The Effect of CEO IT Expertise on the Information Environment:
Evidence from Management Earnings Forecasts

The Effect of CEO IT Expertise on the Information Environment:
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ABSTRACT

Firms depend on information technology to provide high quality internal information, but prior research suggests that IT is underutilized (Venkatesh and Bala 2008). Therefore, using a sample of firms with equivalent levels of technology in their information systems, I investigate whether firms that employ CEOs with IT expertise make forecasts that are more accurate. I argue that CEOs with IT expertise are more likely to encourage the utilization of IT in making earnings forecasts, thus increasing the accuracy of the forecasts. This argument is supported by prior research that suggests that people are more likely to utilize technology if they have more experience with IT (Venkatesh et al. 2012). This research suggests that executives with IT experience are more likely to utilize IT because they perceive it as easy to use. Overall, I find that CEOs with IT expertise make forecasts that are more accurate. In additional tests, I also find that CEOs with IT expertise do not manage earnings to maintain accuracy. Finally, I find that analysts are more likely to rely on information provided by CEOs with IT expertise. Additionally, analysts benefit from the high quality information provided by CEOs with IT expertise because analysts that revise their forecasts following a forecast issued by a CEO with IT expertise make forecasts that are more accurate.

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DEDICATION

To my son Atticus, you infuse excitement into every situation, I could not ask for a better best bud. To my daughter Hadley, you create joy in the lives of everyone you encounter, my life was forever improved when you were born. Finally, to my beautiful wife Angela, I would not be here without your love, encouragement, and support. You are my everything.

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I. INTRODUCTION

Managers rely on their information systems to provide information for internal decisions and external financial reporting. Following Dorantes et al. (2013), I refer to this flow of information to the manager as the internal information environment. A high quality internal information environment is one in which managers can access an abundance of accurate information from a variety of business processes in a timely fashion. Extant literature finds that effective information technology (IT) is the foundation of a high quality internal information environment (Li et al. 2012; Dorantes et al. 2013). Recent surveys of corporate directors document that firms recognize the importance of IT. However, these directors also admit that the majority of their firms lack adequate IT expertise to utilize IT effectively (KPMG 2012; PwC 2012). Therefore, I examine whether firms that employ a Chief Executive Officer (CEO) with IT expertise maintain a higher quality internal information environment, as evidenced through management earnings forecast accuracy.

Firms depend on IT for timely and accurate information for decision-making. For this reason, most publicly traded firms use some type of integrative IT, such as an enterprise system[1], to capture accounting and non-accounting information flows (Leib 2002; Brazel and Dang 2008; Cullinan et al. 2010). Prior research finds that implementing new IT improves the internal information environment (Dorantes et al. 2013), as evidenced by more accurate earnings forecasts issued by managers (hereafter referred to as management forecasts). Further evidence suggests that firms experience operational benefits from IT (Dehning and Richardson 2002;

[1] Enterprise systems are a general type of IT commonly used by firms. Firms use these systems to integrate and automate business processes. They are used to connect processes within one organization or across multiple organizations. Firms use these systems to produce information used in operational and financial reporting decisions (Hitt et al. 2002; Sia et al. 2002; Dorantes et al. 2013).

Dehning et al. 2003; Kobelsky et al. 2008); however, the literature also suggests that firms underutilize IT leading to poorer than expected outcomes (Venkatesh and Bala 2008).

A stream of research investigates why people choose not to adopt and utilize new IT (Venkatesh 2000; Venkatesh et al. 2003). Extant research shows that a primary reason managers are reluctant to adopt and utilize new technology is a lack of experience with IT (Armstrong and Sambamurthy 1999; Venkatesh 2000; Bassellier et al. 2003; Venkatesh et al. 2003; Venkatesh et al. 2012). Based on the evidence from these prior studies, and given that most firms have implemented technology based information systems, CEOs with IT expertise should be more likely to encourage the adoption, implementation, and utilization of those systems (Armstrong and Sambamurthy 1999; Venkatesh 2000; Bassellier et al. 2003; Venkatesh et al. 2003; Venkatesh et al. 2012). Therefore IT experience among executives may be beneficial to firms seeking to improve their internal information environment, because IT utilization should improve information flows.

Managers make earnings forecasts using both accounting and non-accounting information provided by the firm's information systems. Therefore, the accuracy of management forecasts are an external signal of the quality of the internal information environment. According to disclosure theory, when managers have access to better internal information they will make voluntary disclosures, such as earnings forecasts, to reduce agency costs and to signal their abilities (Trueman 1986; Verrecchia 1990). However, since managers face consequences for making poor quality forecasts they may choose to make less specific or fewer forecasts if their firm has a low quality internal information environment (Graham et al. 2005; Feng et al. 2009). Given their willingness to utilize IT, CEOs with IT expertise should be able to produce an internal information environment that allows them to make higher quality earnings forecasts.

I examine whether CEOs with IT expertise foster stronger internal information environments as evidenced by management forecasts that are more accurate than those made by other CEOs. Using biographies for CEOs from S&P 1500 firms, I construct a measure of IT expertise similar to Li et al. (2007), Haislip et al. (2013), and Lim et al. (2013). I develop this measure using information from the CEOs' work and educational backgrounds.[2] I argue that CEOs develop an expertise with IT through experience working in IT related positions and/or training associated with a degree in an IT related field. This expertise should affect the CEOs strategic priorities regarding IT, and increase their willingness to utilize IT. I predict that their experience with IT fosters a culture in which the use of IT is encouraged, which will also improve the quality of the information environment and the accuracy of management forecasts.

Despite the benefits of CEO IT expertise, obtaining such expertise is not costless. There are undoubtedly opportunity costs associated with gaining IT expertise. For example, a CEO that previously served as a Chief Information Officer (CIO) likely will not have the financial reporting expertise a CEO that served as a Chief Financial Officer has. Therefore, the CEO with IT expertise in this example would lack financial reporting expertise (Krishnan 2005; Krishnan and Visvanathan 2008). It is unclear whether the benefits from IT expertise outweigh the opportunity costs of lacking other skills; however, IT is a key factor in an effective internal information environment (Masli et al. 2010; Dorantes et al. 2013; Li et al. 2012) and therefore is potentially an area where IT expertise provides the greatest benefit.

[2] A more thorough discussion of the sample selection process and development of the IT expertise measure appear in the research design section.

I apply my measure of CEO IT expertise to a sample of 16,899[3] annual[4] forecasts made by S&P 1500 firms. I find that CEOs with IT expertise make forecasts that are more accurate. This is consistent with my prediction that their willingness to utilize IT improves the internal information environment allowing them to make forecasts that are more accurate. These results hold when I include a control variable for the financial expertise of the CEO. I find no association between forecast accuracy and CEO financial expertise, suggesting that in this particular setting IT expertise is more valuable. Additionally, I find that CEOs with IT expertise maintain an accuracy advantage regardless of the forecast horizon. For each firm's fiscal year I examine their first forecast, their final forecast, and the average forecast error for the year, and find that CEOs with IT expertise consistently make forecasts that are more accurate. Additionally, I find that CEOs with IT expertise do not differ from other CEOs for other forecast characteristics, such as frequency, precision, or bias. This suggests that CEOs with IT expertise do not achieve their accuracy through imprecise forecasts and are not subject to biases.

An alternative explanation of the greater forecast accuracy is that these CEOs are managing earnings to meet their forecasts. It is possible that CEOs with IT expertise may be more prone to this because as Lynch and Gomaa (2003) suggest, managers may be able to use IT to engage in fraudulent activity. To rule out this explanation, I test whether CEOs with IT expertise are associated with indicators of earnings management. I find that CEOs with IT expertise are not more likely to engage in earnings management activities. Specifically, I find no association between CEO IT expertise and the likelihood to just meet or beat their forecast using

[3] I additionally use a matched control sample in which I match each treatment forecast with a control forecast based on year, industry, firm size, forecast horizon, and forecast difficulty. Further discussion of this appears in the research design and results sections.

[4] I additionally test my hypotheses utilizing quarterly forecasts and arrive at similar results. See the additional analysis section for further discussion of this test.

discretionary accruals. Additionally, I find that CEOs with IT expertise are associated with fewer financial misstatements. This provides evidence that the IT expertise of the CEO improves the internal information environment as opposed to increasing their propensity to manage earnings.

In other tests, I also find that analysts are more likely to rely on management forecasts issued by CEOs with IT expertise. I specifically find that analysts are more likely to revise their forecasts following a management forecast if that management forecast is made by a CEO with IT expertise. I also find that analysts revise their forecasts to a greater degree following forecasts made by CEOs with IT expertise. Finally, I find that these analyst revisions are more accurate than other analyst forecasts. These results suggest that forecasts made by CEOs with IT expertise provide high quality information in their forecasts that analysts benefit from. Overall, the results show that CEOs with IT expertise foster high quality information environments for both internal and external users.

This paper contributes to the ongoing stream of research examining the relationship between IT and the internal information environment. For example, some recent studies find that IT improves financial reporting quality for firms that implement IT related to internal controls over financial reporting, and specific financial reporting technology, such as eXtensible Business Reporting Language (XBRL) (Hodge et al. 2004; Hunton et al. 2008; Masli et al. 2010). In addition, Dorantes et al. (2013) and Li et al. (2012) show that IT improves the quality of management forecasts. My study differs from these in that I examine the IT expertise of the CEO, as opposed to the effect of the specific IT itself. If the implementation of IT improves the internal information environment, then a CEO who is more willing to fully utilize the IT should maximize the quality of the internal information environment. I specifically provide evidence documenting the positive effect of CEO IT expertise on management forecast accuracy.

My study also contributes to the growing literature investigating the positive effects of CEO IT expertise. Li et al. (2007) and Haislip et al. (2013) examine the ability of CEOs with IT expertise to remediate material weaknesses in internal controls. In addition, Lim et al. (2013) show that CEOs with IT expertise can improve the reputation of a firm. My study complements these prior studies by examining how CEO IT expertise improves the internal information environment. These improvements to the internal information environment can affect many aspects of a firm such as financial reporting quality and day-to-day operational decisions.

Finally, my study contributes to the management forecast disclosure literature. Most prior studies regarding management forecast quality focus on the incentives CEOs face when making their forecasts, such as avoiding litigation and strategically altering stock prices (Kaznik and Lev 1995; Cotter et al. 2006). However, few papers examine the abilities of the CEOs making the forecasts. Baik et al. (2011) find that CEOs with better managing abilities (using measures such as press citations and industry-adjusted return on assets) make forecasts that are more accurate. My study extends this research by examining a specific CEO attribute that improves the overall information environment for the firm thus improving the quality of earnings forecasts.

I organize the remainder of the paper as follows. First, I develop my hypothesis, which includes a review of the IT acceptance and information quality literature. Second, I describe my sample and research design. Finally, I discuss the results and provide a conclusion to the study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 IT Acceptance and the Internal Information Environment

Essentially all large public firms have adopted some form of enterprise system or some other integrative IT system to improve the responsiveness of their internal information systems (Leib 2002; Brazel and Dang 2008; Cullinan et al. 2010). Overall, the evidence suggests that the implementation of IT improves the internal information environment. For example, Brazel and Dang (2008), find that after implementing an enterprise resource planning system, firms reduce the time between their fiscal year end and earnings announcement date. The authors attribute this to enterprise systems providing real-time financial information from multiple accounting cycles and departments, therefore improving the timeliness of information. In addition, Masli et al. (2010) find that implementing IT specifically aimed at monitoring the effectiveness of internal controls decreases the likelihood of material weaknesses and improves the financial reporting lag, again suggesting that IT improves the quality and timeliness of information. Complementing these studies, Li et al. (2012) find that when IT is not working properly, there are detrimental effects on the information environment. Specifically they find that firms that report IT related material weaknesses in internal controls also make less accurate earnings forecasts, suggesting that the information used by the CEO making the forecast is poor in quality. Finally, Dorantes et al. (2013) find that implementing an enterprise system improves the accuracy of management forecasts. The authors attribute the improved accuracy to an improved information environment created by the enterprise system. Overall, the extant literature suggests that properly functioning IT improves the internal information environment. However, as the literature also suggests, simply implementing IT is not enough, but that actual utilization of the system leads to success (Rai et al. 2002).

Not every IT implementation occurs with resounding success. In 2000, Nike lost $100 million in sales and faced a 20% drop in stock price due to a failed IT implementation (Koch

2004). Similarly, in 2004 Hewlett-Packard (HP) lost $40 million in sales on a $30 million failed IT implementation (Koch 2007). While these are extreme examples of what can go wrong, the returns associated with implementing new IT are often less than expected (Devaraj and Kohli 2003; Venkatesh and Bala 2008). As noted by Venkatesh and Bala (2008), possible causes of this result are low adoption and underutilization of the new IT. Executives often view IT as a commodity that they purchase for their business to stay competitive, but believe that no further attention is required from them following the purchase (Koch 2007). However, when upper management neglects IT, it can create massive problems for the firm, or at best the firm will never realize the full benefits of the IT (Rai et al. 2002; Venkatesh and Bala 2008; Haislip et al. 2013). Therefore, firms face potential benefits if they can utilize IT to its full potential.

A stream of information systems literature investigates what affects a person's willingness to adopt and utilize new IT (Venkatesh 2000; Venkatesh et al. 2003; Venkatesh and Bala 2008; Brown et al. 2012; Venkatesh et al. 2012). Bedard et al. (2003) apply a similar approach in their study where they investigate auditors' willingness to utilize an electronic work paper system. The authors of these papers find that the two main factors that affect a person's willingness to accept new technology are the perceived ease of use and the perceived usefulness of the technology. Essentially a person is more willing to use a technology if they believe they will understand how to use it and/or they believe that it is useful. Recent work finds that past experience with IT increases the perceived ease of use (Venkatesh 2000; Bedard et al. 2003; Venkatesh et al. 2003; Venkatesh et al. 2012). Additionally, the combination of experience and perceived ease of use have a positive effect on perceived usefulness. Therefore, a person with experience working with IT perceives new IT as easier to work with and this in turn gives them a better appreciation of how useful it is. This shows that experience is an effective contributing factor to a person's willingness to adopt and utilize IT.

