyst's earnings forecasts proxy largely for future cash flow uncertainty. Goodman et al. (2013) argue that uncertainty in firms' environment could affect investment quality and use analyst forecast accuracy and analyst forecast dispersion to capture the uncertainty. Given that investors avoid those firms that are fundamentally more risky and difficult to value (Dechow and Ge, 2006), accurate forecasts and small forecast dispersion should increase investors' willingness to follow a firm. Managers are aware of this and feel either under increased scrutiny when making their investment decisions or under excessive pressure to meet these forecasts.

In contrast, when analyst forecasts are less accurate and there is a lower consensus among them, managers will feel under less scrutiny to be efficient and may succumb to those pressures that lead to under- or over-investment. For example, Ding (2015) shows that belief dispersion in the financial sector (measured by analyst forecast dispersion) can lead to risk-taking behaviors in corporate investment. However, the market pressure imposed by those low-quality forecasts on managers is also smaller and they are less likely to be perceived by market as performance benchmarks.

Our empirical analyses explicitly control for other corporate governance mechanisms that have been documented in the prior literature to be determinants of investment efficiency (e.g., Biddle et al., 2009; Hartzell et al., 2014). These governance mechanisms include the firm's financial reporting quality, institutional stock ownership, analyst coverage, and anti-takeover defense measures. The quality of analyst earnings forecasts is also dependent on the firm's existing information environment. Bhat et al. (2006) show that corporate governance transparency has a positive impact on analyst forecast accuracy. In light of this finding, our

⁵ We rely on the evidence provided by literature (e.g., Mikhail et al., 1999; Jackson, 2005) that, given the concerns of reputation and career prospects, financial analysts have strong incentives to give accurate earnings forecasts and to monitor management actions. Moreover, the accuracy of earnings forecasts is an important factor for the annual ranking of financial analysts published by the Wall Street Journal (Byard et al., 2006).

analysis controls for the quality of a firm's financial disclosures and it is the incremental effect of the quality of analyst earnings forecasts on investment efficiency that we wish to investigate.

3. Data sources, variable construction, and research methodology

3.1 Data sources

We obtain data on earnings forecasts made by financial analysts and the actual earnings of firms, respectively, from the Unadjusted Detail History file and Unadjusted Detail Actuals file of the Institutional Brokers Earnings Systems (I/B/E/S).⁶ Annual financial data on firms are from Compustat and historical daily stock trading data are from the Center for Research in Security Prices (CRSP). We also collect institutional stock ownership data from the Thomson Reuters Institutional database (13f). Firms are classified into 48 industry sectors according to Fama and French (1997). Our dataset covers a period from 1983 to 2011.⁷

For each firm in a year, we use the earnings forecasts made by financial analysts during the three months prior to the annual earnings announcement. Prior literature shows that the optimistic bias in analyst forecasts is more pronounced for those released at the beginning of each year and thus suggests using the forecasts released close to the firm's annual earnings announcement (e.g., O'Brien, 1988; Easterwood and Nutt, 1999). Following O'Brien (1990) and Loh and Mian (2006), we limit the length of the window to three months because when forecasts are not equally recent, analysts who make forecasts later have an informational advantage over those who release forecasts earlier. Moreover, a three-month window provides us with sufficient observations throughout our sample period.⁸ To construct our measures of analyst forecast quality, i.e., forecast dispersion and accuracy, we require at least two analysts providing earnings per share forecasts for each firm in a year.

⁶ The I/B/E/S database adjusts the data of forecasted and actual earnings for stock splits and rounds them to the 2nd and 4th decimal respectively in the summary file and detail file. Such an approximation introduces measurement errors as it artificially reduces forecast standard deviation and increases forecast accuracy, as suggested by Payne and Thomas (2003). Therefore, we collect the raw data from the unadjusted files of the I/B/E/S that have not been adjusted for stock splits and make the adjustments ourselves following the instructions provided by the Wharton Research Data Services (WRDS). However, please note that when we replicate our tests using the adjusted I/B/E/S files we obtain similar results.

⁷ The I/B/E/S database provides data on analyst earnings forecasts starting from 1976 for U.S. firms. Our sample starts from 1983 because, after combining the available data across data sources, we do not have enough observations for earlier years (1976 to 1982) to conduct our analysis according to the methodologies outlined below.

⁸ Although we use a three-month window in the tests reported in the paper, sensitivity tests using shorter and longer windows yield similar results.

We exclude firms in the financial industry (SIC codes 6000 – 6999) as their financial ratios are not directly comparable to those of the firms in other industry sectors, and firms in the utility industry (SIC codes 4900 – 4999) because their investment decisions are heavily regulated and subject to constraints. In order to mitigate the influence of outliers, we winsorize the top and bottom 2% of all continuous variables in each year. The final dataset contains 31,544 firm-year observations for 4,991 firms from 1983 to 2011.

3.2 Variable construction and descriptive statistics

A firm's total investment for a year, denoted by *Investment*, is measured as the sum of research and development, capital expenditure, and acquisition expenditure less the cash receipts from the sales of property, plant, and equipment (PPE) and scaled by lagged total assets. We are interested in how a firm's investment is influenced by the quality of analyst earnings forecasts, namely, the forecast accuracy and forecast dispersion. Following Mansi et al. (2011), forecast accuracy, denoted by *Accuracy*, is defined as negative one times the absolute value of the difference between actual earnings per share and the median earnings forecast, scaled by the stock price at the end of each fiscal year. A higher value for *Accuracy* represents a more accurate forecast (i.e., less error). Forecast dispersion, denoted by *Dispersion*, is negative one times the standard deviation of analyst earnings forecasts, deflated by the stock price at the end of each fiscal year. We multiply the standard deviation by negative one so that *Dispersion* decreases with the differences among analyst earnings forecasts. The variables *Accuracy* and *Dispersion* are proxies of the quality of the analysts' work and both increase with the overall effort and expertise of analysts to disseminate information and monitor management.

Following Biddle et al. (2009) and Cheng et al. (2013), our analysis controls for a group of variables capturing corporate governance mechanisms, including the quality of financial reporting, institutional stock ownership, analyst coverage, and the entrenchment index (Bebchuk et al., 2009; Hartzell et al., 2014; Chen et al., 2015). The quality of financial reporting measures the precision of the information conveyed in financial reports about a firm's operations, especially its expected cash flows, and is measured using the model developed by Dechow and Dichev (2002) and extended by Francis et al. (2005). Specifically, for firms in each industry with at least 20 observations in a given year, we run a cross-sectional regression of working capital accruals on the lagged, current, and future cash flows plus the change in revenue (scaled by

average total assets) and PPE. A higher standard deviation of the regression residuals implies a higher estimation error embedded in the accruals process and a lower quality of financial reporting. Therefore, accrual quality, AQ , is defined as the standard deviation of the firm-level regression residuals during the years from $t-5$ to $t-1$, and then multiplied by negative one.

The annual institutional stock ownership of a firm, *Institution*, is defined as the average of the quarterly percentage shares owned by institutional investors during a year. Analyst coverage, *Coverage*, refers to the number of analysts following a firm in the three-month window prior to the firm's annual earnings announcement. The last corporate governance variable under consideration is the entrenchment index, *E-index*, that measures a firm's anti-takeover protection (Bhagat and Bolton, 2008; Bebchuk et al., 2009). It is constructed as the total points earned for six anti-takeover provisions with one point for each. These provisions are staggered boards, limitation on amending bylaws, poison pill, golden parachute, supermajority to approve a merger, and limitation on amending the charter. As the data to construct the *E-index* are only available for the period from 1990 to 2011, the regression analysis using this variable is conducted for a shorter sample period than in our main regressions.⁹

Our regression analysis also controls for other firm-specific variables that may be determinants of investment levels. They are firm age (*Age*), which is the difference between the date when a firm first appeared in the CRSP database and the date at the end of a fiscal year, firm size (*Size*) calculated as the logarithm of total assets, and the market-to-book ratio (*Mkt-to-Book*), which is the market value of equity over the book value of common stock. We also include $\sigma(CFO)$, $\sigma(Sales)$, and $\sigma(Investment)$, which are, respectively, the standard deviation of annual cash flow from operations deflated by average total assets, the standard deviation of annual sales deflated by average total assets, and the standard deviation of annual investments, all measured over the years from $t-5$ to $t-1$. *Loss* is an indicator variable that is coded one if net income before extraordinary items is negative in a year and zero otherwise. *Dividend* is an indicator variable

⁹ We collect the annual data of six provisions since 2007 from the Takeover Defense database of the Investor Responsibility Research Center (IRRC) and construct the annual measures of *E-index* by ourselves for the period from 2007 to 2011. The IRRC does not publish data on the annual corporate governance provisions before 2007. The *E-index* estimates from 1990 to 2006 are downloaded directly from the website of Lucian A. Bebchuk (<http://www.law.harvard.edu/faculty/bebchuk/>). We would like to thank Lucian A. Bebchuk for sharing the data online. Our sample includes only the years with corporate governance provisions available. The distributions of the *E-index* in our sample over the sample years and its descriptive statistics are consistent with those reported in Bebchuk et al. (2009).

that is coded one if the firm pays a dividend in a year and zero otherwise. The *Z-score* measures the degree of a firm's financial health. A higher *Z-score* implies a lower probability of corporate default. Other control variables include PPE over total assets, denoted by *Tangibility*; the average time in days between purchasing or acquiring inventory and receiving the cash proceeds from sales, denoted by *OperatingCycle*; and the cash flows from operations over annual sales, denoted by *CFOsale*. The leverage at an industry level, *Ind Leverage*, is also included and defined as the average leverage of firms with the same SIC 4-digit code in each year. The detailed definitions of variables are reported in the Appendix.

Table 1 shows the descriptive statistics of the variables used in our main analysis including the mean, standard deviation (STD), lower quartile (25%), median, and upper quartile (75%). The means of *Dispersion* and *Accuracy* are respectively -0.007 and -0.014, which are consistent with the numbers reported by Mansi et al. (2011). The mean (median) of total investment is 13.7% (10.6%) of the lagged total assets and the mean (median) of AQ is -0.089 (-0.049). These numbers are very similar to those reported in prior studies. As we restrict our sample to the firms with at least two analysts following during the three months prior to the annual earnings announcement, the firms selected are on average larger in size than those in Biddle et al. (2009) and Cheng et al. (2013). Table 2 presents the Pearson correlation matrix of the variables used in our analysis. Both *Dispersion* and *Accuracy* are positively and significantly correlated with the *Investment* in year $t+1$, with correlation coefficients of 5.4% and 3.3%, respectively. As we show later, the relation between these measures and investment is conditional on the firms' proneness to over- or under-invest. Consistent with the prior literature, the quality of financial reporting, *AQ*, is significantly and positively related to *Dispersion* and *Accuracy*.