The fact that a CEO with more IT expertise is more likely to use IT is not in itself enough to improve a firm's information environment. However, when that IT expertise affects the entire organization there should be benefits to the overall information environment. First, a CEO with IT expertise is more likely to be involved in the process of procuring new IT (Jarvenpaa and Ives 1991; Bassellier et al. 2003). The CEO's involvement will likely aid the company in acquiring the IT that most aligns with the firm's strategic priorities (Jarvenpaa and Ives 1991; Thong and Yap 1995; Armstrong and Sambamurthy 1999). For example, as stated before, the majority of large public companies utilize some type of ERP system. However, these ERP systems are comprised of multiple modules (such as human resource, inventory, purchase, finance & accounting, customer relationship management, and supply chain management). Therefore the firm is able to choose which modules best fit with their organization. A CEO with IT expertise will most likely be more involved in this process and choose the modules that will best improve the information environment (Jarvenpaa and Ives 1991; Thong and Yap 1995; Armstrong and Sambamurthy 1999).

In addition to choosing the IT that their firms will implement, CEOs with IT expertise can also influence the degree to which IT is actually used throughout the firm. Hunton et al. (2011) find that the tone set by the CEO affects how rigorously controls are implemented and tested throughout the firm. Similarly, other papers show that the values and preferences of the CEO affect the decisions made by employees made throughout the firm (Wally and Baum 1994; Berson et al. 2008). More relevant to this study, many papers show that when the CEO has some degree of IT knowledge or supports the implementation of IT, then the IT is more likely to be accepted throughout the firm (Thong and Yap 1995; Bassellier et al. 2003; Li 2005; Finney and Corbett 2007). Overall, the evidence suggests that CEOs are able to influence the degree to which IT is accepted within their firm.

In summary, prior research suggests that implementing new IT positively affects the internal information environment by providing more information from throughout the firm in a timely and accurate fashion. As shown by Dorantes et al. (2013), a quality information environment improves the quality of management forecasts. However, prior research also shows that firms do not usually experience the full benefits of IT due to a lack of utilization. As shown by prior research, experience with IT increases a person's willingness to utilize IT. Therefore, it logically follows that CEOs with IT expertise are more willing to utilize IT than other CEOs. In agreement with this prediction, Bassellier et al. (2003) find that CEOs with a better understanding of IT are more likely to implement and encourage the use of IT. This allows them to extract superior information creating an improved internal information environment. In the following section, I examine the linkages between CEO IT expertise and a distinct output of the internal information environment, specifically management forecasts.

2.2 The Information Environment and Management Forecasts

According to disclosure theory, managers have incentives to provide voluntary disclosures as they receive better internal information. These incentives involve either reducing agency costs or signaling their own abilities to manage the firm and provide quality information (Diamond 1985; Trueman 1986; Verrecchia 1990; Coller and Yohn 1997; Graham et al. 2005). One form of voluntary disclosure is management forecasts. Diamond (1985) argues that a primary reason that managers choose to release internal information is to reduce the cost shareholders face in acquiring private information. Prior literature finds that management forecasts influence stock prices and analyst forecasts, suggesting that investors and analysts do rely on management forecasts (Patell 1976; Penman 1980; Pownall and Waymire 1980; Waymire 1984; Waymire 1986; Jennings 1987; Baginski and Hassell 1990; Williams 1996). Complementing these studies, Trueman (1986) argues that managers use earnings forecasts to signal their own superior abilities to manage the firm. Trueman goes on to state that this decision to release internal earnings forecasts is dependent on the quality of the internal information used by the CEO. Verrechia (1990) explores this further by suggesting that when the quality of the internal information increases, managers will make more voluntary disclosures. There is also evidence supporting the notion that executives are hesitant to release forecasts and that forecasts are less specific when managers only have access to low quality internal information (Feng et al. 2009). This is most likely because managers are concerned about their reputations for making quality forecasts (Graham et al. 2005). Additionally, managers potentially face stock market and labor market penalties when they release poor quality forecasts (Lee et al. 2012), thus justifying their hesitance in making earnings forecasts based on low quality information. Overall, the evidence suggests that managers want to make forecasts that are accurate, and thus desire to obtain access to the highest quality internal information possible.

As mentioned, the two primary reasons for issuing management forecasts are to mitigate information asymmetry and to provide a signal about management's ability. Healy and Palepu (2001) argue that the extent to which managers are able to achieve either of these goals is largely dependent on the accuracy of their earnings forecasts. The extant literature focuses on how the quality of the inputs affects the accuracy of forecasts. For example, Feng et al. (2009) and Li et al. (2012) find that material weaknesses in internal control are negatively associated with management forecast accuracy, suggesting that these weaknesses negatively affect the informational inputs used by management to make forecasts. Additional research finds that CEOs develop forecasting reputations (Ng et al. 2013) and that CEOs with better managing abilities make more accurate forecasts (Baik et al. 2011). However, the extant literature does not examine any other abilities of CEOs that could improve the quality of information inputs to improve earnings forecasts.

I argue that management forecasts depend on both the quality of the internal information used by managers and the ability of the manager to interpret and use that information. IT expertise should enhance a CEO's ability to extract more information and to interpret the information more fully, and therefore CEOs with IT expertise should be able to make more accurate earnings forecasts. A CEO with IT expertise should be able to obtain more accurate, timely, and precise internal information that will allow them to make earnings forecasts that are more accurate. Based on disclosure theory and the improvements to the internal information environment provided by CEO IT expertise, my hypothesis is as follows:

> Hypothesis: CEOs with IT expertise make higher quality management forecasts, as measured by forecast accuracy, than CEOs without IT expertise.

3. RESEARCH DESIGN

3.1 Sample Selection

My initial sample includes annual management forecasts (obtained from First Call) for S&P 1500 firms from 2004 through 2010. Following prior literature I exclude financial services and utility firms (SIC codes 4900-4999 and 6000-6999) because these firms are highly regulated and their disclosure polices differ from other firms (Karamanou and Vafeas 2005). I begin the sample period in 2004 because I use data from SOX 404 internal control reports to construct some of the control variables. My sample is limited to S&P 1500 firms because I want to limit the sample to firms with some type of integrative IT implemented in their information system.

Based on prior literature and anecdotal evidence essentially all large public firms utilize some type of enterprise system within their firm (Leib 2002; Brazel and Dang 2008; Cullinan et al. 2010). Therefore, for my sample it is not the decision to implement the system that affects the quality of the forecasts because all of the firms in the sample utilize some type of enterprise system. I finally also eliminate any firms that are missing the data necessary (obtained from Computstat, CRSP, and Audit Analytics) to calculate the variables used in my models. After applying these requirements my sample includes 16,899 individual annual forecasts from 3,529 firm-year observations.[5,6] Panel A of Table 1 presents a reconciliation of my sample. I additionally use a matched sample design in which I match each CEO IT expertise forecast with a control forecast from the same industry and year. I make the matches with the requirements that *LnAT* must be within 30% and that the horizon of the forecast is within 90 days. Finally, after I identify potential matches that meet these criteria I match the treatment forecast to the control forecast with the closest *Std_AF,* as this is a proxy for forecast difficulty (Ajinkya et al. 2005). This yields a sample of 900 forecasts, 450 of which are forecasts issued by CEOs with IT expertise.[7]

[Insert Table 1 Here]

[5] One of my variables, *Std_AF*, requires the firm to be followed by multiple analysts. This variable is responsible for the largest reduction in my sample size. In untabulated results, I run my models excluding this variable on the larger sample and arrive at similar results.
[6] I match each forecast with the CEO that issued the forecast based on the data of the forecast and the dates the CEO was in office. In years of turnover, the new CEO may make operational decisions that affect the quality of the initial CEO's forecast. Therefore in untabulated results I run my analysis removing forecasts made in years of CEO turnover and arrive at similar results. I alternatively include an indicator variable for CEO turnover and also arrive at similar results.
[7] In untabulated results, I also run all of the models winsorizing all continuous variables at the 99% and 1% levels to mitigate the effects of outliers. I arrive at similar results to those presented in the tables.

I measure CEO IT expertise similar to Li et al. (2007), Haislip et al. (2013), and Lim et al. (2013). To identify potential IT expertise I read the biographies of the CEOs found using the Corporate Library, BusinessWeek, and Forbes. There are two potential ways that a CEO that can be considered to have IT expertise. First, if the executive has a graduate level academic degree[8] that is IT related which includes degrees in Computer Sciences, Electrical Engineering, or Information Systems. The second potential method for acquiring IT expertise is through working in an IT-related position of employment. The IT-related jobs identified in my sample are: Chief Information Officer, Chief Technology Officer, Vice President of Information Technology, or IT Consultant.[9] If the CEO meets either of these criteria then they are considered to possess IT expertise and I code the *IT Expert* variable as a one. Either working in an IT position or acquiring a graduate level degree should provide the CEO with enough experience to be comfortable working with IT.[10] Panel B of Table 1 provides the distribution of the sample across time. The distribution of the sample is fairly even through time, with a slight increasing trend within the IT expertise firms, which is in line with recent surveys suggesting that firms are increasingly recognizing the importance of IT (KPMG 2012; PWC 2012). Panel C of Table 1 provides an industry distribution of the sample. It appears that overall firms are distributed similarly between the treatment and control groups, with a slightly larger percentage of CEOs

[8] The results remain essentially the same if I include undergraduate degrees in this measure.
[9] In additional analysis I control for the presence of a CIO within the organization. I find that this variable is not significant and does not affect the results presented. See the additional analysis section for further discussion of this test.
[10] Li et al. (2007), Haislip et al. (2013), and Lim et al. (2013) additionally use a third criteria in which they consider a CEO to possess IT expertise if they work for an IT firm. I do not include this measurement because these CEOs tend to remain at IT companies and therefore it is unclear if the effects are from the IT expertise or an industry effect. I choose to limit IT expertise to the two criteria I use because it is a clearer measure is this situation.

with IT expertise working in services firms.[11] Table 2 provides definitions for all other variables used throughout the paper. Finally, Table 3 provides descriptive statistics for all of the firms in the sample. As expected, since my sample only includes S&P 1500 firms, the firms in the sample are large, profitable firms that tend to use Big 4 auditors and these firms tend not to be overly leveraged. Also of note, more than 3% of the firms in the sample employ a CEO with IT expertise.

[Insert Table 3 Here]

3.2 Model Specifications

To examine the potential impact that CEO IT expertise has on the internal information environment, I investigate whether CEO IT expertise affects the accuracy of management forecasts. I use management forecasts because they are an external signal of the quality of the internal information environment. I therefore use the following OLS regression model to test my Hypothesis (see table 2 for variable definitions):

$$\begin{aligned} Abs\_Error_{j,i,t} = {} & \beta_0 + \beta_1 IT\ Expert_{j,i,t} + \beta_2 LnAT_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Loss_{i,t} + \beta_5 Leverage_{i,t} + \\ & \beta_6 EarnVol_{i,t} + \beta_7 CFOVol_{i,t} + \beta_8 Growth_{i,t} + \beta_9 IndCon_{i,t} + \beta_{10} Big4_{i,t} + \\ & \beta_{11} LnAnalysts_{i,t} + \beta_{12} Std\_AF_{j,i,t} + \beta_{13} Surprise_{j,i,t} + \beta_{14} Horizon_{j,i,t} + \\ & \beta_{15} Litigation_{i,t} + \beta_{16} High\ Tech_{i,t} + \beta_{17} Weak_{i,t} + \varepsilon_{j,i,t} \end{aligned} \qquad (1)$$

For this model, I include year fixed effects and estimate robust standard errors clustered by firm[12] following Petersen (2009). I measure the variables, depending on their nature, for forecast *j,* of firm *i,* in year *t*. *Abs_Error* is the absolute value of management forecast error, measured as realized earnings less the management forecast, scaled by the closing stock price on the last day

[11] The results of my empirical tests remain essentially the same if I include industry indicator variables in the models.
[12] The results remain essentially unchanged if I alternatively cluster standard errors by CEO or dual clustering by firm and year.

of the previous fiscal year. Therefore, a larger number is an indicator of greater error and less accurate forecasts.

My variable of interest is *IT Expert* and I describe the measurement of this variable in the previous section. I expect CEOs with IT expertise to make forecasts that are more accurate than other CEOs. Therefore, consistent with my hypothesis that CEO IT expertise improves the internal information environment, I expect the coefficient on *IT Expert* (β_1) to be negative and significant, signifying lower forecast errors. I initially run this model at the individual forecast level, and therefore when appropriate I measure the variables at the forecast level. As discussed earlier, a CEO that acquires IT expertise is most likely sacrificing an opportunity to gain another type of expertise. Therefore, I additionally run the model including a variable to control for the financial expertise of the CEO, *Financial Exp*. This alternative model should provide evidence as to the true strategic benefits of IT expertise as it applies to the firm's internal information environment. To alleviate concerns that firms that employ CEOs with IT expertise are simply inherently different from other firms, and that these other differences could cause the improved management forecasts, I additionally utilize a matched control group sample. I match each of the forecasts made by CEOs with IT expertise with a control forecast within the same industry-year based on size, forecast horizon, and forecast difficulty. Therefore, the primary difference between the treatment and control observations is the IT expertise of the CEO. I again run the same model (Model 1), to measure forecast accuracy using this matched sample.

I follow prior literature by including additional independent variables to control for other possible determinants of management forecast quality. Definitions of all variables are in Table 2. Larger firms have more experienced and knowledgeable staff and therefore I expect firm size (*LnAT)* to be positively associated with management forecast quality (Kasznik and Lev 1995).

Baik et al. (2011) find that executives with better operations performance make higher quality forecasts and therefore I include the return on assets (*ROA*). Hayn (1995) find that earnings of firms that report losses are less informative than profitable firms. Therefore, extant literature predicts and finds a negative relationship between *Loss* firms and the quality of management forecasts (Ajinkya et al. 2005; Baik et al. 2011). Similarly, Feng et al. (2009) find that firms facing financial challenges make forecasts that are of lower quality. Therefore, I include both *Loss* and *Leverage* in my model. Firms with highly volatile earnings face greater difficulty in forecasting future earnings (Feng et al. 2009; Dorantes et al. 2013). Therefore, I include *EarnVol* and *CFOVol* to control for any effects of this volatility. Feng et al. (2009) additionally find that sales *Growth* can negatively affect the quality of earnings forecasts. Firms that operate in industries with low competitive pressures face different incentives for disclosures than firms within highly competitive industries (Bamber and Cheon 1998). I therefore include *IndCon* (measured using the Herfindahl index), to control for the effects of industry concentration on earnings forecasts. Prior research also documents that firms that engage *Big4* auditors tend to have higher quality disclosures and more accurate earnings forecasts (Lang and Lundholm 1993; Ajinkya et al. 2005; Feng et al. 2009). Prior research finds a similar positive affect on disclosures for firms with large analyst following, thus I include *LnAnalysts* (Lang and Lundholm 1996). Prior literature uses the dispersion of analysts' forecasts (*Std_AF*) to capture the uncertainty of earnings prospects for a firm (Ajinkya and Gift 1984; Brown et al. 1985; Swaminathan 1991). Recent literature applies this measurement to proxy for the forecast difficulty managers face (Ajinkya et al. 2005). *Surprise* captures the difference between the management forecast and the consensus analyst forecast, and recent literature finds this to be associated with forecast quality (Ajinkya et al. 2005). As discussed thoroughly in prior literature it is more difficult to forecast earnings further from the fiscal period-end date (Baginski and Hassell 1997; Ajinkya et al. 2005), therefore I include a control for the forecast *Horizon*. Firms that operate in industries that are more subject to shareholder litigation face different disclosure incentives, and therefore I include *Litigation* (Francis et al. 1994). I am interested in the IT expertise of the CEO, and therefore I include a control for *High Tech* firms, because these types of firms may be more likely to employ a CEO with IT expertise. Finally, recent literature shows that material weaknesses in internal controls detrimentally affect the accuracy of management forecasts (Feng et al. 2009; Li et al. 2013). I therefore control for the presence of material weaknesses by including *Weak.*

4. RESULTS

4.1 Univariate Results

Table 4 presents univariate results of comparisons between firms that employ CEOs with IT expertise and control firms. Based on these results it appears that firms that employ CEOs with IT expertise tend to be smaller, less leveraged, report more volatile earnings and cash flows, experience greater sales growth, operate in less concentrated industries, operate in highly litigious industries, operate in high tech industries, and report fewer material weaknesses in internal controls. However, most of these differences are relatively small and are included as control variables in my models because they may be associated with forecast quality.