[Table 1 Here]

3.3 Research design

We apply the methodology of Biddle et al. (2009) and Cheng et al. (2013) to determine firms' investment efficiency and augment the model by introducing the effects of the quality of analyst earnings forecasts, i.e., *Dispersion* and *Accuracy*. More specifically, our regression model to determine the investment for firm i in year $t+1$, $Investment_{i,t+1}$, is specified as follows:

$$Investment_{i,t+1} = \alpha_0 + \alpha_1 Analyst_{i,t} + \alpha_2 Analyst_{i,t} \times OverFirm_{i,t} + \alpha_3 Gov_{i,t} +$$

$$\alpha_4 Gov_{i,t} \times OverFirm_{i,t} + \alpha_5 OverFirm_{i,t} + \gamma Control_{i,t} + \varepsilon_{i,t+1} \quad eq.(1)$$

where $Analyst_{i,t}$ refers to either $Dispersion_{i,t}$ or $Accuracy_{i,t}$; $OverFirm$ is a ranked variable that captures a firm's likelihood to over- or under-invest; and Gov and $Control$ are, respectively, a set of corporate governance proxies and a set of other firm-specific control variables. The regression model includes industry-fixed effects. Following Petersen (2009), we compute the t-statistics of the estimated coefficients from the heteroskedasticity-consistent standard errors clustered at the firm and year dimensions.

We follow Biddle et al. (2009) and Cheng et al. (2013) to construct a proxy of a firm's likelihood to over- and under-invest relying on firm-specific characteristics. Firms with more cash in hand are subject to higher agency costs and have a greater potential to over-invest (Jensen, 1986), while those with a lack of cash and/or a high leverage may be financially constrained and thus are more likely to under-invest (Aivazian et al., 2005). Therefore, a firm's likelihood to over-invest (or under-invest) is associated with higher cash and lower leverage (or lower cash and higher leverage). In each year, we rank firms in an industry sector into deciles based on each of the two firm-specific variables, cash balance and leverage (we multiply leverage by minus one before ranking so that it is increasing with the likelihood of over-investment), according to the Fama-French 48 industry classifications. The ranked numbers are rescaled to range between zero and one. Such rankings give the highest ranks to the firms that are most likely to over-invest and the lowest ranks to those that are most likely to under-invest. We then construct a variable, $OverFirm$, which is the average of the two rescaled ranks.¹⁰ A high score for $OverFirm$ is indicative of a firm that is prone to over-invest and a low score is indicative of a firm that is prone to under-invest. Table 1 shows that the mean and standard deviation of $OverFirm$ are, respectively, 0.469 and 0.252. The correlation coefficient between $OverFirm$ and $Investment_{t+1}$ is 0.302 and is significantly different from zero at the 1% level in Table 2.

[Table 2 Here]

In our main regression analysis, we use the scaled decile ranks of $Dispersion$ and

¹⁰ Untabulated analyses show that our conclusions do not alter when we construct $OverFirm$ using only the rank of cash or leverage of each firm. The results are available upon request.

Accuracy by ranking firms in each industry and each year into decile groups¹¹. According to Francis et al. (2005) and Bhattacharya et al. (2011), using the decile ranks of variables can help control for the effects of outliers, impose a weaker restriction on the linear relationship between the dependent variable and the main explanatory variables of interest, and facilitate the interpretations of economic meanings. As a robustness test, we also estimate the regression model of eq. (1) using the levels of *Dispersion* and *Accuracy* directly and the untabulated results are consistent with those reported here.

In eq. (1), the coefficient on $Analyst_{i,t}$, α_1 , measures the effects of *Analyst* in year t on *Investment* in year $t+1$ among the firms that are most likely to under-invest (when $OverFirm = 0$). The effects of *Analyst* on *Investment* among the firms that are more prone to over-invest is captured by the sum of the coefficients on $Analyst_{i,t}$ and the interaction term of $Analyst_{i,t} \times OverFirm_{i,t}$, which is $\alpha_1 + \alpha_2$. In our regression model of eq. (1), we also include a set of proxies of governance mechanisms as well as their interactions with *OverFirm*.

4. Empirical results

This section presents the regression results of our main analysis and investigates whether the quality of analyst earnings forecasts, captured by *Dispersion* and *Accuracy*, are associated with firms' over- and under-investment. We also conduct further explorations on the relations by examining the circumstances under which the influence of *Dispersion* and *Accuracy* is more pronounced, using sub-sample analysis.

4.1 An analysis of analyst forecast quality and investment efficiency

Panel A of Table 3 shows the results of our main regressions specified by eq. (1). In column (1), the quality of analyst earnings forecast is captured by *Dispersion*. The estimated coefficient on *Dispersion* is 0.0516 and is statistically significant at the 1% level. Therefore, for the firms that are most likely to under-invest ($OverFirm = 0$), a higher *Dispersion* is associated with a higher future investment, where *Dispersion* is the scaled decile ranking of the negative standard deviation of analyst earnings forecasts. In terms of economic significance, when *Dispersion* increases by one decile, the total investment of under-investing firms will increase by

¹¹ The scaled decile rank is constructed by first ranking observations each year in an industry into ten groups from zero to nine, and then scaling the ranking by nine so that the scaled rank variable ranges between zero and one.

0.0052¹²; this suggests a difference of 0.0468 (nine steps of 0.0052 each) in total investment between the top and bottom *Dispersion* deciles. Given that the mean investment of the full sample is 0.137, the effect of a one decile increase in *Dispersion* corresponds to an increase of 3.77%¹³ in investment.

[Table 3 Here]

The estimated coefficient on the interaction term, *Dispersion*×*OverFirm*, is -0.0929 and is significantly negative. The overall effect of *Dispersion* on investment among the firms that are more prone to over-invest is captured by the sum of the coefficient estimates on *Dispersion* and *Dispersion*×*OverFirm*, i.e. $\alpha_1 + \alpha_2$ in eq. (1). The joint significance test strongly rejects the null hypothesis that the sum of the coefficients, -0.0413, is zero at the 1% level. In terms of economic significance, when *Dispersion* increases by one decile, the investment in year $t+1$ among the firms that are likely to over-invest will decrease by 0.0041, which corresponds to about 3.01%¹⁴ of investment. The results lend support to H1a that analysts' forecast quality is positively associated with firms' investment efficiency.

The quality of analyst forecasts is captured by *Accuracy* in column (2) of Panel A. The estimated coefficients on the main explanatory variables of interest have the signs predicted by H1a and are all statistically significant at the 1% level. For the firms that are most likely to under-invest, the estimated coefficient on *Accuracy*, α_1 , is 0.0363, indicating that when the accuracy of analyst forecasts increases by one decile, the total investment of these firms will increase by 0.0036 or 2.65% of investment. According to the joint test, $\alpha_1 + \alpha_2$ is -0.0291 and significant at the 1% level. Therefore, among the firms that are prone to over-invest, a one-decile increase in *Accuracy* will induce investment to decrease by 0.0029 or about 2.12% of investment. Therefore, the results in column (2) for *Accuracy* also support H1a.

Both regressions in columns (1) and (2) control for the variables of corporate governance mechanisms and their interaction term with *OverFirm* and show consistent results with the prior literature. The effects of accrual quality, *AQ*, and its interaction term with *OverFirm* are significantly positive and negative, respectively. The institutional stock ownership also appears

¹² This figure is calculated as $0.0516/10=0.0052$.

¹³ This figure is calculated as $(0.0516/10)/0.137=3.77\%$.

¹⁴ This figure is calculated as $(0.0413/10)/0.137=3.01\%$.

to be an effective governance mechanism for reducing under- and over-investment. Our regression analysis also controls for the number of analysts following a firm. Similar to the findings of Biddle et al. (2009) and Cheng et al. (2013), the estimated coefficients on *Coverage* and *Coverage*×*OverFirm* are not statistically significant.

The estimated coefficients on the other control variables that determine a firm's investment level are consistent with those reported in Biddle et al. (2009) in terms of the signs and significance levels. Specifically, investment increases with the market-to-book ratio, CFO volatility, investment volatility, tangibility, and decreases with the book value of assets, sales volatility, negative income, dividend, z-score, operating cycle, CFO sales, and industry-level leverage.

In Panel B of Table 3, we estimate the same regression model of eq. (1) but include the *E-index* as an additional governance mechanism covering a later sample period from 1990 to 2011. In both columns (1) and (2), the estimated coefficients on the *E-index* and its interactions with *OverFirm* have the predicted signs but are not statistically significant. The effects of *Dispersion* and *Accuracy* on over- and under-investment continue to be significant and consistent with those in Panel A. The joint significance for *Accuracy* in column (2) becomes less significant and the estimated coefficients on *Dispersion*, *Accuracy*, and *Accuracy*×*OverFirm* are slightly smaller in magnitude. Overall, our conclusions do not change after controlling for the anti-takeover index and for a more recent sample period.

To summarize, the results are consistent with the prediction of information intermediary, monitoring agent, and investor recognition arguments that the quality of analyst earnings forecasts improve the investment efficiency of firms instead of supporting the market pressure view. More specifically, the dispersion (or negative standard deviation) among, and the accuracy of, analyst earnings forecasts increase investments for firms that are most likely to under-invest and decrease investment for those that are more prone to over-invest.

It is important to note that all our analyses control for the quality of financial reporting as well as for general firm-specific variables such as firm size and age, which capture the information environment of firms. As analyst forecast dispersion and accuracy can be influenced by the disclosure quality of firms (Bhat et al., 2006), we further examine this issue and re-estimate our basic model of eq. (1) using the proportions of *Dispersion* and *Accuracy* that are not

related to the accrual quality. For the firms in each industry and year, we run a cross-sectional regression of *Dispersion* (or *Accuracy*) on *AQ* and use the regression residual for a firm-year, denoted by *Res_Dispersion* (or *Res_Accuracy*), as the proportion of *Dispersion* (or *Accuracy*) that is not explained by accrual quality. The variable *Analyst* in eq. (1) is then measured by either *Res_Dispersion* or *Res_Accuracy* and the regression results are presented in Table 4. For the regressions with *Res_Dispersion* and *Res_Accuracy*, the estimated coefficients, α_1 and $\alpha_1 + \alpha_2$, always have signs consistent with those in Table 3 and remain significant at the 10% level or higher.¹⁵ The control variables are consistent with those for the main regressions presented in Table 3. These results therefore indicate that *Accuracy* and *Dispersion*, which measure the quality of analysts' earnings forecasts, are not simply proxies for an overall better financial reporting quality. Instead, they provide incremental information over and above the effects of financial reporting quality with respect to investment efficiency.

[Table 4 Here]

4.2 Further explorations about the association between investment efficiency and analyst forecast quality

Our results show economically significant associations between analyst earnings forecast quality and firms' investment efficiency and the information intermediary, monitoring agent and investor recognition effects of analysts dominate the market pressure effect. In this section, we use sub-sample analyses to examine the roles played by various factors on the empirical association and explore the channels through which forecast quality affects investment efficiency.

4.2.1 Firms with high unexpected investments

Prior literature suggests that the information discovery and monitoring roles played by financial analysts are more important for the firms that already have poor performance and/or corporate frauds (Dyck et al., 2010). Accordingly, we expect that firms characterized by high levels of unexpected investment (an indicator of poor performance) will be more influenced by analyst forecast quality on investment efficiency than firms with low levels of unexpected investment. To determine the deviation of a firm's investment from the expected level, we use a

¹⁵ When we use the decile ranks of *Res_Dispersion* and *Res_Accuracy*, the results are similar. The estimated coefficients of the ranked values of *Res_Dispersion* and *Res_Accuracy* are close in magnitude to those of the main regression presented in Table 3.

benchmark model similar to that used in McNichols and Stubben (2008), Biddle et al. (2009), and Goodman et al. (2013). Specifically, we run a regression of total investment in year t on lagged Tobin's Q for all firms in an industry with no less than 20 observations and define the unexpected investment as the absolute regression residual of each firm. The lagged Tobin's Q measures a firm's growth opportunities.¹⁶ The subsample of firms with high unexpected investment (high- UI) is made up of the observations with absolute residuals higher than the median of the full sample, and that the subsample of low unexpected investment (low- UI) is made up of the observations with absolute residuals lower than the median.¹⁷

We then re-estimate the regression model of eq. (1) for the high- UI and low- UI subsamples separately. The regression results are reported in Table 5, with *Dispersion* as the proxy of Analyst in columns (1) and (2) and *Accuracy* in columns (3) and (4). For the results with *Dispersion*, the main explanatory variables of interest remain highly significant for both subsamples. The estimated coefficients on *Dispersion*, *Dispersion* $\times$ *OverFirm*, and *OverFirm* for the high- UI subsample in column (1) are all larger in magnitudes than those for the low- UI subsample and the full sample (the full sample results shown in Table 3). In terms of economic significance, in column (2), a one-decile increase in *Dispersion* causes $Investment_{t+1}$ to increase by 4.26% for under-investing firms, and causes $Investment_{t+1}$ to decrease by 3.64% for over-investing firms. The economic effects are larger in magnitude than those shown for the full-sample in Table 3 and those shown for the low- UI subsample. When replacing *Dispersion* by *Accuracy* in columns (3) and (4), the results are also more pronounced for the subsample with high unexpected investment than for the full sample analysis.¹⁸ The results confirm our conjecture that the positive effects of analyst forecasts on investment efficiency are stronger for the firms that already have a high deviation from the expected investment level.

[Table 5 Here]

4.2.2 Firms with high asymmetric information

¹⁶ In untabulated analysis, we find consistent results when replacing Tobin's Q by sales growth, which is the percentage change in annual sales from year $t-2$ to $t-1$. The results are available upon request.

¹⁷ As a robustness test, we also split the full sample into high- UI and low- UI subsamples, according to the median level of firms' absolute residuals in each industry in year t . The results are consistent.

¹⁸ Specifically, in column (4) for the high- UI subsample, a one-decile increase in *Accuracy* causes $Investment_{t+1}$ to increase by 3.11% if the firm is likely to under-invest, and to decrease by 2.66% if the firm is more prone to over-invest. While for the low- UI subsample, a one-decile increase in *Accuracy* causes $Investment_{t+1}$ to increase by 1.80% if the firm is likely to under-invest, and to decrease by 1.23% if the firm is more prone to over-invest.

As the information intermediary view suggests, financial analysts play as information intermediary and analyst forecasts increase investment efficiency by reducing information asymmetry about a firm and increasing corporate transparency. If this argument holds, the effect of forecast quality on investment efficiency should be more pronounced for firms with higher information asymmetry. To test this conjecture, we re-estimate our major regression model of eq. (1) by partitioning the sample into two subsamples, one with low information asymmetry and the other with high information asymmetry. We expect that the investment decisions of firms with high information asymmetry are more influenced by analyst forecast dispersion and accuracy. The level of information asymmetry is measured by the probability of informed trade, *PIN*.¹⁹ We take the *PIN* for each firm spanning the period from 1993 to 2010 from the database provided by Stephen Brown (Brown and Hillegeist, 2007).²⁰ The high-*PIN* subsample includes the observations with *PIN* higher than the median of *PIN* over the full sample and the low-*PIN* subsample includes those with *PIN* lower than the sample median.²¹

The results of the subsample regressions explaining $Investment_{t+1}$ are shown in Table 6. We find that, while the main explanatory variables of interest are significant and have the consistent signs in both subsamples, the effects of *Dispersion* and *Accuracy* on over- and under-investments are more pronounced in the subsample with high information asymmetry than in the sub-sample with low information asymmetry. In column (2) for the high-*PIN* subsample, a one-decile increase in *Dispersion* increases investment in year $t+1$ by 3.88% for under-investing firms and decreases investment by 2.79% for over-investing firms. The corresponding economic effects in column (1) for the low-*PIN* subsample are, respectively, 2.58% and 2.63%. A similar stronger effect is also shown in column (4) of the high-*PIN* subsample, than in column (3) of the

¹⁹ As an alternative measure of information asymmetry to *PIN*, we also calculate the annual bid-ask spread of each firm, which is the average of the daily bid and ask spread in a year, with data provided by CRSP, from 1983 to 2011. The untabulated results of subsample regressions for firms with high or low bid-ask spread yield the same conclusions as those reported here using *PIN*. The results are available upon request.

²⁰ The probability of informed trade, *PIN*, is measured by the microstructure model developed by Easley et al. (1997) and extended by Venter and de Jongh (2006). We would like to thank Stephen Brown (<http://www.rhsmith.umd.edu/faculty/sbrown/pinsdata.html>) for providing the annual data of *PIN* from 1993 to 2010 on his website.

²¹ We split the sample equally by the median of *PIN* of the full sample instead of the median across firms in each year, because there is a declining trend of the average information asymmetry over time during our sample period. This is similar to the approach we use for institutional stock ownership as outlined in Section 4.2.3, which has an increasing trend over time.

low-*PIN* subsample, when replacing *Dispersion* by *Accuracy*.²² These results indicate that the benefits of analyst forecast quality are increasing with the level of information asymmetry, suggesting that analysts' information intermediary role is one channel through which analyst forecasts help increase investment efficiency.

[Table 6 Here]

4.2.3 Firms with low institutional ownership

Kim and Lu (2011) find that weak external governance leaves more room for agency problems to arise and it is for these firms that the monitoring roles played by financial analysts are most important. This is consistent with the substitution effects between analyst monitoring and other corporate governance mechanisms documented by Irani and Oesch (2013). If analysts' forecasts increase investment efficiency through their monitoring role in managerial investment decisions, we expect the effect is weaker for firms with strong existing governance mechanism. Here we consider institutional stock ownership as another potentially external governance mechanism. We partition our sample into two equally numbered subsamples. The high-*Institution* subsample includes the observations with institutional stock ownership, *Institution*, higher than the median of the full sample and the low-*Institution* subsample includes those observations that are below the median. The regression model of eq. (1) is then estimated separately for the two subsamples and the results are presented in Table 7.

In Table 7, the estimated coefficients on the main explanatory variables of interests are again consistently significant at the 1% level and have the signs predicted by H1a across four columns for high or low institutional ownerships and for *Dispersion* and *Accuracy*. Consistent with a substitution effect, analyst properties have stronger impacts on investment efficiency for the subsample with lower institutional ownership. For instance, when using *Accuracy* as the proxy of analyst quality, in the low-*Institution* subsample, a one-decile increase in *Accuracy* is associated with a lower investment of 2.61% for over-investing firms, and a higher investment of 3.69% for under-investing firms. In the high-*Institution* subsample, the corresponding effects are weaker at 1.43% (for over-investing firms) and 1.47% (for under-investing firms) of investments. Therefore, our results show that the effects of financial analysts on a firm's investment efficiency

²² For brevity, we only report results of forecast quality measures, corporate governance variables and their interactions with *Overfirm* in the tables for all sub-sample tests.

are weaker if the firm's institutional investors possess stronger governance abilities (i.e., they have greater ownership rights), suggesting that monitoring role of analyst forecasts is an explanation for why forecast quality affect investment efficiency.

[Table 7 Here]

4.2.4 Firms with low investor recognition

According to agency theory, managers have the incentives to conduct inefficient investments for their private objectives and benefits (e.g., Jensen, 1986; Blanchard et al., 1994). Such investments could destroy firm value if they are not identified and limited by investors timely. Investor recognition view argues that high-quality analyst forecasts increase the visibility of these value-destroying activities to the public, reducing firms' incentives to conduct such inefficient investments. If this argument holds, we expect that the effect of forecast quality on investment efficiency to be more pronounced for firms with low visibility. To examine this conjecture, we adopt whether a firm is included in the Standard & Poor's (S&P) 1,500 index as the measure of visibility. We separate firms into S&P 1500 firms and non-S&P 1500 firms and S&P 1500 firms are relatively large, having high press coverage, and therefore more visible to the public. We re-estimate our eq. (1) separately for S&P 1500 firms and non-S&P 1500 firms and the results are reported in Table 8.

In table 8, the estimated coefficients on the main explanatory variables of interests are all statistically significant at conventional level with predicted signs for both *Dispersion* and *Accuracy*. However, we do not find evidence that the effect of forecast quality on under- and over-investment are overall stronger for low visible firms (non-S&P 1500 firms) than for high visible firms (S&P 1500 firms). For instance, when using *Dispersion* as the proxy of analyst quality, the effect of analyst quality on over-investment is actually stronger for S&P 1500 firms. Therefore, the results reported in Table 8 suggest that the investor recognition view is not an explanation for why forecast quality affects investment efficiency.