Table 4 also presents the results for my main dependent variable (*Abs_Error)*. These results show that firms that employ a CEO with IT expertise tend to make forecasts with smaller errors. This suggests that CEOs with IT expertise have access to superior internal information that allows them to make earnings forecasts that are more accurate.

[Insert Table 4 Here]

4.2 Multivariate Results

Table 5 presents the accuracy of management forecasts regression results (when necessary additional control variables are presented in separate tables). The results in Table 5 utilize ordinary least squared regressions where the dependent variable is management forecast error measured as the absolute value of realized earnings less the management forecast scaled by lagged stock price. The sample for Columns 1 through 3 consists of all forecasts with the necessary data. I find that the coefficient on my variable of interest is negative and significant (*IT Expert* coefficient = -0.005, p-value = 0.005) in Column 1. In other words, CEOs with IT expertise make earnings forecasts that are more accurate, which I argue is due to a high quality internal information environment. In Column 2, I additionally include the *Financial Exp* variable to control for the financial expertise of the CEO. I include this variable to determine if the incremental benefits of IT expertise outweigh the opportunity costs of giving up financial expertise as it applies to management forecasts. I find that the coefficient for my variable of interest remains negative and significant (*IT Expert* coefficient = -0.005, p-value = 0.005), and that the coefficient on *Financial Exp* is not significant (p-value = 0.195). This result confirms my prediction that for purposes of the internal information environment IT expertise is more beneficial than financial expertise. However, as seen in Column 3, there are incremental benefits for CEOs with IT expertise to also have financial expertise (*IT Expert* coefficient = -0.004, p-value = 0.029; coefficient on the interaction of *IT Expert* and *Financial Exp* = -0.006, p-value = 0.100). Therefore, while CEOs with IT expertise do improve the quality of the information environment yielding more accurate earnings forecasts, the optimal CEO may be one with both IT and financial expertise. Finally, Column 4 uses a matched sample approach.[13] I again find

[13] See the research design section for a more thorough discussion of this approach.

that CEO IT expertise is associated with lower forecast error (*IT Expert* coefficient = -0.002, p-value = 0.004). Therefore, my results hold when comparing to a control group of firms of similar size and forecasting difficulty.

[Insert Table 5 Here]

Complementing the results in Table 5, Table 6 examines forecast error for forecasts made at varying horizons. Column 1 presents results using only the first management forecast made for each firm-year. Column 2 presents results using only the most recent management forecast made before the firm formally announces earnings. Finally, the dependent variable for Column 3 is the average management forecast error for the given firm-year. In all three models, I find that CEOs with IT expertise make earnings forecasts that are more accurate, as the coefficient on *IT Expert* is negative and significant in all three columns ($p<0.05$). This suggests that regardless of the forecast horizon, CEOs with IT expertise are consistently more accurate than other CEOs.

[Insert Table 6 Here]

5. ADDITIONAL ANALYSIS

5.1 Other Forecasting Attributes

Prior literature examines other forecasting attributes and finds that they are often associated with forecast accuracy (Ajinkya et al. 2005; Dorantes et al. 2013). These attributes include the number of forecasts issued in a given year (*Frequency*), the precision of the forecast (*Precision* and *PointF*), and the bias of the forecast (*Bias*). Given that I find that CEOs with IT expertise make forecasts that are more accurate, I examine whether there are any other significant differences in the forecasting behavior of CEOs with IT expertise. To test this I run variations of the following model, which is a slight modification of Model (1) (see Table 2 for variable definitions):

$Attribute_{j,i,t} = \alpha_0 + \alpha_1 IT\ Expert_{j,i,t} + \alpha_2 Financial\ Exp_{j,i,t} + \alpha_3 LnAT_{i,t} + \alpha_4 Loss_{i,t} + \alpha_5 Leverage_{i,t} + \alpha_6 EarnVol_{i,t} + \alpha_7 CFOVol_{i,t} + \alpha_8 Growth_{i,t} + \alpha_9 IndCon_{i,t} + \alpha_{10} Big4_{i,t} + \alpha_{11} LnAnalysts_{i,t} + \alpha_{12} Std\_AF_{j,i,t} + \alpha_{13} High\ Tech_{i,t} + \alpha_{14} Surprise_{j,i,t} + \alpha_{15} Horizon_{j,i,t} + 3_{j,i,t.}$
(2).

I run the model four separate times using the four different *Attributes* (*Frequency, Precision, PointF,* and *Bias)* as the dependent variables. The model that uses *Frequency* as the dependent variable uses a firm-year sample and therefore any variables measured at the forecast level are the average for that firm-year. I run the remaining models at the individual forecast level, and I therefore measure all of the variables at the forecast level. *Frequency* is a count variable and therefore I run its model as an OLS regression. *PointF* is an indicator variable and therefore I run its associated model as a logistic regression. *Precision* is an ordinal variable that ranges from zero to three and therefore I run its associated model as an ordered logistic regression model.[14] Finally, *Bias* is a continuous variable, and therefore I run its model as an OLS regression. I include year fixed effects in all of the models and estimate robust standard errors clustered by firm. As before, my variable of interest is *IT Expert*; if it is significant in any of the models then this would signify that CEOs with IT expertise display forecasting behavior that is different from other CEOs.

Table 7 presents the regression results for the other forecasting attributes tests. As the table shows, *IT Expert* is not significant (p>0.10) in any of the columns. This suggests that on average, other than forecast accuracy, CEOs with IT expertise do not differ in their forecasting behavior from other CEOs. Therefore, CEOs with IT expertise make forecasts as frequently and

[14] Following Choi et al. (2010), I alternatively measure *Precision* using a sample limited to point and range forecasts. For this measure I set precision equal to 0 for point forecasts and for range forecasts I use the range of the forecast scaled by the lagged stock price multiplied by negative one. I still find that *IT Expert* is not significant using this measure as the dependent variable.

as precise as other CEOs, but the forecasts made by the CEOs with IT expertise are more accurate.

[Insert Table 7 Here]

5.2 Alternative Earnings Management Explanation

For my hypothesis, I assume that CEOs with IT expertise make earnings forecasts that are more accurate because these CEOs foster a high quality internal information environment. However, another possible explanation for the improved accuracy of their earnings forecasts is that CEOs with IT expertise may be more willing or able to manage earnings to meet their forecasts. Lynch and Gomaa (2003) suggest that newly implemented IT may allow management to commit fraud. Additionally, Brazel and Dang (2008) find that firms report higher levels of abnormal discretionary accruals after implementing new IT, specifically enterprise resource planning systems. I therefore provide additional tests to determine that the results that I find are truly due to improvements in the internal information environment and are not related to earnings management.

I specifically test the association between CEOs with IT expertise and common earnings management proxies identified in prior research. The specific proxies that I use are the likelihood of reported earnings meeting or just beating the amount forecasted by management[15] (*Just Beat*), the likelihood of just beating using discretionary accruals (*Just Beat with DAs*), and the likelihood of earnings misstatements (*Misstate*). See the Appendix for a detailed description of the calculation of these variables. I use the following regression model adapted from prior

[15] In untabulated results, I alternatively use the likelihood of meeting or just beating the most recent analyst forecast and arrive at similar results.

research (Frankel et al. 2002; Ashbaugh et al. 2003) to test the association between CEO IT expertise and earnings management (see Table 2 for variable definitions):

$$[\text{Earnings Management}]_{i,t} = \psi_0 + \psi_1 IT\ Expert_{i,t} + \psi_2 Financial\ Exp_{j,i,t} + \psi_3 LnAT_{i,t} + \psi_4 ROA_{i,t} + \psi_5 Leverage_{i,t} + \psi_6 Loss_{i,t} + \psi_7 Return_{i,t} + \psi_8 CFO_{i,t} + \psi_9 Merger_{i,t} + \psi_{10} CFOVol_{i,t} + \psi_{11} EarnVol_{i,t} + \psi_{12} Big4_{i,t} + \psi_{13} Horizon_{i,t} + \psi_{14} HighTech_{i,t} + \psi_{15} Financial\ Exp_{j,i,t} + 3_{j,i,t.} \quad (3).$$

I run the model three separate times, using my three different proxies for earnings management as the dependent variables. All three variables are indicator variables, so each time I run the model as a logistic regression, and I include year indicators and estimate robust standard errors clustered by firm. The sample for the model that uses *Just Beat* as the dependent variable only includes the last forecast before the earnings announcement for each firm. The sample for the model that uses *Just Beat with DAs* limits the previous sample further by only including observations with reported earnings before discretionary accruals that are at or below the forecasted amount. I measure the independent variables for the model that uses *Misstate* as the dependent variable at the firm-year level.[16] If the alternate explanation that CEOs with IT expertise make earnings forecast that are more accurate because they manage earnings, then I expect the coefficient on *IT Expert* to be positive and significant in all of the models. However, if my hypothesis is correct that CEOs wit IT expertise improve the internal information environment, then I do not expect the coefficient on *IT Expert* to be significant.

Table 8 presents the regression results for the earnings management tests. The coefficient on *IT Expert* is not positive and significant in any of the columns, suggesting that CEOs with IT expertise are not more likely to engage in earnings management activities. This supports my

[16] This model does not include *Horizon* as a control variable because I do not estimate the model at the forecast level. However, in untabulated results I include the average forecast *Horizon* as a control variable and the results remain essentially the same.

hypothesis that CEOs with IT expertise make earnings forecasts that are more accurate because they improve the internal information environment, and not because they manage earnings. In fact, in Column 3 *IT Expert* is negative and significant (p=0.061), which suggests that firms that employ a CEO with IT expertise are less likely to misstate their financial statements. This could be due to improvements in the internal information environment positively affecting financial reporting quality. Overall, these results fail to support the alternative explanation that CEOs with IT expertise achieve forecast accuracy through earnings management.

[Insert Table 8 Here]

5.3 Analyst Earnings Forecast Revisions

Analysts have an incentive to issue accurate earnings forecasts, because their careers are dependent on the quality of their forecasts (Hong and Kubik 2003). Therefore, analysts should desire to utilize high quality information when making their earnings forecasts. One source of information that analysts use to make their forecasts is management forecasts (Baginski and Hassell 1990; Williams 1996; Cotter et al. 2006). However, recent studies find that when analysts rely too strongly on the information in management forecasts, it can negatively affect their accuracy (Cotter et al. 2006; Feng and McVay 2010). This suggests that the information provided by management is not always of the highest quality.

My initial results suggest that CEOs with IT expertise make forecasts that are more accurate. However, if these CEOs with IT expertise improve the quality of the internal information environments, then their forecasts should also be more informative. Essentially, I predict that in addition to improvements to the internal information environment, CEOs with IT expertise improve the quality of all information provided to parties external to the firm. I therefore provide additional tests to determine if CEOs with IT expertise improve the quality of the overall information environment surrounding the firm, as evidenced through analyst forecast revisions.

I specifically examine analyst forecast revisions made within 15 days following the issuance of a management forecast. I first examine whether forecasts made by CEOs with IT expertise affect the analysts' revision decisions. Specifically, I test the likelihood that the analysts revise their forecasts following a management forecast (*Revise*). I additionally test the extent to which analysts rely on the management forecast by examining the amount of the revision (*RevisionAmount*). Finally, because prior literature finds that relying on management forecasts can negatively affect the accuracy of analyst forecasts, I examine the accuracy of the analyst forecast revisions (*AFE_Post*). I use the following regression models adapted from prior research (Feng and McVay 2010) to test the association between CEO IT expertise and analyst forecast revisions (see Table 2 for variable definitions):

$$Revise_{j,i,t} = \lambda_0 + \lambda_1 IT\ Expert_{j,i,t} + \lambda_2 Surprise_{j,i,t} + \lambda_3 Down_{j,i,t} + \lambda_4 Horizon_{j,i,t} + \lambda_5 LnAnalysts_{j,i,t} + \lambda_6 Range_{j,i,t} + \lambda_7 Loss_{i,t} + \lambda_8 LnAT_{i,t} + \varepsilon_{j,i,t}. \quad (4)$$

$$RevisionAmount_{j,i,t} = \varphi_0 + \varphi_1 IT\ Expert_{j,i,t} + \varphi_2 Surprise_{j,i,t} + \varphi_3 Down_{j,i,t} + \varphi_4 Horizon_{j,i,t} + \varphi_5 LnAnalysts_{j,i,t} + \varphi_6 Range_{j,i,t} + \varphi_7 Loss_{i,t} + \varphi_8 LnAT_{i,t} + \varphi_9 Surprise{*}IT\ Expert_{j,i,t} + \varphi_{10} Surprise{*}Down_{j,i,t} + \varphi_{11} Surprise{*}Horizon_{j,i,t} + \varphi_{12} Surprise{*}LnAnalysts_{j,i,t} + \varphi_{13} Surprise{*}Range_{j,i,t} + \varphi_{14} Surprise{*}Loss_{j,i,t} + \varphi_{15} Surprise{*}LnAT_{j,i,t} + \varepsilon_{j,i,t}. \quad (5)$$

$$AFE\_Post_{j,i,t} = \pi_0 + \pi_1 IT\ Expert_{j,i,t} + \pi_2 Down_{j,i,t} + \pi_3 Horizon_{j,i,t} + \pi_4 LnAnalysts_{j,i,t} + \pi_5 Range_{j,i,t} + \pi_6 Loss_{i,t} + \pi_7 LnAT_{i,t} + \pi_8 RevisionAmount_{j,i,t} + \pi_9 ROA_{,i,t} + \pi_{10} Merger_{i,t} + \pi_{11} Foreign_{i,t} + \pi_{12} Std\_AF\_Post_{j,i,t} + \varepsilon_{j,i,t}. \quad (6).$$

Revise is an indicator variable and therefore model (4) is run as a logistic regression. *RevisionAmount* and *AFE_Post* are both continuous variables and therefor I estimate models (5) and (6) using OLS regressions. In all of the models, I include year indicator variables and estimate robust standard errors clustered by firm. My variable of interest is *IT Expert*. In model

(4) I expect the coefficient on *IT Expert* to be positive and significant, indicating that analysts are more likely to revise their earnings forecasts following a management forecast if a CEO with IT expertise issues the forecast. I also expect a positive and significant coefficient on the interaction of *IT Expert* and *Surprise* in model (5). A positive coefficient in model (5) would indicate that the analysts are more strongly relying on the information provided by forecasts made by CEOs with IT expertise. Finally, I expect a negative and significant coefficient on *IT Expert* in model (6). In line with my hypothesis, I expect the overall quality of the information environment for firms that employ CEOs with IT expertise to be better. This in turn should improve the quality of analyst forecasts, and therefore I predict that analyst revisions are more accurate if they follow a management forecast issued by a CEO with IT expertise.