[Table 8 Here]

5. The endogeneity problem and robustness checks

In this section, we redo the regression analyses considering the potential endogeneity problems, which are followed by sub-period regressions, other robustness checks, and an

additional analysis about the effects of *Accuracy* and *Dispersion* on firms' future performance.

5.1 Endogeneity between analyst forecast quality and investment efficiency

A problem could occur if a variable that affects both the firm's investment decision and the analyst forecast quality is not included in our regression model (i.e., the omitted variable bias). For example, in the anticipation of future investment opportunities, managers, especially in the under-investing firms, have the incentive to manage earnings in order to hit a certain earnings target, for which the consensus (or median) of analyst earnings forecasts could be one candidate (Graham et al., 2005). If managers succeed, they can reduce the firm's cost of capital and raise funds to increase future investment. Otherwise, the managers' attempts to manage earnings can aggravate the adverse selection problem and cause under-investment. To address such a potential endogeneity issue, we use the firm and year fixed-effect regression model and the standard two-stage-least-squares (2SLS) methodology with instrumental variables of forecast quality.

The firm-fixed effect model controls for the possibility that endogeneity arises from unobserved firm-level, time-invariant factors that simultaneously determine analyst forecast quality and investment efficiency. Table 9 reports the results of the firm and year fixed-effect regressions. The estimated coefficient on *Dispersion* (*Accuracy*) is 0.0366 (0.0248) and significant at the 1% level, indicating that the analyst forecast quality increases investment for the firm that are most likely to under-invest. Meanwhile, the joint tests are also significant at the 1% level and negative in columns (1) and (2), consistent with the argument that the analysts' forecast quality reduces future investment if the firms are prone to over-invest. The results are largely consistent with our main analysis presented in Table 3. As predicted, the magnitudes and significance levels of the key explanatory variables are slightly lower than before.

[Table 9 Here]

As an alternative way to address the potential endogeneity problem, we use the lagged *Dispersion* and lagged *Accuracy* of each firm, respectively, as the instrumental variables of *Dispersion* and *Accuracy*, and estimate the standard 2SLS regressions. A financial analyst typically focuses on analyzing a number of listed firms in a specific industry sector and they make earnings forecasts periodically. Hence, there should be some persistence in the researching and analyzing abilities of these analysts, which are not related to the firms being analyzed, and that can cause autocorrelations in the quality of analyst earnings forecasts. Moreover, our sample

uses the one-year-ahead earnings forecasts conducted by financial analysts. So the *Dispersion* and *Accuracy* in year $t-1$ are less likely to be related with the residual, ε_{t+1} , of the regression model to explain the investment in year $t+1$.

In the first-stage regressions, the *Dispersion*, *Accuracy*, and their respective interaction terms with *OverFirm* are instrumented by functions including the lagged *Dispersion*, lagged *Accuracy*, as well as the control variables included in the main regression models in Table 3. The first-stage regression results are provided in Panel A of Table 10. The lagged quality measures are positively and significantly related to the current quality measures. The Partial R^2 and the partial F -statistics confirm the appropriateness of the instrumental variables after removing the contributions of the control variables (Larcker and Rusticus, 2010).

[Table 10 Here]

The predicted values of *Dispersion*, *Dispersion*×*OverFirm*, *Accuracy*, and *Accuracy*×*OverFirm* obtained from the first-stage regressions are included in the main regression model, specified by eq.(1), as the second-stage regression. The results are presented in Panel B of Table 10. It shows that the 2SLS estimates have the same signs and similar significance levels as those presented for the main regression analysis in Panel A of Table 3.²³ The results of the control variables are also consistent. Therefore, our conclusions do not change when we adopt the instrumental variable estimations using the lagged analyst forecast quality²⁴.

5.2 Over- and under-investments at the industry level

As pointed out by Biddle et al. (2009), the variable that measures the likelihood of a firm's disposition to over- and under-invest, *OverFirm*, can be endogenously determined. As a sensitivity test, we use the investment aggregated at the industry level as the proxy for the likelihood of a firm's over- and under-investment, based on the idea that the aggregate investment is less likely to be affected by the quality of earnings forecasts made by financial

²³ Diagnostic tests suggest that our instruments are both valid and relevant. In particular, the Hausman tests reject the exogeneity of *Dispersion* and *Accuracy*, respectively, with $F=20.86$ ($P<0.001$) and $F=20.21$ ($P<0.001$).

²⁴ We admit that the two methods we have used cannot totally eliminate endogenous concern. To provide further support to the causal effect of forecast quality on investment efficiency, we also conduct tests using a small sample of observations with exogenous drop in analyst coverage caused by broker closures and mergers. The untabulated results indicate that exogenous drop in analyst coverage does reduce investment efficiency by increasing the likelihood of both under- and over-investing. However, as analyst coverage is not an unambiguous proxy of forecast quality, we perceive the findings only as supplement to the above three methods to support our causality argument. The results are available upon request.

analysts on each individual firm. Specifically, for each year, we run a regression of the average investment of firms in an industry on the average Tobin's Q for all industries with at least 20 observations. The residuals from the industry-year estimation are then ranked into deciles and rescaled from zero to one to form a measure of over-investment, *OverIndustry*.

We re-estimate the regression model specified by eq. (1) by replacing *OverFirm* by *OverIndustry* and the regression results are presented in Table 11. The estimated coefficients on *Dispersion* and *Accuracy* have the predicted signs in both columns (1) and (2). The interaction terms are also significantly different from zero. Except that the joint test with *Accuracy* in column (2) is not statistically significant at the conventional level but is negative as predicted, all results are consistent with those when *OverFirm* is used. Table 11 confirms a positive relation between *Dispersion* (or *Accuracy*) and investment among the under-investing firms and a negative relation between them among over-investing firms. Hence, our results are again robust to the alternative specification of the likelihoods of over- or under-investment.

[Table 11 Here]

5.3 The effects of the Regulation Fair Disclosure (Reg FD)²⁵

In order to stamp out the practice of “selective disclosure”, the U.S. Securities and Exchange Commission (SEC) promulgates Regulation Fair Disclosure, also commonly referred to as Reg FD, in August 2000. In “selection disclosure”, companies reveal material information only to certain analysts and institutional investors prior to disclosing it to public at large. Prior to enactment of the Reg FD, investors typically rely on analysts for earnings forecasts because of their information advantage. Therefore, Reg FD is predicted to diminish the information role of analysts since it restricts the private communication channels between managers and analysts (Gomes et al., 2007). Consistent with this prediction, prior studies find that private information flows to analysts decline after the implementation of Reg FD and investors react less to analyst forecasts (e.g., Gintchel and Markov, 2004; Agrawal et al., 2006). As the Reg FD is expected to reduce the informational advantage of professional financial analysts, we predict that the effect of forecast quality on investment efficiency become weaker in Post-Reg FD period.

²⁵ We thank an anonymous reviewer for suggesting this test.

To examine the impact of the Reg FD, we re-estimate our regression model of eq. (1) for two sub-periods, from 1983 to 1999 (pre-Reg FD) and from 2000 to 2011 (post-Reg FD), and present the results in Table 12. The quality of analyst forecasts is respectively captured by *Dispersion* in columns (1) and (2) and *Accuracy* in columns (3) and (4). For all four columns, the estimated coefficients of the main explanatory variables as well as the joint tests have the predicted signs of H1a and are statistically significant at the 1% level. However, the quality of analysts' earnings forecasts has a stronger effect on both over- and under-investment for the pre-Reg FD period than for the post-Reg FD period. For example, in the pre-Reg FD sample in column (2), a one-decile increase in *Dispersion* causes under-investing firms to increase investment by 4.18% and causes over-investing firms to decrease investment by 3.16%. The corresponding effects in column (1) for the post-Reg FD period are respectively 3.15% and 2.57%. Thus the effects of financial analysts on investment efficiency are stronger during the earlier period when financial analysts have information advantage. Therefore, Reg FD does reduce the overall effectiveness of analyst forecast quality on firms' investment efficiency.

[Table 12 Here]

5.4 Capital expenditure versus non-capital expenditure

In the previous sections, we follow Biddle et al. (2009) and Cheng et al. (2013) and conduct our analyses on a firm's total investment including both capital and non-capital expenditures. As a robustness test, we further examine the effects of analyst forecast quality on each of capital expenditure and non-capital expenditure, and evaluate whether our conclusions are driven by either or both types of investment (Richardson, 2006). The capital investment is scaled by lagged property, plant and equipment and is denoted by *Capex*, and the non-capital investment, *non-Capex*, is measured as the sum of R&D expenditures and acquisitions, scaled by lagged total assets. The regression model of eq. (1) is estimated by replacing the dependent variable, *Investment*, by *Capex* and *non-Capex* respectively. Untabulated regression results for *Capex* and *non-Capex* are consistent with what we find for the total investment. The only exception is the insignificant but negative effect of *Accuracy* on the efficiency of capital investment (*Capex*) for the firms that are prone to over-invest.

5.5 Analyst forecast quality and future firm performance

If the quality of analysts' earnings forecasts improves firms' investment efficiency, it

should also have a positive effect on the firms' future profitability. Therefore, we conduct an additional analysis on how the *Accuracy* and *Dispersion* are associated with the firms' future value, which is measured by cash flows from operations, Tobin's Q, profit margin (net income over assets) and return on assets. We use the time-series average of each of these variables over the three years of $t+1$, $t+2$ and $t+3$ as the dependent variable. The explanatory variables include the decile ranks of *Accuracy* (or *Dispersion*) in year t and all the control variables in eq. (1). The estimated coefficients of *Accuracy* and *Dispersion* are always positive and significant at the 1% significance level. The results are available from the authors on request.

6. Conclusions

Our study investigates whether the quality of the earnings forecasts made by financial analysts provides information about the efficiency of firms' investment decisions. Prior studies suggest different channels through which analyst forecasts affect investment. According to the information intermediary, monitoring agent, and investor recognition arguments, high forecast quality increases investment efficiency, whereas market pressure argument predicts a negative effect of forecast quality on investment efficiency. Using the dispersion among, and the accuracy of, analyst earnings forecasts as the measures of analyst quality, we find results consistent with the positive effect prediction. More specifically, our regression analyses show that analyst quality increases a firm's investment if the firm is more likely to under-invest and decreases a firm's investment if the firm has a higher likelihood to over-invest. Therefore, the quality of external analysts' expertise and effort can reduce a firm's over- or under-investment.