Panels A, B, and C of Table 9 present the regression results for the analyst forecast revision tests. As expected, the coefficient on *IT Expertise* is significant ($p<0.10$) and in the predicted direction in all three columns. In Column 1, the positive coefficient signifies that analysts are more likely to revise their forecasts immediately following a management forecast if a CEO with IT expertise issues that forecast. In Column 2, the positive coefficient on the interaction of *IT Expert* and *Surprise s*uggests that analysts will revise their forecasts to a greater degree if they are doing so in response to a forecast issued by a CEO with IT expertise. Overall, these results support my hypothesis that analysts are more likely to rely on the information provided by CEOs with IT expertise. Finally, the negative coefficient on *IT Expertise* in Column 3 (in Panel C) means that analyst forecast revisions are more accurate if they are made using information from management forecasts issued by CEOs with IT expertise. This result somewhat contradicts prior research that finds that analysts that follow management forecasts too closely suffer from decreased accuracy (Feng and McVay 2010). Overall, these results suggest that CEOs with IT expertise foster a quality information environment that improves the quality of information flows both internally and externally.

[Insert Table 9 Here]

5.4 Self-Selection Bias

In previous tests, I use a matched sample of firms to identify a control group that is most similar to my treatment group across multiple characteristics. However, that sample fails to alleviate all of the concerns regarding self-selection bias. It is possible that firms with superior IT capabilities will choose to employ CEOs with IT expertise and therefore it is not necessarily the expertise of the CEO that leads to accurate earnings forecasts. In this section, I examine this potential self-selection bias by using the Heckman two-stage model (Heckman 1979). To use this model I regress the choice of employing a CEO with IT expertise on a set of variables shown to be associated with firms making IT governance changes (Haislip et al. 2013). I use this first stage to calculate the Inverse Mills Ratio (*IMR*). The first stage probit models is as follows:

$$IT\ Expert_{i,t} = \Omega_0 + \Omega_1 LnAT_{i,t} + \Omega_2 ROA_{i,t} + \Omega_3 Leverage_{i,t} + \Omega_4 High\ Tech_{i,t} + \Omega_5 CIO_{i,t} + \Omega_6 ITWeak_{i,t} + \Omega_7 SalesVol_{i,t} + \Omega_8 Std\_Return_{i,t} + \Omega_9 Foreign_{i,t} + \Omega_{10} Merger_{i,t} + \Omega_{11} Restruct_{i,t} + \Omega_{12} Prodcut\_Diff_{i,t} + \Omega_{13} Cost\_Leader_{i,t} + \Omega_{14} Transform_{i,t} \quad (7)$$

where:

CIO	= 1 if the firm employs a chief information officer or chief technology officer that is among the top five compensated employees, and 0 otherwise;
ITWeak	= 1 if the firm reports an IT material weakness in internal controls, and 0 otherwise;
SalesVol	= the standard deviation of sales growth for the previous five years;
Std_Return	= the standard deviation of returns for the previous five years;
Restruct	= 1 if the firm engages in restructuring activity, and 0 otherwise;
Product_Diff	= operating income divided by sales;
Cost_Leader	= sales divided by total assets;

Transform = 1 if the firm is in a transform industry IT role, and 0 otherwise;

and all other variables are as previously defined.

Panels A and B of Table 10 present the results of this first stage model. The sample for Column 1 includes all available forecasts. All of the variables for Column 2, including the dependent variable, are the averages for each company year. The sample for Column 3 utilizes a matched sample as discussed in the research design section. There is some indication in the results that firms that employ CEOs with IT expertise are smaller, more profitable, and less leveraged firms. In addition, it appears that these firms tend to operate in high tech industries and employ a CIO. These firms also have highly volatile sales. They are more likely to have foreign operations, but are less likely to be involved in a merger or restructuring. It also appears that these firms choose are apt to choose a product differentiation strategy over a cost leadership strategy. Finally, these firms are likely to operate in a *Transform* industry. These results are in line with the expectations developed in Haislip et al. (2013).

I next include the *IMR* calculated from the first stage in my main model of forecast error which again includes year indicator variables and robust standard errors clustered by firm (model 1). Panels C and D of Table 10 present the regression results from the second stage model of the self-selection bias tests. The sample for Column 1 includes all available forecast observations. All of the variables in Column 2, including the dependent variable, are the averages for each firm-year. The sample for Column 3 utilizes the matched sample design discussed in the research design section. My variable of interest is again *IT Expert* which I expect to be negative and significant. As can be seen in Table 10, the coefficient on *IT Expert* is negative and significant ($p<0.05$) in all three columns. This suggests that even after controlling for self-selection bias, I still find that firms with CEOs with IT expertise issue more accurate earnings forecasts. Interestingly, in Column 1 the coefficient on *IMR* is statistically significant (p=0.012). This suggests that self-selection bias may be a legitimate concern in this research design, and therefore controlling for the inverse mills ratio is appropriate.

[Insert Table 10 Here]

5.5 Quarterly Forecasts

In my primary tests I only examine forecasts of annual earnings. Forecasts of quarterly earnings are made less frequently and often with shorter horizons, and therefore they may be affected differently by the expertise of the CEO. In this section I examine the effect of CEO IT expertise on quarterly earnings forecasts.

Not all firms choose to issue quarterly earnings forecasts. Prior research suggests that managers with superior information may be inclined to issue more voluntary disclosures to signal their superior ability or to reduce information asymmetry (Trueman 1986; Verrechia 1990). Therefore because a CEO with IT expertise improves the internal information environment of their firm, firms that employ these CEOs may be more likely to issue quarterly earnings forecasts.

In my first test of quarterly earnings forecasts, I examine the likelihood of a firm issuing any quarterly forecasts during the year. To test this I use model 2, but replace the dependent variable with *Issued_Quarterly*. *Issued_Quarterly* is an indicator variable coded one if the firm issues any quarterly earnings forecasts in year t and zero otherwise. I use model 2 because the decision to issue a quarterly earnings forecast is similar to the decision to issue a greater number of annual forecasts (*Frequency*). I estimate the model using a logistic regression with robust standard errors clustered by firm. As before, my variable of interest is *IT Expert*. I expect this variable to be positive and significant, signifying that firms that employ CEOs with IT expertise are more likely to issue quarterly forecasts. In my second test of quarterly earnings forecasts I run a modified version of model 1. In this test I am examining if CEOs with IT expertise are able to maintain their accuracy advantage in the quarterly forecast setting. Therefore, I run model 1 the same as in the initial tests, but the sample consists of all available quarterly earnings forecasts. This model is estimated using an OLS regression with robust standard errors clustered by firm. Finally, my variable of interest is again *IT Expert*. I expect this variable to be negative and significant, indicating that CEOs with IT expertise issue quarterly earnings forecasts that are more accurate than those issued by other CEOs.

Table 11 presents the results from the quarterly forecast tests. Column 1 presents the results of the model testing the likelihood of issuing a quarterly forecasts. The coefficient on *IT Expert* is positive, but not significant (p=0.170). This suggests that CEOs with IT expertise are not any more likely than other CEOs to issue a quarterly earnings forecasts. However, the coefficient on *IT Expert* is negative and significant (p=0.027) in Column 2. This column presents the results from the model testing the accuracy of quarterly forecasts. The negative coefficient indicates that CEOs with IT expertise do issue quarterly forecasts that are more accurate than other CEOs. This provides further evidence that CEOs with IT expertise help create an improved internal information environment in their firms, which leads to more accurate earnings forecasts.

In further testing, I run the analysis separately by each fiscal quarter. The results for this analysis are presented in panels C-F of Table 11. Column 1 presents the results for Q1, Column 2 presents the results for Q2, Column 3 presents the results for Q3, and Column 4 presents the results for Q4. The coefficient on *IT Expert* is negative and significant in columns 2, 3, and 4. This suggests that CEOs with IT expertise are more accurate at forecasts earnings for every fiscal quarter except for the first quarter of the year. This suggests that the improvements that CEOs with IT expertise make to the information environment show benefits throughout the majority of the year.

[Insert Table 11 Here]

5.6 Presence of CIO

Given that prior research finds that when a firm's IT is working effectively they have a high quality internal information environment (Li et al. 2012; Dorantes et al. 2013), it may be important to consider the presence and role of a CIO. A CIO or Chief Technology Officer (CTO) should have ultimate responsibility regarding IT. If a CIO is given sufficient power and responsibility they should be able to positively influence the information environment by ensuring that the firm's IT is working effectively. Therefore, it may be possible that CEOs with IT expertise may be more likely to employ and rely on a CIO, and thus not directly affect the utilization of IT.

To test this alternative explanation I first use Execucomp to identify firms with a CIO or CTO among their top five paid employees. This should identify those firms that feature a CIO in a prominent enough role to effectively influence the usage of IT in the firm. I then run model 1 as before, but I include *CIO*, which is an indicator variable coded one if the firm has a CIO or CTO in their top five paid employees in year t and zero otherwise. I again run the model as an OLS regression using robust standard errors clustered by firm. If the CIO significantly affects the information environment as suggested above, then I expect the coefficient on *CIO* to be negative and significant. I also expect the coefficient on *IT Expert* to be negative and significant, because I still predict that CEOs with IT expertise are able to improve the information environment above whatever benefits a CIO provides.[17]

Table 12 presents the results from the CIO alternative explanation tests. The sample for Column 1 includes all available forecast observations. All of the variables in Column 2, including the dependent variable, are the averages for each firm-year. The sample for Column 3 utilizes the matched sample design discussed in the research design section. In all three columns, the coefficient on *IT Expert* is negative and significant ($p<0.01$), suggesting that even in the presence of a CIO a CEO with IT expertise is found to positively influence the information environment. In addition, the coefficient on *CIO* is not significant ($p>0.10$) in any of the columns suggesting that the tone set by the CEO is truly what determines the degree to which IT is utilized to improve the information environment.

[Insert Table 12 Here]

5.7 IT Expertise, Management Forecast Accuracy, and Internal Controls

Prior literature finds that material weaknesses in internal control over financial reporting detrimentally affect management forecast accuracy (Feng et al. 2009; Li et al. 2012). These authors argue that CEOs at firms with material weaknesses in internal controls must rely on information that is of low quality. Ineffective controls create an internal information environment that produces low quality information. Prior literature also examines the association between executive IT expertise and material weaknesses in internal controls, and documents mixed results. Li et al. (2007) do not find any association between executive IT

[17] In untabulated analysis I also run the model including an interaction of *IT Expert* and *CIO* to identify the marginal benefits of employing both a CEO with IT expertise and a CIO. However, neither the interaction term nor the main effect of *CIO* are statistically significant ($p>0.10$) in this analysis.

expertise and IT material weaknesses. However, Haislip et al. (2013) find that firms that report an IT material weakness report fewer weaknesses in the future if they replace their Chief Financial Officer with one that has IT expertise. Therefore, another possible explanation for my documented improvements in management forecast accuracy could be that CEOs with IT expertise create a better internal control environment. While this should also create a better internal information environment, it is a second-order effect as opposed to my predicted first-order effect. I therefore provide additional tests to examine this possibility.

I first test the association between CEOs with IT expertise and material weaknesses in internal controls. I use the following logistic regression, adapted from prior research (Ge and McVay 2005; Doyle et al. 2007; Li et al. 2007; Haislip et al. 2013), to test this association (see Table 2 for variable definitions):

$$Weak_{,i,t} = \gamma_0 + \gamma_1 IT\ Expert_{i,t} + \gamma_2 Financial\ Exp_{i,t} + \gamma_3 LnAT_{i,t} + \gamma_4 ROA_{i,t} + \gamma_5 Big4_{i,t} + \gamma_6 Leverage_{i,t} + \gamma_7 Loss_{i,t} + \gamma_8 Growth_{i,t} + \gamma_9 Segment_{i,t} + \gamma_{10} Foreign_{i,t} + \gamma_{11} Merger_{i,t} + \gamma_{12} Hightech_{i,t} + \varepsilon_{i,t} \quad (3).$$

The dependent variable, *Weak*¸ is an indicator variable coded as one if the firm reports any material weaknesses in internal controls in the current year, and zero otherwise. I additionally run the model limiting the dependent variable to IT related material weakness, because CEOs with IT expertise may be especially adept at preventing these types of weaknesses. I then run the model a third time using only non-IT related material weaknesses. I include year fixed effects in all of the models and estimate robust standard errors clustered by firm. My variable of interest is *IT Expert.* If the coefficient on this variable is significant in any of the models than this would suggest a relationship exists between CEO IT expertise and the likelihood of a firm reporting a material weakness in internal controls.

Table 13 presents the regression results for the likelihood of material weakness tests. *IT Expert* is not significant (p>0.10) in any of the columns. This suggests that CEOs with IT expertise are not any better or worse than other CEOs at preventing material weaknesses in internal controls of any kind. This supports my prediction that CEOs with IT expertise directly improve the quality of the internal information environment.

[Insert Table 13 Here]

To test this alternative explanation further, I run the following modification to model (1) (see Table 2 for variable definitions):

$$Abs\_Error_{j,i,t} = \delta_0 + \delta_1 IT\ Expert_{j,i,t} + \delta_2 Weak_{i,t} + \delta_3 Weak{*}IT\ Expert_{j,i,t} + \delta_4 Financial\ Exp_{j,i,t} + \delta_5 LnAT_{i,t} + \delta_6 ROA_{i,} + \delta_7 Loss_{i,t} + \delta_8 Leverage_{i,t} + \delta_9 EarnVol_{i,t} + \delta_{10} CFOVol_{i,t} + \delta_{11} Growth_{i,t} + \delta_{12} IndCon_{i,t} + \delta_{13} Big4_{i,t} + \delta_{14} LnAnalysts_{i,t} + \delta_{15} Std\_AF_{j,i,t} + \delta_{16} High\ Tech_{i,t} + \delta_{17} Surprise_{j,i,t} + \delta_{18} Horizon_{j,i,t} + 3_{j,i,t.} \quad (4).$$

This model is my primary model with the addition of the *Weak* variable as well as the interaction of *IT Expert* and *Weak*. As in the previous model, I run this model three separate times using the different material weakness categories (any material weaknesses, only IT weaknesses, and only non-IT weaknesses). I estimate this model using an OLS regression, and I include year fixed effects and estimate robust standard errors clustered by firm. I expect the coefficient on *IT Expert* to be negative, suggesting that CEOs with IT expertise make earnings forecasts that are more accurate after controlling for the presence of material weaknesses. I expect the coefficient on *Weak* to be positive because prior literature suggests that firms with material weaknesses in internal controls issue earnings forecasts that are less accurate (Feng at al. 2009; Li et al. 2012). Finally, I am also interested in the interaction of these two variables (*IT Expert* and *Weak*). I expect this variable to be negative and significant. I predict that CEOs with IT expertise are able to reduce the negative effects to the information environment created by the material weaknesses in internal controls.

Table 14 (Panel A) presents the regression results for the management forecast error and material weakness tests. *IT Expert* is negative and significant ($p<0.01$) in all four columns, suggesting that even when controlling for the presence of material weaknesses, CEOs with IT expertise still make earnings forecasts that are more accurate. As expected, in the majority of the columns material weaknesses are associated with management forecasts that are less accurate (In Column 1 *Weak* is positive and significant $p=0.037$; in Columns 3 and 4 *NonITWeak* is positive and significant $p<0.10$). This agrees with prior literature that finds that firms with material weaknesses issue less accurate earnings forecasts (Feng et al. 2009). Finally, in every column the coefficient on the interaction terms are negative and significant ($p<0.05$). This suggests that CEOs with IT expertise are able to mitigate the negative effects created by material weaknesses in internal controls. In fact, F-tests show that in Columns 2 and 4 CEOs with IT expertise are able to completely overcome and eliminate the negative effects created by IT material weaknesses. Overall, the evidence suggests that CEOs with IT expertise are not more accurate because of improvements to internal control, but instead are accurate in spite of poor internal controls.

[Insert Table 14 Here]

6. CONCLUSION

The extant literature documents that benefits firms receive from implementing IT, specifically improvements to the internal information environment. However, prior literature also documents that firms often do not utilize IT fully. Researchers also suggest that people with experience working with IT are more likely to utilize IT in the future. Using a sample of firms that all utilize IT for their internal information system, I provide evidence of the further benefits firms can extract from IT if they employ a CEO with IT expertise. Specifically, I examine whether CEOs with IT expertise issue earnings forecasts that are more accurate. My study extends the literature by documenting how CEOs with IT expertise can improve the internal information environment, as evidenced by management forecasts.

I find that IT expertise allows CEOs to improve the quality of internal information environment. Specifically CEOs with IT expertise issue earnings forecasts that are more accurate (an external signal of the quality of internal information). This evidence suggests that IT expertise can be a vital attribute for firms to consider when making employment decisions. I additionally document that these CEOs do not achieve this improved accuracy through earnings management mechanisms. Finally, I find that immediately following an earnings forecast issued by a CEO with IT expertise, analysts are more likely to revise their forecasts. Additionally, I find that these same analyst revisions are of a greater amount, and that they are more accurate. Overall, the evidence suggests that CEOs with IT expertise foster a high quality information environment.

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Table 1
Sample Selection Process

Panel A: Sample selection and data sources	Number of Firm-Years	Number of Forecasts
Sample of S&P 1500 firms 2004-2010	10,500	
Less: firms in Financial Services or Utilities industries (SIC codes 4900-4999 and 6000-6999)	2,376	
Sample of S&P 1500 firms from 2004 to 2010 within desired industries	**8,124**	
Less: firms without necessary data from Compustat or Audit Analytics	490	
Sample of S&P 1500 firms from 2004 to 2010 with necessary data from Compustat and Audit Analytics	**7,634**	
Less: firms with missing First Call data or without multiple analysts following	3,752	
Sample of S&P 1500 firms from 2004 to 2010 with all necessary data	**3,882**	**18,151**
Less: firms with no annual point or range forecasts	353	1,252
Final Sample of usable observations	**3,529**	**16,899**

Panel B: Year Distributions

Year	**IT Expertise Forecasts**	**IT Expertise Firms**	**All Other Forecasts**	**All Other Firms**	**All Forecasts**	**All Firms**
2004	20	7	1,653	383	1,673	390
2005	59	13	2,430	509	2,489	522
2006	61	16	2,581	538	2,642	554
2007	69	18	2,491	535	2,560	553
2008	78	22	2,664	524	2,742	546
2009	83	20	2,217	450	2,300	470
2010	91	22	2,402	472	2,493	494
Total	461	118	16,438	3,411	16,899	3,529

Panel C: Industry Distributions

Industry	2-Digit SIC Code	IT Expertise Forecasts	IT Expertise Firms	All Other Forecasts	All Other Firms	All Forecasts	All Firms
Chemicals	28-29	45	9	1,902	350	1,947	359
Electrical	36, 38	97	26	2,420	510	2,517	536
Equipment	35	12	2	1,109	225	1,121	227
Retail Sales	50-59	58	15	3,157	655	3,215	670
Services	70-79	214	57	1,964	467	2,178	524
All Others	All Others	35	9	5,886	1204	5,921	1,213
Total		461	118	16,438	3,411	16,899	3,529

Table 2 Variable Definitions

Panel A: Dependent Variable Definitions

Variable	Definition
Abs_Error	the absolute value of the management forecast error (realized earnings less the management forecast) / lagged stock price.
Bias	the signed value of the management forecast error (realized earnings less the management forecast)/ lagged stock price
Precision	an ordinal variable coded 3 for point forecasts, 2 for range forecasts, 1 for open ended forecasts, and 0 for all other forecasts.
PointF	an indicator variable coded one if the forecast is a point forecast and zero otherwise.
Frequency	the number of management forecasts issued for fiscal year t.
Just Beat	an indicator variable coded one if earnings are equal to or within two cents greater than the management forecast, and zero otherwise.
Just Beat with DAs	an indicator variable coded one if the earnings are equal to or within two cents greater than the management forecast, but earnings before discretionary accruals are less than the management forecast, and zero otherwise.
Misstatement	an indicator variable coded one if the firm has a material misstatement in year t, and zero otherwise.
Revise	an indicator variable coded one if there is a revision to the consensus analyst forecast made within 15 days following the management forecast, and zero otherwise.
RevisionAmount	the difference between the revised consensus analyst forecast (made within 15 days after the management forecast) and the preexisting consensus analyst forecast, scaled by lagged stock price.
AFE_Post	the absolute value of the median consensus analyst forecast error 15 days following a management forecast, scaled by lagged stock price.
Issued_Quarterly	an indicator variable coded one if the firm issues any quarterly forecasts in year t and zero otherwise.

Table 2 Variable Definitions

Panel B: Independent Variable Definitions

Variable	Definition
IT Expert	an indicator variable coded one if the CEO is considered to have IT expertise based on work experience or education background as described in the research design section, and zero otherwise.
LnAT	the natural log of total assets in year t.
Loss	an indicator variable coded one if the firm reports a net loss in year t, and zero otherwise.
Leverage	total liabilities divided by total assets in year t.
EarnVol	the standard deviation of ROA over the prior 10 years.
CFOVol	the standard deviation of operating cash flows over the prior 10 years.
Growth	percentage of sales growth from year t-1 to year t.
IndCon	the Herfindahl index in year t, measured as the sum of the squares of the market shares of all firms within the same three-digit SIC industry.
Big4	an indicator variable coded one if the firm engages a Big 4 auditor in year t, and zero otherwise.
LnAnalysts	the natural log of the number of analysts following the firm at the end of year t.
Std_AF	the standard deviation of the individual analyst forecasts for year t, immediately prior to the management forecast for year t.
News	the management forecast value less the pre-existing median analyst forecast scaled by lagged stock price.
Horizon	the number of days between the date of issuance for the management forecast and the fiscal year end date.

Table 2 Variable Definitions

Panel B: Independent Variable Definitions continued

Variable	Definition
Litigation	an indicator variable coded one if the firm operates in an industry that is associated with increased litigation (SIC codes 2833-2836, 3570-3577, 7370-7374, and 3600-3674 following Francis et al. 1994) and zero otherwise.
High Tech	an indicator variable coded one if the firm operates in a high tech industry (as identified by Francis and Schipper 1999), and zero otherwise.
Segment	the total number of reportable segments in year t.
Foreign	an indicator variable coded one if the firm engaged in foreign transaction in year t, and zero otherwise.
Merger	an indicator variable coded one if the firm engaged in mergers and acquisitions in year t, and zero otherwise.
ROA	the return on assets calculated as net income before extraordinary items divided by total assets in year t.
Return	the 12-month buy and hold return before the date of the management forecast.
CFO	cash flows from operations divided by total assets.
Weak	an indicator variable coded one if the firm reports any material weaknesses in internal controls in year t, and zero otherwise
Financial Exp	an indicator variable coded one if the CEO has financial expertise through possessing a CPA license, previously working in public accounting, or previously working in another financial related position such as chief financial officer, and zero otherwise.

Table 3
Descriptive Statistics

Variable	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
LnAT	7.767	1.455	6.696	7.620	8.635
ROA	0.063	0.083	0.038	0.064	0.097
Loss	0.081	0.273	0.000	0.000	0.000
Leverage	0.510	0.187	0.391	0.510	0.621
EarnVol	0.036	0.054	0.017	0.025	0.038
CFOVol	0.415	0.032	0.025	0.035	0.050
Growth	0.103	0.189	0.018	0.083	0.160
IndCon	0.068	0.074	0.037	0.051	0.071
Big4	0.951	0.215	1.000	1.000	1.000
LnAnalysts	2.302	0.620	1.946	2.303	2.773
Std_AF	0.105	0.914	0.033	0.055	0.098
News	-0.003	0.080	-0.002	0.000	0.001
Horizon	204.970	69.419	180.000	202.000	233.000
Litigation	0.194	0.396	0.000	0.000	0.000
High Tech	0.241	0.428	0.000	0.000	0.000
Weak	0.045	0.207	0.000	0.000	0.000
Financial Exp	0.137	0.344	0.000	0.000	0.000
IT Expert	0.034	0.179	0.000	0.000	0.000
Abs_Error	0.014	0.043	0.002	0.005	0.014

Table 4
Univariate Analysis

	IT Expertise Observations N= 118	**All Other Observations** N = 3,411	**Difference**	**P-Value**
Panel A: Control Variables				
LnAT	7.413	7.779	-0.366	0.007***
Loss	0.068	0.082	-0.014	0.592
Leverage	0.422	0.513	-0.091	<0.001***
EarnVol	0.084	0.034	0.050	<0.001***
CFOVol	0.072	0.040	0.032	<0.001***
Growth	0.134	0.101	0.033	0.064*
IndCon	0.042	0.069	-0.027	<0.001***
Big4	0.958	0.951	0.007	0.744
LnAnalysts	2.383	2.299	0.084	0.149
Std_AF	0.066	0.106	-0.040	0.638
News	-0.001	-0.003	0.002	0.775
Horizon	205.85	204.939	0.911	0.889
Litigation	0.568	0.182	0.386	<0.001***
High Tech	0.568	0.230	0.338	<0.001***
ROA	0.074	0.062	0.011	0.148
Weak	0.022	0.046	-0.024	0.015**
Financial Exp	0.144	0.137	0.007	0.831
Abs_Error	0.007	0.014	-0.007	0.062*

All p-values are two-tailed. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 respectively.

Table 5
Management Earnings Forecast Error

Panel A **Variables**	**Pred**	**Column 1** **Absolute Forecast Error**	**Column 2** **Absolute Forecast Error**
Intercept	?	0.018***	0.018***
		(0.000)	(0.000)
IT Expert	-	-0.005***	-0.005***
		(0.005)	(0.005)
Financial Exp	-		-0.001
			(0.195)
LnAT	-	-0.001*	-0.001*
		(0.069)	(0.066)
ROA	-	-0.077***	-0.077***
		(0.002)	(0.002)
Loss	+	0.008**	0.008**
		(0.023)	(0.022)
Leverage	+	0.000	0.000
		(0.475)	(0.447)
EarnVol	+	-0.005	-0.004
		(0.635)	(0.611)
CFOVol	+	0.046	0.045
		(0.114)	(0.118)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.330	0.330
F-Statistic		7.680***	7.410***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for columns 1-3 includes all available forecasts. The sample for column 4 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 5
Management Earnings Forecast Error

Panel B		**Column 1**	**Column 2**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Growth	+	-0.005	-0.005
		(0.979)	(0.979)
IndCon	-	-0.003	-0.003
		(0.311)	(0.319)
Big4	?	0.004***	0.004***
		(0.006)	(0.007)
LnAnalysts	-	0.000	0.000
		(0.594)	(0.586)
Std_AF	+	0.001	0.001
		(0.203)	(0.203)
News	-	-0.279***	-0.279***
		(0.000)	(0.000)
Horizon	+	0.000***	0.000***
		(0.000)	(0.000)
Litigation	-	-0.005**	-0.005**
		(0.032)	(0.033)
High Tech	?	-0.002	-0.002
		(0.508)	(0.485)
Weak	+	0.008**	0.008**
		(0.042)	(0.042)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.330	0.330
F-Statistic		7.680***	7.410***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for columns 1-3 includes all available forecasts. The sample for column 4 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 5
Management Earnings Forecast Error