We further show that such effects are stronger for those firms with higher information asymmetry and lower institutional ownership, which provides support to the information intermediary and monitoring agent explanation for why analyst quality increases investment efficiency. Our subsample tests are not supportive of the notion that analyst forecasts increase investment efficiency through increasing investor recognition of firms' investment decisions. We also perform several methods to address endogeneity concerns (e.g., firm fixed effect and IV estimation), and our results are robust across these tests. The effects of analyst forecast quality remain highly significant even after controlling for the quality of financial reporting as well as other governance mechanisms. Therefore, the information and monitoring roles played by

financial analysts are not subsumed by other information intermediaries, attributes of the information environment of firms, or other governance mechanisms.

In summary, the analyses and results of our study provide support to the view that the quality of analyst information gathering and monitoring, as reflected in their earnings forecasts, can enhance firms' investment efficiency. We thus shed light on the potential channel through which the external governance mechanisms can improve firm value. Our study contributes to the literature on the determinants of firm-level investment efficiency and the roles played by financial analysts in corporate decisions.

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Table 1 Descriptive statistics

The table presents the descriptive statistics of the variables in our main analysis, including the mean, standard deviation (STD), 25%, median, and 75%. The sample includes 31,544 firm-year observations during the period from 1983 to 2011 for all variables, except that for the *E-index* where there are 8,178 observations during the period from 1990 to 2011. $Investment_{t+1}$ is the *Investment* in year $t+1$. Detailed definitions of variables are reported in the Appendix.

	Mean	STD	25%	Median	75%
<i>Investment and analyst earnings forecasts variables</i>					
$Investment_{t+1}$	0.137	0.111	0.059	0.106	0.181
Dispersion	-0.007	0.017	-0.006	-0.002	-0.001
Accuracy	-0.014	0.038	-0.010	-0.003	-0.001
<i>Governance mechanism variables</i>					
AQ	-0.089	0.110	-0.098	-0.049	-0.027
Coverage	7.013	7.327	3.000	4.000	8.000
Institution	0.577	0.241	0.395	0.591	0.765
<i>Other variables</i>					
Age	19.459	17.672	6.751	13.551	25.279
Size	6.745	1.767	5.454	6.626	7.929
Mkt-to-Book	2.973	2.834	1.399	2.189	3.553
$\sigma(\text{CFO})$	0.093	0.082	0.043	0.068	0.110
$\sigma(\text{Sales})$	0.222	0.171	0.105	0.171	0.284
$\sigma(\text{Investment})$	0.076	0.072	0.027	0.051	0.098
Loss	0.209	0.407	0.000	0.000	0.000
Dividend	0.519	0.500	0.000	1.000	1.000
Z-score	1.480	1.064	0.881	1.481	2.088
Tangibility	0.318	0.229	0.132	0.263	0.460
OperatingCycle	129.667	80.763	73.172	114.258	167.595
CFOsale	0.035	0.411	0.026	0.080	0.149
Ind Leverage	0.127	0.132	0.011	0.087	0.204
OverFirm	0.469	0.252	0.278	0.444	0.667
E-index	2.598	1.352	2	3	4

Table 2 Correlation matrices of variables

The table presents the Pearson correlations for the variables in our main analysis. $Investment_{t+1}$ is the *Investment* in year $t+1$. Detailed definitions of variables are given in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by ^c, ^b, and ^a, respectively.

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Investment _{t+1}	1																			
Dispersion	0.054 ^a	1																		
Accuracy	0.033 ^a	0.571 ^a	1																	
AQ	-0.081 ^a	0.052 ^a	0.053 ^a	1																
Coverage	-0.004	0.009	0.069 ^a	0.050 ^a	1															
Institution	-0.046 ^a	0.164 ^a	0.204 ^a	-0.150 ^a	0.141 ^a	1														
Age	-0.154 ^a	0.042 ^a	0.076 ^a	0.116 ^a	0.264 ^a	0.137 ^a	1													
Size	-0.208 ^a	0.091 ^a	0.147 ^a	0.015 ^a	0.424 ^a	0.404 ^a	0.481 ^a	1												
Mkt-to-Book	0.198 ^a	0.148 ^a	0.119 ^a	-0.086 ^a	0.000	0.063 ^a	-0.024 ^a	0.012 ^b	1											
σ(CFO)	0.206 ^a	-0.101 ^a	-0.129 ^a	-0.370 ^a	-0.125 ^a	-0.111 ^a	-0.277 ^a	-0.346 ^a	0.119 ^a	1										
σ(Sales)	-0.052 ^a	-0.027 ^a	-0.046 ^a	-0.143 ^a	-0.090 ^a	-0.097 ^a	-0.150 ^a	-0.235 ^a	-0.012 ^b	0.335 ^a	1									
σ(Investment)	0.161 ^a	-0.087 ^a	-0.099 ^a	-0.124 ^a	-0.084 ^a	-0.053 ^a	-0.216 ^a	-0.158 ^a	0.013 ^b	0.272 ^a	0.117 ^a	1								
Loss	0.071 ^a	-0.300 ^a	-0.292 ^a	-0.130 ^a	-0.068 ^a	-0.123 ^a	-0.146 ^a	-0.200 ^a	-0.060 ^a	0.256 ^a	0.047 ^a	0.190 ^a	1							
Dividend	-0.191 ^a	0.071 ^a	0.092 ^a	0.204 ^a	0.169 ^a	-0.015 ^a	0.430 ^a	0.397 ^a	-0.036 ^a	-0.365 ^a	-0.183 ^a	-0.216 ^a	-0.255 ^a	1						
Z-score	-0.195 ^a	0.203 ^a	0.207 ^a	0.200 ^a	0.007	0.009	0.105 ^a	-0.012 ^b	0.038 ^a	-0.244 ^a	0.232 ^a	-0.302 ^a	-0.537 ^a	0.213 ^a	1					
Tangibility	0.018 ^a	-0.058 ^a	-0.027 ^a	0.217 ^a	0.236 ^a	-0.097 ^a	0.095 ^a	0.200 ^a	-0.152 ^a	-0.282 ^a	-0.220 ^a	0.025 ^a	-0.068 ^a	0.240 ^a	-0.059 ^a	1				
OperatingCycle	0.033 ^a	0.008	0.002	0.034 ^a	-0.063 ^a	-0.060 ^a	-0.017 ^a	-0.121 ^a	0.033 ^a	0.064 ^a	-0.114 ^a	-0.055 ^a	0.025 ^a	-0.060 ^a	-0.134 ^a	-0.325 ^a	1			
CFOsale	-0.168 ^a	0.130 ^a	0.174 ^a	0.095 ^a	0.103 ^a	0.094 ^a	0.109 ^a	0.213 ^a	-0.033 ^a	-0.267 ^a	-0.016 ^a	-0.143 ^a	-0.413 ^a	0.174 ^a	0.402 ^a	0.195 ^a	-0.080 ^a	1		
Ind Leverage	-0.248 ^a	-0.083 ^a	-0.058 ^a	0.215 ^a	0.046 ^a	-0.080 ^a	0.137 ^a	0.202 ^a	-0.227 ^a	-0.260 ^a	-0.091 ^a	-0.036 ^a	-0.078 ^a	0.262 ^a	0.051 ^a	0.453 ^a	-0.250 ^a	0.115 ^a	1	
OverFirm	0.302 ^a	0.075 ^a	0.059 ^a	-0.146 ^a	-0.087 ^a	-0.076 ^a	-0.219 ^a	-0.379 ^a	0.269 ^a	0.310 ^a	0.144 ^a	-0.056 ^a	0.032 ^a	-0.259 ^a	0.039 ^a	-0.441 ^a	0.140 ^a	-0.140 ^a	-0.489 ^a	1

Table 3 Investment and analyst forecast quality

The table presents the regression results of eq.(1), specified as: $Investment_{i,t+1} = \alpha_0 + \alpha_1 Analyst_{i,t} + \alpha_2 Analyst_{i,t} \times OverFirm_{i,t} + \alpha_3 Gov_{i,t} + \alpha_4 Gov_{i,t} \times OverFirm_{i,t} + \alpha_5 OverFirm_{i,t} + \gamma Control_{i,t} + \varepsilon_{i,t+1}$, where $Investment_{i,t+1}$ refers to the total investment of firm i in year $t+1$, $OverFirm_{i,t}$ is a ranked variable based on the average rank of a firm's cash and leverage (multiplied by minus one), and $Analyst_{i,t}$ represents the analyst forecast quality measured by the decile ranks of either analyst forecast dispersion (multiplied by minus one), denoted by *Dispersion*, or the forecast accuracy, denoted by *Accuracy*. *Gov* is represented by *AQ*, *Coverage*, and *Institution*. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***. In Panel A, the regression model is estimated for the full sample period from 1983 to 2011. In Panel B, the regression model is estimated for a subsample period from 1990 to 2011, when the measures of the entrenchment index (*E-index*) constructed following Bebchuk et al. (2009) are available and included as an additional control variable.

Panel A Full sample analysis

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Dispersion (1)	Accuracy (2)
Analyst	0.0516*** (10.77)	0.0363*** (7.63)
Analyst × OverFirm	-0.0929*** (-10.44)	-0.0654*** (-7.40)
Joint significance	-0.0413*** (-7.07)	-0.0291*** (-5.15)
AQ	0.0442* (1.93)	0.0474** (2.08)
AQ × OverFirm	-0.0579* (-1.93)	-0.0628** (-2.08)
Coverage	0.0002 (0.89)	-0.0001 (-0.26)
Coverage × OverFirm	0.0003 (0.53)	0.0009 (1.49)
Institution	0.0267** (2.35)	0.0286** (2.46)
Institution × OverFirm	-0.0234 (-1.57)	-0.0275* (-1.81)
OverFirm	0.1345*** (12.78)	0.1193*** (11.17)
Age	-0.0001 (-1.43)	-0.0001 (-1.39)
Size	-0.0090*** (-7.88)	-0.0090*** (-7.78)
Mkt-to-Book	0.0044*** (8.43)	0.0044*** (8.63)
σ(CFO)	0.0725*** (4.92)	0.0726*** (4.89)
σ(Sales)	-0.0425***	-0.0430***

σ(Investment)	(-6.49) 0.1147***	(-6.68) 0.1148***
Loss	(6.68) -0.0214***	(6.62) -0.0223***
Dividend	(-7.14) -0.0088***	(-7.50) -0.0086***
Z-score	(-3.63) -0.0054***	(-3.55) -0.0057***
Tangibility	(-3.10) 0.1228***	(-3.27) 0.1223***
OperatingCycle	(15.61) -0.0001***	(15.51) -0.0001***
CFOsale	(-4.90) -0.0212***	(-4.96) -0.0215***
Ind Leverage	(-3.87) -0.0713***	(-3.91) -0.0744***
Intercept	(-6.22) 0.1219***	(-6.45) 0.1310***
	(5.81)	(6.28)
Industry dummies	Yes	Yes
Number of observations	31,544	31,544
R ²	0.291	0.289

Panel B Subsample analysis with E-index

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Dispersion (1)	Accuracy (2)
Analyst	0.0359*** (4.95)	0.0204*** (2.87)
Analyst × OverFirm	-0.0793*** (-4.17)	-0.0393** (-2.44)
Joint significance	-0.0434*** (-3.29)	-0.0189* (-1.72)
AQ	0.0718*** (3.26)	0.0758*** (3.45)
AQ × OverFirm	-0.0931** (-2.52)	-0.0982*** (-2.71)
Coverage	-0.0000 (-0.03)	-0.0002 (-0.51)
Coverage × OverFirm	0.0002 (0.28)	0.0006 (0.80)
Institution	0.0136 (0.88)	0.0169 (1.07)
Institution × OverFirm	0.0081 (0.30)	-0.0010 (-0.03)
E-index	0.0020 (1.16)	0.0022 (1.23)
E-index × OverFirm	-0.0016 (-0.36)	-0.0021 (-0.46)
OverFirm	0.0975*** (4.03)	0.0772*** (3.87)
Age	-0.0001 (-1.44)	-0.0001 (-1.44)
Size	-0.0057*** (-3.87)	-0.0057*** (-3.85)
Mkt-to-Book	0.0034*** (5.23)	0.0033*** (5.08)
σ(CFO)	0.0893*** (3.29)	0.0935*** (3.26)
σ(Sales)	-0.0465*** (-4.73)	-0.0469*** (-4.80)
σ(Investment)	0.1025*** (3.21)	0.1013*** (3.22)
Loss	-0.0164*** (-3.16)	-0.0169*** (-3.26)
Dividend	-0.0119*** (-3.69)	-0.0119*** (-3.76)
Z-score	0.0005 (0.19)	0.0002 (0.07)
Tangibility	0.1280*** (11.63)	0.1274*** (11.52)
OperatingCycle	-0.0000 (-1.38)	-0.0000 (-1.38)

CFOsale	-0.0032 (-0.56)	-0.0039 (-0.67)
Ind Leverage	-0.0682*** (-5.66)	-0.0721*** (-6.11)
Intercept	0.0936** (2.51)	0.1035*** (2.88)
Industry dummies	Yes	Yes
Number of observations	8,178	8,178
R ²	0.277	0.275

Table 4 Investment and analyst forecast quality, with *AQ*-adjusted *Dispersion* and *Accuracy*

The table presents the regression results of eq.(1), specified as: $Investment_{i,t+1} = \alpha_0 + \alpha_1 Analyst_{i,t} + \alpha_2 Analyst_{i,t} \times OverFirm_{i,t} + \alpha_3 Gov_{i,t} + \alpha_4 Gov_{i,t} \times OverFirm_{i,t} + \alpha_5 OverFirm_{i,t} + \gamma Control_{i,t} + \varepsilon_{i,t+1}$, where $Investment_{i,t+1}$ refers to the total investment of firm i in year $t+1$, $OverFirm_{i,t}$ is a ranked variable based on the average rank of a firm's cash and leverage (multiplied by minus one), and $Analyst_{i,t}$ represents the analyst forecast quality measured by *Res_Dispersion* or *Res_Accuracy*. Specifically, *Res_Dispersion* or *Res_Accuracy* are respectively the regression residuals of regressing *Dispersion* and *Accuracy* on accounting quality (*AQ*), for firms in each industry and a year. *Gov* is represented by *Coverage* and *Institution*. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1983 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Res_Dispersion (1)	Res_Accuracy (2)
Analyst	0.2443* (1.90)	0.0776* (1.67)
Analyst × OverFirm	-0.5188** (-2.45)	-0.1989* (-1.83)
Joint significance	-0.2745*** (-2.89)	-0.1213* (-1.90)
Coverage	0.0001 (0.37)	0.0001 (0.33)
Coverage × OverFirm	0.0006 (1.00)	0.0006 (1.01)
Institution	0.0300** (2.65)	0.0305*** (2.69)
Institution × OverFirm	-0.0324** (-2.16)	-0.0323** (-2.16)
OverFirm	0.1000*** (9.40)	0.1002*** (9.26)
Age	-0.0001 (-1.05)	-0.0001 (-1.05)
Size	-0.0090*** (-7.66)	-0.0090*** (-7.69)
Mkt-to-Book	0.0045*** (8.55)	0.0045*** (8.61)
σ(CFO)	0.0705*** (4.54)	0.0715*** (4.59)
σ(Sales)	-0.0436*** (-6.79)	-0.0436*** (-6.81)
σ(Investment)	0.1142*** (6.60)	0.1136*** (6.50)
Loss	-0.0240*** (-7.49)	-0.0243*** (-7.95)
Dividend	-0.0084***	-0.0083***

Z-score	(-3.45) -0.0061***	(-3.44) -0.0061***
Tangibility	(-3.51) 0.1227***	(-3.50) 0.1226***
OperatingCycle	(15.67) -0.0001***	(15.66) -0.0001***
CFOsale	(-5.16) -0.0223***	(-5.19) -0.0222***
Ind Leverage	(-4.02) -0.0767***	(-4.01) -0.0760***
Intercept	(-6.73) 0.1438***	(-6.72) 0.1433***
	(6.71)	(6.71)
Industry dummies	Yes	Yes
Number of observations	31,544	31,544
R ²	0.287	0.287

Table 5 Investment and analyst forecast quality, with high and low unexpected investments

The table presents the regression results of eq. (1) for two subsamples including the firms with high or low unexpected investments (*UI*). To measure the unexpected investments, for each industry in year *t*, we run a cross-sectional regression of firms' investment on lagged Tobin's *Q* and use the absolute value of each firm's residual. The high-*UI* subsample includes the firms with regression residuals higher than the median of the full sample and the low-*UI* subsample includes those firms with regression residuals lower than the median. The details of the regression specifications of eq. (1) are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1983 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment			
	Dispersion		Accuracy	
	Low- <i>UI</i> (1)	High- <i>UI</i> (2)	Low- <i>UI</i> (3)	High- <i>UI</i> (4)
Analyst	0.0309*** (5.93)	0.0643*** (9.58)	0.0222*** (3.68)	0.0469*** (6.73)
Analyst × OverFirm	-0.0488*** (-4.67)	-0.1191*** (-8.82)	-0.0373*** (-3.07)	-0.0869*** (-6.79)
Joint significance	-0.0179*** (-2.61)	-0.0549*** (-6.28)	-0.0151 (-2.09)	-0.0401*** (-5.12)
AQ	0.0415 (1.49)	0.0168 (0.64)	0.0440 (1.56)	0.0191 (0.74)
AQ × OverFirm	-0.0685* (-1.72)	-0.0164 (-0.47)	-0.0719* (-1.79)	-0.0191 (-0.55)
Coverage	0.0000 (0.08)	0.0005 (1.36)	-0.0002 (-0.58)	0.0001 (0.33)
Coverage × OverFirm	-0.0003 (-0.47)	0.0009 (1.01)	0.0000 (0.06)	0.0017** (2.00)
Institution	0.0152 (1.44)	0.0405*** (2.68)	0.0160 (1.48)	0.0425*** (2.75)
Institution × OverFirm	0.0001 (0.01)	-0.0429** (-2.08)	-0.0013 (-0.08)	-0.0474** (-2.26)
OverFirm	0.0809*** (7.42)	0.1716*** (12.39)	0.0746*** (6.54)	0.1522*** (10.79)
Intercept	0.0758*** (3.94)	0.1307*** (4.03)	0.0797*** (4.05)	0.1428*** (4.53)
Controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of observations	14,632	15,039	14,632	15,039
R ²	0.307	0.293	0.306	0.290

Table 6 Investment and analyst forecast quality, with high and low information asymmetry

The table presents the regression results of eq. (1) for two subsamples including firms with high or low information asymmetry. The annual level of information asymmetry for a firm is measured by the probability of informed trade, *PIN*, following the microstructure model developed by Easley et al. (1997) and adopted by Brown and Hillegeist (2007). The high-*PIN* subsample includes the firms with *PIN* higher than the median of the full sample, and the low-*PIN* subsample includes those firms with *PIN* lower than the median. The details of the model specification of eq. (1) are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1993 to 2010. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment			
	Dispersion		Accuracy	
	Low- <i>PIN</i> (1)	High- <i>PIN</i> (2)	Low- <i>PIN</i> (3)	High- <i>PIN</i> (4)
Analyst	0.0353*** (4.62)	0.0562*** (8.61)	0.0117* (1.77)	0.0452*** (5.50)
Analyst × OverFirm	-0.0713*** (-4.49)	-0.0966*** (-6.96)	-0.0253 (-1.46)	-0.0798*** (-4.71)
Joint significance	-0.0360*** (-3.48)	-0.0404*** (-4.08)	-0.0136 (-1.15)	-0.0346*** (-3.29)
AQ	0.0079 (0.36)	0.0467* (1.67)	0.0118 (0.55)	0.0500* (1.79)
AQ × OverFirm	0.0262 (0.76)	-0.0416 (-1.18)	0.0198 (0.56)	-0.0458 (-1.24)
Coverage	0.0003 (0.94)	0.0000 (0.04)	0.0001 (0.37)	-0.0006 (-1.11)
Coverage × OverFirm	-0.0005 (-0.77)	0.0011 (0.96)	-0.0001 (-0.20)	0.0022* (1.90)
Institution	0.0025 (0.19)	0.0375*** (2.89)	0.0051 (0.37)	0.0384*** (2.88)
Institution × OverFirm	-0.0152 (-0.57)	-0.0483** (-2.31)	-0.0214 (-0.80)	-0.0508** (-2.36)
OverFirm	0.1438*** (5.87)	0.1428*** (10.27)	0.1201*** (5.07)	0.1305*** (8.67)
Intercept	0.1303** (3.19)	0.1526*** (5.40)	0.1442*** (3.53)	0.1594*** (5.62)
Controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of observations	10,967	10,967	10,967	10,967
R ²	0.302	0.316	0.300	0.315

Table 7 Investment and analyst forecast quality, with high and low institutional stock ownership