Panel C Variables	**Pred**	**Column 3** Absolute Forecast Error	**Column 4** Absolute Forecast Error
Intercept	?	0.018***	0.013***
		(0.000)	(0.001)
IT Expert	-	-0.004**	-0.002***
		(0.029)	(0.004)
Financial Exp	-	-0.001	-0.002**
		(0.235)	(0.030)
Financial Exp IT Expert*	-	-0.006*	
		(0.100)	
LnAT	-	-0.001*	-0.000
		(0.068)	(0.166)
ROA	-	-0.076***	-0.017*
		(0.002)	(0.074)
Loss	+	0.008**	0.006
		(0.023)	(0.112)
Leverage	+	0.001	-0.002
		(0.415)	(0.623)
EarnVol	+	-0.002	0.002
		(0.559)	(0.418)
CFOVol	+	0.047	0.007
		(0.113)	(0.332)
Year Indicators		Included	Included
Number of observations		16,899	900
Adjusted R2		0.330	0.253
F-Statistic		7.290***	8.270***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for columns 1-3 includes all available forecasts. The sample for column 4 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 5
Management Earnings Forecast Error

Panel D Variables	Pred	Column 3 Absolute Forecast Error	Column 4 Absolute Forecast Error
Growth	+	-0.005	-0.004
		(0.979)	(0.801)
IndCon	-	-0.003	0.040
		(0.310)	(0.777)
Big4	?	0.004***	-0.001
		(0.007)	(0.664)
LnAnalysts	-	0.000	-0.001**
		(0.571)	(0.040)
Std_AF	+	0.001	0.019***
		(0.204)	(0.001)
News	-	-0.279***	0.307***
		(0.000)	(0.002)
Horizon	+	0.000***	0.000***
		(0.000)	(0.000)
Litigation	-	-0.005**	0.002
		(0.031)	(0.817)
High Tech	?	-0.002	-0.002
		(0.478)	(0.200)
Weak	+	0.008**	-0.000
		(0.042)	(0.527)
Year Indicators		Included	Included
Number of observations		16,899	900
Adjusted R2		0.330	0.253
F-Statistic		7.290***	8.270***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for columns 1-3 includes all available forecasts. The sample for column 4 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 6
Management Earnings Forecast Error Using Different Forecast Horizons

Panel A Variables	**Pred**	**Column 1** Absolute Error of Most Recent Forecast	**Column 2** Absolute Error of First Forecast	**Column 3** Average Absolute Forecast Error
Intercept		0.014**	0.020***	0.014***
		(0.012)	(0.000)	(0.006)
IT Expert	-	-0.003**	-0.005**	-0.004**
		(0.040)	(0.024)	(0.024)
Financial Exp	-	-0.001	-0.002	-0.001
		(0.279)	(0.161)	(0.203)
LnAT	-	-0.001**	-0.001*	-0.001
		(0.045)	(0.076)	(0.133)
ROA	-	(-0.090)	(-0.105)	(-0.098)
		(0.007)	(0.003)	(0.005)
Loss	+	0.009*	0.017***	0.014***
		(0.054)	(0.001)	(0.005)
Leverage	+	0.001	0.001	-0.001
		(0.377)	(0.435)	(0.630)
EarnVol	+	-0.004	-0.016	-0.009
		(0.610)	(0.861)	(0.714)
CFOVol	+	0.034	0.073**	0.055
		(0.236)	(0.048)	(0.112)
Year Indicators		Included	Included	Included
Number of observations		3,529	3,529	3,529
Adjusted R2		0.311	0.323	0.342
F-Statistic		8.780***	10.810***	11.020***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes the first annual forecast for each company year. The sample for column 2 only includes the most recent annual forecast made before earnings are announced. All of the variables for column 3, including the dependent variable, are the averages for each company year. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 6
Management Earnings Forecast Error Using Different Forecast Horizons

Panel B		**Column 1**	**Column 2**	**Column 3**
Variables	**Pred**	**Absolute Error of Most Recent Forecast**	**Absolute Error of First Forecast**	**Average Absolute Forecast Error**
Growth	+	-0.004	-0.008	-0.004
		(0.872)	(0.973)	(0.838)
IndCon	-	0.002	0.002	-0.002
		(0.608)	(0.601)	(0.416)
Big4	?	0.005**	0.004*	0.005**
		(0.013)	(0.085)	(0.017)
LnAnalysts	-	0.001	-0.000	-0.001
		(0.828)	(0.455)	(0.154)
Std_AF	+	-0.000	0.001**	0.002***
		(0.506)	(0.032)	(0.006)
News	-	-0.270***	-0.262***	-0.256***
		(0.005)	(0.002)	(0.000)
Horizon	+	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.001)
Litigation	-	-0.004	-0.007**	-0.004
		(0.182)	(0.041)	(0.141)
High Tech	?	-0.001	0.000	-0.001
		(0.749)	(0.995)	(0.709)
Weak	+	0.003	0.004	0.004
		(0.183)	(0.190)	(0.170)
Year Indicators		Included	Included	Included
Number of observations		3,529	3,529	3,529
Adjusted R2		0.311	0.323	0.342
F-Statistic		8.780***	10.810***	11.020***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes the first annual forecast for each company year. The sample for column 2 only includes the most recent annual forecast made before earnings are announced. All of the variables for column 3, including the dependent variable, are the averages for each company year. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 7
Other Forecasting Attributes

Panel A Variables	Pred	Column 1 Frequency	Column 2 Precision
Intercept 1	?	0.352	-8.204***
		(0.444)	(0.000)
Intercept 2	?		-3.694***
			(0.000)
Intercept 3	?		2.273***
			(0.000)
IT Expert	+	-0.275	0.252
		(0.840)	(0.208)
Financial Exp	+	-0.204	-0.199
		(0.887)	(0.926)
LnAT	+	0.259***	0.028
		(0.000)	(0.329)
Loss	-	-0.277	0.472
		(0.139)	(0.996)
Leverage	-	1.521	-0.713**
		(0.999)	(0.030)
EarnVol	-	0.406	0.000
		(0.608)	(0.976)
CFOVol	-	-1.795	-0.000
		(0.234)	(0.300)
Year Indicators		Included	Included
Number of observations		3,882	18,151
Adjusted or Pseudo R2		0.081	0.007
F-Statistic or Chi2 Statistic		9.931***	35.240**

The dependent variable for column 1 is the number of annual forecasts the firm makes for fiscal year t. The dependent variable for column 2 is set to 3 if the forecast is a point forecast, 2 if a range forecast, 1 if an open-ended forecast, and 0 otherwise. The dependent variable for column 3 is set to 1 if the forecast is a point forecast and 0 otherwise. The dependent variable is the forecast bias of the management forecast, (realized earnings less the management forecast) / lagged stock price.*** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available firm year observations. The sample for columns 2-4 includes all forecasts with the necessary data. The model for columns 1 and 4 are estimated using ordinary least squares regressions. Column 2 utilizes and ordered logistic regression. Column 3 utilizes a logistic regression. All models are estimated with robust standard errors clustered by firm.

Table 7

Other Forecasting Attributes

Panel B Variables	**Pred**	**Column 1 Frequency**	**Column 2 Precision**
Growth	-	0.317	0.339
		(0.866)	(0.924)
IndCon	+	3.300**	0.943*
		(0.014)	(0.073)
Big4	?	-0.031	-0.175
		(0.889)	(0.471)
LnAnalysts	+	0.570***	0.109
		(0.000)	(0.125)
Std_AF	-	-0.062**	0.021
		(0.032)	(0.876)
High Tech	?	-0.352**	-0.046
		(0.035)	(0.754)
News	-		0.210
			(0.830)
Horizon	-		-0.000
			(0.246)
Year Indicators		Included	Included
Number of observations		3,882	18,151
Adjusted or Pseudo R2		0.081	0.007
F-Statistic or Chi2 Statistic		9.931***	35.240**

The dependent variable for column 1 is the number of annual forecasts the firm makes for fiscal year t. The dependent variable for column 2 is set to 3 if the forecast is a point forecast, 2 if a range forecast, 1 if an open-ended forecast, and 0 otherwise. The dependent variable for column 3 is set to 1 if the forecast is a point forecast and 0 otherwise. The dependent variable is the forecast bias of the management forecast, (realized earnings less the management forecast) / lagged stock price.*** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available firm year observations. The sample for columns 2-4 includes all forecasts with the necessary data. The model for columns 1 and 4 are estimated using ordinary least squares regressions. Column 2 utilizes and ordered logistic regression. Column 3 utilizes a logistic regression. All models are estimated with robust standard errors clustered by firm.

Table 7
Other Forecasting Attributes

Variables	**Pred**	**Column 3** **PointF**	**Column 4** **Bias**
Intercept	?	-2.546***	0.015***
		(0.000)	(0.000)
IT Expert	+	0.403	-0.001
		(0.136)	(0.340)
Financial Exp	+	-0.239	0.001
		(0.880)	(0.746)
LnAT	+	0.072	-0.001*
		(0.188)	(0.071)
Loss	-	0.461	0.027***
		(0.983)	(0.000)
Leverage	-	-0.978**	0.000
		(0.043)	(0.945)
EarnVol	-	0.000	-0.014
		(0.995)	(0.290)
CFOVol	-	-0.000	-0.002
		(0.375)	(0.943)
Year Indicators		Included	Included
Number of observations		18,151	16,899
Adjusted or Pseudo R2		0.016	0.361
F-Statistic or Chi2 Statistic		45.460***	12.998***

The dependent variable for column 1 is the number of annual forecasts the firm makes for fiscal year t. The dependent variable for column 2 is set to 3 if the forecast is a point forecast, 2 if a range forecast, 1 if an open-ended forecast, and 0 otherwise. The dependent variable for column 3 is set to 1 if the forecast is a point forecast and 0 otherwise. The dependent variable is the forecast bias of the management forecast, (realized earnings less the management forecast) / lagged stock price.*** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available firm year observations. The sample for columns 2-4 includes all forecasts with the necessary data. The model for columns 1 and 4 are estimated using ordinary least squares regressions. Column 2 utilizes and ordered logistic regression. Column 3 utilizes a logistic regression. All models are estimated with robust standard errors clustered by firm.

Table 7

Other Forecasting Attributes

Panel D Variables	**Pred**	**Column 3 PointF**	**Column 4 Bias**
Growth	-	0.540	-0.016***
		(0.982)	(0.000)
IndCon	+	0.985	-0.006
		(0.113)	(0.340)
Big4	?	-0.129	0.002
		(0.708)	(0.312)
LnAnalysts	+	0.145	-0.001
		(0.144)	(0.390)
Std_AF	-	0.026	0.000
		(0.910)	(0.929)
High Tech	?	-0.049	-0.003**
		(0.785)	(0.019)
News	-	0.771	0.327***
		(0.777)	(0.001)
Horizon	-	-0.001	0.000***
		(0.229)	(0.000)
Year Indicators		Included	Included
Number of observations		18,151	16,899
Adjusted or Pseudo R2		0.016	0.361
F-Statistic or Chi2 Statistic		45.460***	12.998***

The dependent variable for column 1 is the number of annual forecasts the firm makes for fiscal year t. The dependent variable for column 2 is set to 3 if the forecast is a point forecast, 2 if a range forecast, 1 if an open-ended forecast, and 0 otherwise. The dependent variable for column 3 is set to 1 if the forecast is a point forecast and 0 otherwise. The dependent variable is the forecast bias of the management forecast, (realized earnings less the management forecast) / lagged stock price.*** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available firm year observations. The sample for columns 2-4 includes all forecasts with the necessary data. The model for columns 1 and 4 are estimated using ordinary least squares regressions. Column 2 utilizes and ordered logistic regression. Column 3 utilizes a logistic regression. All models are estimated with robust standard errors clustered by firm.

Table 8
Earnings Management

Panel A		**Column 1**	**Column 2**	**Column 3**
Variables	**Pred**	**Just Beat**	**Just Beating Using DAs**	**Misstatement**
Intercept	?	-1.155**	-2.222***	-0.926
		(0.021)	(0.000)	(0.212)
IT Expert	?	0.240	-0.199	-1.161*
		(0.515)	(0.702)	(0.061)
Financial EXP	?	0.086	0.330	-0.162
		(0.624)	(0.144)	(0.544)
LnAT	-	-0.021	0.067	-0.131*
		(0.341)	(0.877)	(0.067)
ROA	+/-	1.694**	2.329	0.370
		(0.036)	(0.966)	(0.632)
Leverage	+	-0.435	-0.084	-0.354
		(0.863)	(0.569)	(0.705)
Loss	-/+	0.233	0.318	0.307
		(0.792)	(0.834)	(0.158)
Return	-	-0.646***	-0.547**	-0.517**
		(0.000)	(0.016)	(0.017)
Year Indicators		Included	Included	Included
Number of observations		3,003	1,593	3,529
Pseudo R2		0.035	0.041	0.039
Chi2 Statistic		72.170***	40.360***	54.400***

The dependent variable for column 1 is coded as a 1 if the firm reported earnings than were just above (between 0 and 0.02) the management forecast, and 0 otherwise. The dependent variable for column 2 is coded as a 1 if the firm reported earnings that just above (between 0 and 0.02) the management forecast and their earnings before considering discretionary accruals were below the forecast, and 0 otherwise. The dependent variable for column 3 is coded as 1 if the firm has a material misstatement in year t, and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes the most recent forecast for each firm with all necessary data. The sample for column 2 only includes the most recent annual forecast made before earnings are announced, and is limited to firms whose earnings before discretionary accruals are less than 0.02 above the management forecast. The sample for column 3 includes all available firm year observation. The models are estimated using logistic regressions with robust standard errors clustered by firm.

Table 8
Earnings Management

Panel B		**Column 1**	**Column 2**	**Column 3**
Variables	**Pred**	**Just Beat**	**Just Beating Using DAs**	**Misstatement**
CFO	-	-0.374	-0.879	-1.213
		(0.358)	(0.257)	(0.209)
Merger	+	0.046	0.124	-0.065
		(0.397)	(0.283)	(0.617)
CFOVol	+	-3.913	-1.433	1.770
		(0.896)	(0.619)	(0.343)
EarnVol	+	0.969	0.512	-7.374
		(0.229)	(0.441)	(0.967)
Big4	-	0.314	0.201	0.613
		(0.864)	(0.712)	(0.915)
Horizon	-	-0.005***	-0.005***	
		(0.000)	(0.000)	
High Tech	?	0.131	0.454**	0.492**
		(0.414)	(0.030)	(0.042)
Year Indicators		Included	Included	Included
Number of observations		3,003	1,593	3,529
Pseudo R2		0.035	0.041	0.039
Chi2 Statistic		72.170***	40.360***	54.400***

The dependent variable for column 1 is coded as a 1 if the firm reported earnings than were just above (between 0 and 0.02) the management forecast, and 0 otherwise. The dependent variable for column 2 is coded as a 1 if the firm reported earnings that just above (between 0 and 0.02) the management forecast and their earnings before considering discretionary accruals were below the forecast, and 0 otherwise. The dependent variable for column 3 is coded as 1 if the firm has a material misstatement in year t, and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes the most recent forecast for each firm with all necessary data. The sample for column 2 only includes the most recent annual forecast made before earnings are announced, and is limited to firms whose earnings before discretionary accruals are less than 0.02 above the management forecast. The sample for column 3 includes all available firm year observation. The models are estimated using logistic regressions with robust standard errors clustered by firm.