The table presents the regression results of eq. (1) for two subsamples including firms with high or low institutional stock ownership. The high-*Institution* subsample includes the firms with institutional stock ownership, *Institution*, higher than the median of the full sample and the low-*Institution* subsample includes those firms where *Institution* is lower than the median. The details of the model specification of eq. (1) are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1983 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment			
	Dispersion		Accuracy	
	high- <i>Institution</i>	low- <i>Institution</i>	high- <i>Institution</i>	low- <i>Institution</i>
	(1)	(2)	(3)	(4)
Analyst	0.0330*** (5.81)	0.0698*** (10.46)	0.0195*** (2.97)	0.0516*** (9.23)
Analyst × OverFirm	-0.0634*** (-5.60)	-0.1189*** (-9.50)	-0.0385*** (-2.67)	-0.0882*** (-8.62)
Joint significance	-0.0304*** (-3.86)	-0.0491*** (-6.38)	-0.0190*** (-2.04)	-0.0366*** (-5.77)
AQ	0.0474** (2.18)	0.0215 (0.77)	0.0488** (2.31)	0.0278 (0.95)
AQ × OverFirm	-0.0657** (-2.01)	-0.0244 (-0.58)	-0.0670** (-2.06)	-0.0365 (-0.82)
Coverage	0.0001 (0.49)	-0.0000 (-0.00)	-0.0000 (-0.16)	-0.0005 (-1.15)
Coverage × OverFirm	0.0007 (1.02)	0.0004 (0.44)	0.0010 (1.56)	0.0013 (1.48)
Institution	0.0031 (0.13)	0.0584*** (3.69)	0.0041 (0.17)	0.0596*** (3.73)
Institution × OverFirm	-0.0436 (-1.27)	-0.0450 (-1.51)	-0.0463 (-1.34)	-0.0477 (-1.60)
OverFirm	0.1400*** (5.23)	0.1474*** (10.26)	0.1266*** (4.75)	0.1284*** (8.45)
Intercept	0.1440*** (4.46)	0.1082*** (5.61)	0.1514*** (4.74)	0.1207*** (6.20)
Controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of observations	15,772	15,772	15,772	15,772
R ²	0.284	0.306	0.283	0.303

Table 8 Investment and analyst forecast quality, with S&P 1500 firms and non-S&P 1500 firms

The table presents the regression results of eq. (1) for two subsamples including S&P 1500 firms and non-S&P 1500 firms. The S&P 1500 subsample includes the firms incorporated in the Standard & Poor's (S&P) 1,500 index, and the non-S&P 1500 subsample includes other firms. The details of the model specification of eq. (1) are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1992 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment			
	Dispersion		Accuracy	
	(1) S&P firms	(2) Non-S&P firms	(3) S&P firms	(4) Non-S&P firms
Analyst	0.0258*** (3.71)	0.0460*** (4.98)	0.0203*** (2.81)	0.0297*** (2.75)
Analyst × OverFirm	-0.0740*** (-4.63)	-0.0710*** (-3.64)	-0.0417* (-2.30)	-0.0535*** (-2.60)
Joint significance	-0.0482*** (-4.43)	-0.0249* (-1.96)	-0.0214* (-1.76)	-0.0238 (-2.02)
AQ	0.0710** (2.59)	0.0832** (2.18)	0.0727*** (2.68)	0.0889** (2.28)
AQ × OverFirm	-0.0922* (-1.92)	-0.0937 (-1.51)	-0.0940** (-1.97)	-0.1005 (-1.52)
Coverage	-0.0004 (-1.23)	0.0006 (1.15)	-0.0005 (-1.50)	0.0002 (0.37)
Coverage × OverFirm	0.0010 (1.32)	-0.0008 (-0.61)	0.0013* (1.78)	-0.0001 (-0.11)
Institution	0.0038 (0.20)	0.0034 (0.21)	0.0032 (0.17)	0.0063 (0.37)
Institution × OverFirm	-0.0340 (-1.14)	0.0284 (0.88)	-0.0344 (-1.15)	0.0252 (0.75)
OverFirm	0.1295*** (4.77)	0.0973*** (3.98)	0.1072*** (3.93)	0.0870*** (3.61)
Intercept	0.1112*** (3.07)	0.2104*** (6.23)	0.1195*** (3.38)	0.2171*** (6.80)
Controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of observations	9,545	6,455	9,545	6,455
R²	0.270	0.282	0.268	0.280

Table 9 Investment and analyst forecast quality – Firm and year fixed-effect model

The table presents the regression results of the firm and year fixed-effect model, specified as: $Investment_{i,t+1} = \alpha_{0,i} + \alpha_1 Analyst_{i,t} + \alpha_2 Analyst_{i,t} \times OverFirm_{i,t} + \alpha_3 Gov_{i,t} + \alpha_4 Gov_{i,t} \times OverFirm_{i,t} + \alpha_5 OverFirm_{i,t} + \gamma Control_{i,t} + \varepsilon_{i,t+1}$, where $Investment_{i,t+1}$ refers to the total investment of firm i in year $t+1$, $OverFirm_{i,t}$ is a ranked variable based on the average rank of a firm's cash and leverage (multiplied by minus one), and $Analyst_{i,t}$ represents the analyst forecast quality measured by the decile ranks of either analyst forecast dispersion (multiplied by minus one), denoted by *Dispersion*, or the forecast accuracy, denoted by *Accuracy*. *Gov* is represented by *AQ*, *Coverage*, and *Institution*. Detailed definitions of variables are reported in the Appendix. The model is estimated for the period from 1983 to 2011. T-statistics are reported in brackets. Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Dispersion (1)	Accuracy (2)
Analyst	0.0366*** (9.49)	0.0248*** (6.50)
Analyst × OverFirm	-0.0515*** (-7.16)	-0.0391*** (-5.37)
Joint significance	-0.0150*** (-3.47)	-0.0143*** (-3.23)
AQ	0.0213* (1.65)	0.0225* (1.75)
AQ × OverFirm	-0.0552** (-2.37)	-0.0570** (-2.44)
Coverage	0.0004** (2.03)	0.0001 (0.53)
Coverage × OverFirm	-0.0009** (-2.48)	-0.0005 (-1.42)
Institution	0.0141** (2.10)	0.0147** (2.18)
Institution × OverFirm	0.0097 (0.84)	0.0088 (0.76)
OverFirm	0.1144*** (13.29)	0.1081*** (12.78)
Age	0.0009*** (6.94)	0.0009*** (6.82)
Size	-0.0263*** (-23.33)	-0.0259*** (-23.00)
Mkt-to-Book	0.0024*** (10.78)	0.0025*** (11.16)
σ(CFO)	-0.0322** (-2.24)	-0.0329** (-2.29)
σ(Sales)	-0.0262*** (-4.59)	-0.0265*** (-4.64)
σ(Investment)	-0.0409*** (-4.13)	-0.0407*** (-4.11)
Loss	-0.0175*** (-10.00)	-0.0182*** (-10.42)

Dividend	0.0041** (2.05)	0.0041** (2.07)
Z-score	0.0168*** (13.50)	0.0170*** (13.69)
Tangibility	0.0629*** (8.45)	0.0642*** (8.62)
OperatingCycle	-0.0000 (-0.12)	0.0000 (0.11)
CFOsale	-0.0124*** (-5.96)	-0.0125*** (-6.00)
Ind Leverage	-0.0747*** (-9.74)	-0.0754*** (-9.82)
Intercept	0.1969*** (19.81)	0.1999*** (20.14)
Number of observations	31,544	31,544
R ²	0.134	0.132

Table 10 The standard 2SLS regression results with instrumental variables

The table presents the results of the two-stage-least-square (2SLS) regressions with lagged analyst quality (*LagAnalyst*), which are lagged *Dispersion* and lagged *Accuracy*, as the instrumental variables. Panel A shows the results of the first-stage regression. The predicted value of *Dispersion*, *Dispersion*×*OverFirm*, *Accuracy*, and *Accuracy*×*OverFirm* are then included as the main explanatory variables to replace the original measures in the regression model of eq.(1), with the results shown in Panel B. The details of the model specification of eq. (1) in the second stage are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the period from 1983 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

Panel A First-stage regression results

<i>Analyst forecast quality</i> <i>Dependent variable</i>	Dispersion		Accuracy	
	Dispersion	Dispersion × <i>OverFirm</i>	Accuracy	Accuracy × <i>OverFirm</i>
LagAnalyst	0.4564*** (32.23)	-0.0179*** (-2.69)	0.7107*** (49.53)	-0.0115* (-1.65)
LagAnalyst × <i>OverFirm</i>	-0.0629** (-2.19)	0.4670*** (34.57)	-0.2093*** (-7.15)	0.4247*** (43.88)
Control variables	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Number of observations	24,883	24,883	24,883	24,883
Number of firms	4,133	4,133	4,133	4,133
Partial F	1802.58 (p=0.0000)	2038.04 (p=0.0000)	3373.66 (p=0.0000)	3199.61 (p=0.0000)
Partial R ²	R ² =0.1370	R ² =0.1524	R ² =0.2558	R ² =0.2453
R ²	0.257	0.269	0.329	0.326

Panel B Second-stage regression results

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Predicted Dispersion (1)	Predicted Accuracy (2)
Analyst	1.7725*** (9.08)	0.5437*** (8.71)
Analyst × <i>OverFirm</i>	-2.8395*** (-7.27)	-0.9483*** (-7.19)
Joint significance	-1.0670*** (-4.17)	-0.4046*** (-4.43)
AQ	0.0383*** (2.91)	0.0501*** (3.88)
AQ × <i>OverFirm</i>	-0.0520** (-2.29)	-0.0688*** (-3.08)
Coverage	0.0001 (0.64)	-0.0000 (-0.18)
Coverage × <i>OverFirm</i>	0.0005 (1.55)	0.0007** (2.23)
Institution	0.0134**	0.0189***

	(2.18)	(3.18)
Institution $\times$ OverFirm	-0.0036	-0.0111
	(-0.32)	(-1.03)
OverFirm	0.0547***	0.0623***
	(6.56)	(7.96)
Age	-0.0001	-0.0001
	(-1.36)	(-1.42)
Size	-0.0094***	-0.0095***
	(-18.03)	(-18.37)
Mkt-to-Book	0.0039***	0.0040***
	(16.77)	(17.74)
σ (CFO)	0.0769***	0.0746***
	(7.30)	(7.10)
σ (Sales)	-0.0484***	-0.0481***
	(-11.43)	(-11.38)
σ (Investment)	0.1222***	0.1198***
	(12.87)	(12.66)
Loss	-0.0144***	-0.0183***
	(-6.71)	(-9.32)
Dividend	-0.0083***	-0.0079***
	(-5.56)	(-5.27)
Z-score	-0.0028***	-0.0031***
	(-2.89)	(-3.25)
Tangibility	0.1205***	0.1193***
	(28.25)	(28.03)
OperatingCycle	-0.0001***	-0.0001***
	(-9.17)	(-9.22)
CFOsale	-0.0169***	-0.0169***
	(-7.55)	(-7.49)
Ind Leverage	-0.0724***	-0.0776***
	(-11.04)	(-12.02)
Intercept	0.1752***	0.1722***
	(12.08)	(11.92)
Industry dummies	Yes	Yes
Number of observations	24,883	24,883
Hausman test	F=29.86 (P=0.000)	F=20.21 (P=0.000)
R ²	0.282	0.284

Table 11 Investment and analyst forecast quality with an OverIndustry measure

The table presents the regression results of eq.(1), specified as: $Investment_{i,t+1} = \alpha_0 + \alpha_1 Analyst_{i,t} + \alpha_2 Analyst_{i,t} \times OverIndustry_{i,t} + \alpha_3 Gov_{i,t} + \alpha_4 Gov_{i,t} \times OverIndustry_{i,t} + \alpha_5 OverIndustry_{i,t} + \gamma Control_{i,t} + \varepsilon_{i,t+1}$, where $Investment_{i,t+1}$ refers to the total investment of firm i in year $t+1$, and $Analyst_{i,t}$ represents the analyst forecast quality measured by the decile ranks of either analyst forecast dispersion (multiplied by minus one), denoted by *Dispersion*, or the forecast accuracy, denoted by *Accuracy*. We run a regression in each year of the average investment on the average Tobin's Q for all industries with at least 20 observations. The regression residuals of firms are then ranked into deciles and rescaled from zero to one to form a measure of aggregate industry-year over-investment measure, *OverIndustry*. *Gov* is represented by *AQ*, *Coverage*, and *Institution*. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications and is estimated for the full sample period from 1983 to 2011. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment	
	Dispersion (1)	Accuracy (2)
Analyst	0.0364*** (9.97)	0.0273*** (7.24)
Analyst × OverIndustry	-0.0456*** (-6.42)	-0.0334*** (-4.89)
Joint significance	-0.0092* (-1.68)	-0.0061 (-1.19)
AQ	0.0377** (2.04)	0.0395** (2.16)
AQ × OverIndustry	-0.0365 (-1.46)	-0.0396 (-1.61)
Coverage	0.0005*** (3.17)	0.0003* (1.71)
Coverage × OverIndustry	0.0005 (1.30)	0.0007** (2.10)
Institution	0.0177* (1.93)	0.0190** (1.99)
Institution × OverIndustry	-0.0071 (-0.51)	-0.0092 (-0.62)
OverIndustry	0.0552*** (5.09)	0.0478*** (4.67)
Age	-0.0001** (-2.02)	-0.0001** (-2.09)
Size	-0.0123*** (-10.75)	-0.0123*** (-10.73)
Mkt-to-Book	0.0052*** (9.66)	0.0053*** (9.98)
σ(CFO)	0.1015*** (6.56)	0.1008*** (6.46)
σ(Sales)	-0.0431*** (-6.63)	-0.0439*** (-6.84)

$\sigma(\text{Investment})$	0.0708*** (4.06)	0.0715*** (4.09)
Loss	-0.0251*** (-8.59)	-0.0258*** (-8.80)
Dividend	-0.0087*** (-3.62)	-0.0085*** (-3.52)
Z-score	-0.0056*** (-3.41)	-0.0053*** (-3.22)
Tangibility	0.0952*** (12.54)	0.0950*** (12.55)
OperatingCycle	-0.0001*** (-6.48)	-0.0001*** (-6.46)
CFOsale	-0.0220*** (-4.21)	-0.0227*** (-4.30)
Ind Leverage	-0.0992*** (-8.88)	-0.1014*** (-8.84)
Intercept	0.2000*** (10.43)	0.2055*** (10.57)
Industry dummies	Yes	Yes
Number of observations	31,544	31,544
R^2	0.273	0.271

Table 12 The effect of the Regulation Fair Disclosure (Reg FD) in 2000

The table presents the regression results of eq. (1) separately for two subsample periods: from 1983 to 1999 and from 2000 to 2011, in order to test the effect of the Regulation FD enacted in 2000. The details of the model specification of eq. (1) are the same as those in Table 3. Detailed definitions of variables are reported in the Appendix. The regression model controls for the fixed-industry effect based on the Fama-French 48 industry classifications. T-statistics are reported in brackets with heteroskedasticity-consistent standard errors clustered at the firm and year dimensions based on the method in Petersen (2009). Significance at the 10%, 5% and 1% levels is respectively indicated by *, ** and ***.

<i>Analyst forecast quality</i>	Dependent variable: Investment			
	Dispersion		Accuracy	
	Post- Reg FD (1)	Pre- Reg FD (2)	Post- Reg FD (3)	Pre- Reg FD (4)
Analyst	0.0444*** (6.25)	0.0552*** (9.42)	0.0280*** (4.48)	0.0421*** (8.30)
Analyst × OverFirm	-0.0806*** (-6.53)	-0.0969*** (-8.98)	-0.0567*** (-5.06)	-0.0734*** (-6.65)
Joint significance	-0.0363*** (-4.39)	-0.0417*** (-6.21)	-0.0287*** (-3.72)	-0.0313*** (-4.36)
AQ	0.0012 (0.06)	0.1978*** (3.51)	0.0031 (0.16)	0.2062*** (3.68)
AQ × OverFirm	-0.0251 (-0.87)	-0.4299*** (-5.51)	-0.0269 (-0.95)	-0.4500*** (-5.70)
Coverage	0.0004 (1.04)	-0.0005 (-1.50)	0.0001 (0.31)	-0.0009*** (-2.60)
Coverage × OverFirm	-0.0009 (-1.14)	0.0025*** (4.06)	-0.0004 (-0.51)	0.0032*** (5.18)
Institution	0.0191* (1.66)	0.0629*** (4.72)	0.0218* (1.79)	0.0647*** (4.94)
Institution × OverFirm	-0.0128 (-0.78)	-0.0324 (-1.50)	-0.0173 (-0.99)	-0.0361* (-1.70)
OverFirm	0.1330*** (9.06)	0.1098*** (8.53)	0.1214*** (9.31)	0.0949*** (6.58)
Intercept	0.1126*** (3.53)	0.1388*** (5.29)	0.1206*** (3.78)	0.1469*** (5.66)
Controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	yes	Yes
Number of observations	15,188	16,356	15,188	16,356
R ²	0.328	0.281	0.326	0.279

Appendix: Variable definition

Name	Definition
Main variables	
Investment	The sum of research and development expenditure (item 46), capital expenditure (item 128), and acquisition expenditure (item 129) less cash receipts from the sale of property, plant, and equipment (item 107) and scaled by lagged total assets (item 6).
Dispersion	The standard deviation of analysts' earnings forecasts scaled by fiscal year end price and multiplied by minus one.
Accuracy	The absolute earnings forecast error: actual EPS-median forecast EPS scaled by fiscal year end price and then multiplied by minus one.
OverFirm	A ranked variable, which is the average of ranked (deciles) measures of cash and leverage of each firm in each industry during a year. The variable is rescaled to range between zero and one. We multiply leverage by minus one before ranking so that both variables are increasing with the likelihood of over-investment.
Monitoring or governance variables	
AQ	The standard deviation of the firm-level residuals from the model developed by Dechow and Dichev (2002) and extended by Francis et al. (2005) during the years $t-5$ to $t-1$, and multiplied by negative one. The model is a regression of working capital accruals on lagged, current, and future cash flows plus the change in revenue and plant, property and equipment (PPE). All variables are scaled by average total assets. The model is estimated cross-sectionally for each industry with at least 20 observations in a given year based on the Fama and French (1997) 48-industry classification.
Coverage	The number of analysts following the firm as provided by IBES.
Institution	The percentage of firm's common shares held by institutional investors.
E-index	The measure of anti-takeover protection created by Bebchuk et al. (2009) and multiplied by minus one.
Other variables	
Q	The ratio of market value of total assets to book value of total assets, which is calculated as: [book value of assets (item 6) + market value of common stock (item 25 $\times$ item 199) - book value of common stock (item 60) - balance sheet deferred taxes (item 74)]/book value of assets (item 6).
Cash	The ratio of cash (item 1) to total assets (item 6).
Leverage	The ratio of long-term debt (item 9) to the sum of long-term debt to the market value of equity (item 9 + item 25 $\times$ item 199).
Age	The difference between the first date when a firm appears in CRSP and the current fiscal year end date.
Size	The logarithm of total assets (item 6).
Mkt-to-Book	The ratio of the market value of equity (item 25 $\times$ item 199) to the book value of common stock (item 60).
$\sigma(\text{CFO})$	The standard deviation of the cash flow from operations (CFO) deflated by the average total assets from years $t-5$ to $t-1$.
$\sigma(\text{Sales})$	The standard deviation of the sales (item 12) deflated by the average total

	assets from years $t-5$ to $t-1$.
$\sigma(\text{Investment})$	The standard deviation of investment from years $t-5$ to $t-1$.
Loss	An indicator variable that takes the value of one if net income before extraordinary items (item 18) is negative, and zero otherwise.
Dividend	An indicator variable that takes the value of one if the firm pays a dividend (i.e., if item 21>0 or item 127>0), and zero otherwise.
Z-score	A measure of a firm's financial health, which is calculated as: $[3.3 \times \text{Pretax Income} + \text{Sales} + 0.25 \times \text{Retained Earnings} + 0.5 \times (\text{Current Assets} - \text{Current liabilities})] / \text{Total Assets}$, or $[3.3 \times \text{item 170} + \text{item 12} + 0.25 \times \text{item 36} + 0.5 \times (\text{items 4} - \text{item 5})] / \text{item 6}$.
Tangibility	The ratio of tangible assets (item 8) to total assets (item 6).
OperatingCycle	The average time in days between purchasing or acquiring inventory and receiving the cash proceeds from its sale = $(\text{item 2} / \text{item 12} + \text{item 3} / \text{item 41}) \times 360$.
CFOsale	The ratio of CFO to sales (item 12).
Ind Leverage	The average leverage for firms in the same SIC 4-digit industry.