Table 9
Analyst Forecast Revisions Following Management Forecasts

		Column 1	Column 2
Panel A	**Pred**	**Revise**	**RevisionAmount**
Intercept		2.257***	0.034
		(0.000)	(0.360)
IT Expert	+	0.893***	0.000
		(0.004)	(0.467)
News	+	-1.071	-0.133
		(0.858)	(0.859)
Down	+	-0.372	0.001***
		(0.999)	(0.000)
Horizon	+	0.002***	0.000
		(0.000)	(0.411)
LnAnalysts	?	0.689***	-0.003***
		(0.000)	(0.000)
Range	-	40.429	-0.408
		(0.996)	(0.173)
Loss	-	0.131	0.001
		(0.759)	(0.673)
LnAT	?	-0.137***	0.000*
		(0.001)	(0.101)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted or Psuedo R2		0.031	0.130
F-Statistic or Chi2 Statistic		209.010***	28.110***

The dependent variable for column 1 an indicator variable coded one if there is a revision to the consensus analyst forecast within 15 days following the management forecast, and zero otherwise. The dependent variable for column 2 is the amount of the analyst forecast revision 15 days following the management forecast scaled by lagged stock price. p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for both of the columns utilizes all management forecasts with the necessary data. The model for column 1 utilizes a logistic regression. The model for column 2 is estimated using an ordinary least squares regression. All models are estimated with robust standard errors clustered by firm.

Table 9
Analyst Forecast Revisions Following Management Forecasts

Panel B	Pred	Column 1 Revise	Column 2 RevisionAmount
*News*IT Expert*	+		0.138*
			(0.092)
*News*Down*	+		-0.025
			(0.860)
*News*Horizon*	+		-0.000
			(0.619)
*News*LnAnalysts*	?		0.107***
			(0.006)
*News*Range*	-		0.465
			(0.757)
*News*Loss*	-		-0.208***
			(0.000)
*News*LnAT*	?		-0.014**
			(0.017)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted or Pseudo R2		0.031	0.130
F-Statistic or Chi2 Statistic		209.010***	28.110***

The dependent variable for column 1 an indicator variable coded one if there is a revision to the consensus analyst forecast within 15 days following the management forecast, and zero otherwise. The dependent variable for column 2 is the amount of the analyst forecast revision 15 days following the management forecast scaled by lagged stock price. p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for both of the columns utilizes all management forecasts with the necessary data. The model for column 1 utilizes a logistic regression. The model for column 2 is estimated using an ordinary least squares regression. All models are estimated with robust standard errors clustered by firm.

Table 9
Analyst Forecast Revisions Following Management Forecasts

		Column 3
Panel C	**Pred**	**AFE_Post**
Intercept		0.019***
		(0.001)
IT Expert	-	-0.003**
		(0.025)
Horizon	+	0.000***
		(0.002)
LnAnalysts	-	-0.003**
		(0.049)
Range	+	0.959**
		(0.017)
Loss	+	0.013***
		(0.005)
LnAT	-	0.000
		(0.800)
RevisionAmount	+	-0.204
		(0.790)
ROA	?	-0.076***
		(0.002)
Merger	+	-0.002
		(0.939)
Foreign	+	0.000
		(0.485)
Std_AF_Post	+	0.332
		(0.192)
Year Indicators		Included
Number of observations		16,899
Adjusted R2		0.126
F-Statistic		15.480***

The dependent variable is the analyst forecast error based on the median consensus forecast 15 days following the management forecast scaled by lagged stock price. p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample utilizes all management forecasts with the necessary data. The model is estimated using an ordinary least squares regression. The model is estimated with robust standard errors clustered by firm.

Table 10

Self-Selection Bias

Panel A **Variables**	**Column 1** **IT Expert**	**Column 2** **IT Expert**	**Column 3** **IT Expert**
Intercept	-1.266***	-1.447***	-0.308
	(0.000)	(0.000)	(0.408)
LnAT	-0.083***	-0.057	0.013
	(0.000)	(0.113)	(0.737)
ROA	1.058***	0.544	1.174*
	(0.002)	(0.422)	(0.059)
Leverage	-0.440***	-0.583**	0.130
	(0.000)	(0.024)	(0.555)
High Tech	0.365***	0.402***	0.145
	(0.000)	(0.000)	(0.181)
CIO	0.173***	0.208*	0.367***
	(0.003)	(0.073)	(0.002)
ITWeak	0.058	0.175	0.027
	(0.848)	(0.720)	(0.964)
SalesVol	0.003*	0.001	0.091***
	(0.095)	(0.761)	(0.002)
Number of observations	16,899	3,529	900
Pseudo R2	0.103	0.091	0.066
Chi2 Statistic	439.500***	91.590***	83.810***

The dependent variable is an indicator variable coded as one if the company employs a CEO with IT Expertise in year t, and zero otherwise. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions.

Table 10
Self-Selection Bias

Panel B **Variables**	**Column 1** **IT Expert**	**Column 2** **IT Expert**	**Column 3** **IT Expert**
Std_Return	0.012	0.013	0.364
	(0.790)	(0.869)	(0.135)
Foreign	0.077*	0.069	0.012
	(0.090)	(0.459)	(0.902)
Merger	-0.274***	-0.257*	-0.502***
	(0.000)	(0.065)	(0.000)
Restruct	-0.060	-0.023	-0.248**
	(0.208)	(0.818)	(0.014)
Product_Diff	0.598**	0.642	0.494
	(0.028)	(0.257)	(0.361)
Cost_Leader	-0.194***	-0.097	-0.179*
	(0.001)	(0.348)	(0.067)
Transform	0.351***	0.283***	-0.036
	(0.000)	(0.005)	(0.725)
Number of observations	16,899	3,529	900
Pseudo R2	0.103	0.091	0.066
Chi2 Statistic	439.500***	91.590***	83.810***

The dependent variable is an indicator variable coded as one if the company employs a CEO with IT Expertise in year t, and zero otherwise. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions.

Table 10
Self-Selection Bias

Panel C **Variables**	**Pred**	**Column 1** **Absolute Forecast Error**	**Column 2** **Absolute Forecast Error**	**Column 3** **Absolute Forecast Error**
Intercept	?	0.008	0.004	0.009*
		(0.131)	(0.679)	(0.052)
IT Expert	-	-0.004**	-0.004**	-0.002***
		(0.016)	(0.043)	(0.007)
Financial Exp	-	-0.001	-0.001	-0.002**
		(0.267)	(0.248)	(0.050)
LnAT	-	-0.002*	-0.001*	-0.000
		(0.026)	(0.089)	(0.173)
ROA	-	-0.068***	-0.093***	-0.014*
		(0.006)	(0.008)	(0.120)
Loss	+	0.007**	0.014**	0.007
		(0.028)	(0.005)	(0.106)
Leverage	+	-0.002	-0.004	-0.002
		(0.743)	(0.835)	(0.882)
EarnVol	+	-0.002	-0.008	0.004
		(0.551)	(0.690)	(0.314)
CFOVol	+	0.039	0.051	0.007
		(0.160)	(0.129)	(0.316)
Year Indicators		Included	Included	Included
Number of observations		16,899	3,529	900
Adjusted R2		0.332	0.343	0.252
F-Statistic		6.930***	10.870***	7.930***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 10

Self-Selection Bias

Panel D **Variables**	**Pred**	**Column 1** **Absolute Forecast Error**	**Column 2** **Absolute Forecast Error**	**Column 3** **Absolute Forecast Error**
Growth	+	-0.005	-0.004	-0.004
		(0.978)	(0.853)	(0.784)
IndCon	-	-0.003	-0.002	0.034
		(0.318)	(0.378)	(0.250)
Big4	?	0.004***	0.005***	-0.001
		(0.007)	(0.016)	(0.598)
LnAnalysts	-	0.000	-0.001	-0.001**
		(0.560)	(0.157)	(0.092)
Std_AF	+	0.001	0.002	0.019***
		(0.213)	(0.006)	(0.001)
News	-	-0.281***	-0.256***	0.295***
		(0.000)	(0.000)	(0.998)
Horizon	+	0.000***	0.000***	0.000***
		(0.000)	(0.001)	(0.000)
Litigation	-	-0.004**	-0.004**	0.001
		(0.058)	(0.157)	(0.767)
High Tech	?	0.001	0.001	-0.001
		(0.751)	(0.803)	(0.396)
Weak	+	0.008**	0.005**	-0.000
		(0.047)	(0.158)	(0.555)
IMR	?	0.006**	0.006	0.004
		(0.012)	(0.216)	(0.192)
Year Indicators		Included	Included	Included
Number of observations		16,899	3,529	900
Adjusted R2		0.332	0.343	0.252
F-Statistic		6.930***	10.870***	7.930***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 11
Quarterly Forecasts

Panel A		**Column 1**	**Column 2**
Variables	**Pred**	**Issued Quarterly Forecast**	**Absolute Forecast Error**
Intercept		1.326***	0.001
		(0.004)	(0.622)
IT Expert	+/-	0.348	-0.001**
		(0.170)	(0.027)
Financial Exp	+/-	-0.024	-0.001***
		(0.558)	(0.005)
LnAT	+/-	-0.001	0.000
		(0.506)	(0.914)
ROA	-		-0.006*
			(0.069)
Loss	-/+	-0.005	0.000
		(0.487)	(0.348)
Leverage	-/+	-0.904***	-0.000
		(0.007)	(0.646)
EarnVol	-/+	-1.114	0.000
		(0.245)	(0.471)
CFOVol	-/+	0.596	0.022**
		(0.589)	(0.049)
Year Indicators		Included	Included
Number of observations		3,529	8,036
Adjusted or Pseudo R2		0.028	0.493
F-Statistic or Chi2 Statistic		95.090***	10.870***

The dependent variable in column 1 is an indicator coded as one if the firm issues any quarterly forecasts in year t and zero otherwise. The dependent variable in column 2 is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes all firm year observations. The sample for column 2 includes all available quarterly forecasts. The model in column 1 utilizes a logistic regression. The model in column 2 is estimated using an ordinary least squares regression. Both models are estimated with robust standard errors clustered by company.

Table 11
Quarterly Forecasts

Panel B		**Column 1**	**Column 2**
Variables	**Pred**	**Issued Quarterly Forecast**	**Absolute Forecast Error**
Growth	-/+	-0.021	0.003**
		(0.465)	(0.036)
IndCon	+/-	-1.967	0.003
		(0.992)	(0.762)
Big4	?	0.216	0.002***
		(0.429)	(0.001)
LnAnalysts	-		-0.001***
			(0.000)
Std_AF	+		0.005
			(0.386)
News	-		-0.468***
			(0.000)
Horizon	+		0.000***
			(0.004)
Litigation	-		0.000
			(0.570)
High Tech	?	0.005	-0.002**
		(0.971)	(0.024)
Weak	+		-0.000
			(0.652)
Year Indicators		Included	Included
Number of observations		3,529	8,036
Adjusted or Pseudo R2		0.028	0.493
F-Statistic or Chi2 Statistic		95.090***	10.870***

The dependent variable in column 1 is an indicator coded as one if the firm issues any quarterly forecasts in year t and zero otherwise. The dependent variable in column 2 is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for column 1 only includes all firm year observations. The sample for column 2 includes all available quarterly forecasts. The model in column 1 utilizes a logistic regression. The model in column 2 is estimated using an ordinary least squares regression. Both models are estimated with robust standard errors clustered by company.

Table 11
Quarterly Forecasts

Panel C		**Column 1**	**Column 2**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Intercept	?	0.003*	0.000
		(0.082)	(0.917)
IT Expert	-	-0.000	-0.001**
		(0.233)	(0.033)
Financial Exp	-	-0.000	-0.001**
		(0.346)	(0.039)
LnAT	-	0.000	0.001
		(0.992)	(0.935)
ROA	-	-0.006**	-0.004
		(0.023)	(0.195)
Loss	+	-0.003	0.003
		(0.136)	(0.127)
Leverage	+	-0.001	-0.001
		(0.891)	(0.689)
EarnVol	+	0.009*	-0.001
		(0.079)	(0.573)
CFOVol	+	0.016	0.011
		(0.118)	(0.248)
Year Indicators		Included	Included
Number of observations		1,927	2,085
Adjusted R2		0.308	0.649
F-Statistic		3.317***	51.666***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for each column uses forecasts for each fiscal quarter (column 1 is for Q1, column 2 is for Q2, and so forth). The models are estimated using an ordinary least squares regression with robust standard errors clustered by company.

Table 11

Quarterly Forecasts

Panel D		Column 1	Column 2
Variables	Pred	Absolute Forecast Error	Absolute Forecast Error
Growth	+	0.003*	0.004***
		(0.099)	(0.003)
IndCon	-	-0.002	-0.004
		(0.271)	(0.203)
Big4	?	0.000	0.002***
		(0.647)	(0.002)
LnAnalysts	-	-0.001***	-0.002***
		(0.000)	(0.007)
Std_AF	+	0.031***	0.027*
		(0.008)	(0.068)
News	-	-0.414**	-0.470***
		(0.039)	(0.000)
Horizon	+	-0.000	0.000
		(0.923)	(0.170)
Litigation	-	0.000	0.001
		(0.657)	(0.811)
High Tech	?	-0.001*	-0.002**
		(0.081)	(0.021)
Weak	+	-0.000	0.001
		(0.676)	(0.297)
Year Indicators		Included	Included
Number of observations		1,927	2,085
Adjusted R2		0.308	0.649
F-Statistic		3.317***	51.666***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for each column uses forecasts for each fiscal quarter (column 1 is for Q1, column 2 is for Q2, and so forth). The models are estimated using an ordinary least squares regression with robust standard errors clustered by company.

Table 11

Quarterly Forecasts

Panel E Variables	Pred	Column 3 Absolute Forecast Error	Column 4 Absolute Forecast Error
Intercept	?	-0.000	0.002
		(0.963)	(0.499)
IT Expert	-	-0.001**	-0.001*
		(0.032)	(0.093)
Financial Exp	-	-0.001**	-0.003***
		(0.019)	(0.008)
LnAT	-	0.001	0.000
		(0.937)	(0.703)
ROA	-	-0.002	-0.006
		(0.328)	(0.220)
Loss	+	0.001	0.001
		(0.127)	(0.387)
Leverage	+	0.000	-0.002
		(0.426)	(0.721)
EarnVol	+	-0.002	-0.008
		(0.616)	(0.708)
CFOVol	+	0.016	0.047**
		(0.136)	(0.040)
Year Indicators		Included	Included
Number of observations		2,081	1,937
Adjusted R2		0.745	0.181
F-Statistic		6.888***	4.299***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for each column uses forecasts for each fiscal quarter (column 1 is for Q1, column 2 is for Q2, and so forth). The models are estimated using an ordinary least squares regression with robust standard errors clustered by company.

Table 11

Quarterly Forecasts

Panel F		**Column 3**	**Column 4**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Growth	+	0.005**	0.002
		(0.038)	(0.242)
IndCon	-	0.002	0.020
		(0.622)	(0.992)
Big4	?	0.001	0.004***
		(0.362)	(0.010)
LnAnalysts	-	-0.001**	-0.002***
		(0.010)	(0.005)
Std_AF	+	-0.036	0.045**
		(0.747)	(0.024)
News	-	-0.549***	-0.528***
		(0.002)	(0.002)
Horizon	+	0.000***	0.000
		(0.003)	(0.228)
Litigation	-	-0.000	0.000
		(0.301)	(0.616)
High Tech	?	-0.001	-0.002
		(0.124)	(0.127)
Weak	+	-0.001	-0.002
		(0.818)	(0.959)
Year Indicators		Included	Included
Number of observations		2,081	1,937
Adjusted R2		0.745	0.181
F-Statistic		6.888***	4.299***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The p-values are listed in parentheses under the coefficient. The sample for each column uses forecasts for each fiscal quarter (column 1 is for Q1, column 2 is for Q2, and so forth). The models are estimated using an ordinary least squares regression with robust standard errors clustered by company.

Table 12
Presence of CIO

Panel A **Variables**	**Pred**	**Column 1 Absolute Forecast Error**	**Column 2 Absolute Forecast Error**	**Column 3 Absolute Forecast Error**
Intercept		0.018***	0.014***	0.013***
		(0.000)	(0.007)	(0.001)
IT Expert	-	-0.004***	-0.004**	-0.002***
		(0.005)	(0.023)	(0.004)
CIO	-	-0.000	0.001	-0.001
		(0.432)	(0.342)	(0.156)
Financial Exp	-	-0.001	-0.002	-0.002**
		(0.199)	(0.197)	(0.038)
LnAT	-	-0.001*	-0.001	-0.001
		(0.068)	(0.143)	(0.157)
ROA	-	-0.076***	-0.097***	-0.017*
		(0.002)	(0.005)	(0.078)
Loss	+	0.008**	0.014***	0.007
		(0.021)	(0.005)	(0.105)
Leverage	+	0.000	-0.001	-0.001
		(0.449)	(0.644)	(0.766)
EarnVol	+	-0.004	-0.008	0.003
		(0.611)	(0.705)	(0.365)
CFOVol	+	0.046	0.054	0.005
		(0.114)	(0.113)	(0.380)
Year Indicators		Included	Included	Included
Number of observations		16,899	3,529	900
Adjusted R2		0.330	0.342	0.250
F-Statistic		7.200***	10.940***	8.200***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 12
Presence of CIO

Panel B Variables	Pred	Column 1 Absolute Forecast Error	Column 2 Absolute Forecast Error	Column 3 Absolute Forecast Error
Growth	+	-0.005	-0.004	-0.004
		(0.978)	(0.834)	(0.808)
IndCon	-	-0.003	-0.002	0.034
		(0.324)	(0.403)	(0.749)
Big4	?	0.004***	0.005**	-0.001
		(0.007)	(0.017)	(0.633)
LnAnalysts	-	0.000	-0.001	-0.001*
		(0.576)	(0.134)	(0.055)
Std_AF	+	0.001	0.002***	0.019***
		(0.202)	(0.006)	(0.001)
News	-	-0.279***	-0.255***	0.303
		(0.000)	(0.000)	(0.998)
Horizon	+	0.000***	0.000***	0.000***
		(0.000)	(0.001)	(0.000)
Litigation	-	-0.005**	-0.004	0.002
		(0.033)	(0.136)	(0.804)
High Tech	?	-0.002	-0.001	-0.002
		(0.484)	(0.696)	(0.203)
Weak	+	0.008**	0.004	-0.000
		(0.044)	(0.177)	(0.560)
Year Indicators		Included	Included	Included
Number of observations		16,899	3,529	900
Adjusted R2		0.330	0.342	0.250
F-Statistic		7.200***	10.940***	8.200***

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for column 1 includes all available forecasts. All of the variables for column 2, including the dependent variable, are the averages for each company year. The sample for column 3 utilizes a matched sample as discussed in the research design section. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 13
Likelihood of a Material Weakness in Internal Controls

		Column 1	Column 2	Column 3
Variables	**Pred**	**Weakness**	**IT Weakness**	**Non-IT Weakness**
Intercept		-0.180	-1.095	-0.764
		(0.802)	(0.328)	(0.332)
IT Expert	-	-0.457	0.059	-0.616
		(0.202)	(0.530)	(0.195)
Financial Exp	-	0.012	0.200	-0.024
		(0.518)	(0.633)	(0.464)
LnAT	-	-0.246***	-0.444***	-0.209**
		(0.006)	(0.003)	(0.022)
ROA	-	-3.232***	-1.314	-3.162***
		(0.002)	(0.207)	(0.004)
Big4	-	-0.498**	-1.480***	-0.150
		(0.049)	(0.004)	(0.341)
Leverage	+	0.766*	1.783**	0.526
		(0.059)	(0.014)	(0.163)
Loss	+	0.564**	0.645	0.568**
		(0.043)	(0.213)	(0.048)
Growth	+	-0.151	0.070	-0.189
		(0.636)	(0.460)	(0.648)
Segment	+	0.011	0.018	0.010
		(0.292)	(0.325)	(0.312)
Foreign	+	0.419**	0.866**	0.321*
		(0.013)	(0.032)	(0.054)
Merger	+	0.103	0.459	0.036
		(0.345)	(0.214)	(0.448)
Hightech	?	0.538**	0.208	0.563**
		(0.029)	(0.709)	(0.023)
Year Indicators		Included	Included	Included
Number of observations		3,529	3,529	3,529
Pseudo R2		0.142	0.118	0.139
Chi2 Statistic		156.640***	74.810***	146.890***

The dependent variable is coded as a 1 if the company reported a material weakness of the specified type in year t, and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for all of the columns includes all available company-year observations. The models are estimated using logistic regressions with robust standard errors clustered by company.

Table 14

Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel A: Variables of Interest		**Column 1**	**Column 2**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
IT Expert	-	-0.004***	-0.004***
		(0.013)	(0.007)
Weak	+	0.009**	
		(0.037)	
*Weak*IT Expert*	?	-0.032***	
		(0.050)	
ITWeak	+		0.008
			(0.169)
*ITWeak*IT Expert*	?		-0.098***
			(0.000)
NonITWeak	+		
*NonITWeak*IT Expert*	?		
Test *Weak + Weak * IT Expert = 0*		2.370	
		(0.124)	
Test *ITWeak + ITWeak * IT Expert = 0*			19.640***
			(0.000)
Test *NonITWeak + NonITWeak * IT Expert = 0*			

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for all of the columns includes all available forecasts. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 14
Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel A Cont.: Variables of Interest		**Column 3**	**Column 4**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
IT Expert	-	-0.004***	-0.004***
		(0.008)	(0.014)
Weak	+		
*Weak*IT Expert*	?		
ITWeak	+		0.009
			(0.150)
*ITWeak*IT Expert*	?		-0.097***
			(0.000)
NonITWeak	+	0.009*	0.009*
		(0.058)	(0.058)
*NonITWeak*IT Expert*	?	-0.016**	-0.016**
		(0.031)	(0.027)
Test *Weak + Weak * IT Expert = 0*			
Test *ITWeak + ITWeak * IT Expert = 0*			19.620***
			(0.000)
Test *NonITWeak + NonITWeak * IT Expert = 0*		1.340	1.510
		(0.247)	(0.219)

The dependent variable is forecast error measured as the absolute value of management forecast error, (realized earnings less the management forecast amount)/lagged stock price. *** p<0.01, ** p<0.05, * p<0.10. The p-values are listed in parentheses under the coefficient. The sample for all of the columns includes all available forecasts. The models are estimated using ordinary least squares regressions with robust standard errors clustered by company.

Table 14
Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel B: Control Variables		**Column 1**	**Column 2**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Intercept		0.018***	0.020***
		(0.000)	(0.000)
Financial Exp	-	-0.001	-0.001
		(0.192)	(0.196)
LnAT	-	-0.001*	-0.001*
		(0.066)	(0.054)
ROA	-	(-0.077)	(-0.081)
		(0.002)	(0.001)
Loss	+	0.008***	0.008***
		(0.021)	(0.026)
Leverage	+	0.000	0.001
		(0.453)	(0.422)
EarnVol	+	-0.005	-0.005
		(0.623)	(0.637)
CFOVol	+	0.046	0.048
		(0.117)	(0.109)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.331	0.329
F-Statistic		7.117***	7.800***

Table 14
Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel B Cont.: Control Variables		**Column 1**	**Column 2**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Growth	+	-0.005	-0.005
		(0.980)	(0.978)
IndCon	-	-0.003	-0.004
		(0.320)	(0.303)
Big4	?	0.004***	0.004***
		(0.008)	(0.009)
LnAnalysts	-	0.000	0.000
		(0.596)	(0.597)
Std_AF	+	0.001	0.001
		(0.202)	(0.207)
News	-	-0.279***	-0.280***
		(0.000)	(0.000)
Horizon	+	0.000***	0.000***
		(0.000)	(0.000)
Litigation	-	(-0.005)	(-0.005)
		(0.033)	(0.036)
High Tech	?	-0.002***	-0.001***
		(0.483)	(0.518)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.331	0.329
F-Statistic		7.117***	7.800***

Table 14

Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel B Cont.: Control Variables		**Column 3**	**Column 4**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Intercept		0.018***	0.018***
		(0.000)	(0.000)
Financial Exp	-	-0.001	-0.001
		(0.196)	(0.191)
LnAT	-	-0.001*	-0.001*
		(0.065)	(0.064)
ROA	-	(-0.077)	(-0.078)
		(0.002)	(0.001)
Loss	+	0.008***	0.008***
		(0.021)	(0.025)
Leverage	+	0.000	0.000
		(0.437)	(0.459)
EarnVol	+	-0.004	-0.005
		(0.614)	(0.626)
CFOVol	+	0.045	0.046
		(0.119)	(0.114)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.330	0.331
F-Statistic		7.063***	7.700***

Table 14
Management Earnings Forecast Error and Material Weaknesses in Internal Controls

Panel B Cont.: Control Variables		**Column 3**	**Column 4**
Variables	**Pred**	**Absolute Forecast Error**	**Absolute Forecast Error**
Growth	+	-0.005	-0.005
		(0.979)	(0.979)
IndCon	-	-0.003	-0.003
		(0.324)	(0.317)
Big4	?	0.004***	0.004***
		(0.009)	(0.010)
LnAnalysts	-	0.000	0.000
		(0.574)	(0.610)
Std_AF	+	0.001	0.001
		(0.203)	(0.203)
News	-	-0.279***	-0.280***
		(0.000)	(0.000)
Horizon	+	0.000***	0.000***
		(0.000)	(0.000)
Litigation	-	(-0.005)	(-0.005)
		(0.032)	(0.032)
High Tech	?	-0.002***	-0.002***
		(0.484)	(0.480)
Year Indicators		Included	Included
Number of observations		16,899	16,899
Adjusted R2		0.330	0.331
F-Statistic		7.063***	7.700***

Appendix The Calculation of *Just Beat* and *Just Beat with DAs*

I use earnings management measures similar to those used by Dorantes et al. (2013), and therefore I adapt their measures as follows.

I consider a firm to *Just Beat* if reported earnings per share are between 0.00 and 0.02 greater than the management forecast of earnings.

I calculate discretionary accruals using the modified Jones (1991) approach (Dechow et al. 1995). Following Francis et al. (2008), I estimate the cross-sectional regression model below for each of the Fama-French (1997) 48 industry groups. I require each industry group to have at least 20 firms in year *t*. The models is as follows:

$$\frac{TA_{j,t}}{Asset_{j,t-1}} = K_1 \frac{1}{Asset_{j,t-1}} + K_2 \frac{\Delta Rev_{j,t}}{Asset_{j,t-1}} + K_3 \frac{PPE_{j,t}}{Asset_{j,t-1}} + \varepsilon_{j,t}$$

(7)

where:

$TA_{j,t}$ = firm *j*'s total accruals in year *t*, measured as ($\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t}$).

$\Delta CA_{j,t}$ = firm j's change in current assets between year t-1 and year t;

$\Delta CL_{j,t}$ = firm j's change in current liabilities between year t-1 and year t;

$\Delta Cash_{j,t}$ = firm j's change in cash between year t-1 and year t;

$\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities between year t-1 and year t;

$DEPN_{j,t}$ = firm j's depreciation and amortization expense in year t.

$Asset_{j,t-1}$ = firm *j*'s total assets at the beginning of year *t*.

$\Delta Rev_{j,t}$ = firm *j*'s change in revenues between year $t-1$ and year *t*.

$PPE_{j,t}$ = firm *j*'s gross value of property, plant, and equipment in year *t*.

I then use the industry and year specific parameter estimates obtained from Model (7) to estimate firm-specific normal accruals (*NA*) as a percentage of lagged total assets:

$$NA_{j,t} = \widehat{K}_1 \frac{1}{Asset_{j,t-1}} + \widehat{K}_2 \frac{(\Delta Rev_{j,t} - \Delta AR_{j,t})}{Asset_{j,t-1}} + \widehat{K}_3 \frac{PPE_{j,t}}{Asset_{j,t-1}},$$

(8)

Where:

$\Delta AR_{j,t}$ = firm *j*'s change in accounts receivable between year $t-1$ and year *t*.

Abnormal discretionary accruals in year t is then calculated as $Abnormal\ DA_{j,t} = TA_{j,t} / Asset_{j,t-1} - NA_{j,t}$. Following Kothari et al. (2005), I performance match the absolute value of $Abnormal\ DA_{j,t}$ based on firms' *ROA*. I then calculate each firm's reported earnings before discretionary accruals. A firm is considered to *Just Beat with DAs*, if their earnings before discretionary accruals is below the management forecasted amounts, but the addition of discretionary accruals places them in the *Just Beat* position.